```
In [36]: | from keras import layers
         from keras import models
         from keras.datasets import mnist
         from keras.utils import to_categorical
         import matplotlib.pyplot as plt
         import numpy as np
         (train_images, train_labels), (test_images, test_labels) = mnist.load_data()
In [37]: | model = models.Sequential()
         model.add(layers.Conv2D(32, (3, 3), activation = 'relu', input_shape = (28, 28
         , 1)))
         model.add(layers.MaxPooling2D((2, 2)))
         model.add(layers.Conv2D(64, (3, 3), activation = 'relu'))
         model.add(layers.MaxPooling2D((2, 2)))
         model.add(layers.Conv2D(64, (3, 3), activation = 'relu'))
         model.add(layers.Flatten())
         model.add(layers.Dense(64, activation = 'relu'))
         model.add(layers.Dense(10, activation = 'softmax'))
```

## In [38]: model.summary()

Model: "sequential\_5"

Layer (type)	Output	Shape	Param #
conv2d_15 (Conv2D)	(None,	26, 26, 32)	320
max_pooling2d_10 (MaxPooling	(None,	13, 13, 32)	0
conv2d_16 (Conv2D)	(None,	11, 11, 64)	18496
max_pooling2d_11 (MaxPooling	(None,	5, 5, 64)	0
conv2d_17 (Conv2D)	(None,	3, 3, 64)	36928
flatten_4 (Flatten)	(None,	576)	0
dense_8 (Dense)	(None,	64)	36928
dense_9 (Dense)	(None,	10)	650
	=====	=======================================	======

Total params: 93,322 Trainable params: 93,322 Non-trainable params: 0

```
In [39]: | train_images = train_images.reshape((60000, 28, 28, 1))
         train images = train_images.astype('float32') / 255
         test images = test images.reshape((10000, 28, 28, 1))
         test_images = test_images.astype('float32') / 255
         train_labels = to_categorical(train_labels)
         test_labels = to_categorical(test_labels)
         x_val = train_images[:1000]
         y_val = train_labels[:1000]
         partial_x_train = train_images[1000:]
         partial_y_train = train_labels[1000:]
         #x_train = vectorize_sequences(train_images)
         #x_test = vectorize_sequences(test_images)
         #y train = np.asarray(train labels).astype('float32')
         #y test = np.asarray(test labels).astype('float32')
         model.compile(optimizer = 'rmsprop', loss = 'categorical_crossentropy', metric
         s = ['accuracy'])
         history = model.fit(partial_x_train,
                             partial y train,
                             epochs = 20,
                             batch_size = 64,
                             validation_data = (x_val, y_val))
         #test loss, test acc = model.evaluate(test images, test labels)
```

```
Epoch 1/20
922/922 [========================] - 12s 13ms/step - loss: 0.1700 - acc
uracy: 0.9466 - val_loss: 0.0975 - val_accuracy: 0.9790
922/922 [======================== ] - 12s 13ms/step - loss: 0.0468 - acc
uracy: 0.9850 - val_loss: 0.0861 - val_accuracy: 0.9860
Epoch 3/20
922/922 [================= ] - 12s 13ms/step - loss: 0.0320 - acc
uracy: 0.9901 - val_loss: 0.0668 - val_accuracy: 0.9880
Epoch 4/20
uracy: 0.9926 - val_loss: 0.0516 - val_accuracy: 0.9900
Epoch 5/20
922/922 [================== ] - 12s 13ms/step - loss: 0.0189 - acc
uracy: 0.9941 - val_loss: 0.0661 - val_accuracy: 0.9880
Epoch 6/20
uracy: 0.9949 - val_loss: 0.0554 - val_accuracy: 0.9870
Epoch 7/20
922/922 [================== ] - 12s 13ms/step - loss: 0.0120 - acc
uracy: 0.9959 - val_loss: 0.0474 - val_accuracy: 0.9900
922/922 [========================= ] - 12s 13ms/step - loss: 0.0103 - acc
uracy: 0.9968 - val loss: 0.0620 - val accuracy: 0.9870
Epoch 9/20
922/922 [======================== ] - 12s 13ms/step - loss: 0.0091 - acc
uracy: 0.9973 - val loss: 0.0615 - val accuracy: 0.9890
Epoch 10/20
922/922 [=================== ] - 12s 13ms/step - loss: 0.0075 - acc
uracy: 0.9976 - val loss: 0.1149 - val accuracy: 0.9890
Epoch 11/20
922/922 [======================== ] - 12s 13ms/step - loss: 0.0064 - acc
uracy: 0.9980 - val_loss: 0.0965 - val_accuracy: 0.9880
Epoch 12/20
922/922 [================== ] - 12s 13ms/step - loss: 0.0061 - acc
uracy: 0.9982 - val loss: 0.0850 - val accuracy: 0.9880
Epoch 13/20
922/922 [=================== ] - 12s 13ms/step - loss: 0.0054 - acc
uracy: 0.9984 - val_loss: 0.1128 - val_accuracy: 0.9890
Epoch 14/20
uracy: 0.9985 - val_loss: 0.1155 - val_accuracy: 0.9910
Epoch 15/20
922/922 [================== ] - 12s 13ms/step - loss: 0.0047 - acc
uracy: 0.9987 - val_loss: 0.0951 - val_accuracy: 0.9910
Epoch 16/20
922/922 [======================== ] - 12s 13ms/step - loss: 0.0039 - acc
uracy: 0.9986 - val_loss: 0.1215 - val_accuracy: 0.9880
Epoch 17/20
922/922 [================== ] - 12s 13ms/step - loss: 0.0035 - acc
uracy: 0.9991 - val_loss: 0.1201 - val_accuracy: 0.9920
Epoch 18/20
922/922 [======================== ] - 12s 13ms/step - loss: 0.0043 - acc
uracy: 0.9989 - val_loss: 0.1147 - val_accuracy: 0.9870
Epoch 19/20
922/922 [======================== ] - 12s 13ms/step - loss: 0.0036 - acc
uracy: 0.9989 - val_loss: 0.1253 - val_accuracy: 0.9920
```

In [35]:

```
Out[35]: array([[[[0.],
                      [0.],
                      [0.],
                      . . . ,
                      [0.],
                      [0.],
                      [0.]],
                     [[0.],
                      [0.],
                      [0.],
                      . . . ,
                      [0.],
                      [0.],
                      [0.]],
                     [[0.],
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                      [0.],
                      [0.],
                      [0.]],
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                      [0.],
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                      . . . ,
                      [0.],
                      [0.],
                      [0.]]],
                   [[[0.],
                      [0.],
                      [0.],
                      . . . ,
                      [0.],
```

[0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], . . . , [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]]], [[[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.],

. . . ,

[0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], . . . , [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]]], . . . , [[[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], ..., [0.], [0.],

[0.]],

[[0.], [0.], [0.], . . . , [0.], [0.], [0.]], . . . , [[0.], [0.], [0.], ..., [0.], [0.], [0.]], [[0.], [0.], [0.], ..., [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]]], [[[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . ,

[0.],

[0.], [0.]], . . . , [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]]], [[[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], [[0.], [0.], [0.], . . . , [0.], [0.], [0.]], . . . ,

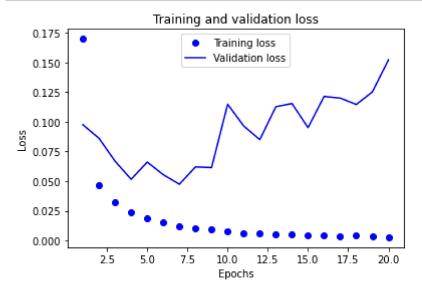
[[0.],

```
[0.],
                   [0.],
                   . . . ,
                   [0.],
                   [0.],
                   [0.]],
                  [[0.],
                   [0.],
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                   . . . ,
                   [0.],
                   [0.],
                   [0.]],
                  [[0.],
                   [0.],
                   [0.],
                   . . . ,
                   [0.],
                   [0.],
                   [0.]]]], dtype=float32)
In [43]: history_dict = history.history
          loss values = history dict['loss']
          accuracy values = history dict['accuracy']
          val_accuracy_values = history_dict['val_accuracy']
          val_loss_values = history_dict['val_loss']
          #print(history_dict['binary_accuracy'])
          print(history_dict.keys())
          dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
In [44]: epochs = range(1, len(accuracy_values) + 1)

plt.plot(epochs, loss_values, 'bo', label = 'Training loss')
plt.plot(epochs, val_loss_values, 'b', label = 'Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

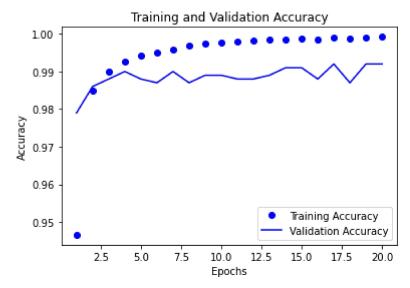
plt.show()
```



```
In [45]: plt.clf()

plt.plot(epochs, accuracy_values, 'bo', label = 'Training Accuracy')
    plt.plot(epochs, val_accuracy_values, 'b', label = 'Validation Accuracy')
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

plt.show()
```



```
In [46]: | model = models.Sequential()
        model.add(layers.Conv2D(32, (3, 3), activation = 'relu', input_shape = (28, 28
        , 1)))
        model.add(layers.MaxPooling2D((2, 2)))
        model.add(layers.Conv2D(64, (3, 3), activation = 'relu'))
        model.add(layers.MaxPooling2D((2, 2)))
        model.add(layers.Conv2D(64, (3, 3), activation = 'relu'))
        model.add(layers.Flatten())
        model.add(layers.Dense(64, activation = 'relu'))
        model.add(layers.Dense(10, activation = 'softmax'))
In [47]: | model.compile(optimizer = 'rmsprop', loss = 'categorical_crossentropy', metric
        s = ['accuracy'])
        history = model.fit(partial x train,
                          partial_y_train,
                          epochs = 7,
                          batch size = 64,
                          validation_data = (x_val, y_val))
        Epoch 1/7
        uracy: 0.9494 - val_loss: 0.1173 - val_accuracy: 0.9690
        Epoch 2/7
        922/922 [=============== ] - 12s 13ms/step - loss: 0.0474 - acc
        uracy: 0.9858 - val loss: 0.0555 - val accuracy: 0.9870
        Epoch 3/7
        922/922 [================= ] - 12s 13ms/step - loss: 0.0322 - acc
        uracy: 0.9901 - val loss: 0.0613 - val accuracy: 0.9860
        Epoch 4/7
        922/922 [================ ] - 12s 13ms/step - loss: 0.0238 - acc
        uracy: 0.9927 - val loss: 0.0723 - val accuracy: 0.9820
        Epoch 5/7
        922/922 [=================== ] - 12s 13ms/step - loss: 0.0193 - acc
        uracy: 0.9944 - val loss: 0.0563 - val accuracy: 0.9850
        Epoch 6/7
        922/922 [=============== ] - 12s 13ms/step - loss: 0.0158 - acc
        uracy: 0.9951 - val loss: 0.0591 - val accuracy: 0.9910
        922/922 [======================== ] - 12s 13ms/step - loss: 0.0134 - acc
        uracy: 0.9961 - val loss: 0.0607 - val accuracy: 0.9870
In [48]: results = model.evaluate(test_images, test_labels)
        313/313 [========================= ] - 1s 4ms/step - loss: 0.0359 - accur
        acy: 0.9908
In [49]: results
Out[49]: [0.035931408405303955, 0.9908000230789185]
In [ ]:
```