

```

1 import numpy as np
2 from keras.models import Sequential
3 from keras.layers import Dense, Dropout, Flatten, BatchNormalization, Activation
4 from keras.layers.convolutional import Conv2D, MaxPooling2D
5 from keras.utils import np_utils
6 from keras.datasets import mnist
7 import PIL
8 import matplotlib.pyplot as plt
9 import tensorflow as tf
10 from tensorflow.keras import layers
11 from tensorflow.keras.models import Sequential
12 from tensorflow import keras

```

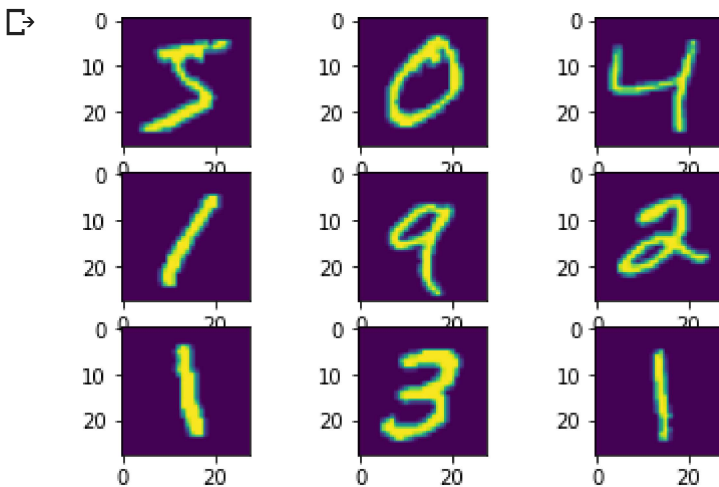
```
1 (x_train, y_train), (x_test, y_test) = mnist.load_data()
```

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist11493376/11490434> [=====] - 0s 0us/step  
 11501568/11490434 [=====] - 0s 0us/step

```

1 import matplotlib.pyplot as plt
2 for i in range(9):
3     plt.subplot(330+i+1)
4     plt.imshow(x_train[i])
5 plt.show()

```



```

1 x = x_test
2 x_train = x_train.astype('float32')
3 x_test = x_test.astype('float32')
4 x_train = x_train/255
5 x_test = x_test/255

```

```
1 y_train = np_utils.to_categorical(y_train,10)
```

```

2 y_test = np_utils.to_categorical(y_test,10)

1 from keras.layers.convolutional import Conv2D, MaxPooling2D
2 from keras.models import Sequential
3 from keras.layers import Dense, Dropout, Flatten, BatchNormalization, Activation
4 from tensorflow.keras.models import Sequential
5 model=Sequential()
6 model.add(Conv2D(64,(3,3),activation='relu',kernel_initializer='he_uniform',padding='same')
7 model.add(Conv2D(64,(3,3),activation='relu',kernel_initializer='he_uniform',padding='same')
8 model.add(MaxPooling2D(2,2))

1 model.add(Flatten())

1 model.add(Dense(128, activation = 'relu', kernel_initializer = 'he_uniform',input_shape=(28
2 model.add(Dropout(0.2))
3 model.add(Dense(10,activation='relu'))
4 model.add(Dropout(0.1))
5 model.add(Dense(10, activation = 'softmax'))

1 from tensorflow.keras.optimizers import SGD
2 opt = SGD(lr = 0.01, momentum = 0.9)
3 from keras.backend import categorical_crossentropy
4 model.compile(optimizer = opt, loss = 'categorical_crossentropy', metrics = ['accuracy'])

/usr/local/lib/python3.7/dist-packages/keras/optimizer_v2/gradient_descent.py:102: Userw
super(SGD, self).__init__(name, **kwargs)

1 history = model.fit(x_train, y_train, epochs = 50, batch_size = 128,validation_data = (x_t
2

```

```

Epoch 23/50
469/469 [=====] - 10s 20ms/step - loss: 0.0260 - accuracy:
Epoch 24/50
469/469 [=====] - 10s 20ms/step - loss: 0.0232 - accuracy:
Epoch 25/50
469/469 [=====] - 10s 21ms/step - loss: 0.0263 - accuracy:
Epoch 26/50
469/469 [=====] - 10s 21ms/step - loss: 0.0245 - accuracy:
Epoch 27/50
469/469 [=====] - 10s 21ms/step - loss: 0.0227 - accuracy:
Epoch 28/50
469/469 [=====] - 10s 21ms/step - loss: 0.0222 - accuracy:
Epoch 29/50
469/469 [=====] - 10s 22ms/step - loss: 0.0229 - accuracy:
Epoch 30/50
469/469 [=====] - 10s 21ms/step - loss: 0.0223 - accuracy:
Epoch 31/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 32/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 33/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 34/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 35/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 36/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 37/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 38/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 39/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 40/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 41/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 42/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 43/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 44/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 45/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 46/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 47/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 48/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 49/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:
Epoch 50/50
469/469 [=====] - 10s 21ms/step - loss: 0.0217 - accuracy:

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469/469 [=====] - 10s 21ms/step - loss: 0.0196 - accuracy:
Epoch 33/50
469/469 [=====] - 10s 21ms/step - loss: 0.0198 - accuracy:
Epoch 34/50
469/469 [=====] - 10s 21ms/step - loss: 0.0196 - accuracy:
Epoch 35/50
469/469 [=====] - 10s 21ms/step - loss: 0.0189 - accuracy:
Epoch 36/50
469/469 [=====] - 10s 21ms/step - loss: 0.0191 - accuracy:
Epoch 37/50
469/469 [=====] - 10s 21ms/step - loss: 0.0183 - accuracy:
Epoch 38/50
469/469 [=====] - 10s 21ms/step - loss: 0.0188 - accuracy:
Epoch 39/50
469/469 [=====] - 10s 21ms/step - loss: 0.0180 - accuracy:
Epoch 40/50
469/469 [=====] - 10s 21ms/step - loss: 0.0177 - accuracy:
Epoch 41/50
469/469 [=====] - 10s 21ms/step - loss: 0.0161 - accuracy:
Epoch 42/50
469/469 [=====] - 10s 21ms/step - loss: 0.0166 - accuracy:
Epoch 43/50
469/469 [=====] - 10s 21ms/step - loss: 0.0164 - accuracy:
Epoch 44/50
469/469 [=====] - 10s 21ms/step - loss: 0.0187 - accuracy:
Epoch 45/50
469/469 [=====] - 10s 21ms/step - loss: 0.0169 - accuracy:
Epoch 46/50
469/469 [=====] - 10s 21ms/step - loss: 0.0159 - accuracy:
Epoch 47/50
469/469 [=====] - 10s 21ms/step - loss: 0.0175 - accuracy:
Epoch 48/50
469/469 [=====] - 10s 21ms/step - loss: 0.0155 - accuracy:
Epoch 49/50
469/469 [=====] - 10s 21ms/step - loss: 0.0143 - accuracy:
Epoch 50/50
469/469 [=====] - 10s 21ms/step - loss: 0.0161 - accuracy:

```

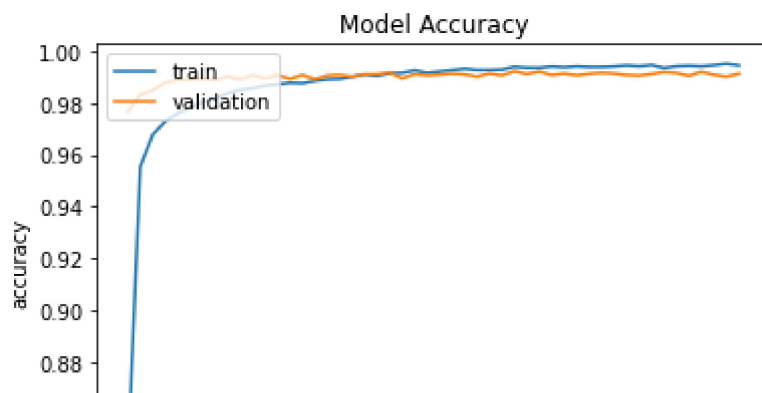
```
1 model.save('final_mnist_cnn.h5')
```

```

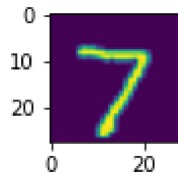
1 plt.plot(history.history['accuracy'])
2 plt.plot(history.history['val_accuracy'])
3 plt.title('Model Accuracy')
4 plt.ylabel('accuracy')
5 plt.xlabel('epoch')
6 plt.legend(['train', 'validation'], loc = 'upper left')

```

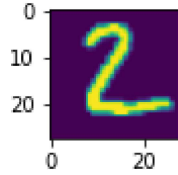
&lt;matplotlib.legend.Legend at 0x7fa2c0671350&gt;



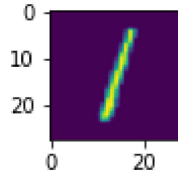
```
1 y_pred=model.predict(x_test)
2 for i in range(9):
3     plt.subplot(330+i+1)
4     plt.imshow(x[i])
5     plt.show()
6     print(np.round(y_pred[i]))
```



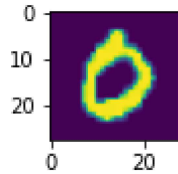
[0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]



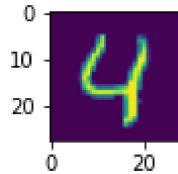
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]



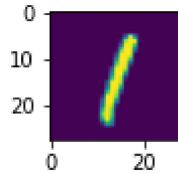
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]



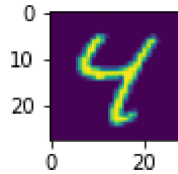
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]



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



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



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

