In [1]:

```
import tensorflow as tf
from tensorflow import keras
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import random
%matplotlib inline
```

In [2]:

```
mnist = tf.keras.datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

len(x_train)

In [3]:

```
x_train.shape
```

Out[3]:

```
(60000, 28, 28)
```

In [4]:

```
x_test.shape
```

Out[4]:

```
(10000, 28, 28)
```

In [5]:

```
x_train[0]
```

Out[5]:

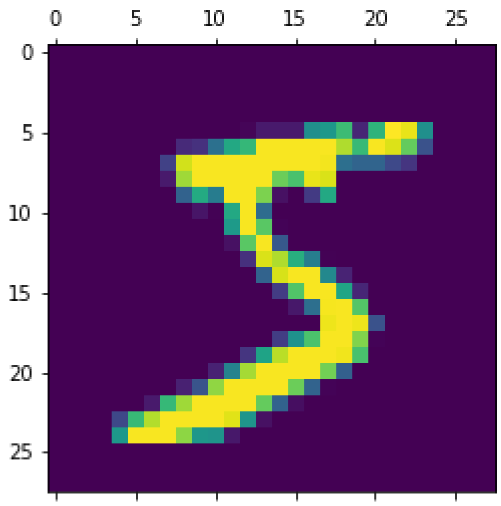
```
array([[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   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,   3,
         18,  18,  18, 126, 136, 175,  26, 166, 255, 247, 127,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,  30,  36,  94, 154, 170,
        253, 253, 253, 253, 253, 225, 172, 253, 242, 195,  64,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,  49, 238, 253, 253, 253, 253,
        253, 253, 253, 253, 251,  93,  82,  82,  56,  39,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,  18, 219, 253, 253, 253, 253,
        253, 198, 182, 247, 241,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,  80, 156, 107, 253, 253,
        205,  11,   0,  43, 154,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,  14,   1, 154, 253,
         90,   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, 139, 253,
        190,   2,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  11, 190,
        253,  70,   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,  35,
        241, 225, 160, 108,   1,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
         81, 240, 253, 253, 119,  25,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,  45, 186, 253, 253, 150,  27,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,  16,  93, 252, 253, 187,   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, 249, 253, 249,  64,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,  46, 130, 183, 253, 253, 207,   2,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  39,
        148, 229, 253, 253, 253, 250, 182,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  24, 114, 221,
        253, 253, 253, 253, 201,  78,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,  23,  66, 213, 253, 253,
        253, 253, 198,  81,   2,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,  18, 171, 219, 253, 253, 253, 253,
        195,  80,   9,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,  55, 172, 226, 253, 253, 253, 253, 244, 133,
         11,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0, 136, 253, 253, 253, 212, 135, 132,  16,   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]], dtype=uint8)
```

In [6]:

```
plt.matshow(x_train[0])
```

Out[6]:

```
<matplotlib.image.AxesImage at 0x2a1ff3e3790>
```



In [7]:

```
x_train = x_train / 255
x_test = x_test / 255
x_train[0]
```

Out[7]:

```
array([[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.        ,
```

In [8]:

```
model = keras.Sequential([
 keras.layers.Flatten(input_shape=(28, 28)),
 keras.layers.Dense(128, activation='relu'),
 keras.layers.Dense(10, activation='softmax')
])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 784)               0

 dense (Dense)               (None, 128)               100480

 dense_1 (Dense)             (None, 10)                1290

=================================================================
Total params: 101,770
Trainable params: 101,770
Non-trainable params: 0
_________________________________________________________________
```

In [9]:

```
model.compile(optimizer='sgd',loss='sparse_categorical_crossentropy',metrics=['accuracy'])
```

In [10]:

```
history=model.fit(x_train,
y_train,validation_data=(x_test,y_test),epochs=10)
```

```
Epoch 1/10
1875/1875 [==============================] - 9s 4ms/step - loss: 0.6465 - ac
curacy: 0.8382 - val_loss: 0.3617 - val_accuracy: 0.9032
Epoch 2/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.3390 - ac
curacy: 0.9051 - val_loss: 0.2994 - val_accuracy: 0.9188
Epoch 3/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.2925 - ac
curacy: 0.9175 - val_loss: 0.2656 - val_accuracy: 0.9279
Epoch 4/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.2629 - ac
curacy: 0.9255 - val_loss: 0.2454 - val_accuracy: 0.9322
Epoch 5/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.2407 - ac
curacy: 0.9325 - val_loss: 0.2263 - val_accuracy: 0.9377
Epoch 6/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.2222 - ac
curacy: 0.9378 - val_loss: 0.2109 - val_accuracy: 0.9413
Epoch 7/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.2069 - ac
curacy: 0.9423 - val_loss: 0.1987 - val_accuracy: 0.9453
Epoch 8/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.1936 - ac
curacy: 0.9455 - val_loss: 0.1871 - val_accuracy: 0.9469
Epoch 9/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.1817 - ac
curacy: 0.9492 - val_loss: 0.1763 - val_accuracy: 0.9500
Epoch 10/10
1875/1875 [==============================] - 6s 3ms/step - loss: 0.1714 - ac
curacy: 0.9521 - val_loss: 0.1695 - val_accuracy: 0.9516
```

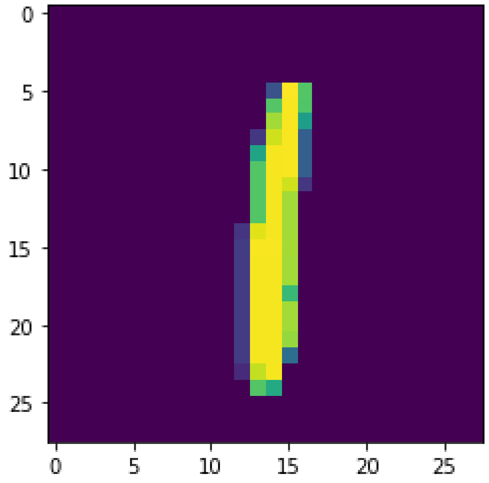
In [11]:

```
test_loss,test_acc=model.evaluate(x_test,y_test)
print("Loss=%.3f" %test_loss)
print("Accuracy=%.3f" %test_acc)
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.1695 - accu
racy: 0.9516
Loss=0.169
Accuracy=0.952
```

In [12]:

```
n=random.randint(0,9999)
plt.imshow(x_test[n])
plt.show()
```



In [13]:

```
predicted_value=model.predict(x_test)
print("Handwritten number in the image is= %d" %np.argmax(predicted_value[n]))
```

```
313/313 [==============================] - 1s 2ms/step
Handwritten number in the image is= 1
```

In [14]:

```
history.history??
```

In [15]:

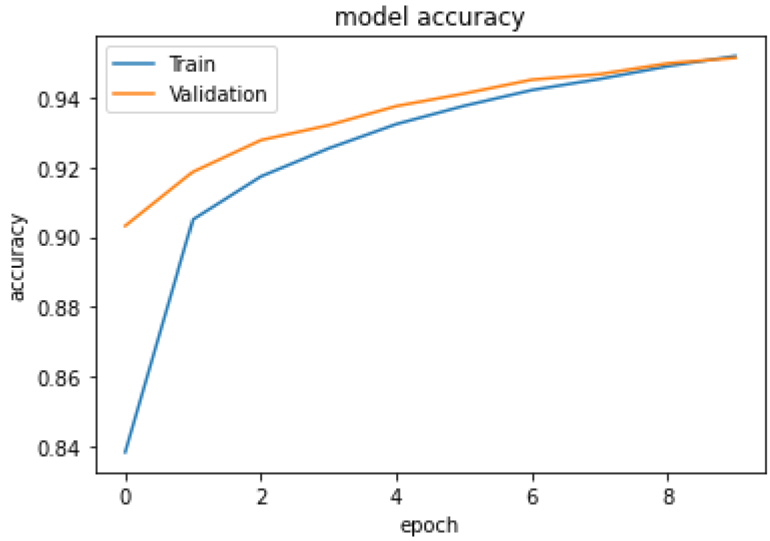
```
history.history.keys()
```

Out[15]:

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

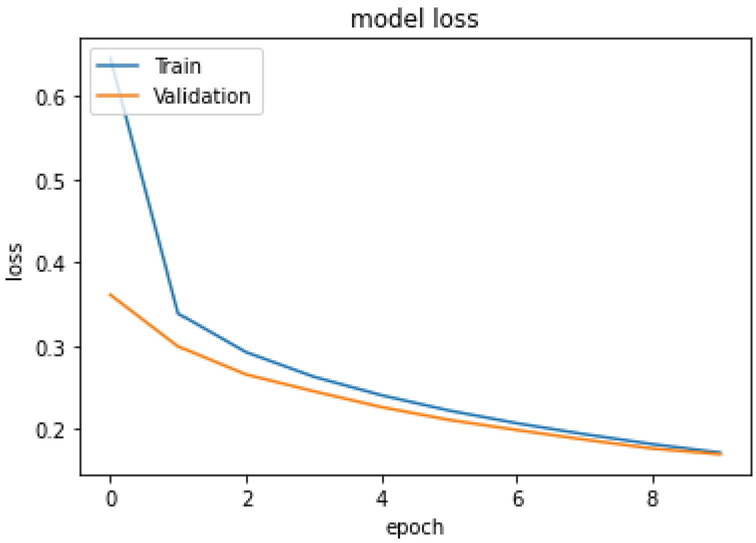
In [16]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```



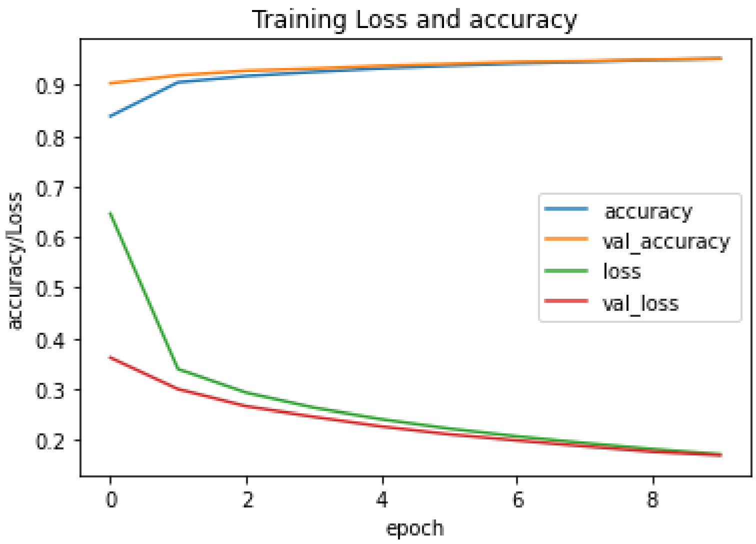
In [17]:

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```



In [18]:

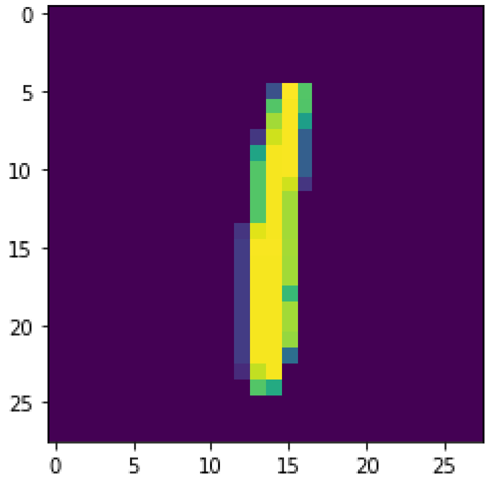
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Training Loss and accuracy')
plt.ylabel('accuracy/Loss')
plt.xlabel('epoch')
plt.legend(['accuracy', 'val_accuracy','loss','val_loss'])
plt.show()
```



In [19]:

```
predicted_value=model.predict(x_test)
plt.imshow(x_test[n])
plt.show()
print(predicted_value[n])
```

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



```
[2.6375056e-07 9.9659353e-01 2.1209990e-04 1.0576770e-03 2.1446573e-05
 8.1445614e-05 9.7952718e-05 3.5272868e-04 1.4787365e-03 1.0399682e-04]
```