Import necessary libraries

In [ ]:
```
!pip install opendatasets
```

```
Requirement already satisfied: opendatasets in c:\users\ananya\appdata\local\prog
rams\python\python311\lib\site-packages (0.1.22)
Requirement already satisfied: tqdm in c:\users\ananya\appdata\local\programs\pyt
hon\python311\lib\site-packages (from opendatasets) (4.66.1)
Requirement already satisfied: kaggle in c:\users\ananya\appdata\local\programs\p
ython\python311\lib\site-packages (from opendatasets) (1.6.6)
Requirement already satisfied: click in c:\users\ananya\appdata\local\programs\py
thon\python311\lib\site-packages (from opendatasets) (8.1.7)
Requirement already satisfied: colorama in c:\users\ananya\appdata\local\programs
\python\python311\lib\site-packages (from click->opendatasets) (0.4.6)
Requirement already satisfied: six>=1.10 in c:\users\ananya\appdata\local\program
s\python\python311\lib\site-packages (from kaggle->opendatasets) (1.16.0)
Requirement already satisfied: certifi in c:\users\ananya\appdata\local\programs
\python\python311\lib\site-packages (from kaggle->opendatasets) (2023.7.22)
Requirement already satisfied: python-dateutil in c:\users\ananya\appdata\local\p
rograms\python\python311\lib\site-packages (from kaggle->opendatasets) (2.8.2)
Requirement already satisfied: requests in c:\users\ananya\appdata\local\programs
\python\python311\lib\site-packages (from kaggle->opendatasets) (2.31.0)
Requirement already satisfied: python-slugify in c:\users\ananya\appdata\local\pr
ograms\python\python311\lib\site-packages (from kaggle->opendatasets) (8.0.4)
Requirement already satisfied: urllib3 in c:\users\ananya\appdata\local\programs
\python\python311\lib\site-packages (from kaggle->opendatasets) (1.26.16)
Requirement already satisfied: bleach in c:\users\ananya\appdata\local\programs\p
ython\python311\lib\site-packages (from kaggle->opendatasets) (6.0.0)
Requirement already satisfied: webencodings in c:\users\ananya\appdata\local\prog
rams\python\python311\lib\site-packages (from bleach->kaggle->opendatasets) (0.5.
1)
Requirement already satisfied: text-unidecode>=1.3 in c:\users\ananya\appdata\loc
al\programs\python\python311\lib\site-packages (from python-slugify->kaggle->open
datasets) (1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\ananya\appdat
a\local\programs\python\python311\lib\site-packages (from requests->kaggle->opend
atasets) (3.2.0)
Requirement already satisfied: idna<4,>=2.5 in c:\users\ananya\appdata\local\prog
rams\python\python311\lib\site-packages (from requests->kaggle->opendatasets) (3.
4)
```

In [ ]:
```
import cv2
import matplotlib.pyplot as plt
```

In [ ]:
```
import opendatasets as od
import pandas as pd

#od.download('https://www.kaggle.com/datasets/dhruvildave/english-handwritten-ch
```

Load the dataset from CSV file

In [ ]:
```
df = pd.read_csv('archive/english.csv')
df
```

Out[ ]:

	image	label
0	Img/img001-001.png	0
1	Img/img001-002.png	0
2	Img/img001-003.png	0
3	Img/img001-004.png	0
4	Img/img001-005.png	0
...	...	...
3405	Img/img062-051.png	z
3406	Img/img062-052.png	z
3407	Img/img062-053.png	z
3408	Img/img062-054.png	z
3409	Img/img062-055.png	z

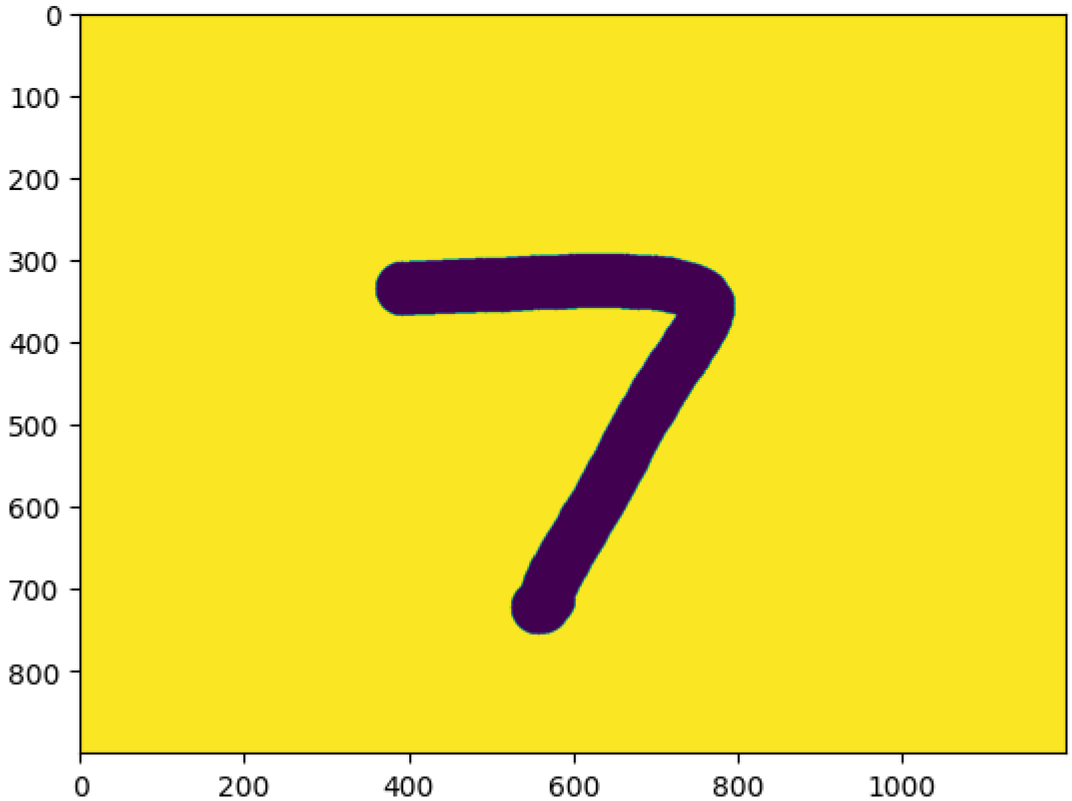
3410 rows × 2 columns

Read an image and display it

In [ ]:

```
img = cv2.imread('archive/Img/img008-025.png', cv2.IMREAD_GRAYSCALE)
plt.imshow(img)
```

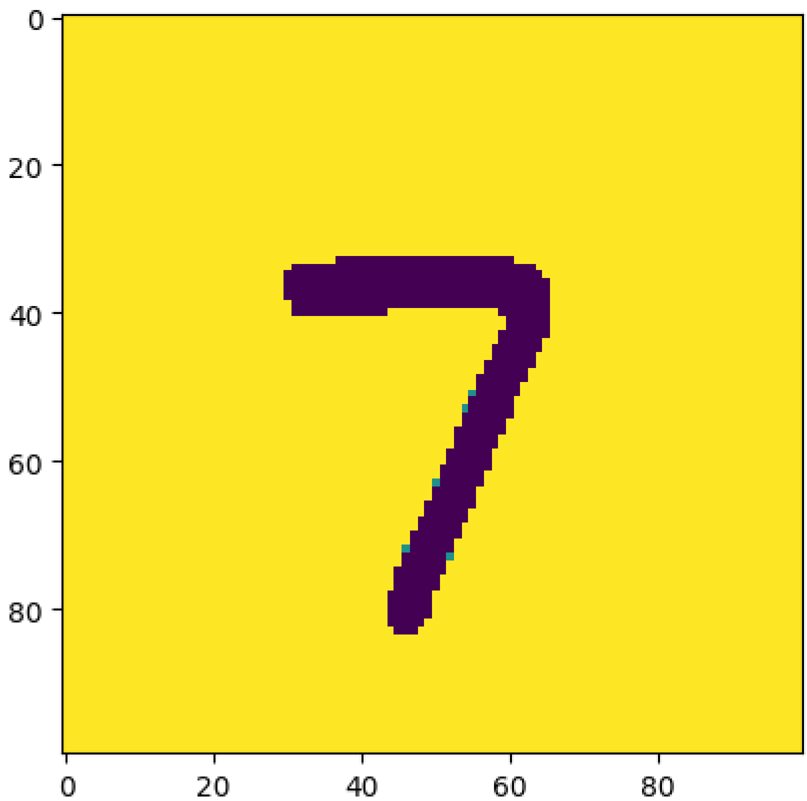
Out[ ]: <matplotlib.image.AxesImage at 0x2caae1ba410>



Resize the image and display it again

In [ ]:
```
img = cv2.resize(img,(100,100))
plt.imshow(img)
```

Out[ ]:
```
<matplotlib.image.AxesImage at 0x2caae240a10>
```



In [ ]:
```
img.shape
```

Out[ ]:
```
(100, 100)
```

Add the image path to the dataset

In [ ]:
```
df['image'] = 'archive/' + df['image']
```

Preprocess the labels

In [ ]:
```
from sklearn import preprocessing

# label_encoder object knows
# how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

# Encode labels in column 'species'.
df['label']= label_encoder.fit_transform(df['label'])
```

In [ ]:
```
df
```

Out[ ]:

	image	label
0	archive/Img/img001-001.png	0
1	archive/Img/img001-002.png	0
2	archive/Img/img001-003.png	0
3	archive/Img/img001-004.png	0
4	archive/Img/img001-005.png	0
...	...	...
3405	archive/Img/img062-051.png	61
3406	archive/Img/img062-052.png	61
3407	archive/Img/img062-053.png	61
3408	archive/Img/img062-054.png	61
3409	archive/Img/img062-055.png	61

3410 rows × 2 columns

Load the images and labels into lists

In [ ]:

```
images = []
labels = []

def imageLoad(row):
  path = row['image']
  img = cv2.imread(path)
  img = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
  img = cv2.resize(img,(100,100))
  images.append(img)
  labels.append(row['label'])
```

In [ ]:

```
df.apply(imageLoad,axis=1)
```

Out[ ]:

```
0       None
1       None
2       None
3       None
4       None
        ...
3405    None
3406    None
3407    None
3408    None
3409    None
Length: 3410, dtype: object
```

Split the dataset into training and testing sets

In [ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(images,labels , random_state
```

Convert the datasets to tensors

In [ ]:
```
import tensorflow as tf

X_train = tf.convert_to_tensor(X_train)

X_test = tf.convert_to_tensor(X_test)
y_train = tf.convert_to_tensor(y_train)
y_test = tf.convert_to_tensor(y_test)
```

Normalize the pixel values

In [ ]:
```
X_train = X_train/255
X_test = X_test/255
```

Define the neural network model

In [ ]:
```
import tensorflow as tf

from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt
```

In [ ]:
```
model = models.Sequential()
model.add(layers.Flatten(input_shape=(100,100,1)))
model.add(layers.Dense(728,activation='relu'))
model.add(layers.Dense(500,activation='relu'))
model.add(layers.Dense(200,activation='relu'))
model.add(layers.Dense(100,activation='relu'))
model.add(layers.Dense(60,activation='relu'))
model.add(layers.Dense(62,activation='softmax'))
```

In [ ]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 flatten (Flatten)           (None, 10000)             0         
                                                                 
 dense (Dense)               (None, 728)               7280728   
                                                                 
 dense_1 (Dense)             (None, 500)               364500    
                                                                 
 dense_2 (Dense)             (None, 200)               100200    
                                                                 
 dense_3 (Dense)             (None, 100)               20100     
                                                                 
 dense_4 (Dense)             (None, 60)                6060      
                                                                 
 dense_5 (Dense)             (None, 62)                3782      
                                                                 
=================================================================
Total params: 7775370 (29.66 MB)
Trainable params: 7775370 (29.66 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Compile the model

In [ ]:
```
model.compile(loss='sparse_categorical_crossentropy', optimizer='sgd', metrics=[
```

Train the model

In [ ]:
```
history = model.fit(X_train, y_train, epochs=150,
                    validation_data=(X_test, y_test))
```

```
Epoch 1/150
86/86 [==============================] - 4s 33ms/step - loss: 4.1398 - accuracy:
0.0202 - val_loss: 4.1282 - val_accuracy: 0.0220
Epoch 2/150
86/86 [==============================] - 3s 30ms/step - loss: 4.1293 - accuracy:
0.0224 - val_loss: 4.1335 - val_accuracy: 0.0235
Epoch 3/150
86/86 [==============================] - 2s 28ms/step - loss: 4.1276 - accuracy:
0.0169 - val_loss: 4.1257 - val_accuracy: 0.0161
Epoch 4/150
86/86 [==============================] - 3s 29ms/step - loss: 4.1197 - accuracy:
0.0231 - val_loss: 4.1176 - val_accuracy: 0.0220
Epoch 5/150
86/86 [==============================] - 3s 29ms/step - loss: 4.1160 - accuracy:
0.0257 - val_loss: 4.1179 - val_accuracy: 0.0220
Epoch 6/150
86/86 [==============================] - 3s 29ms/step - loss: 4.1096 - accuracy:
0.0224 - val_loss: 4.1000 - val_accuracy: 0.0103
Epoch 7/150
86/86 [==============================] - 3s 29ms/step - loss: 4.0989 - accuracy:
0.0275 - val_loss: 4.0961 - val_accuracy: 0.0205
Epoch 8/150
86/86 [==============================] - 3s 30ms/step - loss: 4.0699 - accuracy:
0.0323 - val_loss: 4.1589 - val_accuracy: 0.0191
Epoch 9/150
86/86 [==============================] - 3s 30ms/step - loss: 4.0528 - accuracy:
0.0334 - val_loss: 4.1805 - val_accuracy: 0.0191
Epoch 10/150
86/86 [==============================] - 3s 29ms/step - loss: 4.0275 - accuracy:
0.0341 - val_loss: 4.0932 - val_accuracy: 0.0235
Epoch 11/150
86/86 [==============================] - 3s 30ms/step - loss: 3.9946 - accuracy:
0.0374 - val_loss: 4.1295 - val_accuracy: 0.0161
Epoch 12/150
86/86 [==============================] - 3s 30ms/step - loss: 3.9512 - accuracy:
0.0517 - val_loss: 3.9452 - val_accuracy: 0.0235
Epoch 13/150
86/86 [==============================] - 3s 30ms/step - loss: 3.8858 - accuracy:
0.0572 - val_loss: 4.1248 - val_accuracy: 0.0440
Epoch 14/150
86/86 [==============================] - 3s 30ms/step - loss: 3.8541 - accuracy:
0.0663 - val_loss: 3.7862 - val_accuracy: 0.0836
Epoch 15/150
86/86 [==============================] - 3s 30ms/step - loss: 3.8019 - accuracy:
0.0737 - val_loss: 4.2007 - val_accuracy: 0.0117
Epoch 16/150
86/86 [==============================] - 3s 32ms/step - loss: 3.7661 - accuracy:
0.0762 - val_loss: 3.9056 - val_accuracy: 0.0323
Epoch 17/150
86/86 [==============================] - 3s 30ms/step - loss: 3.6871 - accuracy:
0.0887 - val_loss: 4.0003 - val_accuracy: 0.0674
Epoch 18/150
86/86 [==============================] - 3s 30ms/step - loss: 3.6586 - accuracy:
0.0894 - val_loss: 4.2397 - val_accuracy: 0.0367
Epoch 19/150
86/86 [==============================] - 3s 30ms/step - loss: 3.6168 - accuracy:
0.0953 - val_loss: 3.9081 - val_accuracy: 0.0601
Epoch 20/150
86/86 [==============================] - 3s 31ms/step - loss: 3.5465 - accuracy:
0.1096 - val_loss: 4.1869 - val_accuracy: 0.0425
```

```
Epoch 21/150
86/86 [==============================] - 3s 30ms/step - loss: 3.5223 - accuracy:
0.1103 - val_loss: 3.5221 - val_accuracy: 0.1056
Epoch 22/150
86/86 [==============================] - 3s 30ms/step - loss: 3.4611 - accuracy:
0.1224 - val_loss: 3.6566 - val_accuracy: 0.0836
Epoch 23/150
86/86 [==============================] - 3s 31ms/step - loss: 3.4236 - accuracy:
0.1301 - val_loss: 3.6118 - val_accuracy: 0.0909
Epoch 24/150
86/86 [==============================] - 3s 30ms/step - loss: 3.3715 - accuracy:
0.1422 - val_loss: 4.3091 - val_accuracy: 0.0455
Epoch 25/150
86/86 [==============================] - 3s 30ms/step - loss: 3.3213 - accuracy:
0.1525 - val_loss: 4.0704 - val_accuracy: 0.0484
Epoch 26/150
86/86 [==============================] - 3s 32ms/step - loss: 3.2627 - accuracy:
0.1620 - val_loss: 3.4400 - val_accuracy: 0.0953
Epoch 27/150
86/86 [==============================] - 3s 32ms/step - loss: 3.2165 - accuracy:
0.1800 - val_loss: 4.0521 - val_accuracy: 0.0587
Epoch 28/150
86/86 [==============================] - 3s 32ms/step - loss: 3.1718 - accuracy:
0.1774 - val_loss: 3.3710 - val_accuracy: 0.1158
Epoch 29/150
86/86 [==============================] - 3s 31ms/step - loss: 3.1477 - accuracy:
0.1877 - val_loss: 3.5032 - val_accuracy: 0.1085
Epoch 30/150
86/86 [==============================] - 3s 31ms/step - loss: 3.0904 - accuracy:
0.2031 - val_loss: 3.2707 - val_accuracy: 0.1466
Epoch 31/150
86/86 [==============================] - 3s 36ms/step - loss: 3.0197 - accuracy:
0.2097 - val_loss: 3.3154 - val_accuracy: 0.1217
Epoch 32/150
86/86 [==============================] - 3s 31ms/step - loss: 3.0372 - accuracy:
0.2152 - val_loss: 4.0587 - val_accuracy: 0.0616
Epoch 33/150
86/86 [==============================] - 3s 32ms/step - loss: 2.9381 - accuracy:
0.2309 - val_loss: 3.4804 - val_accuracy: 0.1129
Epoch 34/150
86/86 [==============================] - 3s 33ms/step - loss: 2.9189 - accuracy:
0.2386 - val_loss: 3.0531 - val_accuracy: 0.1994
Epoch 35/150
86/86 [==============================] - 3s 32ms/step - loss: 2.9219 - accuracy:
0.2262 - val_loss: 3.0998 - val_accuracy: 0.1935
Epoch 36/150
86/86 [==============================] - 3s 31ms/step - loss: 2.8449 - accuracy:
0.2507 - val_loss: 3.4858 - val_accuracy: 0.1173
Epoch 37/150
86/86 [==============================] - 3s 31ms/step - loss: 2.7852 - accuracy:
0.2691 - val_loss: 3.6151 - val_accuracy: 0.1026
Epoch 38/150
86/86 [==============================] - 3s 31ms/step - loss: 2.7274 - accuracy:
0.2867 - val_loss: 2.9975 - val_accuracy: 0.2331
Epoch 39/150
86/86 [==============================] - 3s 32ms/step - loss: 2.7379 - accuracy:
0.2650 - val_loss: 2.8751 - val_accuracy: 0.2155
Epoch 40/150
86/86 [==============================] - 3s 31ms/step - loss: 2.6755 - accuracy:
0.2870 - val_loss: 3.4319 - val_accuracy: 0.1481
```

```
Epoch 41/150
86/86 [==============================] - 3s 31ms/step - loss: 2.6171 - accuracy:
0.3006 - val_loss: 4.2460 - val_accuracy: 0.1026
Epoch 42/150
86/86 [==============================] - 3s 30ms/step - loss: 2.6244 - accuracy:
0.2933 - val_loss: 3.3947 - val_accuracy: 0.1525
Epoch 43/150
86/86 [==============================] - 3s 31ms/step - loss: 2.5804 - accuracy:
0.3079 - val_loss: 3.6054 - val_accuracy: 0.1378
Epoch 44/150
86/86 [==============================] - 3s 33ms/step - loss: 2.5519 - accuracy:
0.3076 - val_loss: 2.8019 - val_accuracy: 0.2361
Epoch 45/150
86/86 [==============================] - 3s 31ms/step - loss: 2.5086 - accuracy:
0.3156 - val_loss: 3.1829 - val_accuracy: 0.1701
Epoch 46/150
86/86 [==============================] - 3s 32ms/step - loss: 2.4804 - accuracy:
0.3391 - val_loss: 3.0382 - val_accuracy: 0.2009
Epoch 47/150
86/86 [==============================] - 3s 30ms/step - loss: 2.4464 - accuracy:
0.3391 - val_loss: 3.2072 - val_accuracy: 0.1745
Epoch 48/150
86/86 [==============================] - 3s 31ms/step - loss: 2.3567 - accuracy:
0.3625 - val_loss: 3.1787 - val_accuracy: 0.2053
Epoch 49/150
86/86 [==============================] - 3s 31ms/step - loss: 2.3449 - accuracy:
0.3545 - val_loss: 3.9311 - val_accuracy: 0.1026
Epoch 50/150
86/86 [==============================] - 3s 32ms/step - loss: 2.3141 - accuracy:
0.3691 - val_loss: 4.3240 - val_accuracy: 0.0997
Epoch 51/150
86/86 [==============================] - 3s 32ms/step - loss: 2.3160 - accuracy:
0.3713 - val_loss: 2.6698 - val_accuracy: 0.2757
Epoch 52/150
86/86 [==============================] - 3s 31ms/step - loss: 2.2473 - accuracy:
0.3746 - val_loss: 3.2634 - val_accuracy: 0.1598
Epoch 53/150
86/86 [==============================] - 3s 34ms/step - loss: 2.2457 - accuracy:
0.3812 - val_loss: 2.5210 - val_accuracy: 0.3314
Epoch 54/150
86/86 [==============================] - 3s 30ms/step - loss: 2.1838 - accuracy:
0.3937 - val_loss: 2.9612 - val_accuracy: 0.2185
Epoch 55/150
86/86 [==============================] - 3s 32ms/step - loss: 2.1110 - accuracy:
0.4062 - val_loss: 3.6061 - val_accuracy: 0.1496
Epoch 56/150
86/86 [==============================] - 3s 31ms/step - loss: 2.1536 - accuracy:
0.4003 - val_loss: 2.9849 - val_accuracy: 0.2361
Epoch 57/150
86/86 [==============================] - 3s 31ms/step - loss: 2.0463 - accuracy:
0.4399 - val_loss: 2.6732 - val_accuracy: 0.2830
Epoch 58/150
86/86 [==============================] - 3s 32ms/step - loss: 2.1184 - accuracy:
0.4058 - val_loss: 4.3034 - val_accuracy: 0.1026
Epoch 59/150
86/86 [==============================] - 3s 34ms/step - loss: 2.0756 - accuracy:
0.4201 - val_loss: 2.6085 - val_accuracy: 0.3167
Epoch 60/150
86/86 [==============================] - 3s 31ms/step - loss: 1.9564 - accuracy:
0.4483 - val_loss: 3.1792 - val_accuracy: 0.2155
```

```
Epoch 61/150
86/86 [==============================] - 3s 31ms/step - loss: 1.9567 - accuracy: 0.4428 - val_loss: 3.2416 - val_accuracy: 0.2229
Epoch 62/150
86/86 [==============================] - 3s 31ms/step - loss: 1.9168 - accuracy: 0.4523 - val_loss: 2.6679 - val_accuracy: 0.3196
Epoch 63/150
86/86 [==============================] - 3s 31ms/step - loss: 1.8610 - accuracy: 0.4666 - val_loss: 2.7036 - val_accuracy: 0.2859
Epoch 64/150
86/86 [==============================] - 3s 31ms/step - loss: 1.8731 - accuracy: 0.4534 - val_loss: 3.9003 - val_accuracy: 0.1906
Epoch 65/150
86/86 [==============================] - 3s 32ms/step - loss: 1.8251 - accuracy: 0.4784 - val_loss: 3.3120 - val_accuracy: 0.1642
Epoch 66/150
86/86 [==============================] - 3s 31ms/step - loss: 1.7972 - accuracy: 0.4879 - val_loss: 3.5212 - val_accuracy: 0.2126
Epoch 67/150
86/86 [==============================] - 3s 32ms/step - loss: 1.7884 - accuracy: 0.4938 - val_loss: 3.4576 - val_accuracy: 0.1994
Epoch 68/150
86/86 [==============================] - 3s 31ms/step - loss: 1.7248 - accuracy: 0.5084 - val_loss: 3.5214 - val_accuracy: 0.2053
Epoch 69/150
86/86 [==============================] - 3s 32ms/step - loss: 1.6656 - accuracy: 0.5220 - val_loss: 2.7967 - val_accuracy: 0.3196
Epoch 70/150
86/86 [==============================] - 3s 31ms/step - loss: 1.6342 - accuracy: 0.5238 - val_loss: 3.2141 - val_accuracy: 0.2229
Epoch 71/150
86/86 [==============================] - 3s 30ms/step - loss: 1.6079 - accuracy: 0.5319 - val_loss: 2.2730 - val_accuracy: 0.4326
Epoch 72/150
86/86 [==============================] - 3s 31ms/step - loss: 1.5692 - accuracy: 0.5370 - val_loss: 2.5639 - val_accuracy: 0.3328
Epoch 73/150
86/86 [==============================] - 3s 30ms/step - loss: 1.5566 - accuracy: 0.5407 - val_loss: 2.5149 - val_accuracy: 0.3666
Epoch 74/150
86/86 [==============================] - 3s 30ms/step - loss: 1.5310 - accuracy: 0.5436 - val_loss: 2.7843 - val_accuracy: 0.2889
Epoch 75/150
86/86 [==============================] - 3s 31ms/step - loss: 1.5057 - accuracy: 0.5513 - val_loss: 3.2242 - val_accuracy: 0.2346
Epoch 76/150
86/86 [==============================] - 3s 30ms/step - loss: 1.4150 - accuracy: 0.5847 - val_loss: 3.0998 - val_accuracy: 0.3343
Epoch 77/150
86/86 [==============================] - 3s 31ms/step - loss: 1.4983 - accuracy: 0.5587 - val_loss: 2.4198 - val_accuracy: 0.3328
Epoch 78/150
86/86 [==============================] - 3s 31ms/step - loss: 1.3897 - accuracy: 0.5850 - val_loss: 3.1071 - val_accuracy: 0.2551
Epoch 79/150
86/86 [==============================] - 3s 31ms/step - loss: 1.3780 - accuracy: 0.5898 - val_loss: 3.2071 - val_accuracy: 0.2830
Epoch 80/150
86/86 [==============================] - 3s 31ms/step - loss: 1.3987 - accuracy: 0.5821 - val_loss: 2.2866 - val_accuracy: 0.4120
```

```
Epoch 81/150
86/86 [==============================] - 3s 31ms/step - loss: 1.3038 - accuracy:
0.6092 - val_loss: 2.9664 - val_accuracy: 0.3152
Epoch 82/150
86/86 [==============================] - 3s 31ms/step - loss: 1.2737 - accuracy:
0.6092 - val_loss: 2.5701 - val_accuracy: 0.3710
Epoch 83/150
86/86 [==============================] - 3s 30ms/step - loss: 1.2907 - accuracy:
0.6136 - val_loss: 2.1712 - val_accuracy: 0.4076
Epoch 84/150
86/86 [==============================] - 3s 33ms/step - loss: 1.2829 - accuracy:
0.6096 - val_loss: 2.2144 - val_accuracy: 0.4252
Epoch 85/150
86/86 [==============================] - 3s 31ms/step - loss: 1.2351 - accuracy:
0.6294 - val_loss: 2.4923 - val_accuracy: 0.3695
Epoch 86/150
86/86 [==============================] - 3s 31ms/step - loss: 1.2278 - accuracy:
0.6316 - val_loss: 2.8972 - val_accuracy: 0.2859
Epoch 87/150
86/86 [==============================] - 3s 31ms/step - loss: 1.1775 - accuracy:
0.6422 - val_loss: 2.2766 - val_accuracy: 0.4208
Epoch 88/150
86/86 [==============================] - 3s 31ms/step - loss: 1.1356 - accuracy:
0.6492 - val_loss: 2.8342 - val_accuracy: 0.3651
Epoch 89/150
86/86 [==============================] - 3s 32ms/step - loss: 1.1854 - accuracy:
0.6408 - val_loss: 2.1095 - val_accuracy: 0.4296
Epoch 90/150
86/86 [==============================] - 3s 32ms/step - loss: 1.0953 - accuracy:
0.6624 - val_loss: 2.1086 - val_accuracy: 0.4545
Epoch 91/150
86/86 [==============================] - 3s 31ms/step - loss: 1.0912 - accuracy:
0.6631 - val_loss: 3.2080 - val_accuracy: 0.3196
Epoch 92/150
86/86 [==============================] - 3s 31ms/step - loss: 1.0484 - accuracy:
0.6796 - val_loss: 7.1022 - val_accuracy: 0.1041
Epoch 93/150
86/86 [==============================] - 3s 31ms/step - loss: 1.2375 - accuracy:
0.6433 - val_loss: 2.2658 - val_accuracy: 0.4604
Epoch 94/150
86/86 [==============================] - 3s 31ms/step - loss: 0.9943 - accuracy:
0.6880 - val_loss: 3.4600 - val_accuracy: 0.3167
Epoch 95/150
86/86 [==============================] - 3s 31ms/step - loss: 1.0203 - accuracy:
0.6917 - val_loss: 2.2082 - val_accuracy: 0.4560
Epoch 96/150
86/86 [==============================] - 3s 31ms/step - loss: 0.9294 - accuracy:
0.7056 - val_loss: 4.0039 - val_accuracy: 0.2551
Epoch 97/150
86/86 [==============================] - 3s 30ms/step - loss: 0.9833 - accuracy:
0.6979 - val_loss: 2.4309 - val_accuracy: 0.4135
Epoch 98/150
86/86 [==============================] - 3s 31ms/step - loss: 0.9263 - accuracy:
0.7199 - val_loss: 3.1840 - val_accuracy: 0.3211
Epoch 99/150
86/86 [==============================] - 3s 31ms/step - loss: 0.8656 - accuracy:
0.7353 - val_loss: 2.1505 - val_accuracy: 0.4809
Epoch 100/150
86/86 [==============================] - 3s 31ms/step - loss: 0.8673 - accuracy:
0.7269 - val_loss: 2.3038 - val_accuracy: 0.4413
```

```
Epoch 101/150
86/86 [==============================] - 3s 31ms/step - loss: 0.8224 - accuracy:
0.7434 - val_loss: 2.0906 - val_accuracy: 0.4736
Epoch 102/150
86/86 [==============================] - 3s 31ms/step - loss: 0.8642 - accuracy:
0.7298 - val_loss: 6.5675 - val_accuracy: 0.1716
Epoch 103/150
86/86 [==============================] - 3s 31ms/step - loss: 1.0198 - accuracy:
0.7214 - val_loss: 2.4224 - val_accuracy: 0.4355
Epoch 104/150
86/86 [==============================] - 3s 31ms/step - loss: 1.0085 - accuracy:
0.7155 - val_loss: 2.2942 - val_accuracy: 0.4604
Epoch 105/150
86/86 [==============================] - 3s 31ms/step - loss: 0.7349 - accuracy:
0.7621 - val_loss: 2.1612 - val_accuracy: 0.4663
Epoch 106/150
86/86 [==============================] - 3s 31ms/step - loss: 0.7394 - accuracy:
0.7801 - val_loss: 5.6617 - val_accuracy: 0.1642
Epoch 107/150
86/86 [==============================] - 3s 30ms/step - loss: 1.0307 - accuracy:
0.7203 - val_loss: 3.0148 - val_accuracy: 0.3519
Epoch 108/150
86/86 [==============================] - 3s 31ms/step - loss: 0.7103 - accuracy:
0.7793 - val_loss: 2.7989 - val_accuracy: 0.3798
Epoch 109/150
86/86 [==============================] - 3s 30ms/step - loss: 0.7879 - accuracy:
0.7540 - val_loss: 2.5551 - val_accuracy: 0.4399
Epoch 110/150
86/86 [==============================] - 3s 32ms/step - loss: 0.7071 - accuracy:
0.7764 - val_loss: 2.4797 - val_accuracy: 0.4545
Epoch 111/150
86/86 [==============================] - 3s 31ms/step - loss: 0.6333 - accuracy:
0.7955 - val_loss: 3.9926 - val_accuracy: 0.2742
Epoch 112/150
86/86 [==============================] - 3s 32ms/step - loss: 0.8890 - accuracy:
0.7427 - val_loss: 3.7355 - val_accuracy: 0.2918
Epoch 113/150
86/86 [==============================] - 3s 30ms/step - loss: 0.7859 - accuracy:
0.7687 - val_loss: 2.2741 - val_accuracy: 0.4736
Epoch 114/150
86/86 [==============================] - 3s 31ms/step - loss: 0.5969 - accuracy:
0.8079 - val_loss: 2.3119 - val_accuracy: 0.4487
Epoch 115/150
86/86 [==============================] - 3s 31ms/step - loss: 0.5530 - accuracy:
0.8262 - val_loss: 2.0649 - val_accuracy: 0.5308
Epoch 116/150
86/86 [==============================] - 3s 31ms/step - loss: 0.5772 - accuracy:
0.8204 - val_loss: 2.5847 - val_accuracy: 0.4619
Epoch 117/150
86/86 [==============================] - 3s 31ms/step - loss: 0.5293 - accuracy:
0.8343 - val_loss: 2.6310 - val_accuracy: 0.4560
Epoch 118/150
86/86 [==============================] - 3s 31ms/step - loss: 0.5786 - accuracy:
0.8163 - val_loss: 3.0971 - val_accuracy: 0.4340
Epoch 119/150
86/86 [==============================] - 3s 31ms/step - loss: 0.5898 - accuracy:
0.8229 - val_loss: 2.3542 - val_accuracy: 0.4853
Epoch 120/150
86/86 [==============================] - 3s 32ms/step - loss: 0.4117 - accuracy:
0.8735 - val_loss: 2.1593 - val_accuracy: 0.5249
```

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Epoch 121/150
86/86 [==============================] - 3s 31ms/step - loss: 0.5108 - accuracy:
0.8442 - val_loss: 4.7562 - val_accuracy: 0.2713
Epoch 122/150
86/86 [==============================] - 3s 32ms/step - loss: 0.5993 - accuracy:
0.8266 - val_loss: 3.6787 - val_accuracy: 0.3358
Epoch 123/150
86/86 [==============================] - 3s 32ms/step - loss: 0.4795 - accuracy:
0.8541 - val_loss: 2.2448 - val_accuracy: 0.5220
Epoch 124/150
86/86 [==============================] - 3s 31ms/step - loss: 0.6873 - accuracy:
0.8178 - val_loss: 2.0232 - val_accuracy: 0.5425
Epoch 125/150
86/86 [==============================] - 3s 31ms/step - loss: 0.3937 - accuracy:
0.8772 - val_loss: 5.6609 - val_accuracy: 0.2522
Epoch 126/150
86/86 [==============================] - 3s 32ms/step - loss: 0.6407 - accuracy:
0.8299 - val_loss: 2.2325 - val_accuracy: 0.5323
Epoch 127/150
86/86 [==============================] - 3s 31ms/step - loss: 0.4662 - accuracy:
0.8618 - val_loss: 2.7854 - val_accuracy: 0.4296
Epoch 128/150
86/86 [==============================] - 3s 31ms/step - loss: 0.4288 - accuracy:
0.8658 - val_loss: 3.4640 - val_accuracy: 0.3548
Epoch 129/150
86/86 [==============================] - 3s 32ms/step - loss: 0.5114 - accuracy:
0.8673 - val_loss: 2.1963 - val_accuracy: 0.5279
Epoch 130/150
86/86 [==============================] - 3s 31ms/step - loss: 0.2731 - accuracy:
0.9190 - val_loss: 2.8301 - val_accuracy: 0.4795
Epoch 131/150
86/86 [==============================] - 3s 32ms/step - loss: 0.3916 - accuracy:
0.8746 - val_loss: 3.2845 - val_accuracy: 0.3930
Epoch 132/150
86/86 [==============================] - 3s 31ms/step - loss: 0.4558 - accuracy:
0.8600 - val_loss: 3.1374 - val_accuracy: 0.4252
Epoch 133/150
86/86 [==============================] - 3s 32ms/step - loss: 0.3047 - accuracy:
0.9109 - val_loss: 2.8763 - val_accuracy: 0.4326
Epoch 134/150
86/86 [==============================] - 3s 31ms/step - loss: 0.3333 - accuracy:
0.8941 - val_loss: 7.1154 - val_accuracy: 0.1877
Epoch 135/150
86/86 [==============================] - 3s 33ms/step - loss: 0.8380 - accuracy:
0.7837 - val_loss: 2.1221 - val_accuracy: 0.5293
Epoch 136/150
86/86 [==============================] - 3s 31ms/step - loss: 0.2697 - accuracy:
0.9212 - val_loss: 4.1337 - val_accuracy: 0.3930
Epoch 137/150
86/86 [==============================] - 3s 31ms/step - loss: 0.3748 - accuracy:
0.8834 - val_loss: 2.2416 - val_accuracy: 0.5484
Epoch 138/150
86/86 [==============================] - 3s 31ms/step - loss: 0.7172 - accuracy:
0.8149 - val_loss: 2.4296 - val_accuracy: 0.4912
Epoch 139/150
86/86 [==============================] - 3s 31ms/step - loss: 0.2512 - accuracy:
0.9256 - val_loss: 2.2887 - val_accuracy: 0.5543
Epoch 140/150
86/86 [==============================] - 3s 31ms/step - loss: 0.2005 - accuracy:
0.9457 - val_loss: 4.0899 - val_accuracy: 0.3988
```

```
Epoch 141/150
86/86 [==============================] - 3s 31ms/step - loss: 0.5026 - accuracy:
0.8794 - val_loss: 2.2177 - val_accuracy: 0.5587
Epoch 142/150
86/86 [==============================] - 3s 31ms/step - loss: 0.1771 - accuracy:
0.9498 - val_loss: 3.3524 - val_accuracy: 0.4589
Epoch 143/150
86/86 [==============================] - 3s 32ms/step - loss: 0.5292 - accuracy:
0.8512 - val_loss: 2.2892 - val_accuracy: 0.5176
Epoch 144/150
86/86 [==============================] - 3s 31ms/step - loss: 0.1859 - accuracy:
0.9501 - val_loss: 2.4274 - val_accuracy: 0.5440
Epoch 145/150
86/86 [==============================] - 3s 31ms/step - loss: 0.1556 - accuracy:
0.9586 - val_loss: 2.5070 - val_accuracy: 0.5587
Epoch 146/150
86/86 [==============================] - 3s 31ms/step - loss: 0.1495 - accuracy:
0.9608 - val_loss: 2.3368 - val_accuracy: 0.5718
Epoch 147/150
86/86 [==============================] - 3s 32ms/step - loss: 0.1551 - accuracy:
0.9575 - val_loss: 3.1436 - val_accuracy: 0.4633
Epoch 148/150
86/86 [==============================] - 3s 34ms/step - loss: 0.4842 - accuracy:
0.8695 - val_loss: 2.2966 - val_accuracy: 0.5630
Epoch 149/150
86/86 [==============================] - 3s 31ms/step - loss: 0.1592 - accuracy:
0.9578 - val_loss: 3.1963 - val_accuracy: 0.4472
Epoch 150/150
86/86 [==============================] - 3s 32ms/step - loss: 0.5890 - accuracy:
0.8735 - val_loss: 2.3265 - val_accuracy: 0.5704
```

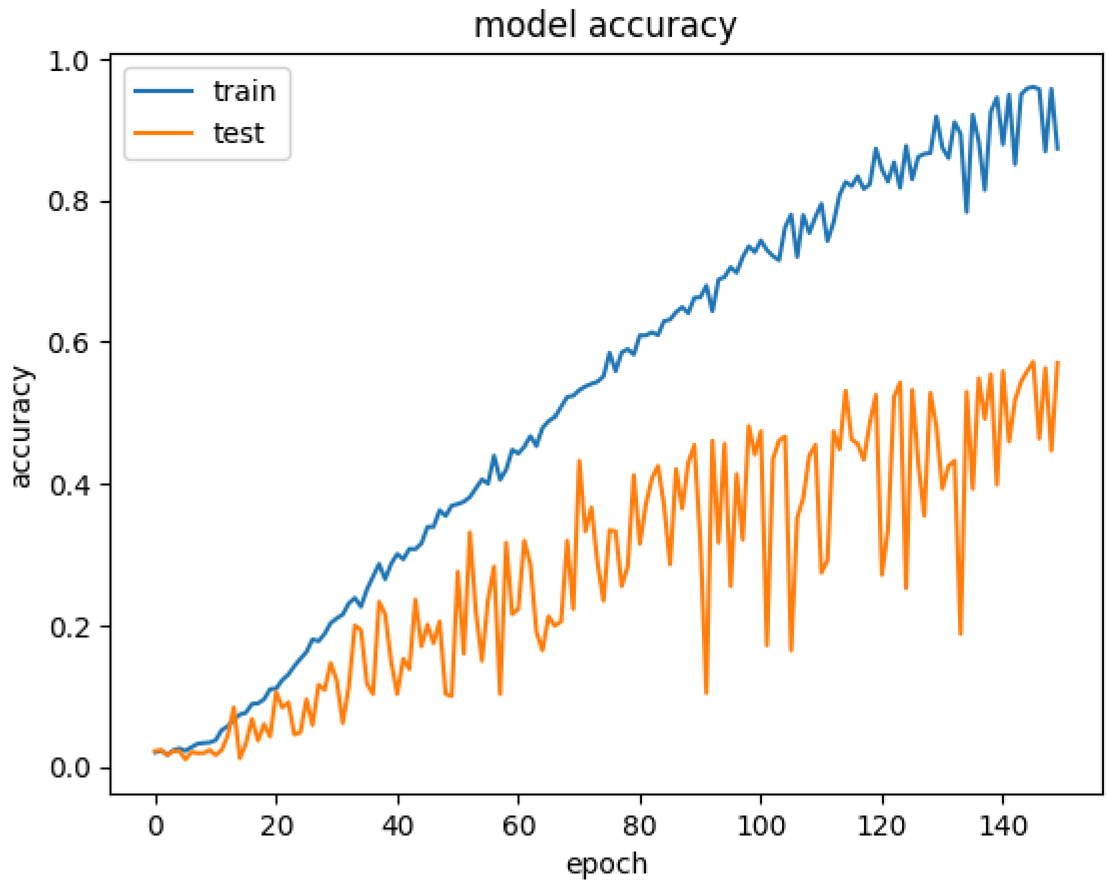
Plot the accuracy and loss of the model

In [ ]:

```
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')
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x2cac9b9e450>
```

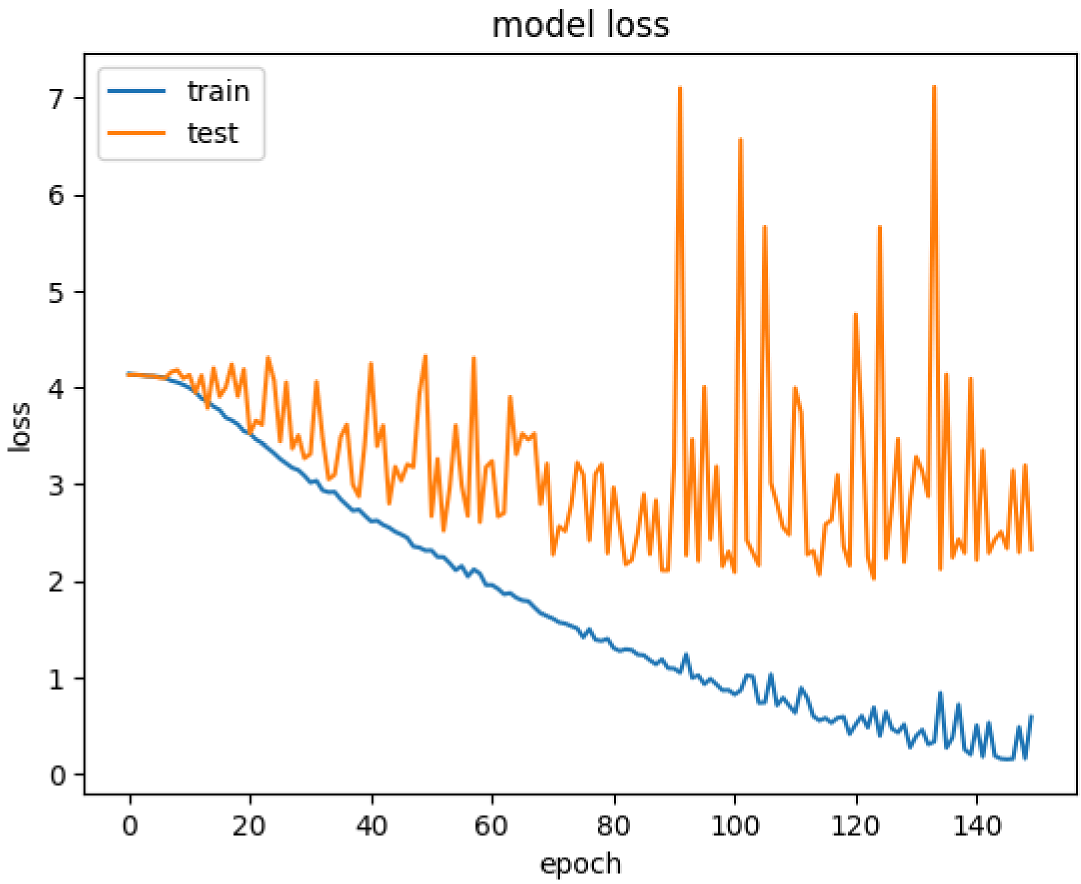


In [ ]:
```
print("Accuracy at 150 epochs: {:.2f}%".format(history.history['val_accuracy'][-
```

```
Accuracy at 150 epochs: 57.04%
```

In [ ]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x2cacc845050>
```



In [ ]:
```
print("Loss at 150 epochs: {:.2f}".format(history.history['loss'][-1]))
```

```
Loss at 150 epochs: 0.59
```