Reverse Image Search

In [74]:

```
#importing the necessary libraries
```

In [75]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [76]:

```
#What is reverse image search?
```

In [77]:

```
#Reverse image search is a search engine technology that takes an image file as input que
ry and returns results
#related to the image.

#Search engines that offer reverse image capability include Google and TinEye.
#Some websites, such as Reddit, also provide a reverse image search capacity.
```

In [78]:

```
train_path ='D:\\M. Tech in Data Science & Machine Learning\\Deep Learning\\Reverse Image
Search\\train_zip\\train\\'
test_path ='D:\\M. Tech in Data Science & Machine Learning\\Deep Learning\\Reverse Image
Search\\test_zip\\test\\'
```

In [79]:

```
import os#OS module in Python provides functions for interacting with the operating syste
m.
import cv2#OpenCV-Python is a library of Python bindings designed to solve computer visio
n problems.
```

In [80]:

```
train_labels=[]#empty list for the train labels
train_images=[]#empty list for train images
for i in os.listdir(train_path):#i is the filename of the image
    if i.split('.')[1] == 'jpg':
        #we have two types of files in the images folders xml and jpg
        #as we need only jpg, we are splitting the image name and extension and if the ex
tension matches with jpg than only
        img=cv2.imread(train_path+i)#joining the full path and the file name (to create i
ndividual location for the image)
        img=cv2.resize(img,(150,150))#Resize the images
        train_images.append(img)#appending to the list of train images
        train_labels.append(i.split('_')[0])#appending only the category name for exampl
e like "Apple", "Banana"
```

In [81]:

```
#converting the image into array
```

In [82]:

```
train_images = np.array(train_images)
```

In [83]:

```
#checking the number of labels and Converting labels into One Hot encoded
```

In [84]:

```
train_label_set = set(train_labels)#by converting to set we get only the unique items as
set dosent take duplicates
print(train_label_set)
```

```
{'mixed', 'apple', 'banana', 'orange'}
```

In [85]:

```
#in total we have 4 categories that are 'apple', 'orange', 'banana', 'mixed fruits'
```

In [86]:

```
train_labels=pd.get_dummies(train_labels).values
train_labels[1:5]#printing some records
```

Out[86]:

```
array([[1, 0, 0, 0],
       [1, 0, 0, 0],
       [1, 0, 0, 0],
       [1, 0, 0, 0]], dtype=uint8)
```

In [87]:

```
#Applying Train test split for Train and validation set
```

In [88]:

```
from sklearn.model_selection import train_test_split
```

In [89]:

```
X_train, X_val, Y_train , Y_val = train_test_split(train_images, train_labels, random_st
ate=2)
```

In [90]:

```
#similary perfroming the same on test data
```

In [91]:

```
test_labels=[]#empty list for the test labels
test_images=[]#empty list for test images
for j in os.listdir(test_path):#i is the filename of the image
    if j.split('.')[1] == 'jpg':
        #we have two types of files in the images folders xml and jpg
        #as we need only jpg, we are splitting the image name and extension and if the ex
tension matches with jpg than only
        img=cv2.imread(test_path+j)#joining the full path and the file name (to create in
dividual location for the image)
        img=cv2.resize(img,(150,150))#Resize the images
        test_images.append(img)#appending to the list of train images
        test_labels.append(j.split('_')[0])#appending only the category name for example
like "Apple", "Banana"
```

In [92]:

```
#converting the image into array
```

In [93]:

```
test_images = np.array(test_images)
```

In [94]:

```
#checking the number of labels and Converting labels into One Hot encoded
```

In [95]:

```
test_label_set = set(test_labels)#by converting to set we get only the unique items as se
t dosent take duplicates
print(test_label_set)
```

```
{'mixed', 'apple', 'banana', 'orange'}
```

In [96]:

```
#in total we have 4 categories that are 'apple', 'orange', 'banana', 'mixed fruits'
```

In [97]:

```
test_labels=pd.get_dummies(test_labels).values
test_labels[1:5]#printing some records
```

Out[97]:

```
array([[1, 0, 0, 0],
       [1, 0, 0, 0],
       [1, 0, 0, 0],
       [1, 0, 0, 0]], dtype=uint8)
```

In [98]:

```
#Model Building
```

In [129]:

```
from keras.models import Sequential,load_model
from keras.layers import Dense, Dropout, Conv2D, MaxPooling2D,Flatten ,Input
```

In [109]:

```
model1=Sequential()
model1.add(Conv2D(filters=32,kernel_size=(3,3),activation='relu',input_shape=(150,150,3)
))
model1.add(MaxPooling2D(pool_size=(2, 2)))
model1.add(Conv2D(filters=30,kernel_size=(3,3),activation='relu'))
model1.add(MaxPooling2D(pool_size=(2, 2)))
model1.add(Conv2D(filters=30,kernel_size=(3,3),activation='relu'))
model1.add(MaxPooling2D(pool_size=(2, 2)))
model1.add(Conv2D(filters=30,kernel_size=(3,3),activation='relu'))
model1.add(Dropout(0.1))
model1.add(Flatten())
model1.add(Dense(25,activation='relu'))
model1.add(Dense(20,activation='relu'))
model1.add(Dense(15,activation='relu'))
model1.add(Dense(4,activation='softmax'))
```

In [110]:

```
print(model1.summary())
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_8 (Conv2D)            (None, 148, 148, 32)      896
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 72, 72, 30)        8670
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 36, 36, 30)        0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 34, 34, 30)        8130
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 17, 17, 30)        0
```

```
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 15, 15, 30)        8130
_________________________________________________________________
dropout_2 (Dropout)          (None, 15, 15, 30)        0
_________________________________________________________________
flatten_2 (Flatten)          (None, 6750)              0
_________________________________________________________________
dense_8 (Dense)              (None, 25)                168775
_________________________________________________________________
dense_9 (Dense)              (None, 20)                520
_________________________________________________________________
dense_10 (Dense)             (None, 15)                315
_________________________________________________________________
dense_11 (Dense)             (None, 4)                 64
=================================================================
Total params: 195,500
Trainable params: 195,500
Non-trainable params: 0
_________________________________________________________________
None
```

In [111]:

```
model1.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
```

In [112]:

```
M1=model1.fit(X_train,Y_train,validation_data=(X_val,Y_val),batch_size=30,epochs=20,verb
ose=1)
```

```
Epoch 1/20
6/6 [==============================] - 10s 943ms/step - loss: 19.7923 - accuracy: 0.2316
- val_loss: 1.7896 - val_accuracy: 0.2333
Epoch 2/20
6/6 [==============================] - 4s 721ms/step - loss: 2.3107 - accuracy: 0.2795 -
val_loss: 1.0491 - val_accuracy: 0.5833
Epoch 3/20
6/6 [==============================] - 5s 816ms/step - loss: 1.2155 - accuracy: 0.5167 -
val_loss: 1.2865 - val_accuracy: 0.4333
Epoch 4/20
6/6 [==============================] - 4s 748ms/step - loss: 1.1708 - accuracy: 0.4057 -
val_loss: 1.1098 - val_accuracy: 0.5667
Epoch 5/20
6/6 [==============================] - 5s 790ms/step - loss: 1.1011 - accuracy: 0.5660 -
val_loss: 0.8936 - val_accuracy: 0.7167
Epoch 6/20
6/6 [==============================] - 5s 805ms/step - loss: 0.7641 - accuracy: 0.6732 -
val_loss: 0.5590 - val_accuracy: 0.8333
Epoch 7/20
6/6 [==============================] - 5s 786ms/step - loss: 0.6320 - accuracy: 0.8448 -
val_loss: 0.5665 - val_accuracy: 0.8167
Epoch 8/20
6/6 [==============================] - 4s 727ms/step - loss: 0.4772 - accuracy: 0.8230 -
val_loss: 0.5665 - val_accuracy: 0.8167
Epoch 9/20
6/6 [==============================] - 4s 735ms/step - loss: 0.3888 - accuracy: 0.8729 -
val_loss: 0.5044 - val_accuracy: 0.8167
Epoch 10/20
6/6 [==============================] - 4s 705ms/step - loss: 0.4081 - accuracy: 0.8963 -
val_loss: 0.5759 - val_accuracy: 0.8167
Epoch 11/20
6/6 [==============================] - 4s 698ms/step - loss: 0.2593 - accuracy: 0.9037 -
val_loss: 0.4266 - val_accuracy: 0.8667
Epoch 12/20
6/6 [==============================] - 4s 742ms/step - loss: 0.2114 - accuracy: 0.9474 -
val_loss: 0.8225 - val_accuracy: 0.8000
Epoch 13/20
6/6 [==============================] - 4s 688ms/step - loss: 0.1729 - accuracy: 0.9387 -
val_loss: 0.6311 - val_accuracy: 0.8333
Epoch 14/20
6/6 [==============================] - 4s 662ms/step - loss: 0.1834 - accuracy: 0.9607 -
val_loss: 0.5354 - val_accuracy: 0.8500
Epoch 15/20
```

```
Epoch 15/20
6/6 [==============================] - 4s 662ms/step - loss: 0.1333 - accuracy: 0.9595 -
val_loss: 0.5558 - val_accuracy: 0.8500
Epoch 16/20
6/6 [==============================] - 4s 659ms/step - loss: 0.1026 - accuracy: 0.9720 -
val_loss: 0.5029 - val_accuracy: 0.8333
Epoch 17/20
6/6 [==============================] - 4s 665ms/step - loss: 0.0989 - accuracy: 0.9791 -
val_loss: 0.6144 - val_accuracy: 0.8167
Epoch 18/20
6/6 [==============================] - 4s 670ms/step - loss: 0.0793 - accuracy: 0.9681 -
val_loss: 0.4617 - val_accuracy: 0.8500
Epoch 19/20
6/6 [==============================] - 4s 665ms/step - loss: 0.0578 - accuracy: 0.9704 -
val_loss: 0.6779 - val_accuracy: 0.8000
Epoch 20/20
6/6 [==============================] - 4s 664ms/step - loss: 0.2362 - accuracy: 0.9212 -
val_loss: 0.9161 - val_accuracy: 0.7167
```

In [113]:

```
#From the model performance we can see that Training accuracy of the model is 92% and val
idation accuracy is 71%
#also as loss 0.23 which is less we can say that the above model is good
```

In [115]:

```
model1.evaluate(test_images,test_labels)
```

```
2/2 [==============================] - 0s 149ms/step - loss: 1.5999 - accuracy: 0.7000
```

Out[115]:

```
[1.5998685359954834, 0.699999988079071]
```

In [116]:

```
#Model evaluation testing accuracy is 70%
```

In [117]:

```
#Plotting the Performance
```

In [118]:

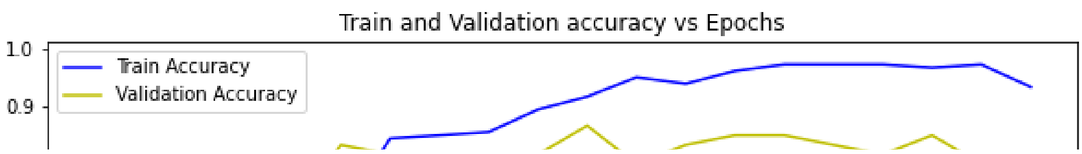
```
def plot_performance1(model):
    plt.figure(figsize=(10,5))
    plt.plot(model.history['accuracy'],'b',label='Train Accuracy')
    plt.plot(model.history['val_accuracy'],'y',label='Validation Accuracy')
    plt.legend()
    plt.title('Train and Validation accuracy vs Epochs')
    plt.show()
```

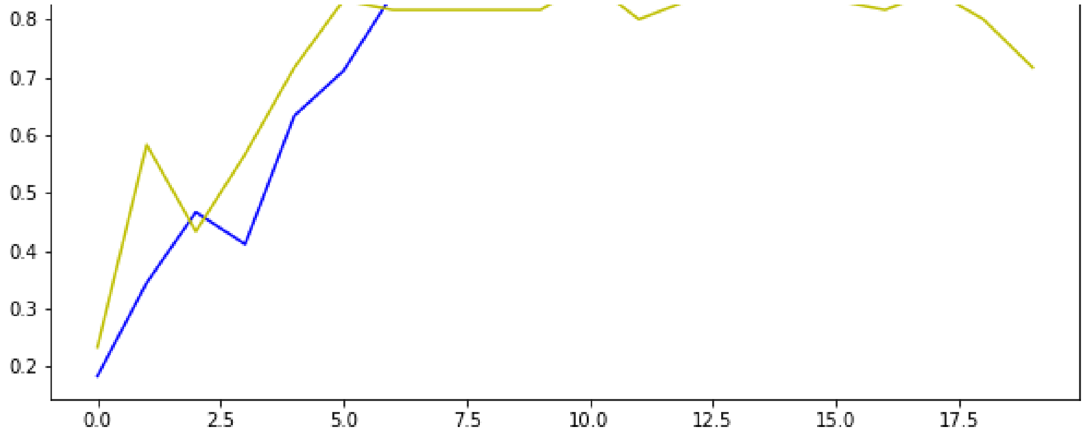
In [119]:

```
def plot_performance2(model):
    plt.figure(figsize=(10,5))
    plt.plot(model.history['loss'],'b--',label='Train loss')
    plt.plot(model.history['val_loss'],'y--',label='Validation loss')
    plt.legend()
    plt.title('Train and Validation loss vs Epochs')
    plt.show()
```

In [120]:

```
plot_performance1(M1)
```



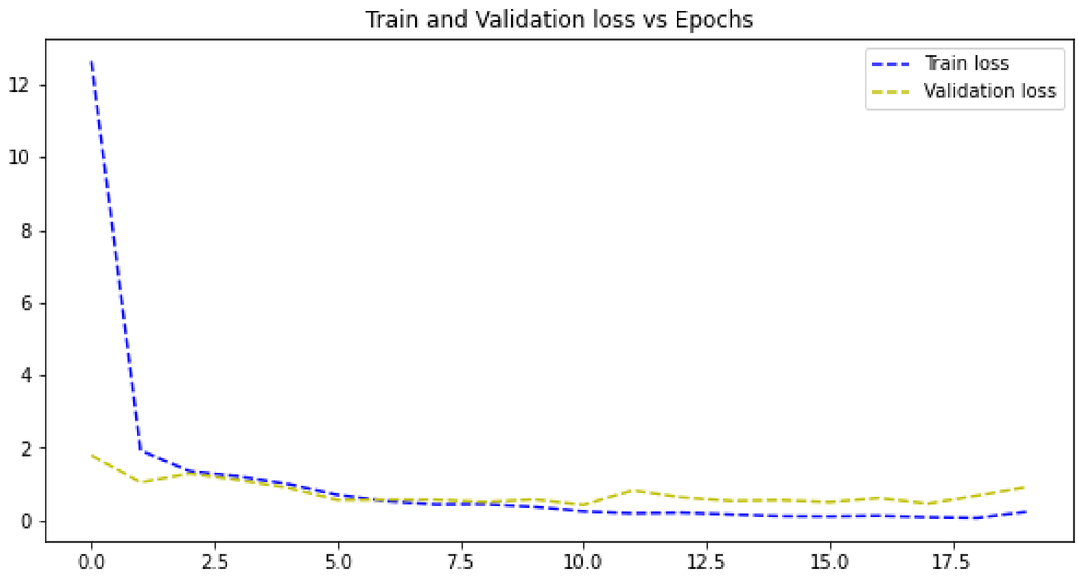


In [121]:

```
#From the above plot we can see that Train accuracy and Validation accuracy are going han
d in hand
```

In [122]:

```
plot_performance2(M1)
```



In [123]:

```
#From the above plot we can see that Train loss and Validation loss are going hand in han
d
```

In [124]:

```
#saving the model weights
```

In [126]:

```
model1.save('Model1.hdf5')
```

In [41]:

```
#Predicting on test image
```

In [42]:

```
#Lets select a randome image from test check the prediction
```

In [ ]:

```
#loading the saved weights
```

In [130]:

```
model_load=load_model('Model1.hdf5')
```

In [195]:

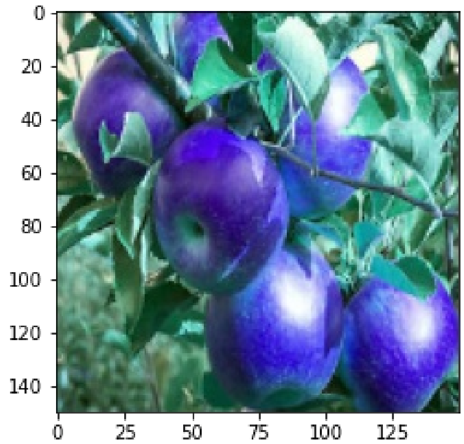
```
checkImage = test_images[0:1]
checklabel = test_labels[0:1]

predict = model_load.predict(checkImage)

output = { 0:'apple',1:'banana',2:'mixed',3:'orange'}#creating a dictionary

print("Actual :- ",checklabel)
print("Predicted :- ",output[np.argmax(predict)])
plt.imshow(test_images[0])# Visualizing Testing data
plt.show()
```

```
Actual :-  [[1 0 0 0]]
Predicted :-  apple
```



In [199]:

```
#Implementing Reverse image search
```

In [ ]:

```
#with the help K nearest neighbors we can find the nerest neighbours
```

In [133]:

```
#Prediction
```

In [164]:

```
from sklearn.neighbors import NearestNeighbors
```

In [169]:

```
neighbors = NearestNeighbors(n_neighbors=5,
                             algorithm='auto',
                             metric='euclidean')#
neighbors.fit(model_predict)
#fitting the model
```

Out[169]:

```
NearestNeighbors(metric='euclidean')
```

In [170]:

```
_, indices = neighbors.kneighbors(model_predict)
#Indices of the nearest points in the population matrix.
```

In [171]:

```
print(indices[56])#for example
```

```
print(indices[56])#1st example
```

```
[56 58 52 50 49]
```

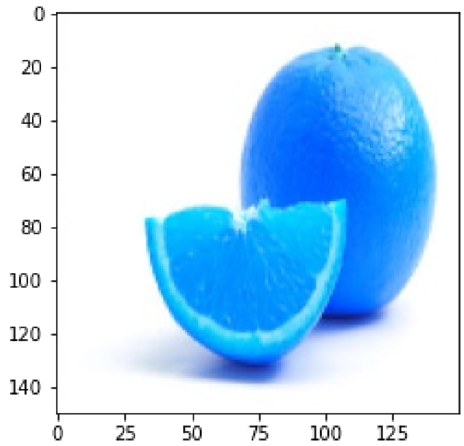
In [ ]:

```
#to the indices 56 we have 58 52 50 49 which are similar.
```

In [207]:

```
print('Original Image')
plt.imshow(test_images[56])
plt.show()
```

```
Original Image
```



In [201]:

```
#function for displying the neighbours of the original image
```

In [202]:

```
def similar_images(indices):
    for index in indices:
        img1=test_images[index]
        plt.imshow(img1)
        plt.show()
```

In [203]:

```
#Similar Images to the original Images
```

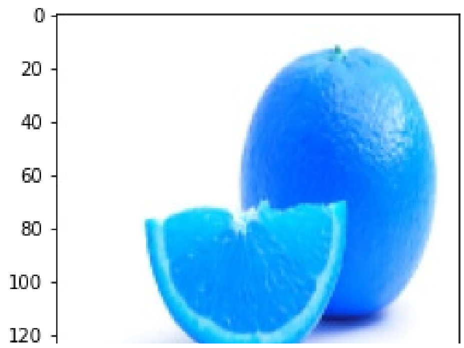
In [ ]:

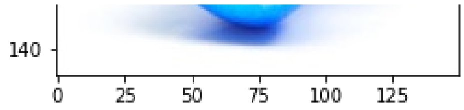
```
#1st example
```

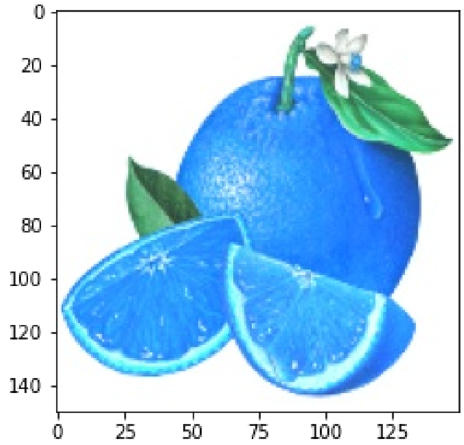
In [204]:

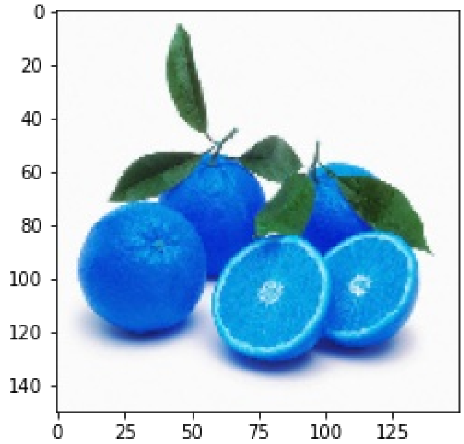
```
print('Similar Images to the original Images:')
print(indices[56])
similar_images(indices[56])
```

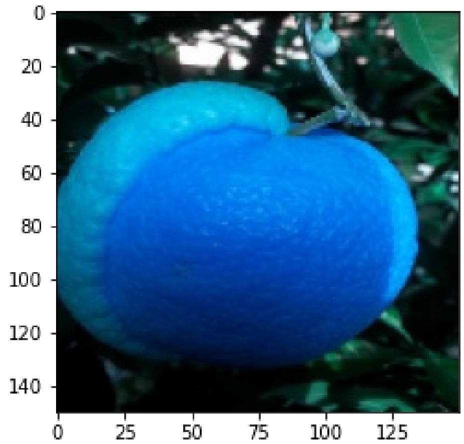
```
Similar Images to the original Images:
[56 58 52 50 49]
```

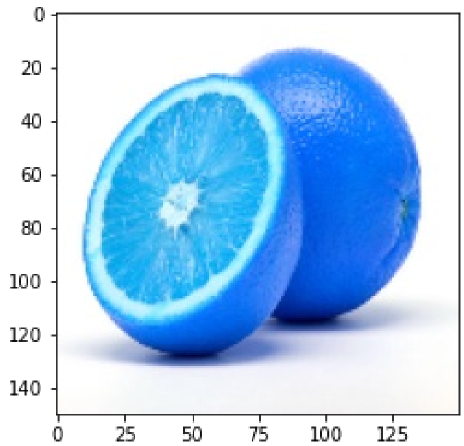












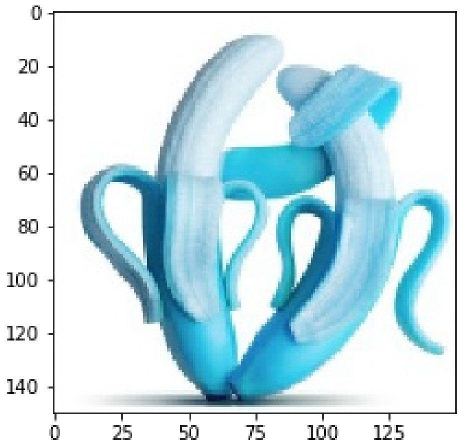
In [205]:

```
#2nd example
```

In [211]:

```
print('Original Image')
plt.imshow(test_images[20], interpolation='nearest')
plt.show()
```

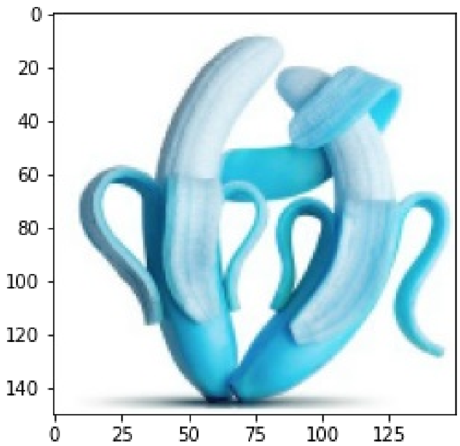
```
Original Image
```

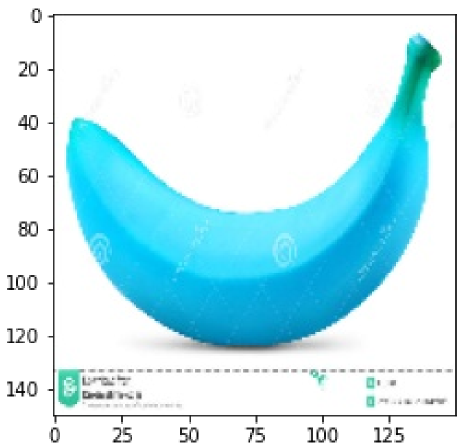


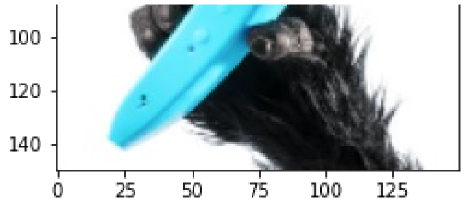
In [212]:

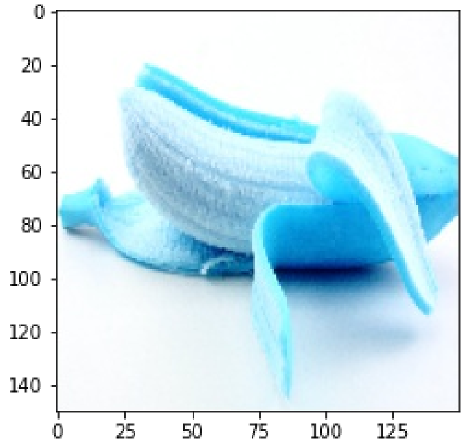
```
print('Similar Images to the original Images:')
print(indices[20])
similar_images(indices[20])
```

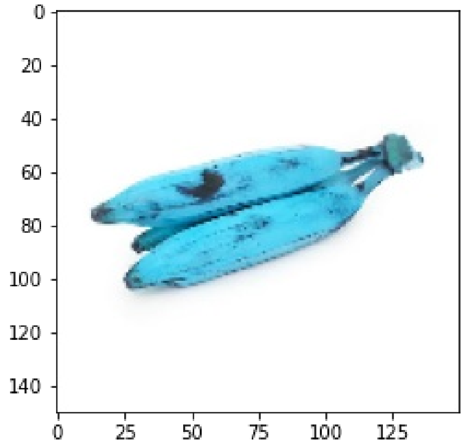
```
Similar Images to the original Images:
[20 21 19 27 22]
```











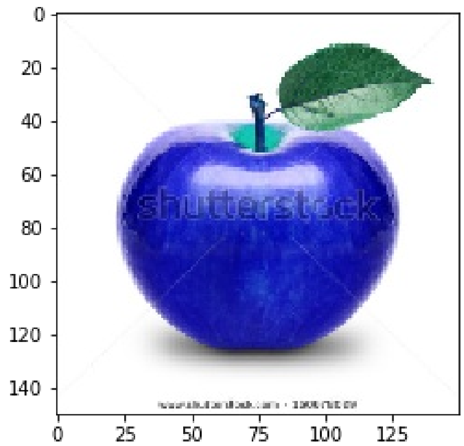
In [ ]:

```
#3rd example
```

In [221]:

```
print('Original Image')
plt.imshow(test_images[5], interpolation='nearest')
plt.show()
```

Original Image

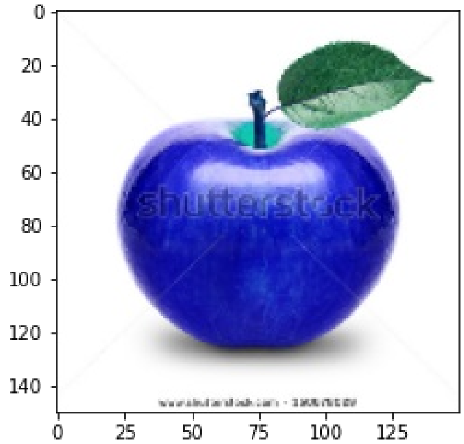


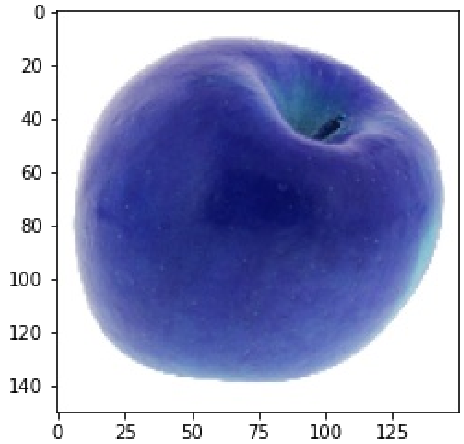
In [222]:

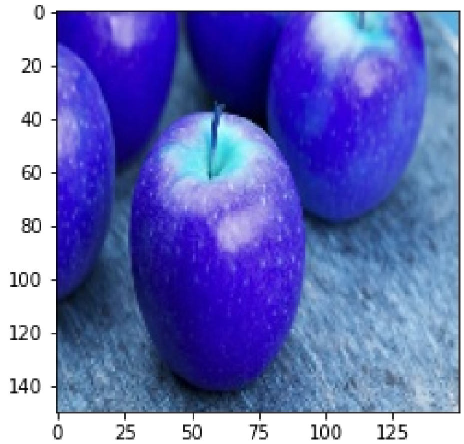
```
print('Similar Images to the original Images:')
print(indices[5])
```

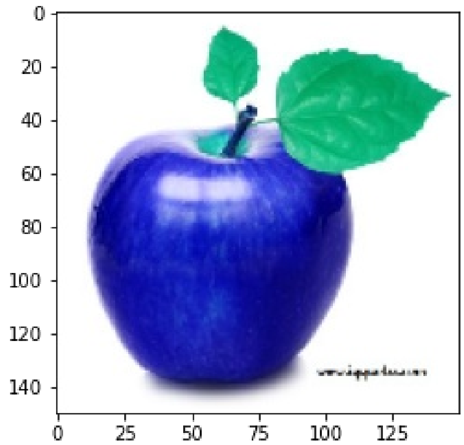
```
similar_images(indices[5])
```

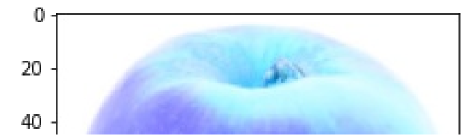
```
Similar Images to the original Images:
[ 5 13 17 10  1]
```

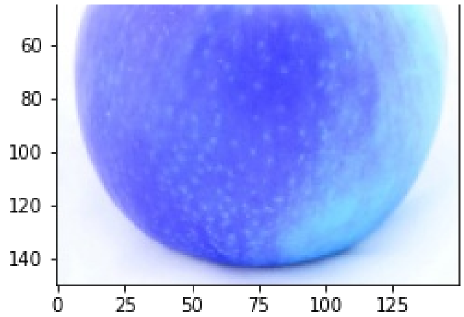












In [ ]:

```
#-------------------------------------END-----------------------------------------------------------------------#
```