Import important libraries and define needed functions and variables

In [1]:
```
import cv2
import tensorflow as tf
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import LearningRateScheduler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix, ConfusionMatrixDisplay
```

```
WARNING:tensorflow:From C:\Users\uyent\anaconda3\Lib\site-packages\keras\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

In [2]:
```
#function to make prediction from probability
def predict(a,thres=0.5):
    if a>= thres:
        return 1
    else:
        return 0
```

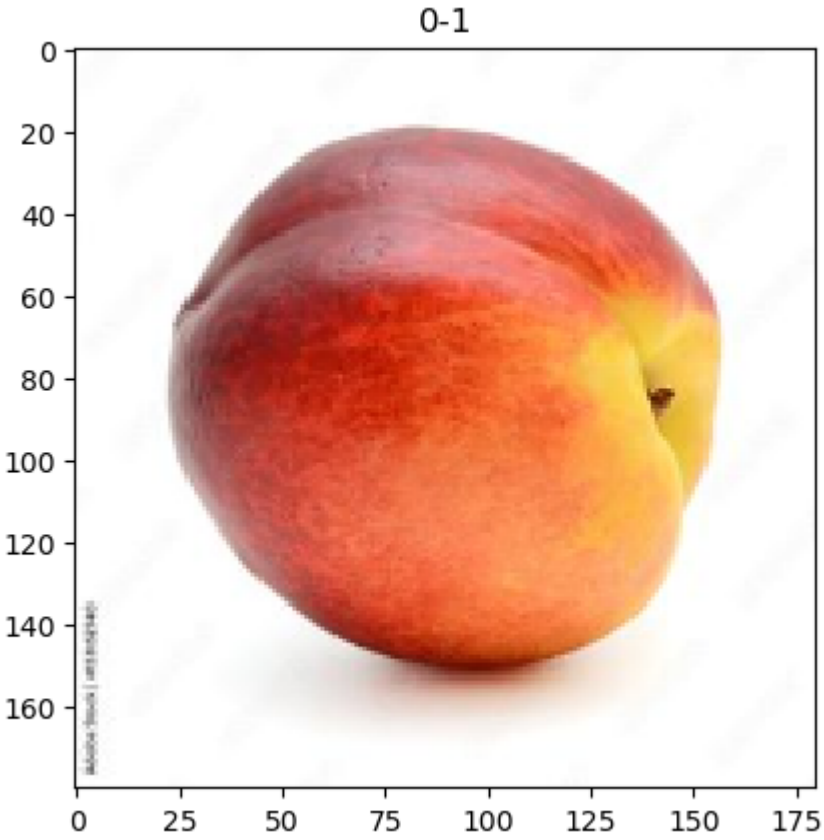
In [3]:
```
# Batch size
batch_size = 32
# image height
img_height = 180
# image width
img_width = 180
```

Data preprocessing

In [4]:
```
#get data from folders
data = []
folders = ['fresh_peaches_done',
 'fresh_pomegranates_done',
 'fresh_strawberries_done',
 'rotten_peaches_done',
 'rotten_pomegranates_done',
 'rotten_strawberries_done'
          ]
for folder in folders:
    if folder.split("_")[0] == 'fresh':
        fresh = 1
    else:
        fresh = 0
    if  folder.split("_")[1] == "peaches":
        class_name = 0
    elif folder.split("_")[1] == "pomegranates":
        class_name = 1
    else:
```

```
        class_name = 2
    for file in os.listdir('data/'+folder):
        img = cv2.imread('data/'+folder+"/"+file)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)     #convert to RGB
        img = cv2.resize(img, (img_height, img_width)) #resize images
        data.append((img, class_name,fresh))
```

In [5]:
```
#plot the first image in the dataset
plt.imshow(data[0][0], interpolation='nearest')
plt.title(str(data[0][1])+ "-"+str(data[0][2]))
plt.show()
```



In [6]:
```
#Split data to X and y. There are 2 target datasets to build 2 different models
X = np.array([i[0] for i in data])
y_class = np.array([i[1] for i in data])
y_fresh = np.array([i[2] for i in data])
print(X.shape)
print(y_class.shape)
print(y_fresh.shape)
```

```
(1585, 180, 180, 3)
(1585,)
(1585,)
```

In [9]:
```
#convert to one-hot
y_class = tf.keras.utils.to_categorical(y_class)
y_class.shape
```

Out[9]:
```
(1585, 3)
```

In [11]:
```
#train-test split
X_train_class,X_test_class,y_train_class,y_test_class = train_test_split(X,y_class,
X_train_fresh,X_test_fresh,y_train_fresh,y_test_fresh = train_test_split(X,y_fresh,
```

Train model to detect fresh or rotten

In [58]:
```
#set learning rate schedule: after 10 epochs, learning rate will decrease gradually
def scheduler(epoch, lr):
    if epoch < 10:
        return lr
    else:
        return lr * tf.math.exp(-0.1)
lr_scheduler = LearningRateScheduler(scheduler)
```

In [59]:
```
#define the model
model_fresh = Sequential([
    # rescaling layer
      layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
    #convolution layers
      layers.Conv2D(32, (3,3), activation='relu'),
      layers.AveragePooling2D((2,2)),
      layers.Conv2D(64, (3,3), activation='relu'),
      layers.AveragePooling2D((2,2)),
      layers.Conv2D(128, (3,3), activation='relu'),
      layers.AveragePooling2D((2,2)),
      layers.Conv2D(256, (3,3), activation='relu'),
      layers.AveragePooling2D((2,2)),
      layers.Conv2D(512, (3,3), activation='relu'),
      layers.AveragePooling2D((2,2)),
    #flatten layer
      layers.Flatten(),
    #dense layers
      layers.Dense(128, activation='relu'),
      layers.Dense(1, activation='sigmoid')
])
```

In [60]:
```
#compile the model
model_fresh.compile(optimizer=keras.optimizers.Adam(learning_rate=0.0005),
              loss=tf.keras.losses.BinaryCrossentropy(),
              metrics=['accuracy'])
```

In [61]:
```
#model summary
model_fresh.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_5 (Rescaling)     (None, 180, 180, 3)       0

 conv2d_23 (Conv2D)          (None, 178, 178, 32)      896

 average_pooling2d_18 (Aver  (None, 89, 89, 32)        0
 agePooling2D)

 conv2d_24 (Conv2D)          (None, 87, 87, 64)        18496

 average_pooling2d_19 (Aver  (None, 43, 43, 64)        0
 agePooling2D)

 conv2d_25 (Conv2D)          (None, 41, 41, 128)       73856

 average_pooling2d_20 (Aver  (None, 20, 20, 128)       0
 agePooling2D)

 conv2d_26 (Conv2D)          (None, 18, 18, 256)       295168

 average_pooling2d_21 (Aver  (None, 9, 9, 256)         0
 agePooling2D)

 conv2d_27 (Conv2D)          (None, 7, 7, 512)         1180160

 average_pooling2d_22 (Aver  (None, 3, 3, 512)         0
 agePooling2D)

 flatten_5 (Flatten)         (None, 4608)              0

 dense_10 (Dense)            (None, 128)               589952

 dense_11 (Dense)            (None, 1)                 129

=================================================================
Total params: 2158657 (8.23 MB)
Trainable params: 2158657 (8.23 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [62]:

```
#train model with 25 epochs
epochs=30
history = model_fresh.fit(
                    X_train_fresh,
                    y_train_fresh,
                    validation_data=(X_test_fresh,y_test_fresh),
                    batch_size=batch_size,
                    epochs=epochs,
                    callbacks= lr_scheduler

)
```

```
Epoch 1/30
40/40 [==============================] - 19s 445ms/step - loss: 0.6024 - accuracy:
0.6735 - val_loss: 0.5135 - val_accuracy: 0.7666 - lr: 5.0000e-04
Epoch 2/30
40/40 [==============================] - 17s 419ms/step - loss: 0.4900 - accuracy:
0.7871 - val_loss: 0.4210 - val_accuracy: 0.8328 - lr: 5.0000e-04
Epoch 3/30
40/40 [==============================] - 17s 424ms/step - loss: 0.4388 - accuracy:
0.7973 - val_loss: 0.3764 - val_accuracy: 0.8454 - lr: 5.0000e-04
Epoch 4/30
40/40 [==============================] - 17s 436ms/step - loss: 0.4083 - accuracy:
0.8210 - val_loss: 0.3886 - val_accuracy: 0.8233 - lr: 5.0000e-04
Epoch 5/30
40/40 [==============================] - 17s 435ms/step - loss: 0.3917 - accuracy:
0.8304 - val_loss: 0.3760 - val_accuracy: 0.8170 - lr: 5.0000e-04
Epoch 6/30
40/40 [==============================] - 17s 436ms/step - loss: 0.3599 - accuracy:
0.8391 - val_loss: 0.3368 - val_accuracy: 0.8801 - lr: 5.0000e-04
Epoch 7/30
40/40 [==============================] - 18s 440ms/step - loss: 0.3646 - accuracy:
0.8486 - val_loss: 0.3640 - val_accuracy: 0.8486 - lr: 5.0000e-04
Epoch 8/30
40/40 [==============================] - 17s 436ms/step - loss: 0.3632 - accuracy:
0.8431 - val_loss: 0.3653 - val_accuracy: 0.8297 - lr: 5.0000e-04
Epoch 9/30
40/40 [==============================] - 17s 437ms/step - loss: 0.3582 - accuracy:
0.8462 - val_loss: 0.3232 - val_accuracy: 0.8738 - lr: 5.0000e-04
Epoch 10/30
40/40 [==============================] - 17s 437ms/step - loss: 0.3350 - accuracy:
0.8620 - val_loss: 0.3435 - val_accuracy: 0.8644 - lr: 5.0000e-04
Epoch 11/30
40/40 [==============================] - 18s 439ms/step - loss: 0.3181 - accuracy:
0.8691 - val_loss: 0.3203 - val_accuracy: 0.8770 - lr: 4.5242e-04
Epoch 12/30
40/40 [==============================] - 18s 445ms/step - loss: 0.2893 - accuracy:
0.8746 - val_loss: 0.2890 - val_accuracy: 0.8801 - lr: 4.0937e-04
Epoch 13/30
40/40 [==============================] - 18s 442ms/step - loss: 0.2824 - accuracy:
0.8864 - val_loss: 0.3137 - val_accuracy: 0.8707 - lr: 3.7041e-04
Epoch 14/30
40/40 [==============================] - 18s 448ms/step - loss: 0.2732 - accuracy:
0.8833 - val_loss: 0.3226 - val_accuracy: 0.8549 - lr: 3.3516e-04
Epoch 15/30
40/40 [==============================] - 18s 455ms/step - loss: 0.2593 - accuracy:
0.8856 - val_loss: 0.2860 - val_accuracy: 0.9022 - lr: 3.0327e-04
Epoch 16/30
40/40 [==============================] - 18s 444ms/step - loss: 0.2362 - accuracy:
0.9046 - val_loss: 0.2660 - val_accuracy: 0.8991 - lr: 2.7441e-04
Epoch 17/30
40/40 [==============================] - 19s 488ms/step - loss: 0.2319 - accuracy:
0.9077 - val_loss: 0.3038 - val_accuracy: 0.8864 - lr: 2.4829e-04
Epoch 18/30
40/40 [==============================] - 20s 508ms/step - loss: 0.2207 - accuracy:
0.9140 - val_loss: 0.2860 - val_accuracy: 0.8864 - lr: 2.2466e-04
Epoch 19/30
40/40 [==============================] - 19s 482ms/step - loss: 0.2116 - accuracy:
0.9251 - val_loss: 0.2935 - val_accuracy: 0.8833 - lr: 2.0328e-04
Epoch 20/30
40/40 [==============================] - 19s 469ms/step - loss: 0.1892 - accuracy:
0.9338 - val_loss: 0.2920 - val_accuracy: 0.8991 - lr: 1.8394e-04
Epoch 21/30
40/40 [==============================] - 19s 476ms/step - loss: 0.2004 - accuracy:
0.9211 - val_loss: 0.2842 - val_accuracy: 0.8896 - lr: 1.6644e-04
Epoch 22/30
```

```
40/40 [==============================] - 18s 446ms/step - loss: 0.1871 - accuracy:
0.9314 - val_loss: 0.2936 - val_accuracy: 0.8833 - lr: 1.5060e-04
Epoch 23/30
40/40 [==============================] - 18s 462ms/step - loss: 0.1815 - accuracy:
0.9361 - val_loss: 0.2704 - val_accuracy: 0.8927 - lr: 1.3627e-04
Epoch 24/30
40/40 [==============================] - 19s 468ms/step - loss: 0.1713 - accuracy:
0.9322 - val_loss: 0.2745 - val_accuracy: 0.8896 - lr: 1.2330e-04
Epoch 25/30
40/40 [==============================] - 19s 485ms/step - loss: 0.1552 - accuracy:
0.9448 - val_loss: 0.2952 - val_accuracy: 0.8864 - lr: 1.1157e-04
Epoch 26/30
40/40 [==============================] - 19s 487ms/step - loss: 0.1496 - accuracy:
0.9440 - val_loss: 0.2931 - val_accuracy: 0.8927 - lr: 1.0095e-04
Epoch 27/30
40/40 [==============================] - 18s 448ms/step - loss: 0.1443 - accuracy:
0.9487 - val_loss: 0.2881 - val_accuracy: 0.8896 - lr: 9.1342e-05
Epoch 28/30
40/40 [==============================] - 45s 1s/step - loss: 0.1342 - accuracy: 0.
9574 - val_loss: 0.3100 - val_accuracy: 0.8864 - lr: 8.2649e-05
Epoch 29/30
40/40 [==============================] - 98s 2s/step - loss: 0.1359 - accuracy: 0.
9495 - val_loss: 0.2851 - val_accuracy: 0.8991 - lr: 7.4784e-05
Epoch 30/30
40/40 [==============================] - 106s 3s/step - loss: 0.1238 - accuracy:
0.9543 - val_loss: 0.3002 - val_accuracy: 0.9022 - lr: 6.7668e-05
```

In [63]:

```
#get train accuracy in history
acc = history.history['accuracy']
#get validation accuracy
val_acc = history.history['val_accuracy']
# get train loss
loss = history.history['loss']
#get validation loss
val_loss = history.history['val_loss']

epochs_range = range(epochs)
# plot accuracy
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot( acc, label='Training Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
# plot loss
plt.subplot(1, 2, 2)
plt.plot( loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

In [64]:
```
#predict model with test data
y_pred_fresh = model_fresh.predict(X_test_fresh)
y_pred_fresh = np.array([predict(y_pred_fresh[i]) for i in range(y_pred_fresh.shape
```

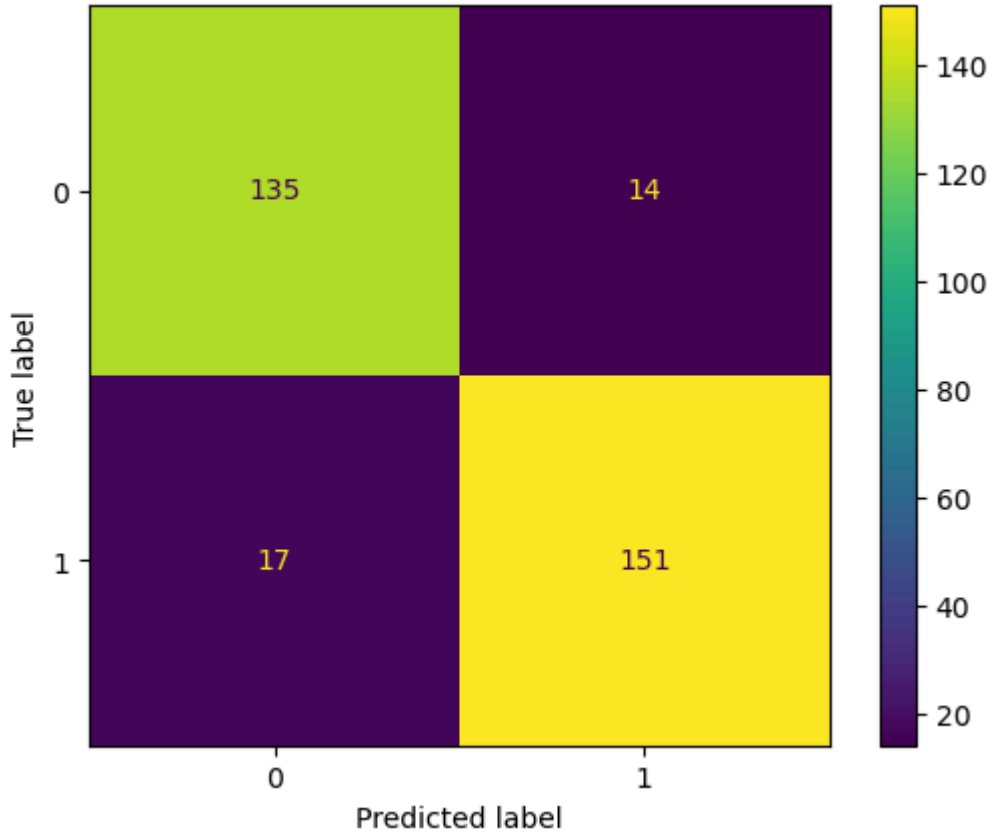
```
10/10 [==============================] - 8s 715ms/step
```

In [65]:
```
#get accuracy
accuracy_score(y_test_fresh,y_pred_fresh)
```

Out[65]:
```
0.9022082018927445
```

In [66]:
```
#confusion matrix
ConfusionMatrixDisplay.from_predictions(y_test_fresh,y_pred_fresh)
```

Out[66]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x240467fadd0>
```



data_augmentation = keras.Sequential([layers.RandomFlip("horizontal", input_shape= (img_height, img_width, 3)), layers.RandomRotation(0.1), layers.RandomZoom(0.1),])

model_aug = Sequential([data_augmentation, layers.Rescaling(1./255), layers.Conv2D(32, (3,3), activation='relu'), layers.MaxPooling2D((2,2)), layers.Conv2D(64, (3,3), activation='relu'), layers.MaxPooling2D((2,2)), layers.Conv2D(64, (3,3), activation='relu'), layers.MaxPooling2D((2,2)), layers.Flatten(), layers.Dense(64, activation='relu'), layers.Dense(1, activation='sigmoid')])

compile the model

model_aug.compile(optimizer='adam', loss=tf.keras.losses.BinaryCrossentropy(), metrics= ['accuracy'])

model_aug.summary()

epochs=15 history_aug = model_aug.fit(X_train_fresh, y_train_fresh, validation_split=0.2, batch_size=batch_size, epochs=epochs

)

In [67]:
```
#Try with different threshold (k) to see if adjusting the threshold can help to red
y_pred_fresh = model_fresh.predict(X_test_fresh)
score = []
for k in [0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1]:
    y_pred_thr = np.array([predict(y_pred_fresh[i],k) for i in range(y_pred_fresh.s
    acc = accuracy_score(y_test_fresh,y_pred_thr)
    FN = cf_matrix = confusion_matrix(y_test_fresh, y_pred_thr,labels=np.unique(y_t
```

```
    FP = cf_matrix = confusion_matrix(y_test_fresh, y_pred_thr,labels=np.unique(y_t
    score.append([k,acc,FN,FP])
```

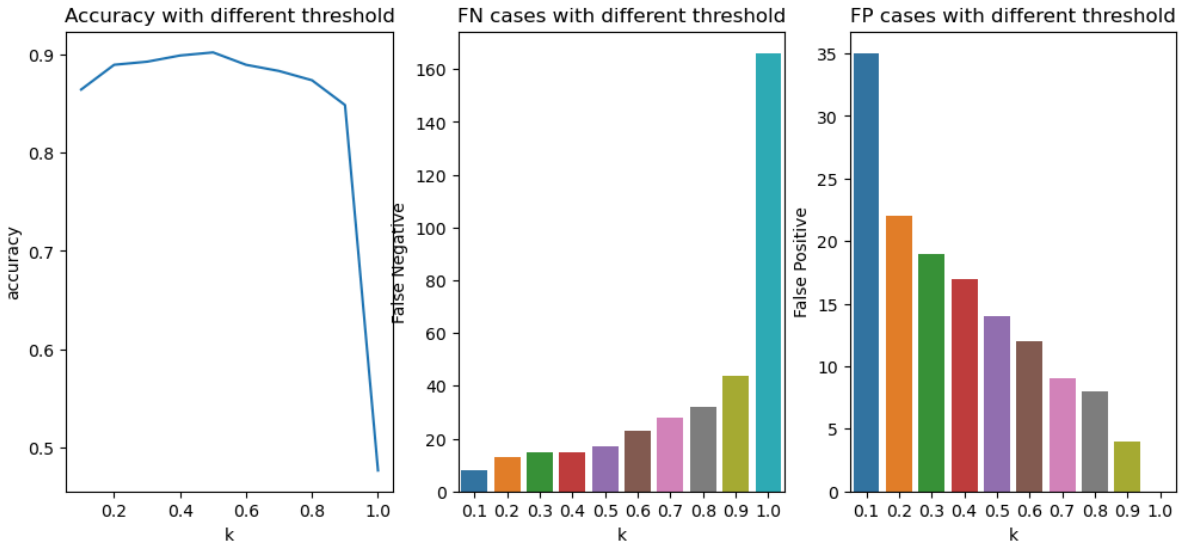
```
10/10 [==============================] - 7s 648ms/step
```

In [68]:
```
score
```

Out[68]:
```
[[0.1, 0.8643533123028391, 8, 35],
 [0.2, 0.889589905362776, 13, 22],
 [0.3, 0.8927444794952681, 15, 19],
 [0.4, 0.8990536277602523, 15, 17],
 [0.5, 0.9022082018927445, 17, 14],
 [0.6, 0.889589905362776, 23, 12],
 [0.7, 0.8832807570977917, 28, 9],
 [0.8, 0.8738170347003155, 32, 8],
 [0.9, 0.8485804416403786, 44, 4],
 [1, 0.47634069400630913, 166, 0]]
```

In [69]:
```
#Get score dataframe
score = pd.DataFrame(data=score,columns=['k','accuracy','False Negative','False Pos
fig,ax = plt.subplots(1,3,figsize=(12,5))
#Plot accuracy by different threshold
sns.lineplot(data=score,x='k',y='accuracy',ax=ax[0])
ax[0].set_title("Accuracy with different threshold")
#Plot number of FN cases by different threshold
sns.barplot(data=score,x='k',y='False Negative',ax=ax[1])
ax[1].set_title("FN cases with different threshold")
#Plot number of PN cases by different threshold
sns.barplot(data=score,x='k',y='False Positive',ax=ax[2])
ax[2].set_title("FP cases with different threshold")
```

Out[69]:
```
Text(0.5, 1.0, 'FP cases with different threshold')
```



In [70]:
```
#save model
model_fresh.save("fresh_prediction_ver4.keras")
```

Train model for fruit type classification

In [31]:
```
#set data agumenation layer
data_augmentation = tf.keras.Sequential([
  layers.RandomFlip("horizontal_and_vertical"),
  layers.RandomRotation(0.2),
])
```

In [32]:
```
#define the model
model_class = Sequential([
      layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
      data_augmentation,
      layers.Conv2D(32, (3,3), activation='relu'),
      layers.MaxPooling2D((2,2),padding='SAME'),
      layers.Conv2D(64, (3,3), activation='relu'),
      layers.MaxPooling2D((2,2),padding='SAME'),
      layers.Conv2D(128, (3,3), activation='relu'),
      layers.MaxPooling2D((2,2),padding='SAME'),
      layers.Conv2D(256, (3,3), activation='relu'),
      layers.MaxPooling2D((2,2),padding='SAME'),
      layers.Conv2D(512, (3,3), activation='relu'),
      layers.MaxPooling2D((2,2),padding='SAME'),
      layers.Flatten(),
      layers.Dense(256, activation='relu'),
      #layers.Dense(128, activation='relu'),
      layers.Dense(3, activation='softmax')
])
```

In [33]:
```
#compile the model
model_class.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accu
```

In [34]:
```
#train model with 40 epochs
epochs=40
history = model_class.fit(
                    X_train_class,
                    y_train_class,
                    validation_data=(X_test_class,y_test_class),
                    epochs=epochs,
                    callbacks= lr_scheduler
)
```

```
Epoch 1/40
40/40 [==============================] - 21s 508ms/step - loss: 1.0849 - accuracy:
0.4203 - val_loss: 1.0418 - val_accuracy: 0.5237 - lr: 0.0010
Epoch 2/40
40/40 [==============================] - 19s 481ms/step - loss: 0.9641 - accuracy:
0.5473 - val_loss: 0.9495 - val_accuracy: 0.4606 - lr: 0.0010
Epoch 3/40
40/40 [==============================] - 19s 476ms/step - loss: 0.8885 - accuracy:
0.5639 - val_loss: 0.8195 - val_accuracy: 0.5300 - lr: 0.0010
Epoch 4/40
40/40 [==============================] - 21s 527ms/step - loss: 0.8102 - accuracy:
0.5820 - val_loss: 0.8419 - val_accuracy: 0.5489 - lr: 0.0010
Epoch 5/40
40/40 [==============================] - 21s 528ms/step - loss: 0.7315 - accuracy:
0.6285 - val_loss: 0.9873 - val_accuracy: 0.5331 - lr: 0.0010
Epoch 6/40
40/40 [==============================] - 21s 523ms/step - loss: 0.6879 - accuracy:
0.6751 - val_loss: 0.6429 - val_accuracy: 0.6435 - lr: 0.0010
Epoch 7/40
40/40 [==============================] - 20s 496ms/step - loss: 0.5691 - accuracy:
0.7248 - val_loss: 0.4620 - val_accuracy: 0.7823 - lr: 0.0010
Epoch 8/40
40/40 [==============================] - 20s 500ms/step - loss: 0.5000 - accuracy:
0.7871 - val_loss: 0.4610 - val_accuracy: 0.8233 - lr: 0.0010
Epoch 9/40
40/40 [==============================] - 22s 540ms/step - loss: 0.5038 - accuracy:
0.7752 - val_loss: 0.4751 - val_accuracy: 0.7981 - lr: 0.0010
Epoch 10/40
40/40 [==============================] - 21s 526ms/step - loss: 0.6785 - accuracy:
0.6640 - val_loss: 0.8052 - val_accuracy: 0.4795 - lr: 0.0010
Epoch 11/40
40/40 [==============================] - 21s 530ms/step - loss: 0.5918 - accuracy:
0.7074 - val_loss: 0.5574 - val_accuracy: 0.7603 - lr: 9.0484e-04
Epoch 12/40
40/40 [==============================] - 20s 500ms/step - loss: 0.4754 - accuracy:
0.8068 - val_loss: 0.7676 - val_accuracy: 0.6845 - lr: 8.1873e-04
Epoch 13/40
40/40 [==============================] - 20s 488ms/step - loss: 0.4351 - accuracy:
0.8099 - val_loss: 0.3574 - val_accuracy: 0.8517 - lr: 7.4082e-04
Epoch 14/40
40/40 [==============================] - 19s 483ms/step - loss: 0.3860 - accuracy:
0.8423 - val_loss: 0.3734 - val_accuracy: 0.8423 - lr: 6.7032e-04
Epoch 15/40
40/40 [==============================] - 19s 485ms/step - loss: 0.3429 - accuracy:
0.8644 - val_loss: 0.4949 - val_accuracy: 0.8044 - lr: 6.0653e-04
Epoch 16/40
40/40 [==============================] - 20s 498ms/step - loss: 0.3494 - accuracy:
0.8446 - val_loss: 0.3950 - val_accuracy: 0.8328 - lr: 5.4881e-04
Epoch 17/40
40/40 [==============================] - 21s 514ms/step - loss: 0.3209 - accuracy:
0.8715 - val_loss: 0.2880 - val_accuracy: 0.9085 - lr: 4.9659e-04
Epoch 18/40
40/40 [==============================] - 20s 495ms/step - loss: 0.3066 - accuracy:
0.8738 - val_loss: 0.3954 - val_accuracy: 0.8486 - lr: 4.4933e-04
Epoch 19/40
40/40 [==============================] - 20s 501ms/step - loss: 0.2986 - accuracy:
0.8746 - val_loss: 0.3723 - val_accuracy: 0.8707 - lr: 4.0657e-04
Epoch 20/40
40/40 [==============================] - 20s 508ms/step - loss: 0.2762 - accuracy:
0.8841 - val_loss: 0.3503 - val_accuracy: 0.8738 - lr: 3.6788e-04
Epoch 21/40
40/40 [==============================] - 20s 504ms/step - loss: 0.2518 - accuracy:
0.8927 - val_loss: 0.3322 - val_accuracy: 0.8707 - lr: 3.3287e-04
Epoch 22/40
```

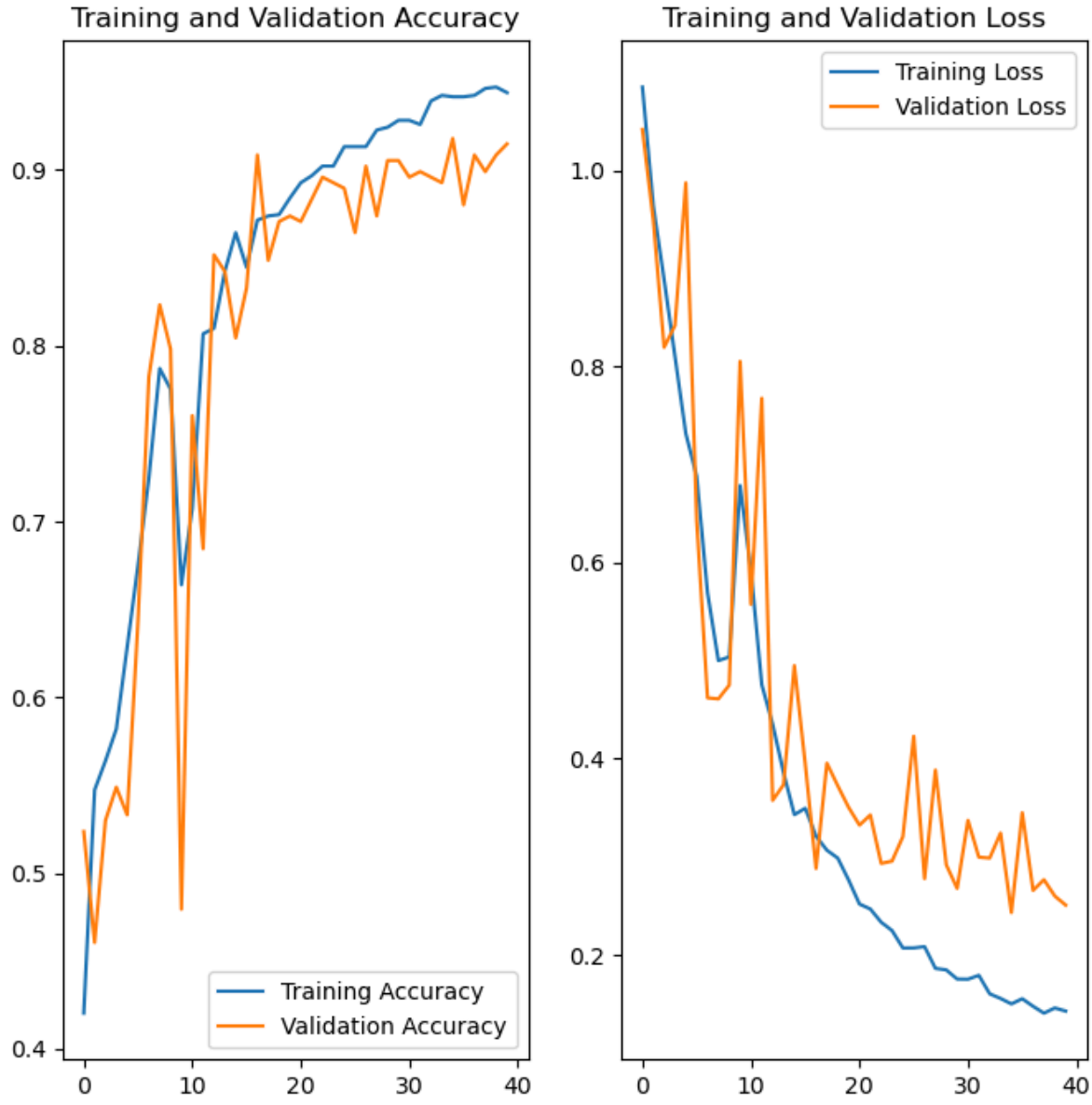
```
40/40 [==============================] - 20s 498ms/step - loss: 0.2467 - accuracy:
0.8967 - val_loss: 0.3426 - val_accuracy: 0.8833 - lr: 3.0119e-04
Epoch 23/40
40/40 [==============================] - 19s 486ms/step - loss: 0.2332 - accuracy:
0.9022 - val_loss: 0.2932 - val_accuracy: 0.8959 - lr: 2.7253e-04
Epoch 24/40
40/40 [==============================] - 20s 489ms/step - loss: 0.2247 - accuracy:
0.9022 - val_loss: 0.2956 - val_accuracy: 0.8927 - lr: 2.4660e-04
Epoch 25/40
40/40 [==============================] - 20s 492ms/step - loss: 0.2070 - accuracy:
0.9132 - val_loss: 0.3205 - val_accuracy: 0.8896 - lr: 2.2313e-04
Epoch 26/40
40/40 [==============================] - 19s 483ms/step - loss: 0.2070 - accuracy:
0.9132 - val_loss: 0.4228 - val_accuracy: 0.8644 - lr: 2.0190e-04
Epoch 27/40
40/40 [==============================] - 19s 484ms/step - loss: 0.2083 - accuracy:
0.9132 - val_loss: 0.2777 - val_accuracy: 0.9022 - lr: 1.8268e-04
Epoch 28/40
40/40 [==============================] - 19s 484ms/step - loss: 0.1862 - accuracy:
0.9227 - val_loss: 0.3884 - val_accuracy: 0.8738 - lr: 1.6530e-04
Epoch 29/40
40/40 [==============================] - 20s 500ms/step - loss: 0.1846 - accuracy:
0.9243 - val_loss: 0.2918 - val_accuracy: 0.9054 - lr: 1.4957e-04
Epoch 30/40
40/40 [==============================] - 19s 486ms/step - loss: 0.1753 - accuracy:
0.9282 - val_loss: 0.2677 - val_accuracy: 0.9054 - lr: 1.3534e-04
Epoch 31/40
40/40 [==============================] - 19s 486ms/step - loss: 0.1751 - accuracy:
0.9282 - val_loss: 0.3372 - val_accuracy: 0.8959 - lr: 1.2246e-04
Epoch 32/40
40/40 [==============================] - 20s 496ms/step - loss: 0.1790 - accuracy:
0.9259 - val_loss: 0.2996 - val_accuracy: 0.8991 - lr: 1.1080e-04
Epoch 33/40
40/40 [==============================] - 20s 499ms/step - loss: 0.1602 - accuracy:
0.9393 - val_loss: 0.2986 - val_accuracy: 0.8959 - lr: 1.0026e-04
Epoch 34/40
40/40 [==============================] - 19s 487ms/step - loss: 0.1555 - accuracy:
0.9424 - val_loss: 0.3242 - val_accuracy: 0.8927 - lr: 9.0718e-05
Epoch 35/40
40/40 [==============================] - 19s 485ms/step - loss: 0.1499 - accuracy:
0.9416 - val_loss: 0.2431 - val_accuracy: 0.9180 - lr: 8.2085e-05
Epoch 36/40
40/40 [==============================] - 20s 494ms/step - loss: 0.1552 - accuracy:
0.9416 - val_loss: 0.3449 - val_accuracy: 0.8801 - lr: 7.4274e-05
Epoch 37/40
40/40 [==============================] - 20s 494ms/step - loss: 0.1475 - accuracy:
0.9424 - val_loss: 0.2657 - val_accuracy: 0.9085 - lr: 6.7206e-05
Epoch 38/40
40/40 [==============================] - 19s 488ms/step - loss: 0.1405 - accuracy:
0.9464 - val_loss: 0.2766 - val_accuracy: 0.8991 - lr: 6.0810e-05
Epoch 39/40
40/40 [==============================] - 20s 488ms/step - loss: 0.1458 - accuracy:
0.9472 - val_loss: 0.2599 - val_accuracy: 0.9085 - lr: 5.5023e-05
Epoch 40/40
40/40 [==============================] - 20s 493ms/step - loss: 0.1426 - accuracy:
0.9440 - val_loss: 0.2507 - val_accuracy: 0.9148 - lr: 4.9787e-05
```

In [35]:

```
#get train accuracy in history
acc = history.history['accuracy']
#get validation accuracy
val_acc = history.history['val_accuracy']
# get train loss
loss = history.history['loss']
#get validation loss
```

```
val_loss = history.history['val_loss']

epochs_range = range(epochs)
# plot accuracy
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot( acc, label='Training Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
# plot loss
plt.subplot(1, 2, 2)
plt.plot( loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



In [36]:
```
#make prediction with testing data
y_pred_class = model_class.predict(X_test_class)
y_pred_class = np.vectorize(predict)(y_pred_class)
```

```
10/10 [==============================] - 1s 112ms/step
```

In [40]:
```
#get accuracy
accuracy_score(y_test_class,y_pred_class)
```

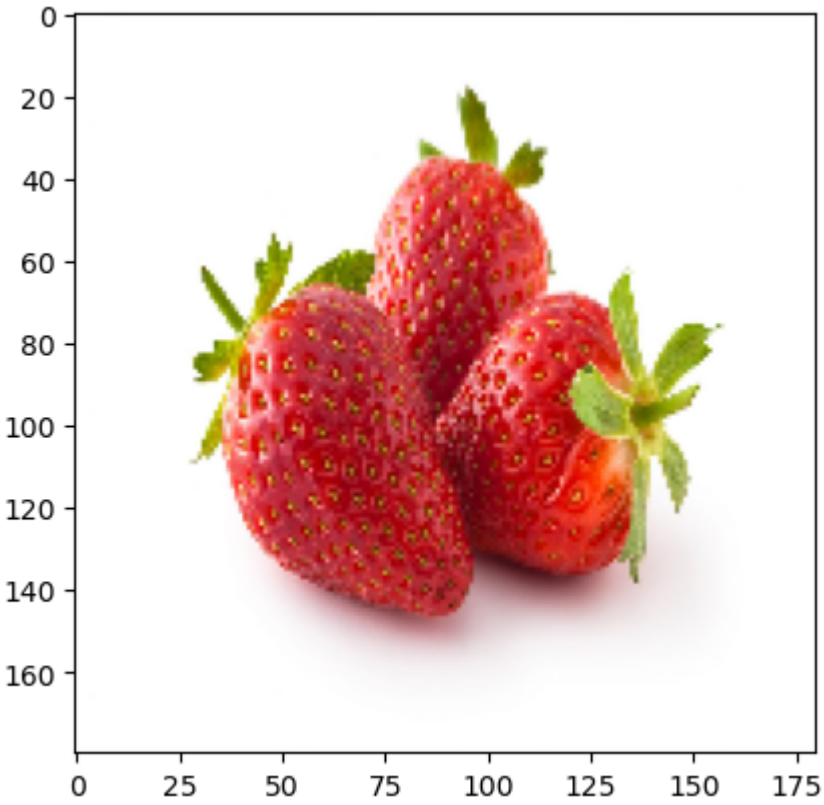
Out[40]:
```
0.9116719242902208
```

In [47]:
```
#save model
model_class.save("class_prediction_ver2.keras")
```

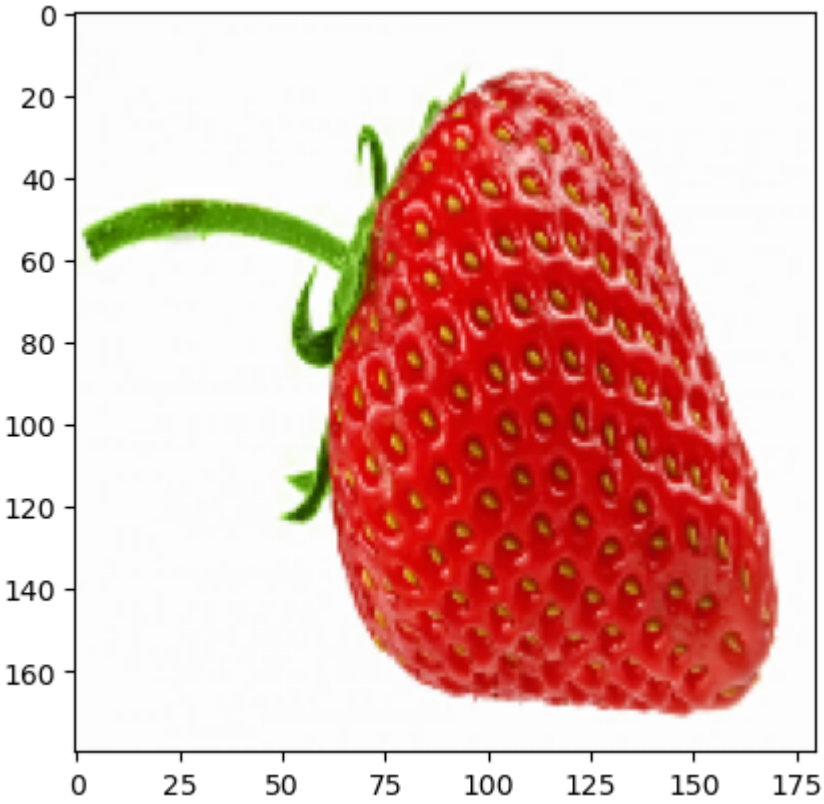
Define function for prediction making

In [41]:
```
def predictions(file_url,model_class,model_fresh):
    #load image from url and prepare data
    img = cv2.imread(file_url)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (img_height, img_width))
    plt.imshow(img)
    plt.show()
    img = np.expand_dims(img, axis=0)
    #fruit type prediction
    class_prediction = model_class.predict(img)
    class_probabilities = class_prediction[0]
    class_predict = np.vectorize(predict)(class_probabilities)
    if class_predict[0] == 1:
        class_type = 'Peach'
    elif class_predict[1]==1:
        class_type='Pomegranate'
    else:
        class_type='Strawberry'
    #frest/rotten prediction
    fresh_probability = model_fresh.predict(img)[0][0]
    fresh_predict = predict(fresh_probability)
    fresh_predict = 'Fresh' if fresh_predict==1 else 'Rotten'
    print(f'class: {class_type} - confident: {class_probabilities}\nquality: {fresh
    #return fruit type, fresh/rotten prediction with probability
    return class_probabilities,class_type,fresh_probability,fresh_predict
```

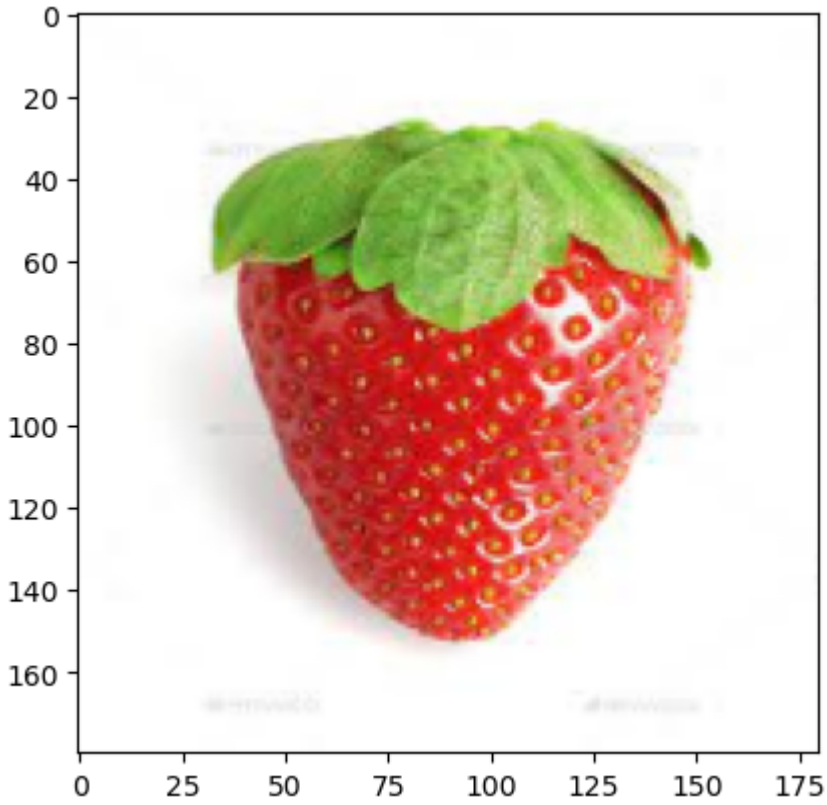
In [76]:
```
#test with data collected from the internet
folder = 'fresh_strawberries'
model_fresh = keras.models.load_model("fresh_prediction_ver4.keras")
model_class = keras.models.load_model("class_prediction_ver2.keras")
for file in os.listdir('test_data/'+folder):
        predictions('test_data/'+folder+"/"+file,model_class,model_fresh)
```



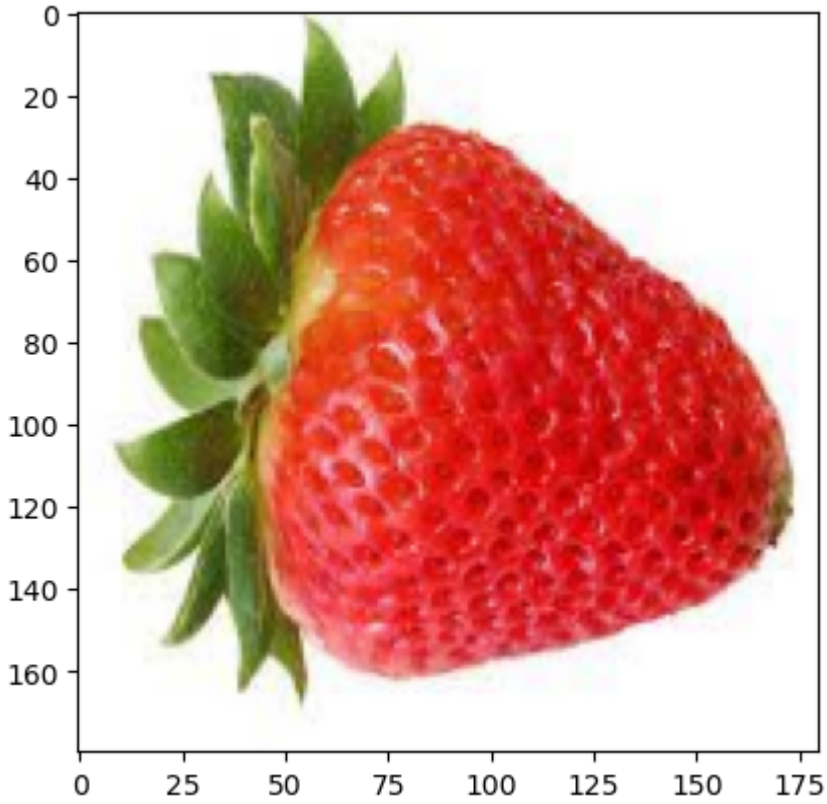

```
1/1 [==============================] - 1s 770ms/step
1/1 [==============================] - 1s 711ms/step
class: Strawberry - confident: [1.2915535e-27 5.3254427e-17 1.0000000e+00]
quality: Fresh - confident: 0.8927685022354126
```



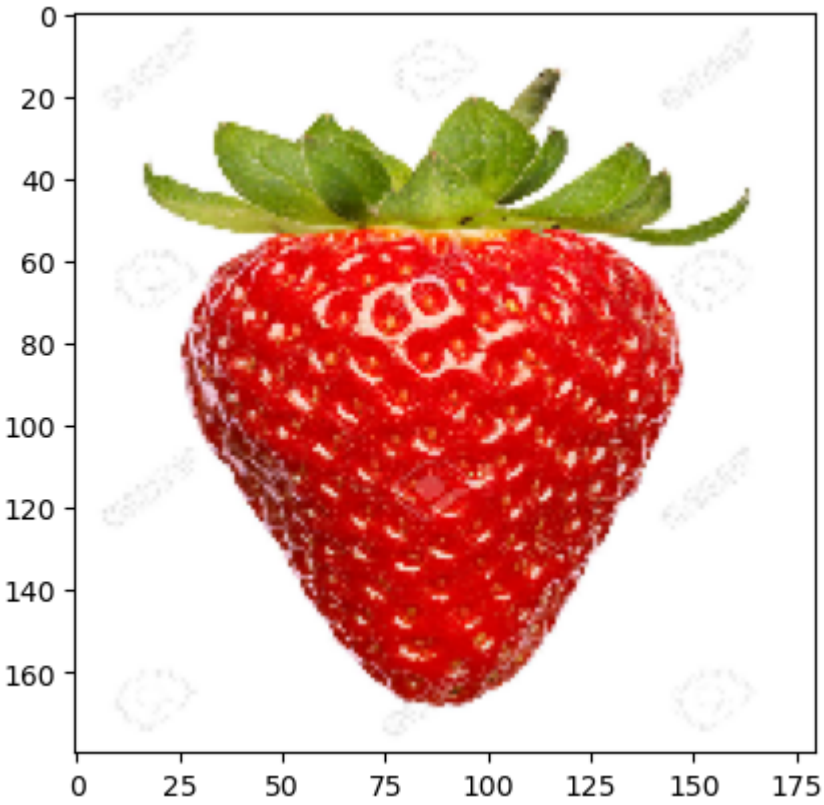

```
1/1 [==============================] - 0s 224ms/step
1/1 [==============================] - 0s 216ms/step
class: Strawberry - confident: [0.0000000e+00 1.1556576e-21 1.0000000e+00]
quality: Fresh - confident: 0.995021641254425
```



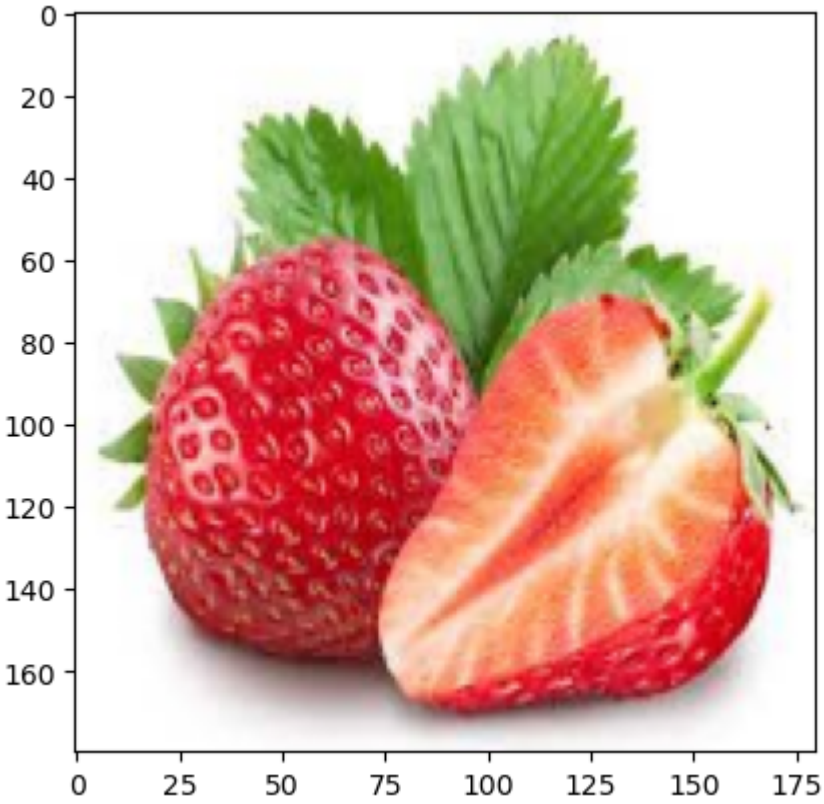

```
1/1 [==============================] - 0s 289ms/step
1/1 [==============================] - 0s 287ms/step
class: Strawberry - confident: [2.7986670e-25 6.7128896e-16 1.0000000e+00]
quality: Fresh - confident: 1.0
```



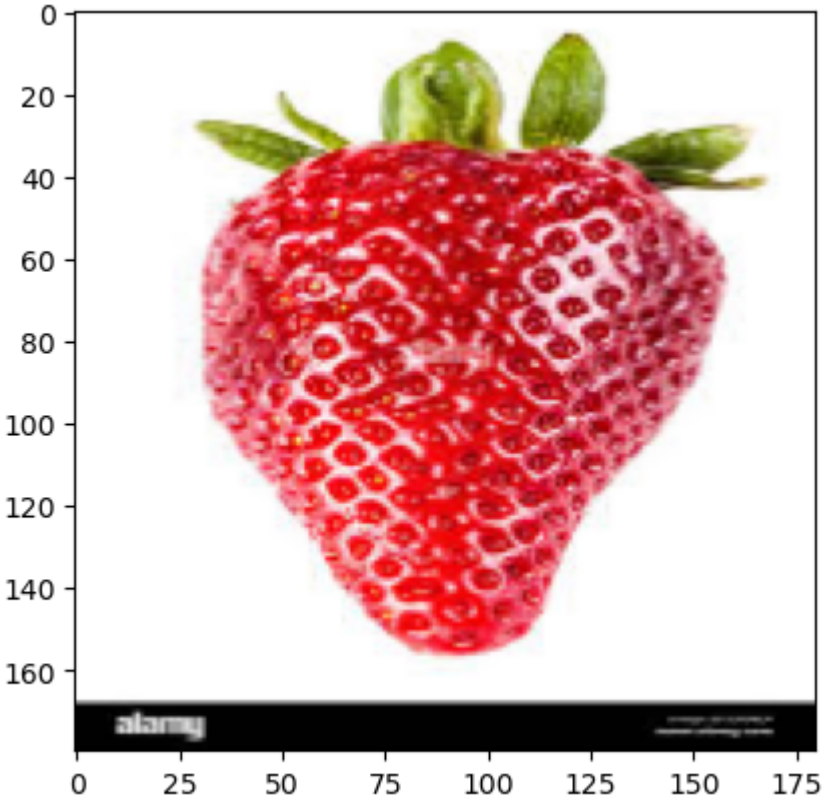

```
1/1 [==============================] - 0s 257ms/step
1/1 [==============================] - 0s 250ms/step
class: Strawberry - confident: [1.3124384e-19 2.1749807e-11 1.0000000e+00]
quality: Fresh - confident: 0.9985256195068359
```



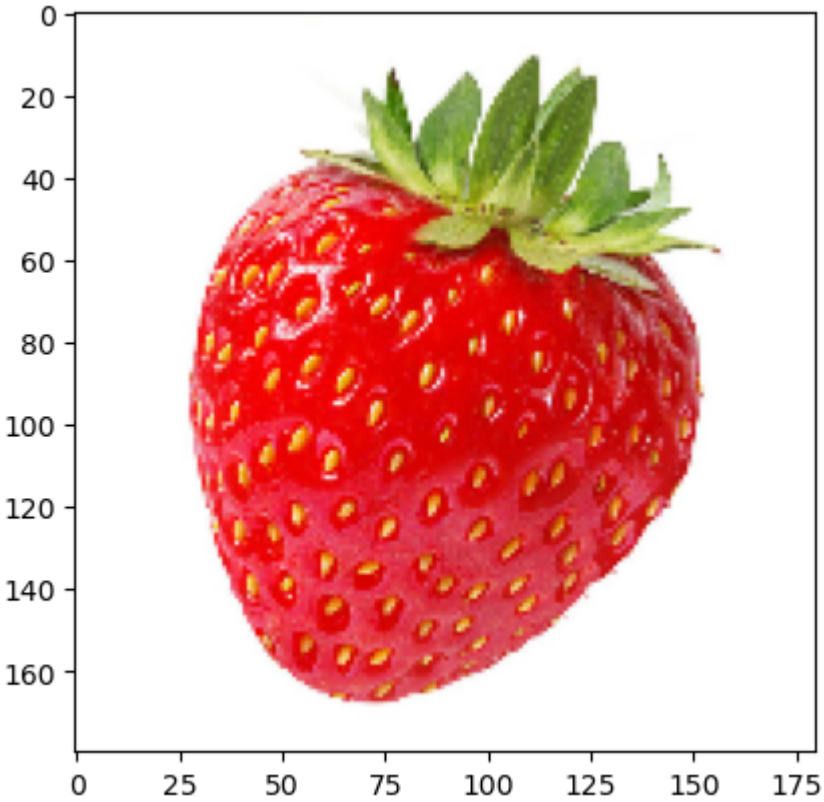

```
1/1 [==============================] - 0s 210ms/step
1/1 [==============================] - 0s 219ms/step
class: Strawberry - confident: [0.000000e+00 3.534869e-23 1.000000e+00]
quality: Fresh - confident: 0.9999938011169434
```



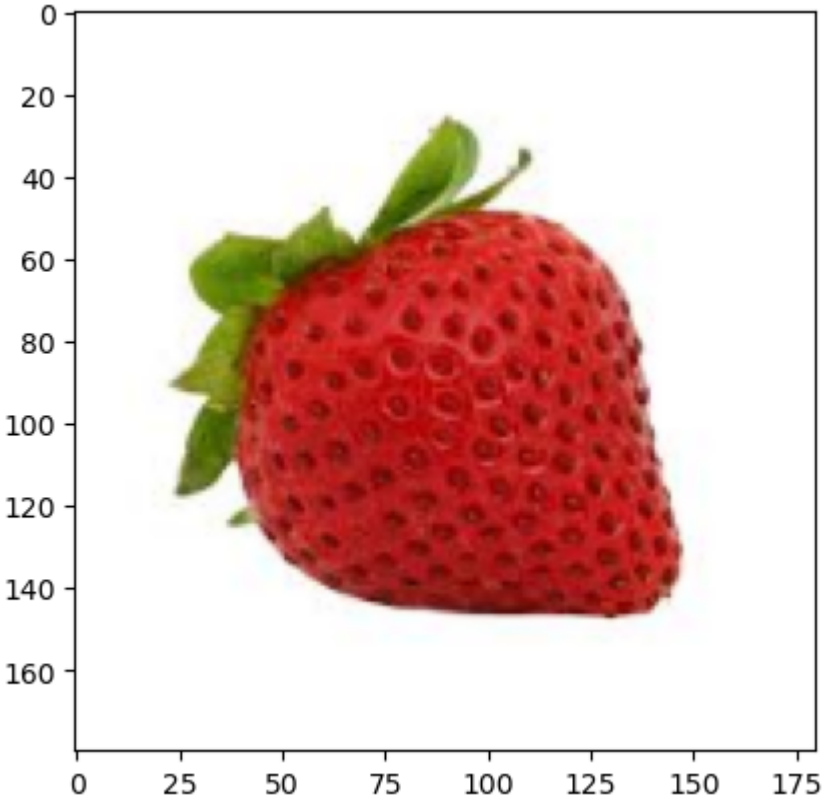

```
1/1 [==============================] - 0s 221ms/step
1/1 [==============================] - 0s 203ms/step
class: Strawberry - confident: [7.697913e-18 3.474027e-10 1.000000e+00]
quality: Fresh - confident: 1.0
```



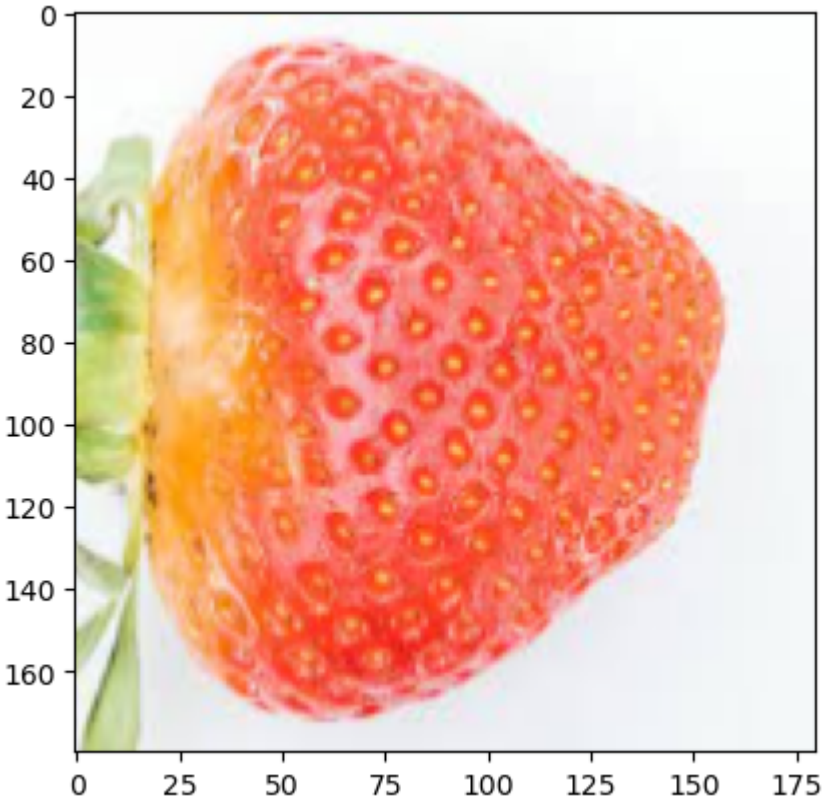

```
1/1 [==============================] - 0s 221ms/step
1/1 [==============================] - 0s 196ms/step
class: Strawberry - confident: [0.000000e+00 4.931548e-24 1.000000e+00]
quality: Fresh - confident: 0.9944270253181458
```



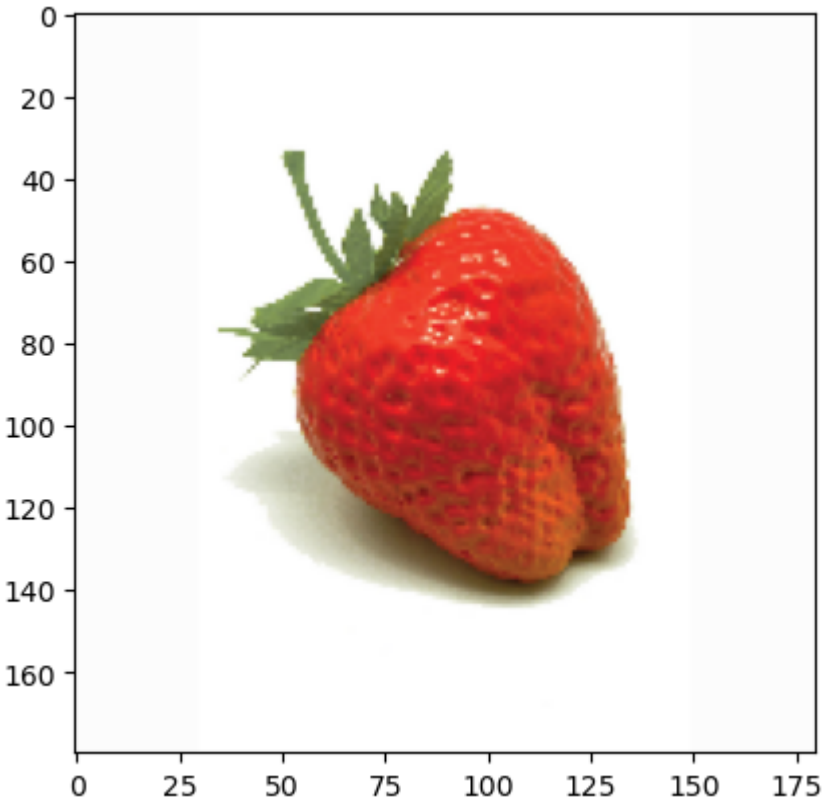

```
1/1 [==============================] - 0s 241ms/step
1/1 [==============================] - 0s 200ms/step
class: Strawberry - confident: [0.0000000e+00 2.9960253e-22 1.0000000e+00]
quality: Fresh - confident: 0.999995768070221
```



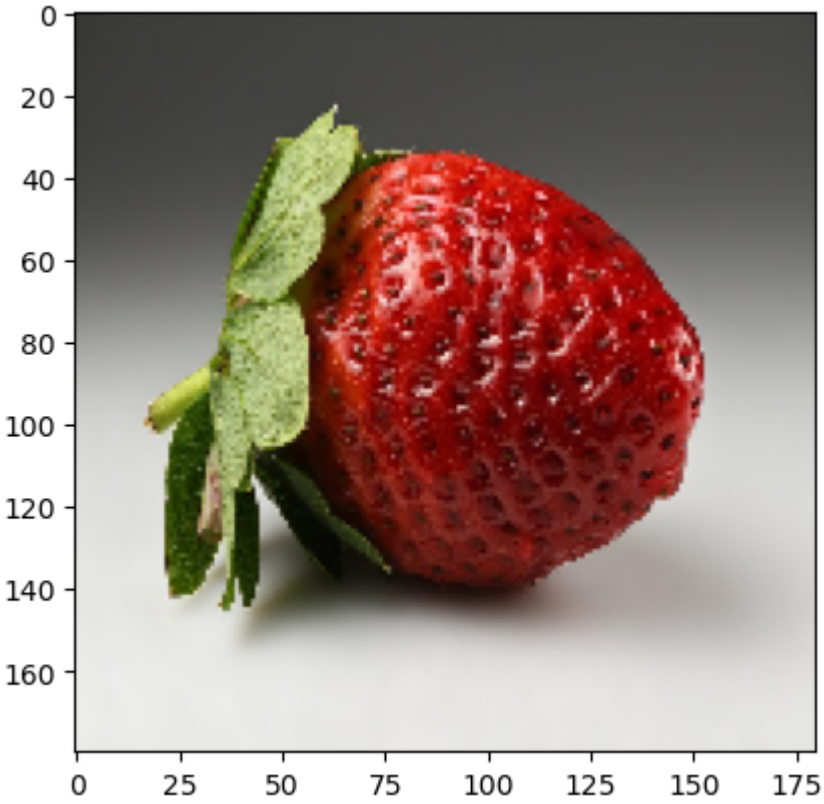

```
1/1 [==============================] - 0s 198ms/step
1/1 [==============================] - 0s 194ms/step
class: Strawberry - confident: [1.0348778e-14 7.6788407e-09 1.0000000e+00]
quality: Fresh - confident: 0.9988881945610046
```



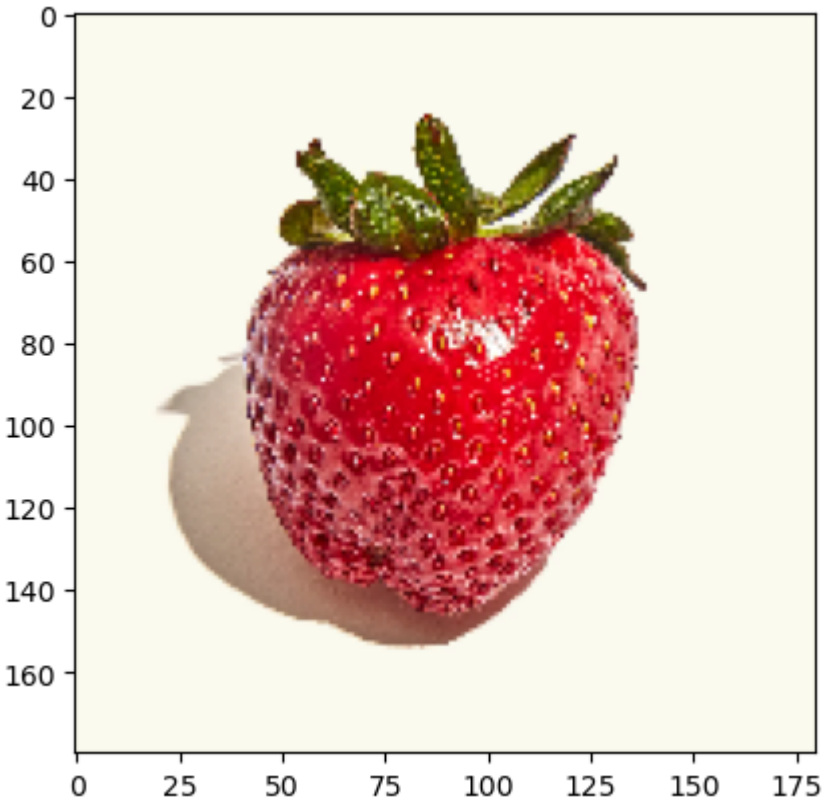

```
1/1 [==============================] - 0s 245ms/step
1/1 [==============================] - 0s 210ms/step
class: Peach - confident: [0.8071357  0.14613783 0.04672648]
quality: Fresh - confident: 0.9555408954620361
```



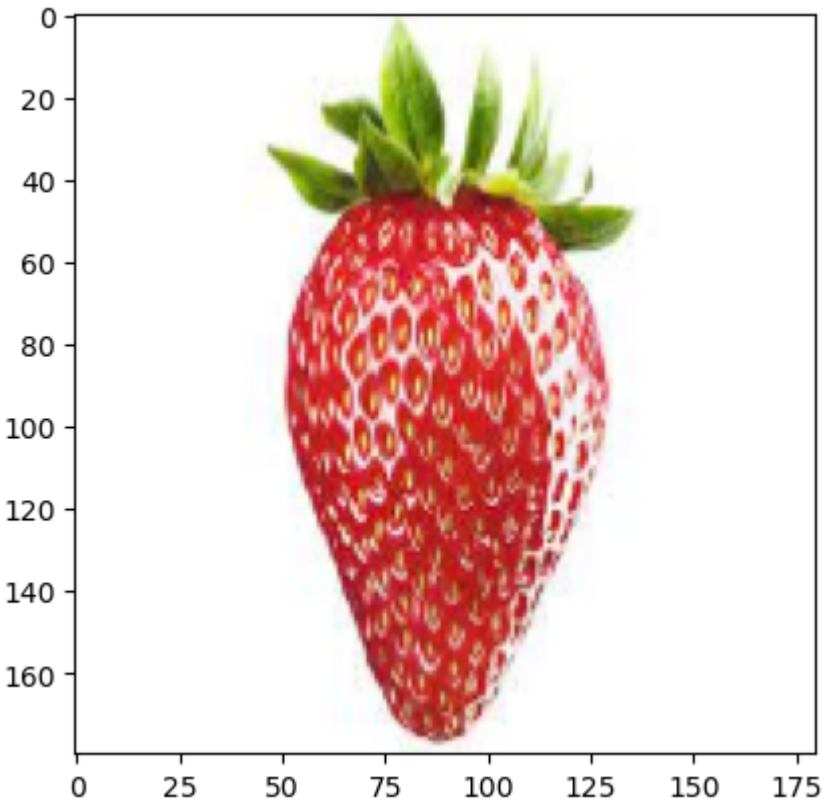

```
1/1 [==============================] - 0s 293ms/step
1/1 [==============================] - 0s 254ms/step
class: Strawberry - confident: [8.3113377e-11 1.2583476e-07 9.9999988e-01]
quality: Fresh - confident: 0.6855490803718567
```



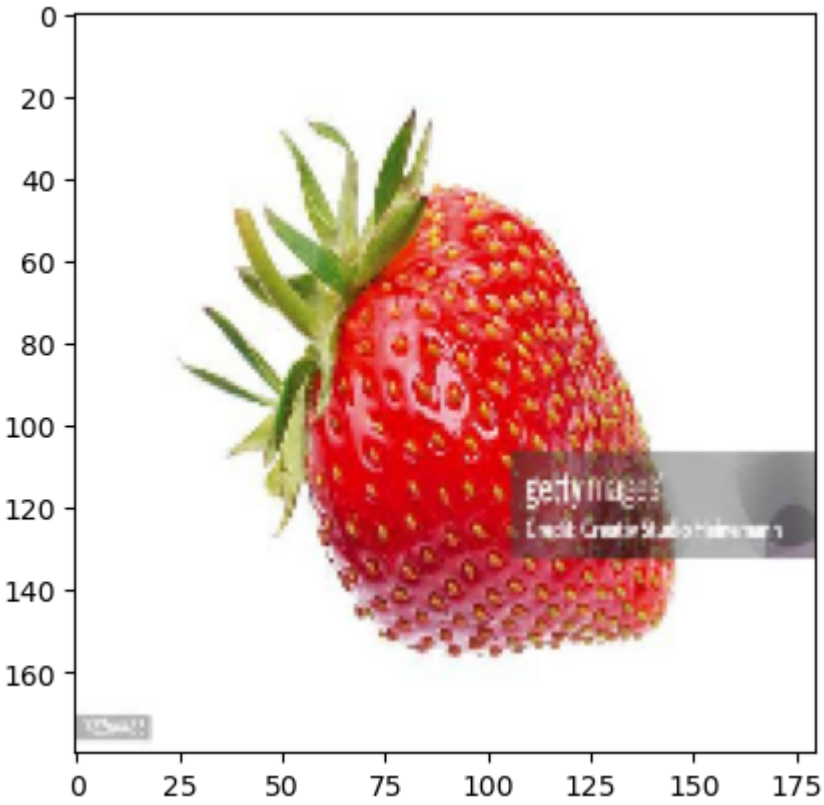

```
1/1 [==============================] - 0s 218ms/step
1/1 [==============================] - 0s 266ms/step
class: Strawberry - confident: [2.4600358e-17 8.8464759e-08 9.9999988e-01]
quality: Rotten - confident: 0.02439679205417633
```



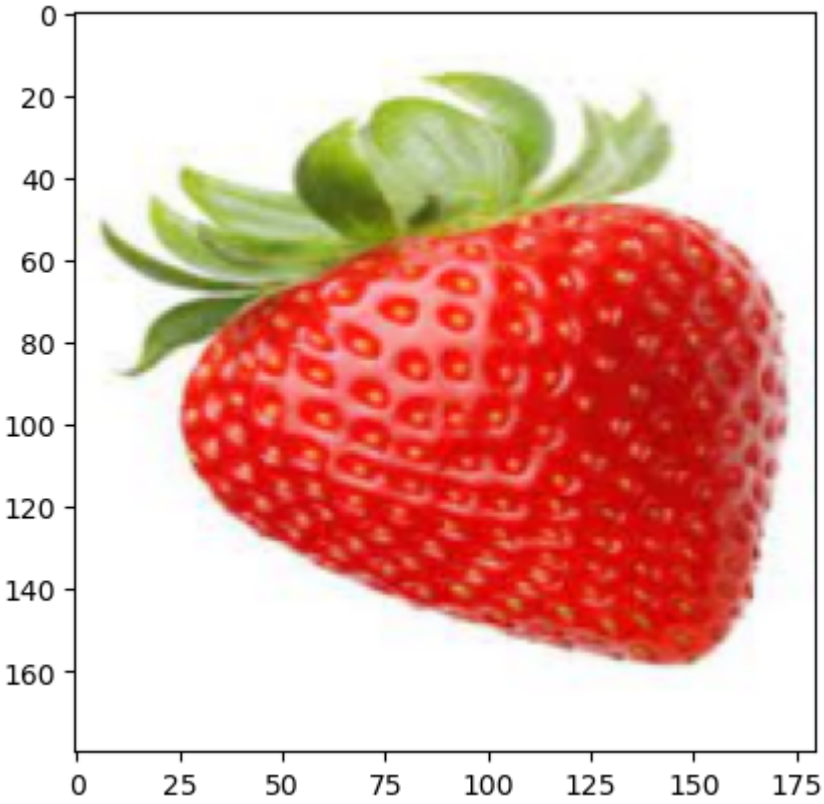

```
1/1 [==============================] - 0s 268ms/step
1/1 [==============================] - 0s 188ms/step
class: Strawberry - confident: [2.6921648e-29 7.1298225e-16 1.0000000e+00]
quality: Fresh - confident: 0.8910195827484131
```



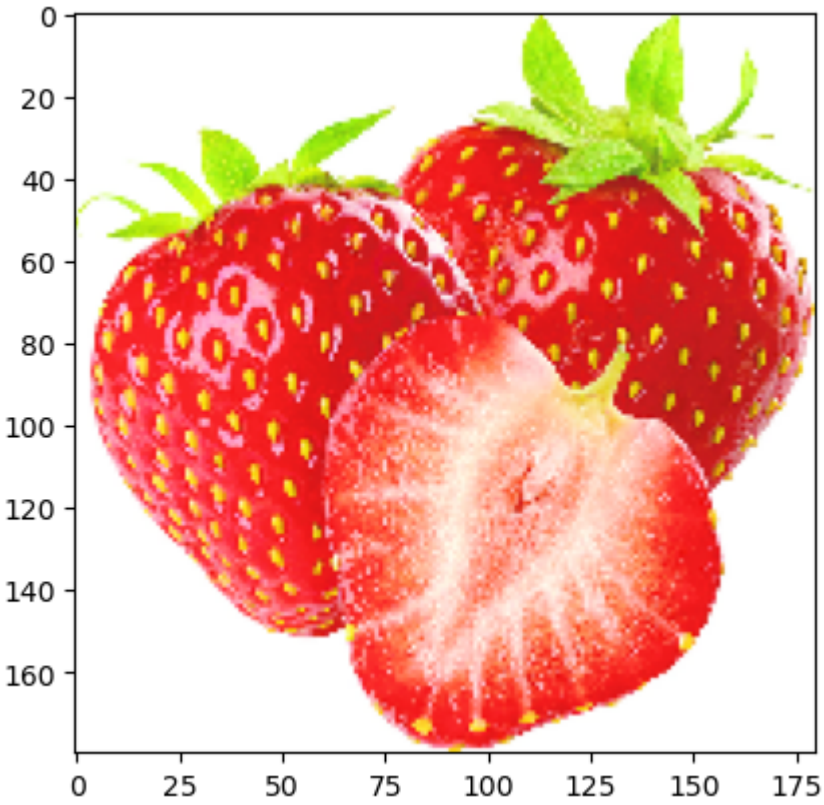

```
1/1 [==============================] - 0s 188ms/step
1/1 [==============================] - 0s 207ms/step
class: Strawberry - confident: [4.7348002e-30 2.7630986e-17 1.0000000e+00]
quality: Fresh - confident: 0.5406882166862488
```



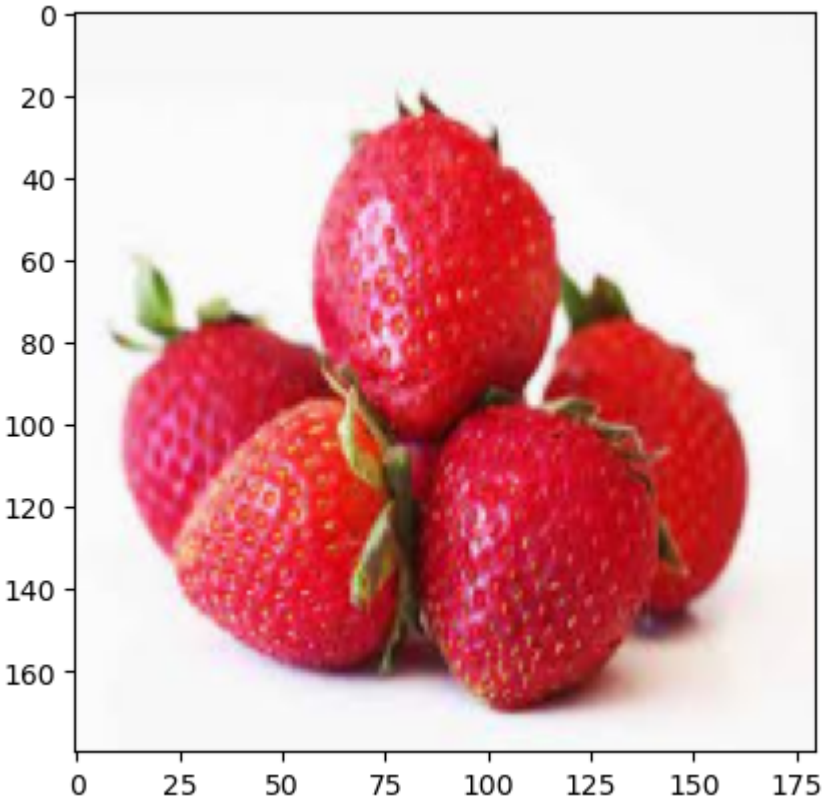

```
1/1 [==============================] - 0s 231ms/step
1/1 [==============================] - 0s 241ms/step
class: Strawberry - confident: [4.3155696e-33 2.6989947e-20 1.0000000e+00]
quality: Fresh - confident: 0.5370805263519287
```



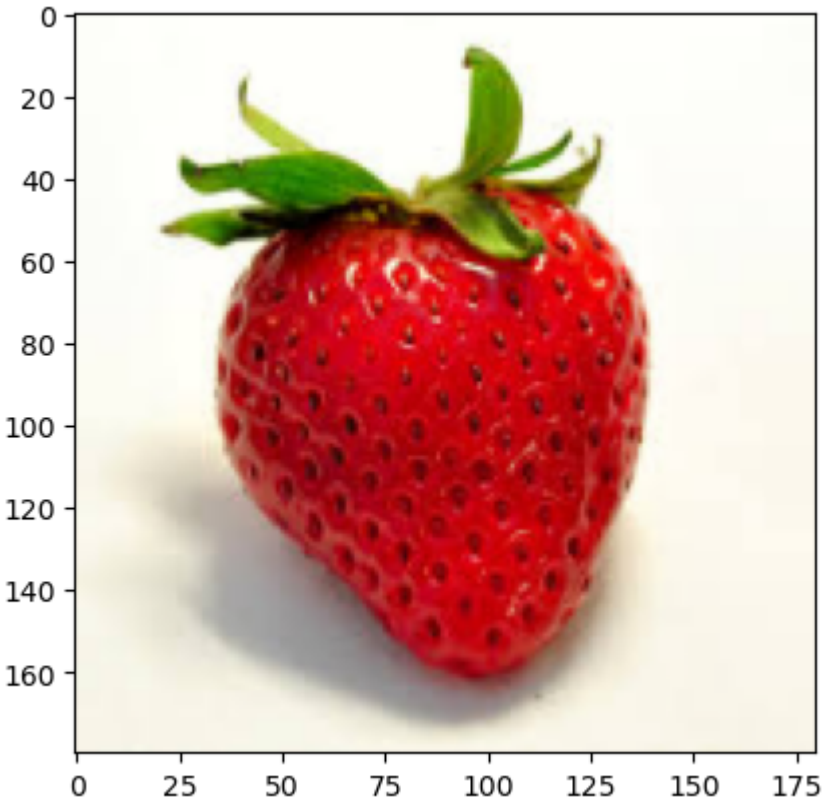

```
1/1 [==============================] - 0s 361ms/step
1/1 [==============================] - 0s 233ms/step
class: Strawberry - confident: [1.589874e-28 1.324390e-16 1.000000e+00]
quality: Fresh - confident: 0.9995427131652832
```




```
1/1 [==============================] - 0s 286ms/step
1/1 [==============================] - 0s 263ms/step
class: Strawberry - confident: [0.0000000e+00 4.2258512e-20 1.0000000e+00]
quality: Rotten - confident: 0.27471476793289185
```




```
1/1 [==============================] - 0s 332ms/step
1/1 [==============================] - 0s 310ms/step
class: Strawberry - confident: [8.9463112e-15 1.0786908e-06 9.9999893e-01]
quality: Fresh - confident: 0.8202763795852661
```




```
1/1 [==============================] - 0s 197ms/step
1/1 [==============================] - 0s 263ms/step
class: Strawberry - confident: [3.053467e-19 9.840189e-10 1.000000e+00]
quality: Fresh - confident: 0.9999786019325256
```