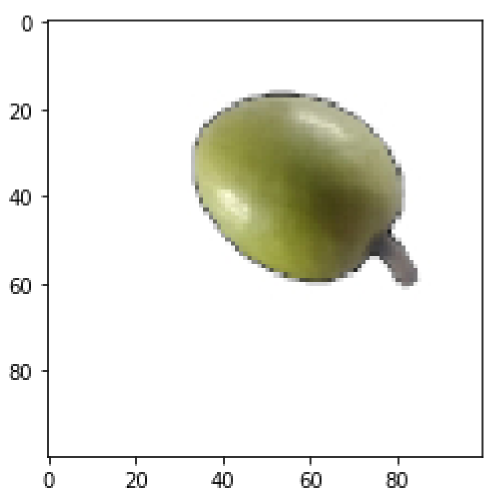
In [1]:
```
#here we have imported necessary libraries
import os
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D,MaxPooling2D
from tensorflow.keras.layers import Activation, Dense, Flatten, Dropout
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras import backend as K
from tensorflow.keras.preprocessing.image import array_to_img, img_to_array, l
oad_img
import keras_preprocessing
from keras_preprocessing import image
from sklearn.datasets import load_files
import matplotlib.image as mpimg
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
from keras.utils import np_utils
```

```
Using TensorFlow backend.
```

In [2]:
```
#view sample training data and shape of data
img = mpimg.imread(r'C:\Users\USER\Desktop\fruit_recognition\fruits-360\Traini
ng\Veralu\Veralu (12).jpg')
print(img.shape)
plt.imshow(img)
```

```
(100, 100, 3)
```

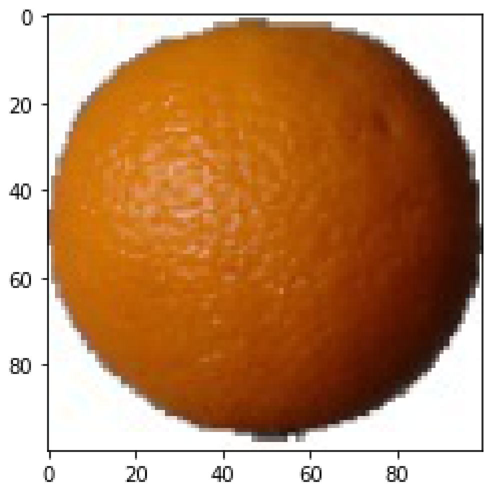
Out[2]: <matplotlib.image.AxesImage at 0x2497cd3cac8>



In [3]:
```
#view sample training data and shape of data
img = mpimg.imread(r'C:\Users\USER\Desktop\fruit_recognition\fruits-360\Training\Orange\0_100.jpg')
print(img.shape)
plt.imshow(img)
```

```
(100, 100, 3)
```

Out[3]:
```
<matplotlib.image.AxesImage at 0x2497cdf1e48>
```



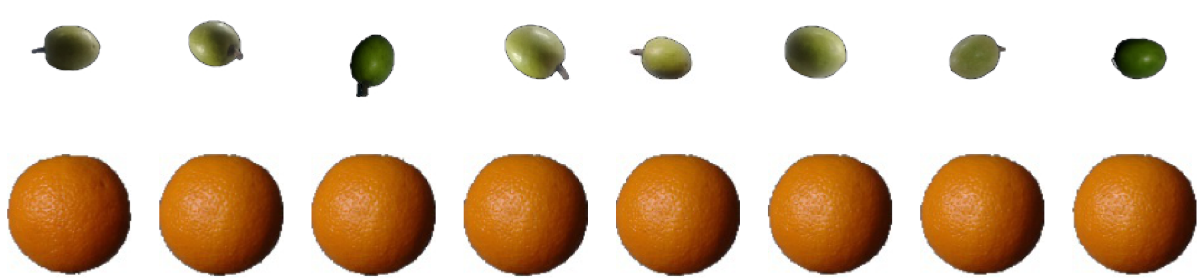
In [4]:
```
#view sample of training data class and shape of data class
train_veralu_dir = r"C:\Users\USER\Desktop\fruit_recognition\fruits-360\Training\Veralu"
number_veralu_train = len(os.listdir(train_veralu_dir))
print("total training veralu images:", number_veralu_train)

#view sample of training data class and shape of data class
train_orange_dir = r"C:\Users\USER\Desktop\fruit_recognition\fruits-360\Training\Orange"
number_orange_train = len(os.listdir(train_orange_dir))
print("total training Orange images:", number_orange_train)
```

```
total training veralu images: 86
total training Orange images: 479
```

In [5]:
```
veralu_names = os.listdir(train_veralu_dir)
veralu_names[:10]

orange_names = os.listdir(train_orange_dir)
orange_names[:10]
```

Out[5]:
```
['0_100.jpg',
 '100_100.jpg',
 '101_100.jpg',
 '102_100.jpg',
 '103_100.jpg',
 '104_100.jpg',
 '105_100.jpg',
 '106_100.jpg',
 '107_100.jpg',
 '108_100.jpg']
```

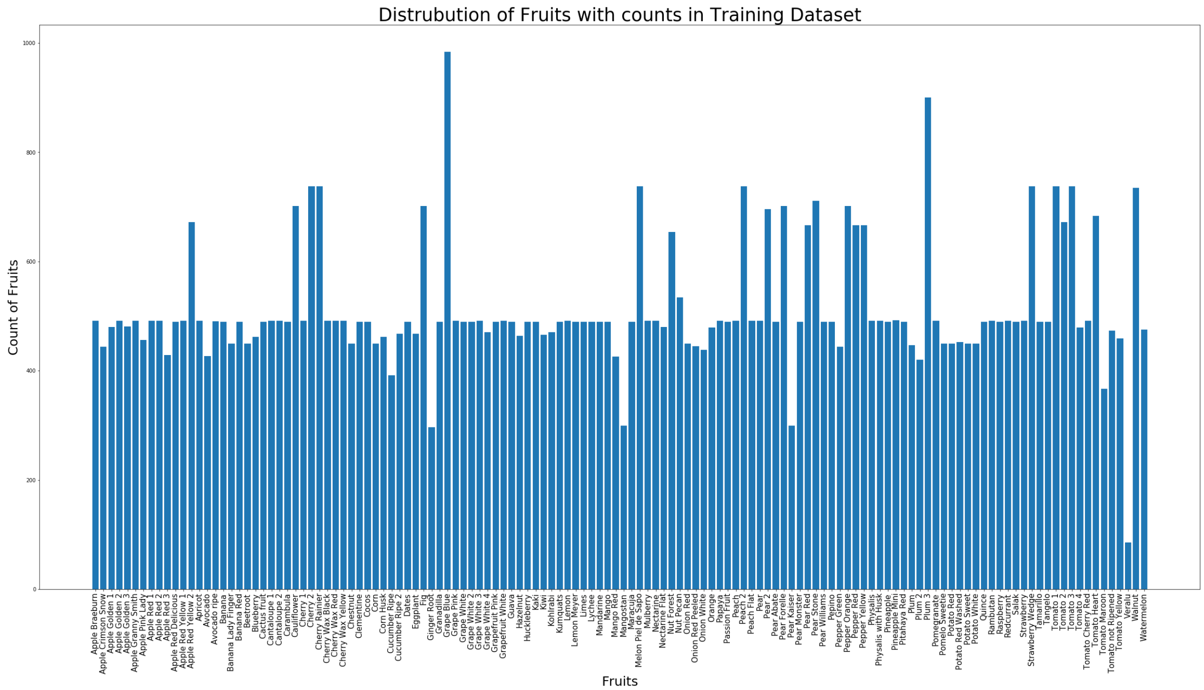
In [6]:
```
#view sample of training data class
nrows = 8
ncols = 8

pic_index = 0

fig = plt.gcf()
fig.set_size_inches(ncols*4, nrows*4)

pic_index+=8

veralu_pic = [os.path.join(train_veralu_dir,fname) for fname in veralu_names[p
ic_index-8:pic_index]]
orange_pic = [os.path.join(train_orange_dir,fname) for fname in orange_names[p
ic_index-8:pic_index]]

for i, img_path in enumerate(veralu_pic + orange_pic):
    sub = plt.subplot(nrows, ncols, i + 1)
    sub.axis("Off")

    img = mpimg.imread(img_path)
    plt.imshow(img)

plt.show()
```



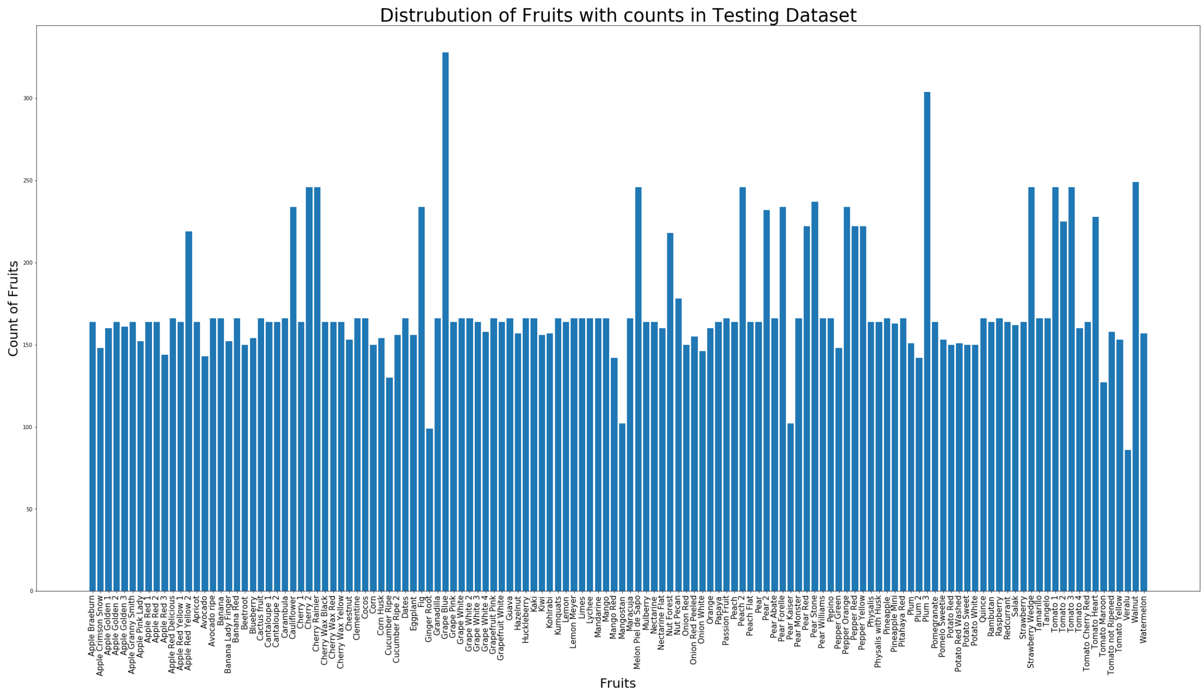
In [7]:
```
#view whole of training data and testing data
import os, os.path
train_categories = []
train_samples = []
for i in os.listdir(r"C:/Users/USER/Desktop/fruit_recognition/fruits-360/Train
ing/"):
    train_categories.append(i)
    train_samples.append(len(os.listdir(r"C:/Users/USER/Desktop/fruit_recognit
ion/fruits-360/Training/"+ i)))

test_categories = []
test_samples = []
for i in os.listdir(r"C:/Users/USER/Desktop/fruit_recognition/fruits-360/Tes
t/"):
    test_categories.append(i)
    test_samples.append(len(os.listdir(r"C:/Users/USER/Desktop/fruit_recogniti
on/fruits-360/Test/"+ i)))


print("Count of Fruits in Training data set:", sum(train_samples))
print("Count of Fruits in Testing data set:", sum(test_samples))
```

```
Count of Fruits in Training data set: 67778
Count of Fruits in Testing data set: 22774
```

In [8]:
```
#distribution of training data
figure_size = plt.rcParams["figure.figsize"]
figure_size[0] = 40
figure_size[1] = 20
plt.rcParams["figure.figsize"] = figure_size
index = np.arange(len(train_categories))
plt.bar(index, train_samples)
plt.xlabel('Fruits', fontsize=25)
plt.ylabel('Count of Fruits', fontsize=25)
plt.xticks(index, train_categories, fontsize=15, rotation=90)
plt.title('Distrubution of Fruits with counts in Training Dataset', fontsize=3
5)
plt.show()
```



In [9]:
```python
#distribution of testing data
index2 = np.arange(len(test_categories))
plt.bar(index2, test_samples)
plt.xlabel('Fruits', fontsize=25)
plt.ylabel('Count of Fruits', fontsize=25)
plt.xticks(index2, test_categories, fontsize=15, rotation=90)
plt.title('Distrubution of Fruits with counts in Testing Dataset', fontsize=35)
plt.show()
```



In [10]:
```python
#datasets mapping to =======> number array
train_dir = r'C:/Users/USER/Desktop/fruit_recognition/fruits-360/Training/'
test_dir = r'C:/Users/USER/Desktop/fruit_recognition/fruits-360/Test/'

def load_dataset(data_path):
    data_loading = load_files(data_path)
    files_add = np.array(data_loading['filenames'])
    targets_fruits = np.array(data_loading['target'])
    target_labels_fruits = np.array(data_loading['target_names'])
    return files_add,targets_fruits,target_labels_fruits

x_train, y_train,target_labels = load_dataset(train_dir)
x_test, y_test,_ = load_dataset(test_dir)
```

In [11]:
```python
no_of_classes = len(np.unique(y_train))
no_of_classes
```

Out[11]: 132

In [12]:
```
#view sample array data
y_train = np_utils.to_categorical(y_train,no_of_classes)
y_test = np_utils.to_categorical(y_test,no_of_classes)
y_train[0]
```

Out[12]:
```
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., 1., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 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=float32)
```

In [13]:
```
#shape of validation data & testing data
x_test,x_valid = x_test[7000:],x_test[:7000]
y_test,y_vaild = y_test[7000:],y_test[:7000]
print('Vaildation X : ',x_valid.shape)
print('Vaildation y :',y_vaild.shape)
print('Test X : ',x_test.shape)
print('Test y : ',y_test.shape)
```

```
Vaildation X :  (7000,)
Vaildation y : (7000, 132)
Test X :  (15774,)
Test y :  (15774, 132)
```

In [14]:
```
#function of images are mapping array
def convert_image_to_array_form(files):
    images_array=[]
    for file in files:
        images_array.append(img_to_array(load_img(file)))
    return images_array

x_train = np.array(convert_image_to_array_form(x_train))
print('Training set shape : ',x_train.shape)

x_valid = np.array(convert_image_to_array_form(x_valid))
print('Validation set shape : ',x_valid.shape)

x_test = np.array(convert_image_to_array_form(x_test))
print('Test set shape : ',x_test.shape)

print('1st training image shape ',x_train[0].shape)
```

```
Training set shape :  (67778, 100, 100, 3)
Validation set shape :  (7000, 100, 100, 3)
Test set shape :  (15774, 100, 100, 3)
1st training image shape  (100, 100, 3)
```

In [15]:
```
#preprocessing data ===> scale
x_train = x_train.astype('float32')/255
x_valid = x_valid.astype('float32')/255
x_test = x_test.astype('float32')/255
```

In [16]:
```
#define our network model
def tensorflow_based_model():
    # step 1
    model = Sequential()
    # step2
    model.add(Conv2D(filters = 16, kernel_size = 2,input_shape=(100,100,3),pad
ding='same'))
    # step3
    model.add(Activation('relu'))
    # step4
    model.add(MaxPooling2D(pool_size=2))
    # repeating step 2 and step3 but with more filters of 32
    model.add(Conv2D(filters = 32,kernel_size = 2,activation= 'relu',padding=
'same'))
    # repeating step 4 again
    model.add(MaxPooling2D(pool_size=2))
    # repeating step 2 and step3 but with more filters of 64
    model.add(Conv2D(filters = 64,kernel_size = 2,activation= 'relu',padding=
'same'))
    # repeating step 4 again
    model.add(MaxPooling2D(pool_size=2))
    # repeating step 2 and step3 but with more filters of 64
    model.add(Conv2D(filters = 128,kernel_size = 2,activation= 'relu',padding=
'same'))
    # repeating step 4 again
    model.add(MaxPooling2D(pool_size=2))
    # step5
    model.add(Dropout(0.3))
    # step 6
    model.add(Flatten())
    # step 7
    model.add(Dense(150))
    # setp 3
    model.add(Activation('relu'))
    # step 5
    model.add(Dropout(0.4))
    # setp3 and step7. but this time, we are using activation function as soft
max
    # (if we train on two classes then we set sigmoid)
    model.add(Dense(132,activation = 'softmax'))
    # function returning the value when we call it
    return model
```

In [17]:
```
# here we are calling the function of created model
model = tensorflow_based_model()
# here we are get the summary of created model
model.summary()
model.compile(loss='categorical_crossentropy', optimizer='rmsprop', metrics=[
'accuracy'])
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 100, 100, 16)      208
_________________________________________________________________
activation (Activation)      (None, 100, 100, 16)      0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 50, 50, 16)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 50, 50, 32)        2080
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 25, 25, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 25, 25, 64)        8256
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 12, 12, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 12, 12, 128)       32896
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 6, 6, 128)         0
_________________________________________________________________
dropout (Dropout)            (None, 6, 6, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 4608)              0
_________________________________________________________________
dense (Dense)                (None, 150)               691350
_________________________________________________________________
activation_1 (Activation)    (None, 150)               0
_________________________________________________________________
dropout_1 (Dropout)          (None, 150)               0
_________________________________________________________________
dense_1 (Dense)              (None, 132)               19932
=================================================================
Total params: 754,722
Trainable params: 754,722
Non-trainable params: 0
_________________________________________________________________
```

In [18]:
```
#model training process and saving process
history = model.fit(x_train,y_train,
        batch_size = 32,
        epochs = 30,
        validation_data=(x_valid, y_vaild),
        verbose=2,
        shuffle=True
)

filepath = r"C:\Users\USER\Desktop\fruit_recognition\fruits-360\model"
tf.keras.models.save_model(
    model,
    filepath,
    overwrite=True,
    include_optimizer=True,
    save_format="tf",
    signatures=None
)
model.save("fruit_classification_model.h5")
```

```
Train on 67778 samples, validate on 7000 samples
Epoch 1/30
67778/67778 - 151s - loss: 0.9732 - accuracy: 0.7348 - val_loss: 0.2462 - val
_accuracy: 0.9346
Epoch 2/30
67778/67778 - 146s - loss: 0.1327 - accuracy: 0.9567 - val_loss: 0.1890 - val
_accuracy: 0.9604
Epoch 3/30
67778/67778 - 145s - loss: 0.0824 - accuracy: 0.9749 - val_loss: 0.1749 - val
_accuracy: 0.9713
Epoch 4/30
67778/67778 - 146s - loss: 0.0720 - accuracy: 0.9788 - val_loss: 0.2315 - val
_accuracy: 0.9621
Epoch 5/30
67778/67778 - 145s - loss: 0.0654 - accuracy: 0.9824 - val_loss: 0.1301 - val
_accuracy: 0.9740
Epoch 6/30
67778/67778 - 146s - loss: 0.0687 - accuracy: 0.9833 - val_loss: 0.2063 - val
_accuracy: 0.9730
Epoch 7/30
67778/67778 - 148s - loss: 0.0717 - accuracy: 0.9822 - val_loss: 0.2010 - val
_accuracy: 0.9761
Epoch 8/30
67778/67778 - 152s - loss: 0.0768 - accuracy: 0.9830 - val_loss: 0.1628 - val
_accuracy: 0.9806
Epoch 9/30
67778/67778 - 204s - loss: 0.0830 - accuracy: 0.9826 - val_loss: 0.1802 - val
_accuracy: 0.9781
Epoch 10/30
67778/67778 - 216s - loss: 0.0911 - accuracy: 0.9824 - val_loss: 0.3451 - val
_accuracy: 0.9737
Epoch 11/30
67778/67778 - 225s - loss: 0.0904 - accuracy: 0.9832 - val_loss: 0.2398 - val
_accuracy: 0.9796
Epoch 12/30
67778/67778 - 210s - loss: 0.1103 - accuracy: 0.9808 - val_loss: 0.8918 - val
_accuracy: 0.9667
Epoch 13/30
67778/67778 - 241s - loss: 0.1099 - accuracy: 0.9820 - val_loss: 0.2785 - val
_accuracy: 0.9766
Epoch 14/30
67778/67778 - 166s - loss: 0.1239 - accuracy: 0.9819 - val_loss: 0.6141 - val
_accuracy: 0.9740
Epoch 15/30
67778/67778 - 153s - loss: 0.1302 - accuracy: 0.9817 - val_loss: 0.3531 - val
_accuracy: 0.9760
Epoch 16/30
67778/67778 - 153s - loss: 0.1380 - accuracy: 0.9820 - val_loss: 0.3720 - val
_accuracy: 0.9686
Epoch 17/30
67778/67778 - 152s - loss: 0.1693 - accuracy: 0.9817 - val_loss: 0.4192 - val
_accuracy: 0.9774
Epoch 18/30
67778/67778 - 149s - loss: 0.1580 - accuracy: 0.9828 - val_loss: 0.6408 - val
_accuracy: 0.9689
Epoch 19/30
67778/67778 - 148s - loss: 0.1614 - accuracy: 0.9823 - val_loss: 0.2943 - val
```

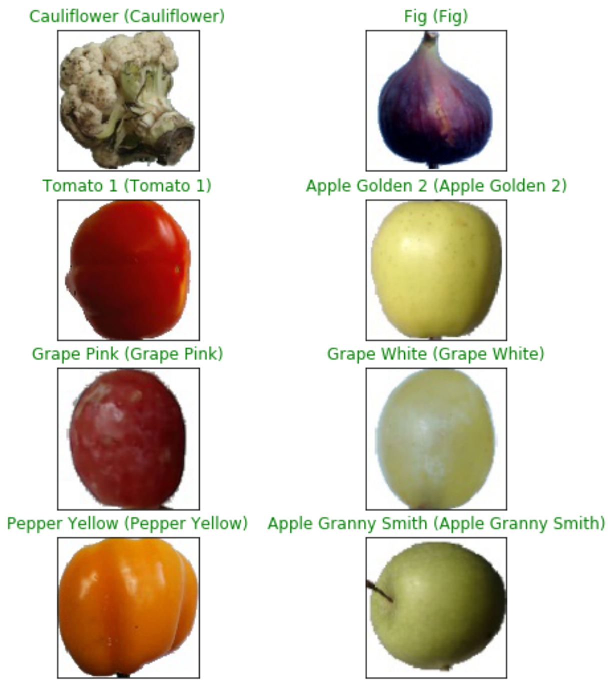
```
_accuracy: 0.9809
Epoch 20/30
67778/67778 - 147s - loss: 0.1722 - accuracy: 0.9824 - val_loss: 0.9479 - val
_accuracy: 0.9679
Epoch 21/30
67778/67778 - 147s - loss: 0.1784 - accuracy: 0.9829 - val_loss: 0.6050 - val
_accuracy: 0.9759
Epoch 22/30
67778/67778 - 147s - loss: 0.1897 - accuracy: 0.9832 - val_loss: 0.3753 - val
_accuracy: 0.9791
Epoch 23/30
67778/67778 - 151s - loss: 0.2097 - accuracy: 0.9833 - val_loss: 2.5743 - val
_accuracy: 0.9713
Epoch 24/30
67778/67778 - 148s - loss: 0.1867 - accuracy: 0.9855 - val_loss: 0.9862 - val
_accuracy: 0.9760
Epoch 25/30
67778/67778 - 147s - loss: 0.1903 - accuracy: 0.9854 - val_loss: 0.6733 - val
_accuracy: 0.9786
Epoch 26/30
67778/67778 - 147s - loss: 0.2135 - accuracy: 0.9854 - val_loss: 0.8831 - val
_accuracy: 0.9767
Epoch 27/30
67778/67778 - 150s - loss: 0.2054 - accuracy: 0.9870 - val_loss: 0.6666 - val
_accuracy: 0.9766
Epoch 28/30
67778/67778 - 149s - loss: 0.2267 - accuracy: 0.9869 - val_loss: 0.8505 - val
_accuracy: 0.9736
Epoch 29/30
67778/67778 - 147s - loss: 0.2258 - accuracy: 0.9860 - val_loss: 1.0086 - val
_accuracy: 0.9813
Epoch 30/30
67778/67778 - 150s - loss: 0.2350 - accuracy: 0.9864 - val_loss: 0.5371 - val
_accuracy: 0.9800
WARNING:tensorflow:From C:\ProgramData\Anaconda3\lib\site-packages\tensorflow
_core\python\ops\resource_variable_ops.py:1786: calling BaseResourceVariable.
__init__ (from tensorflow.python.ops.resource_variable_ops) with constraint i
s deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
INFO:tensorflow:Assets written to: C:\Users\USER\Desktop\fruit_recognition\fr
uits-360\model\assets
```

In [19]:

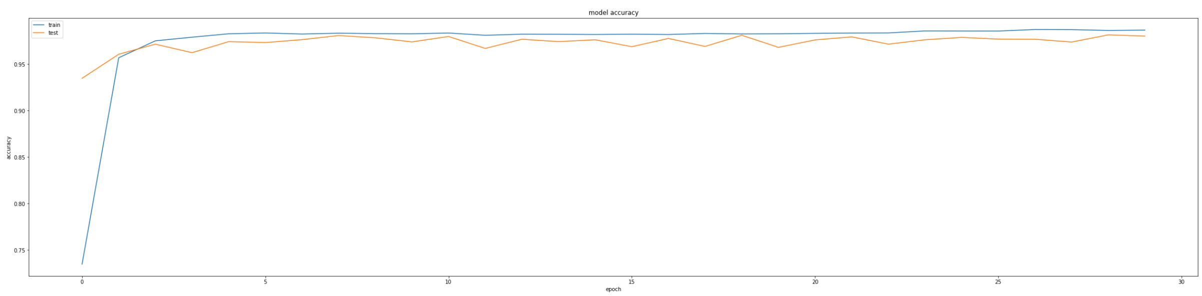
```python
#testing accuracy of trained model
acc_score = model.evaluate(x_test, y_test) #we are starting to test the model
 here
print('\n', 'Test accuracy:', acc_score[1])
```

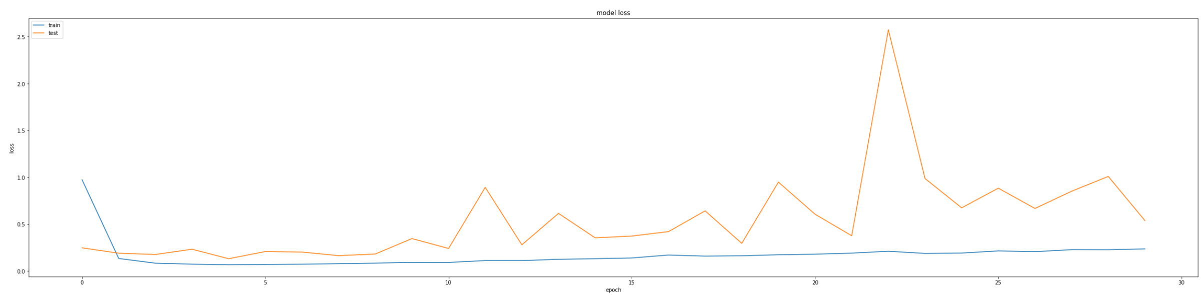
```
15774/15774 [==============================] - 12s 741us/sample - loss: 0.444
6 - accuracy: 0.9786

 Test accuracy: 0.9785723
```

In [20]:
```
#here we check model predictions
predictions = model.predict(x_test)
fig = plt.figure(figsize=(16, 9))
for i, idx in enumerate(np.random.choice(x_test.shape[0], size=16, replace=False)):
    ax = fig.add_subplot(4, 4, i + 1, xticks=[], yticks=[])
    ax.imshow(np.squeeze(x_test[idx]))
    pred_idx = np.argmax(predictions[idx])
    true_idx = np.argmax(y_test[idx])
    ax.set_title("{} ({})".format(target_labels[pred_idx], target_labels[true_idx]),
                 color=("green" if pred_idx == true_idx else "red"))
```



In [21]:
```
#how the model accuracy goes on and loss goes on
plt.figure(1)
plt.subplot(211)
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')

plt.subplot(212)
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')
plt.show()
```





In [ ]: