

Image Classifier for Fruits Dataset - Team 4 Submission for SA4108 CA

Part 2: Convolutional Neural Network

Model 1: Handpicked Validation Data, Adam and RMSprop optimization algorithms; 200 x 200 px

```
In [ ]:
import numpy as np
import sys

# TensorFlow and tf.keras
import tensorflow as tf
from tensorflow.keras.applications.resnet50 import preprocess_input, decode_predictions
from tensorflow.keras.preprocessing import image
```

```
In [ ]:
from zipfile import ZipFile
file_name = 'train.zip'

with ZipFile(file_name, 'r') as zip:
    zip.extractall()
    print('Done extracting train.zip')

Done extracting train.zip
```

```
In [ ]:
from zipfile import ZipFile
file_name = 'test.zip'

with ZipFile(file_name, 'r') as zip:
    zip.extractall()
    print('Done extracting test.zip')

Done extracting test.zip
```

```
In [ ]:
from zipfile import ZipFile
file_name = 'validation.zip'

with ZipFile(file_name, 'r') as zip:
    zip.extractall()
    print('Done extracting validation.zip')

Done extracting validation.zip
```

```
In [ ]:
from zipfile import ZipFile
file_name = 'test1.zip'

with ZipFile(file_name, 'r') as zip:
    zip.extractall()
    print('Done extracting test1.zip')

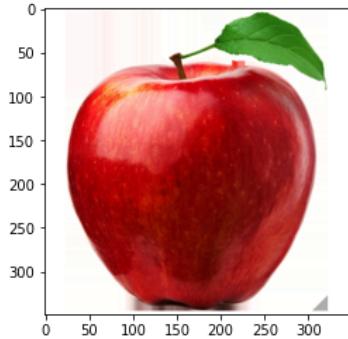
Done extracting test1.zip
```

```
In [ ]:
import numpy as np
import pandas as pd
import tensorflow as tf
import cv2
import matplotlib.pyplot as plot
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image
from tensorflow.keras.optimizers import RMSprop, Adam
import os
import PIL
```

```
In [ ]:
img = image.load_img('train/apple/apple_1.jpg')
```

```
In [ ]:
plot.imshow(img)
cv2.imread("train/apple/apple_1.JPG")

#the only part that uses cv2 actually so cv2 isn't actually required
#other than for the sole purpose of verification if the
```



```
In [ ]: train = ImageDataGenerator(rescale = 1/255)
validation= ImageDataGenerator(rescale = 1/255)
```

```
In [ ]: train_dataset= train.flow_from_directory("train/",
                                             target_size = (200,200),
                                             batch_size=10,
                                             color_mode='rgb',
                                             class_mode ='categorical')

validation_dataset= validation.flow_from_directory("validation/",
                                                 target_size = (200,200),
                                                 batch_size=10,
                                                 color_mode='rgb',
                                                 class_mode ='categorical')
```

Found 240 images belonging to 4 classes.
Found 56 images belonging to 4 classes.

```
In [ ]: validation_dataset= validation.flow_from_directory("test1/",
                                                       target_size = (200,200),
                                                       batch_size=10,
                                                       color_mode='rgb',
                                                       class_mode ='categorical')
```

Found 55 images belonging to 4 classes.

Making my model

```
In [ ]: model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(64,(3,3), activation = 'relu', input_shape =(200,200,3)),
    tf.keras.layers.Conv2D(32,(3,3), activation = 'relu'),
    tf.keras.layers.MaxPool2D(2,2),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128,activation ="relu"),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(4,activation ="softmax")])
```

```
In [ ]: model.compile (loss = "categorical_crossentropy",
                     optimizer = Adam(learning_rate=0.001),
                     metrics =[ 'accuracy'])

#here we decided to try the Adam optimization algorithm,
#best accuracy of 85.5% is achieved, train time of ~624s, with ~21s an epoch and ~2s a step
#we also retrained the model, using data from the test set as for our validation model
#train time of ~685s, with 23s an epoch and ~2 a step
#result of last run of training the model was
#loss: 0.0018 - accuracy: 1.0000 - val_loss: 6.7386e-05 - val_accuracy: 1.0000
#However, actual results translated only a result of 69.1% accuracy when putting the model to evaluate the test set
```

```
In [ ]: model.compile (loss = "categorical_crossentropy",
                     optimizer = RMSprop(learning_rate=0.001),
                     metrics =[ 'accuracy'])

#here we decided to try another optimization algorithm, which we found to yield a better accuracy overall
#best accuracy of 96.43% is achieved, train time of ~647s, ~23s an epoch and ~2s step
#actual results translated only a result of 92.7% accuracy when putting the model to evaluate the test set
#we also retrained the model, using data from the test set as for our validation model
#best accuracy of 92.73% is achieved, train time of ~720s, ~24s an epoch and ~2s step
#result of the last run of training the model is at epoch 3 where we stopped it as 100% accuracy is achieved
#loss: 0.0056 - accuracy: 1.0000 - val_loss: 1.6429e-04 - val_accuracy: 1.0000
#actual accuracy of test set achieved is 92.7% when putting the model to the test
```

```
In [ ]: model_fit =model.fit(train_dataset,
                           steps_per_epoch= 10,
                           epochs =30,
                           validation_data=validation_dataset)

#we found that just running 10 steps per epoch and 30 epochs is sufficient to reach a high enough degree of accuracy
#upon observing an 100% accuracy and validation accurate, we terminated the training to save time
```

```

Epoch 1/30
2/10 [=====>.....] - ETA: 16s - loss: 0.0028 - accuracy: 1.0000
/usr/local/lib/python3.7/dist-packages/PIL/Image.py:960: UserWarning: Palette images with Transparency expressed in bytes should be converted to RGBA images
    "Palette images with Transparency expressed in bytes should be "
10/10 [=====>.....] - 24s 2s/step - loss: 0.0015 - accuracy: 1.0000 - val_loss: 8.8485e-05 - val_accuracy: 1.0000
Epoch 2/30
10/10 [=====>.....] - 24s 2s/step - loss: 0.0244 - accuracy: 0.9900 - val_loss: 0.0134 - val_accuracy: 1.0000
Epoch 3/30
10/10 [=====>.....] - 24s 2s/step - loss: 0.0056 - accuracy: 1.0000 - val_loss: 1.6429e-04 - val_accuracy: 1.0000
Epoch 4/30
4/10 [=====>.....] - ETA: 12s - loss: 1.9507 - accuracy: 0.8500
-----
KeyboardInterrupt                                     Traceback (most recent call last)
<ipython-input-48-fcae1eeef8eba> in <module>()
      2         steps_per_epoch= 10,
      3         epochs =30,
--> 4         validation_data=validation_dataset)
      5
      6 #we found that just running 10 steps per epoch and 30 epochs is sufficient to reach a high enough degree of accuracy

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py in fit(self, x, y, batch_size, epochs, verbose, callbacks, validation_split, validation_data, shuffle, class_weight, sample_weight, initial_epoch, steps_per_epoch, validation_on_steps, validation_batch_size, validation_freq, max_queue_size, workers, use_multiprocessing)
1181             r=1):
1182                 callbacks.on_train_batch_begin(step)
--> 1183                 tmp_logs = self.train_function(iterator)
1184                 if data_handler.should_sync:
1185                     context.async_wait()

/usr/local/lib/python3.7/dist-packages/tensorflow/python/eager/def_function.py in __call__(self, *args, **kwds)
887
888     with OptionalXlaContext(self._jit_compile):
--> 889         result = self._call(*args, **kwds)
890
891     new_tracing_count = self.experimental_get_tracing_count()

/usr/local/lib/python3.7/dist-packages/tensorflow/python/eager/def_function.py in _call(self, *args, **kwds)
915     # In this case we have created variables on the first call, so we run the
916     # defunned version which is guaranteed to never create variables.
--> 917     return self._stateless_fn(*args, **kwds) # pylint: disable=not-callable
918     elif self._stateful_fn is not None:
919         # Release the lock early so that multiple threads can perform the call

/usr/local/lib/python3.7/dist-packages/tensorflow/python/eager/function.py in __call__(self, *args, **kwargs)
3022         filtered_flat_args) = self._maybe_define_function(args, kwargs)
3023     return graph_function._call_flat(
--> 3024         filtered_flat_args, captured_inputs=graph_function.captured_inputs) # pylint: disable=protected-access
3025
3026     @property

/usr/local/lib/python3.7/dist-packages/tensorflow/python/eager/function.py in _call_flat(self, args, captured_inputs, cancellation_manager)
1959         # No tape is watching; skip to running the function.
1960         return self._build_call_outputs(self._inference_function.call(
--> 1961             ctx, args, cancellation_manager=cancellation_manager))
1962     forward_backward = self._select_forward_and_backward_functions(
1963         args)

/usr/local/lib/python3.7/dist-packages/tensorflow/python/eager/function.py in call(self, ctx, args, cancellation_manager)
594
595         inputs=args,
--> 596         attrs=attrs,
597         else:
598             outputs = execute.execute_with_cancellation(


/usr/local/lib/python3.7/dist-packages/tensorflow/python/eager/execute.py in quick_execute(op_name, num_outputs, inputs, attrs, ctx, name)
58     ctx.ensure_initialized()
59     tensors = pywrap_tfe.TFE_Py_Execute(ctx._handle, device_name, op_name,
--> 60                                         inputs, attrs, num_outputs)
61     except core._NotOkStatusException as e:
62         if name is not None:

```

KeyboardInterrupt:

In []: validation_dataset.class_indices

Out[]: {'apple': 0, 'banana': 1, 'mixed': 2, 'orange': 3}

In []: dir_path= 'test/'

```

data = np.asarray(['apple','banana','mixed','orange'])
new_array= np.zeros((1,4))
#instantiates an empty numpy array
total = len(os.listdir(dir_path))
count = 0

for filename in os.listdir(dir_path):
    img = image.load_img(dir_path + filename, target_size=(200,200))
    img_array = image.img_to_array(img)
    img_batch = np.expand_dims(img_array, axis=0)

```

```

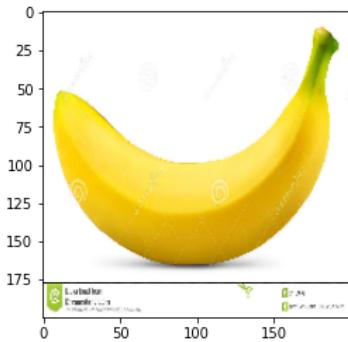
prediction = model.predict(img_batch)
pred = prediction[0]

idx, = np.where(pred==max(pred))
#
# Recording test set as 2D array
new_array = np.vstack([new_array,pred])

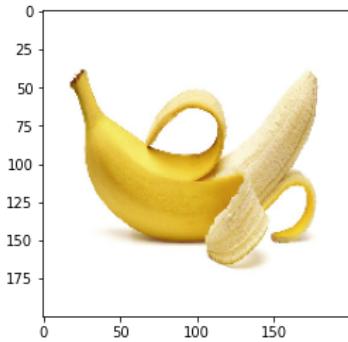
# Display + keep track of no. of correct predictions
if len(idx) >1:
    plot.imshow(img)
    plot.show()
    print(f'{filename:s} is unknown by model, error in prediction')
else:
    j = idx[0]
    plot.imshow(img)
    plot.show()
    print(f'{filename:s} is {data[j]}')
    if data[j] in filename:
        count += 1

print(f'Accuracy of test set is {count/total:0.3f}')
# print(new_array)

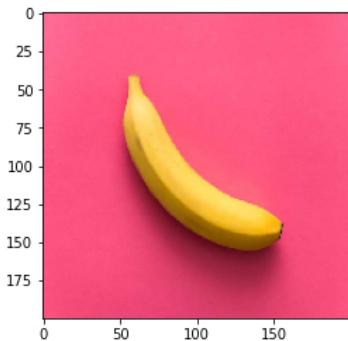
```



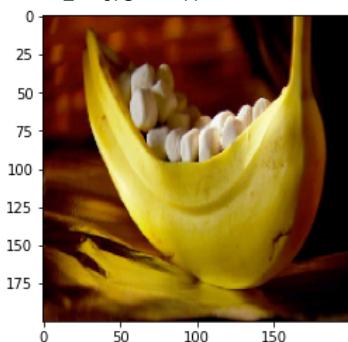
banana_79.jpg is banana



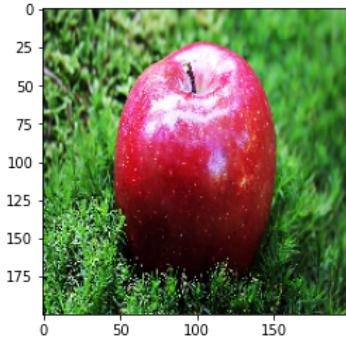
banana_82.jpg is banana



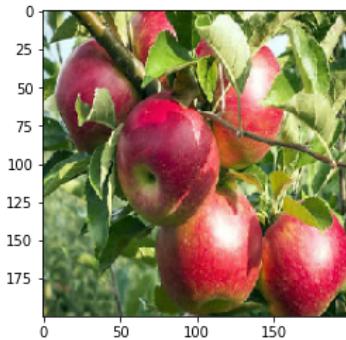
banana_88.jpg is apple



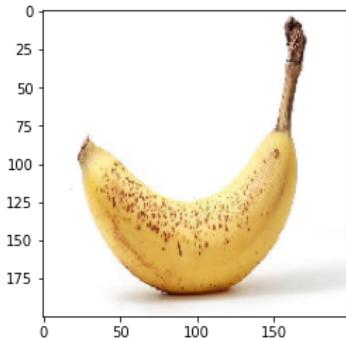
banana_83.jpg is orange



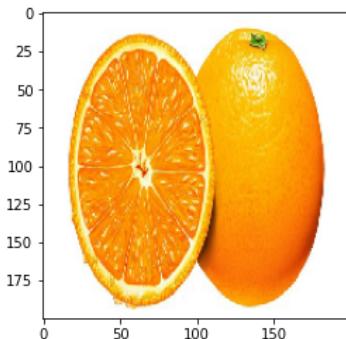
apple_91.jpg is apple



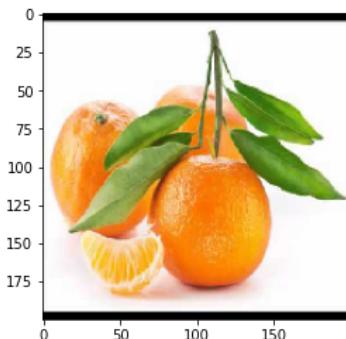
apple_77.jpg is orange



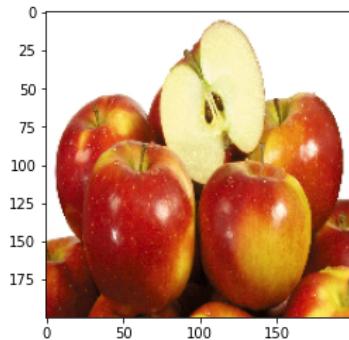
banana_84.jpg is banana



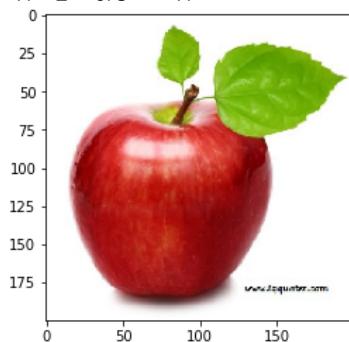
orange_78.jpg is orange



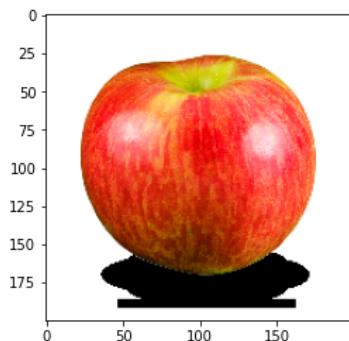
orange_86.jpg is orange



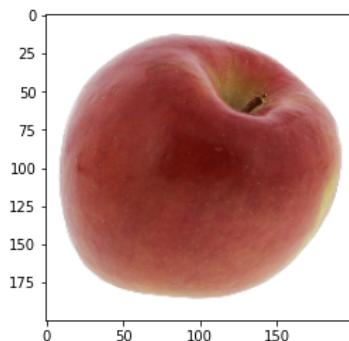
apple_95.jpg is apple



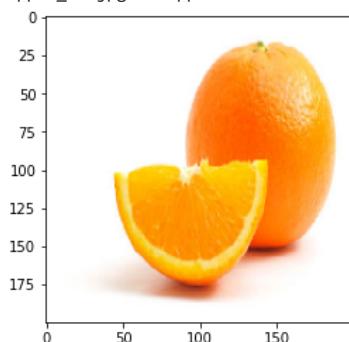
apple_87.jpg is apple



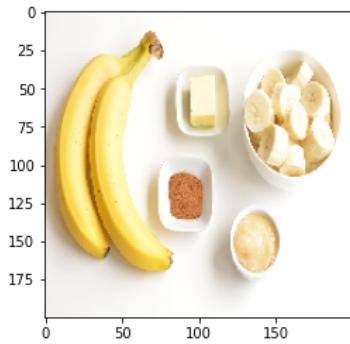
apple_92.jpg is apple



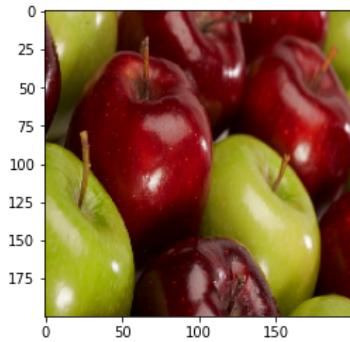
apple_90.jpg is apple



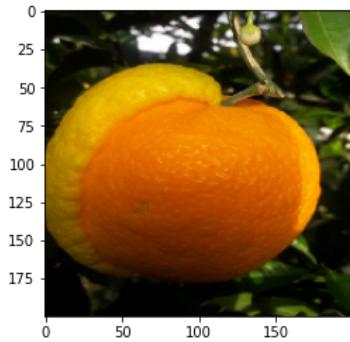
orange_92.jpg is orange



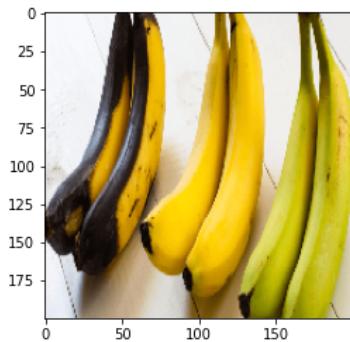
banana_91.jpg is banana



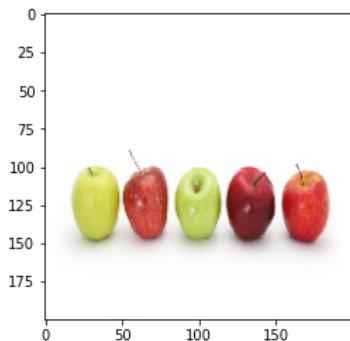
apple_84.jpg is apple



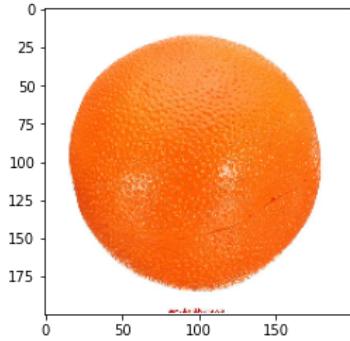
orange_85.jpg is orange



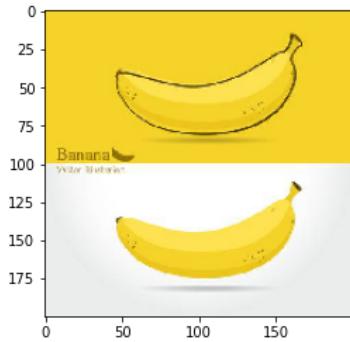
banana_87.jpg is banana



apple_86.jpg is apple



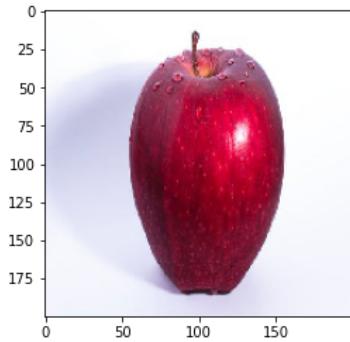
orange_83.jpg is orange



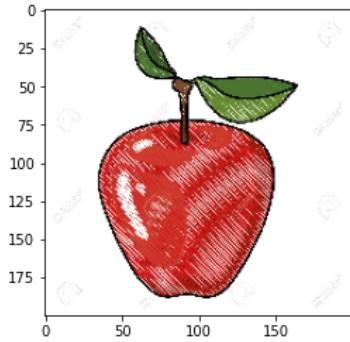
banana_93.jpg is banana



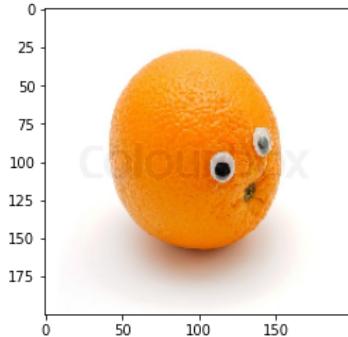
orange_77.jpg is orange



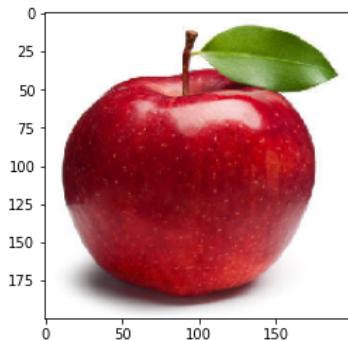
apple_93.jpg is apple



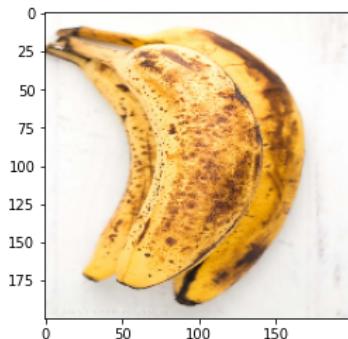
apple_88.jpg is apple



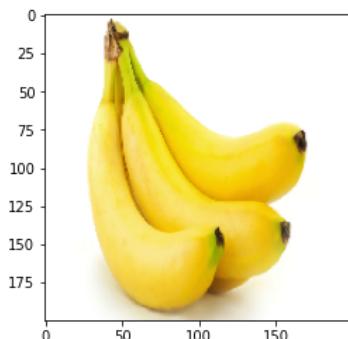
orange_91.jpg is orange



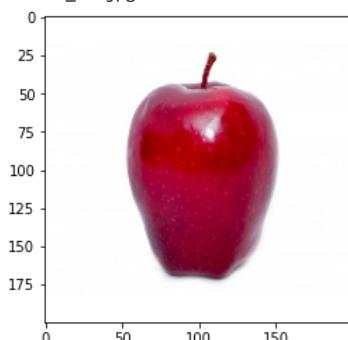
apple_89.jpg is apple



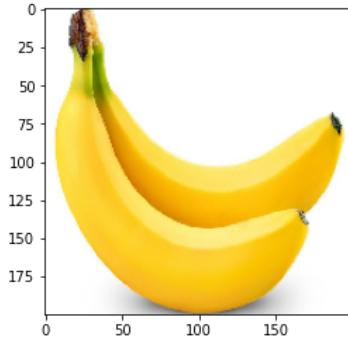
banana_86.jpg is banana



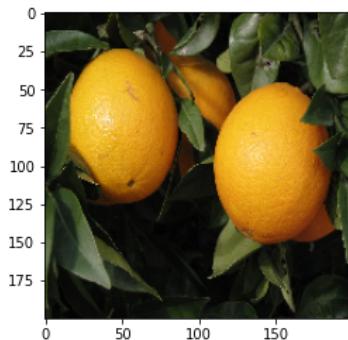
banana_90.jpg is banana



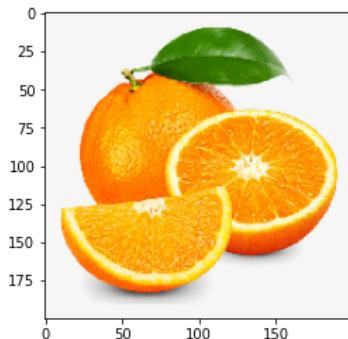
apple_80.jpg is apple



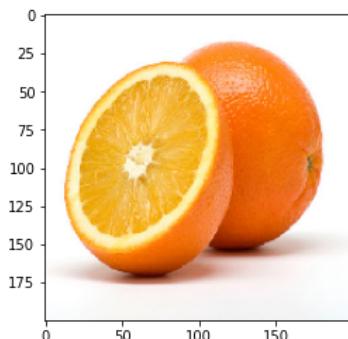
banana_81.jpg is banana



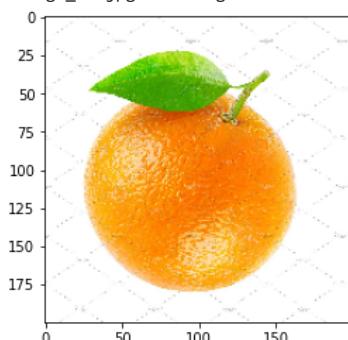
orange_89.jpg is orange



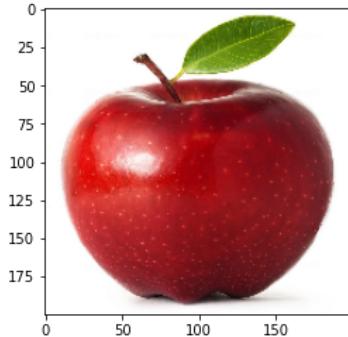
orange_82.jpg is orange



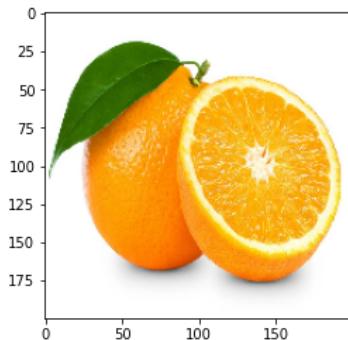
orange_84.jpg is orange



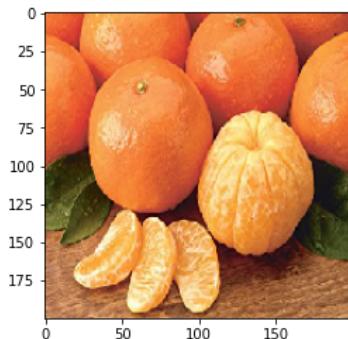
orange_95.jpg is orange



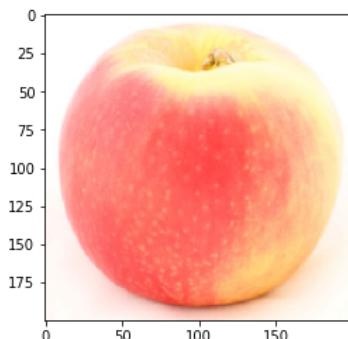
apple_81.jpg is apple



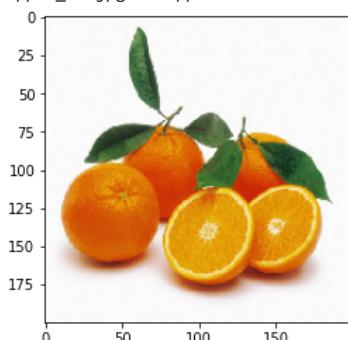
orange_80.jpg is orange



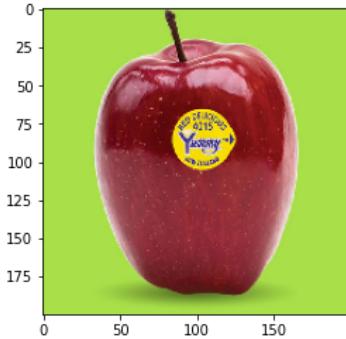
orange_90.jpg is orange



apple_78.jpg is apple



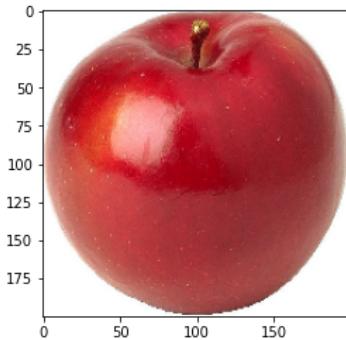
orange_87.jpg is orange



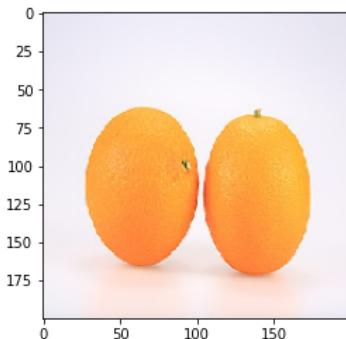
apple_85.jpg is apple



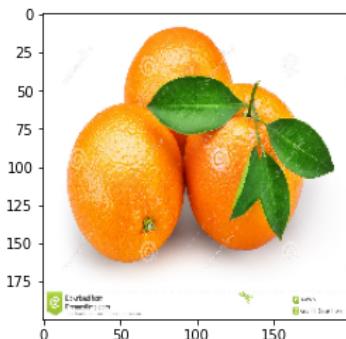
apple_94.jpg is apple



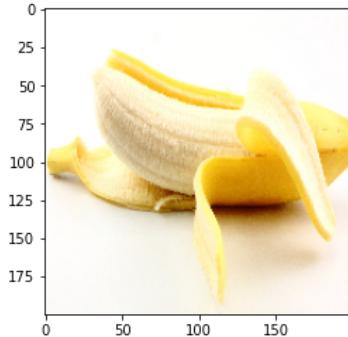
apple_83.jpg is apple



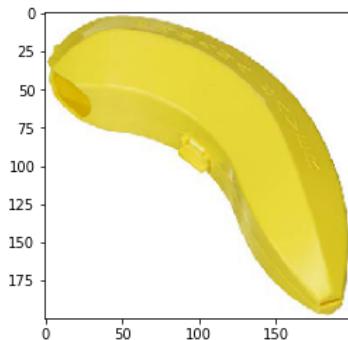
orange_93.jpg is orange



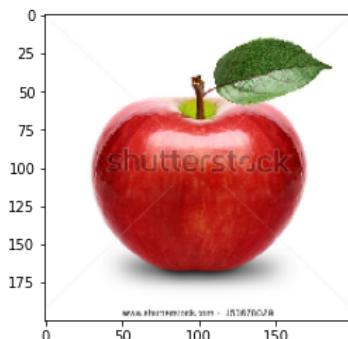
orange_81.jpg is orange



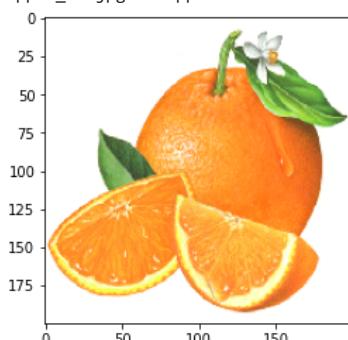
banana_85.jpg is banana



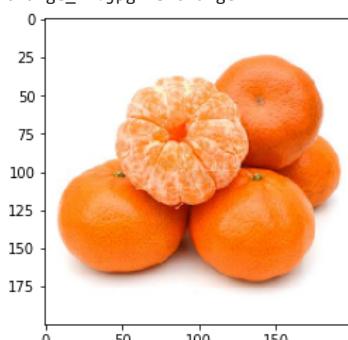
banana_94.jpg is banana



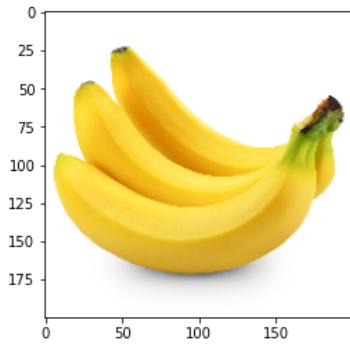
apple_82.jpg is apple



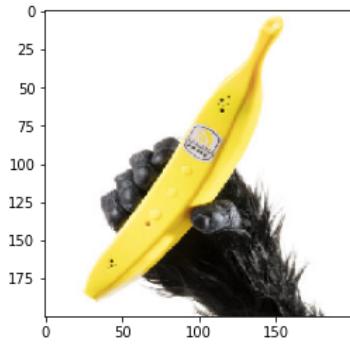
orange_94.jpg is orange



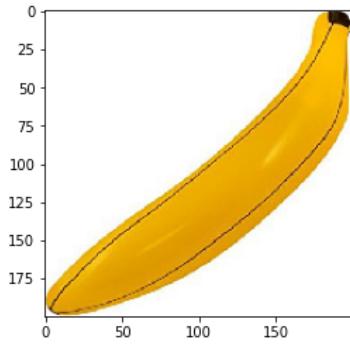
orange_79.jpg is orange



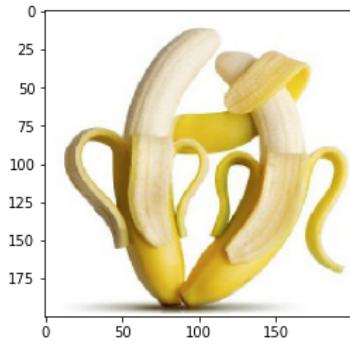
banana_89.jpg is orange



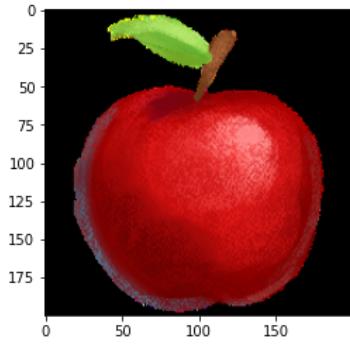
banana_77.jpg is banana



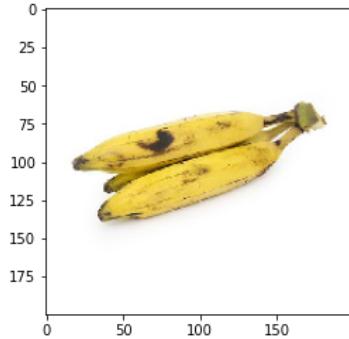
banana_92.jpg is banana



banana_78.jpg is banana



apple_79.jpg is apple



banana_80.jpg is banana
Accuracy of test set is 0.927

Model 2a: Adam and RMSprop optimization algorithms; 30 x 30 px

```
In [ ]:
from PIL import Image
import numpy as np
import tensorflow as tf
from sklearn.preprocessing import LabelEncoder
```

```
In [ ]:
from zipfile import ZipFile
file_name = 'train1.zip'

with ZipFile(file_name, 'r') as zip:
    zip.extractall()
    print('Done extracting train1.zip')
```

Done extracting train1.zip

```
In [ ]:
data=[]
data1=[]
for i in range(1,34):
    img=Image.open("train1/apple_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("apple")

for i in range(35,77):
    img=Image.open("train1/apple_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("apple")

for i in range(1,15):
    img=Image.open("train1/banana_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("banana")

for i in range(16,18):
    img=Image.open("train1/banana_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("banana")

for i in range(20,77):
    img=Image.open("train1/banana_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("banana")

for i in range(1,21):
    img=Image.open("train1/mixed_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("mixed")

for i in range(1,39):
    img=Image.open("train1/orange_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("orange")

for i in range(40,45):
    img=Image.open("train1/orange_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
```

```
array = np.array(img_re)
data.append(array)
data1.append("orange")

for i in range(46,65):
    img=Image.open("train1/orange_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("orange")

for i in range(67,77):
    img=Image.open("train1/orange_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("orange")

feature=np.array(data)
label=np.array(data1)

print(feature)
print(label)
feature.shape

/usr/local/lib/python3.7/dist-packages/PIL/Image.py:960: UserWarning: Palette images with Transparency expressed in bytes should be converted to RGBA images
  "Palette images with Transparency expressed in bytes should be "
[[[255 255 255]
 [255 255 255]
 [255 249 249]
 ...
 [254 253 253]
 [255 255 255]
 [255 255 255]]
 [[255 255 255]
 [255 255 255]
 [255 248 248]
 ...
 [254 252 253]
 [255 255 255]
 [255 255 255]]
 [[255 255 255]
 [255 255 255]
 [255 248 248]
 ...
 [254 254 252]
 [255 255 255]
 [255 255 255]]
 ...
 [[[255 255 255]
 [255 255 255]
 [255 254 251]
 ...
 [255 255 254]
 [255 255 255]
 [255 255 255]]
 [[255 255 255]
 [255 255 255]
 [255 254 251]
 ...
 [225 225 224]
 [255 255 255]
 [255 255 255]]
 [[255 255 255]
 [255 255 255]
 [255 254 252]
 ...
 [212 212 213]
 [255 255 255]
 [255 255 255]]]

[[[255 255 255]
 [255 255 255]
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 ...
 [255 255 255]
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 [255 255 255]]
 [[255 255 255]
 [255 255 255]
 [255 255 255]
 ...
 [255 255 255]
 [255 255 255]
 [255 255 255]]]
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[255 255 255]
...
[255 255 255]
[255 255 255]
[255 255 255]]
```

...

```
[[255 255 255]
[255 255 255]
[255 255 255]
...
[255 255 255]
[255 255 255]
[255 255 255]]]
```

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[[255 255 255]
[255 255 255]
[255 255 255]
...
[255 255 255]
[255 255 255]
[255 255 255]]]
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[[255 255 255]
[255 255 255]
[255 255 255]
...
[255 255 255]
[255 255 255]
[255 255 255]]]
```

```
[[[[168 14 37]
[214 31 83]
[233 56 126]
...
[248 122 97]
[241 102 26]
[169 7 0]]]
```

```
[[[174 1 3]
[193 0 0]
[211 3 12]
...
[240 23 34]
[222 19 29]
[158 1 1]]]
```

```
[[[182 1 3]
[208 1 8]
[237 23 68]
...
[252 71 62]
[229 16 15]
[165 0 0]]]
```

...

```
[[193 7 1]
[166 0 0]
[158 4 2]
...
[254 118 18]
[253 183 77]
[252 208 128]]]
```

```
[[[142 8 17]
[136 42 70]
[185 55 30]
...
[253 154 27]
[251 177 90]
[251 193 143]]]
```

```
[[[120 49 111]
[159 89 152]
[201 48 9]
...
[251 110 21]
[251 144 84]
[251 169 154]]]
```

...

```
[[[248 247 252]
[248 247 252]
[248 247 252]
...
[246 245 250]
[246 245 250]
[246 245 250]]]
```

```
[[[248 247 252]
[248 247 252]
[248 247 252]
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[248 247 252]
[248 247 252]
[248 247 252]]]
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```
[247 245 250]
[246 245 250]
[246 245 250]]
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[[248 247 253]
[248 247 252]
[248 248 253]
...
[247 245 250]
[247 245 250]
[246 245 250]]
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...

```
[[245 243 246]
[246 241 245]
[245 240 244]
...
[252 252 253]
[252 252 254]
[251 251 253]]
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```
[[245 243 246]
[245 243 246]
[245 241 245]
...
[252 252 254]
[251 251 253]
[250 250 252]]
```

```
[[245 243 246]
[245 243 246]
[244 242 245]
...
[250 250 252]
[249 249 251]
[248 248 250]]]
```

```
[[[255 255 255]
[255 255 255]
[255 255 255]
...
[255 255 255]
[255 255 255]
[255 255 255]]]
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[[255 255 255]
[255 255 255]
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[255 255 255]
[255 255 255]
[255 255 255]]
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[[255 255 255]
[255 255 255]
[255 255 255]
...
[255 255 255]
[255 255 255]
[255 255 255]]
```

...

```
[[239 229 219]
[237 226 214]
[233 220 207]
...
[226 203 171]
[229 210 183]
[233 217 193]]
```

```
[[245 236 228]
[242 233 224]
[231 221 211]
...
[229 209 180]
[232 215 190]
[234 219 196]]
```

```
[[247 240 233]
[247 239 231]
[247 238 229]
...
[234 218 194]
[237 222 201]
[238 225 206]]]
```

```
[[[255 152 46]
[246 115 11]
[232 91 0]
...
[188 34 1]
[195 34 1]
[193 31 1]]]
```

[[255 147 18]]

```
[249 118  8]
[236  88  1]
...
[[198  34  1]
[204  34  1]
[191  25  1]]]

[[254 151  9]
[253 127  3]
[236  75  1]
...
[[203  29  1]
[183  19  1]
[123   8  2]]]

...
[[189  54  2]
[ 88  11  2]
[197  52  1]
...
[[233 123  5]
[217 100  4]
[195  76  3]]]

[[202  56  1]
[ 88  12  2]
[177  42  1]
...
[[227 118  6]
[207  90  3]
[184  67  4]]]

[[208  56  2]
[ 85  14  3]
[147  30  2]
...
[[216 102  3]
[197  81  3]
[176  63  7]]]]]

['apple' 'apple' 'apple' 'apple' 'apple' 'apple' 'apple' 'apple'
'apple' 'apple' 'apple' 'banana' 'banana' 'banana' 'banana'
'banana' 'banana' 'banana' 'banana' 'banana' 'banana' 'banana'
'mixed' 'mixed' 'mixed' 'mixed' 'mixed' 'mixed' 'mixed' 'mixed'
'orange' 'orange' 'orange' 'orange' 'orange' 'orange' 'orange'
'orange' 'orange' 'orange' 'orange' 'orange' 'orange' 'orange']]

Out[ ]: (240, 30, 30, 3)
```

```
In [ ]: x_train=np.reshape(feature,(feature.shape[0],30,30,3))
x_train=x_train/255
```

```
In [ ]: encoder=LabelEncoder()
encoder.fit(label)
labels=encoder.transform(label)
y_train=tf.keras.utils.to_categorical(labels)
```

```
In [ ]: model=tf.keras.Sequential()
model.add(tf.keras.layers.Conv2D(filters=64, kernel_size=(3,3), activation="relu", input_shape=(30, 30, 3)))
model.add(tf.keras.layers.Conv2D(filters=32, kernel_size=(3,3), activation="relu"))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2,2)))
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(128, activation="relu"))
model.add(tf.keras.layers.Dropout(0.5))
model.add(tf.keras.layers.Dense(4, activation="softmax"))
```

```
In [ ]: model.compile(loss="categorical_crossentropy", optimizer="adam", metrics=["accuracy"])
#Epoch 30/30
# 22/22 [=====] - 1s 42ms/step - Loss: 0.0221 - accuracy: 0.9907 - val_Loss: 0.6493 - val_accuracy: 0.
#Actual accuracy of test set is 94.5%
```

```
In [ ]: model.compile(loss="categorical_crossentropy", optimizer="RMSprop", metrics=["accuracy"])
# Epoch 30/30
# 22/22 [=====] - 1s 45ms/step - loss: 0.0515 - accuracy: 0.9815 - val_loss: 0.7634 - val_accuracy: 0.
#Actual accuracy of test set is 87.3%
```



```
In [ ]: model.fit(x=x_train, y=y_train, batch_size=10, epochs=30, validation_split=0.1)

Epoch 1/30
22/22 [=====] - 2s 51ms/step - loss: 1.1880 - accuracy: 0.5324 - val_loss: 1.1640 - val_accuracy: 0.12
50
Epoch 2/30
22/22 [=====] - 1s 43ms/step - loss: 0.7352 - accuracy: 0.7176 - val_loss: 0.3245 - val_accuracy: 0.91
67
Epoch 3/30
22/22 [=====] - 1s 44ms/step - loss: 0.4719 - accuracy: 0.8333 - val_loss: 0.7025 - val_accuracy: 0.83
33
Epoch 4/30
22/22 [=====] - 1s 43ms/step - loss: 0.4209 - accuracy: 0.8426 - val_loss: 0.3343 - val_accuracy: 0.95
83
Epoch 5/30
22/22 [=====] - 1s 44ms/step - loss: 0.3911 - accuracy: 0.8611 - val_loss: 1.0890 - val_accuracy: 0.58
33
Epoch 6/30
22/22 [=====] - 1s 43ms/step - loss: 0.2740 - accuracy: 0.9074 - val_loss: 0.1154 - val_accuracy: 0.95
83
Epoch 7/30
22/22 [=====] - 1s 45ms/step - loss: 0.2601 - accuracy: 0.9167 - val_loss: 0.6282 - val_accuracy: 0.79
17
Epoch 8/30
22/22 [=====] - 1s 43ms/step - loss: 0.1813 - accuracy: 0.9537 - val_loss: 0.3131 - val_accuracy: 0.95
83
Epoch 9/30
22/22 [=====] - 1s 45ms/step - loss: 0.2097 - accuracy: 0.9167 - val_loss: 1.8041 - val_accuracy: 0.54
17
Epoch 10/30
22/22 [=====] - 1s 44ms/step - loss: 0.1567 - accuracy: 0.9352 - val_loss: 0.8466 - val_accuracy: 0.87
50
Epoch 11/30
22/22 [=====] - 1s 44ms/step - loss: 0.1102 - accuracy: 0.9583 - val_loss: 0.6041 - val_accuracy: 0.83
33
Epoch 12/30
22/22 [=====] - 1s 44ms/step - loss: 0.1485 - accuracy: 0.9444 - val_loss: 0.3974 - val_accuracy: 0.91
67
Epoch 13/30
22/22 [=====] - 1s 43ms/step - loss: 0.1272 - accuracy: 0.9444 - val_loss: 1.4730 - val_accuracy: 0.66
67
Epoch 14/30
22/22 [=====] - 1s 44ms/step - loss: 0.0783 - accuracy: 0.9676 - val_loss: 0.7081 - val_accuracy: 0.91
67
Epoch 15/30
22/22 [=====] - 1s 44ms/step - loss: 0.0886 - accuracy: 0.9815 - val_loss: 0.5897 - val_accuracy: 0.95
83
Epoch 16/30
22/22 [=====] - 1s 43ms/step - loss: 0.1227 - accuracy: 0.9722 - val_loss: 1.4943 - val_accuracy: 0.83
33
Epoch 17/30
22/22 [=====] - 1s 42ms/step - loss: 0.0231 - accuracy: 0.9907 - val_loss: 1.3014 - val_accuracy: 0.79
17
Epoch 18/30
22/22 [=====] - 1s 44ms/step - loss: 0.1772 - accuracy: 0.9491 - val_loss: 1.4631 - val_accuracy: 0.75
00
Epoch 19/30
22/22 [=====] - 1s 43ms/step - loss: 0.0332 - accuracy: 0.9861 - val_loss: 0.4290 - val_accuracy: 0.95
83
Epoch 20/30
22/22 [=====] - 1s 43ms/step - loss: 0.0555 - accuracy: 0.9815 - val_loss: 1.1392 - val_accuracy: 0.79
17
Epoch 21/30
22/22 [=====] - 1s 43ms/step - loss: 0.0297 - accuracy: 0.9907 - val_loss: 1.4715 - val_accuracy: 0.83
33
Epoch 22/30
22/22 [=====] - 1s 44ms/step - loss: 0.1062 - accuracy: 0.9630 - val_loss: 1.0123 - val_accuracy: 0.87
50
Epoch 23/30
22/22 [=====] - 1s 44ms/step - loss: 0.0282 - accuracy: 0.9861 - val_loss: 0.9399 - val_accuracy: 0.87
50
Epoch 24/30
22/22 [=====] - 1s 44ms/step - loss: 0.0956 - accuracy: 0.9630 - val_loss: 1.2002 - val_accuracy: 0.83
33
Epoch 25/30
22/22 [=====] - 1s 44ms/step - loss: 0.0108 - accuracy: 1.0000 - val_loss: 0.9764 - val_accuracy: 0.87
50
Epoch 26/30
22/22 [=====] - 1s 44ms/step - loss: 0.0015 - accuracy: 1.0000 - val_loss: 0.8680 - val_accuracy: 0.91
67
Epoch 27/30
22/22 [=====] - 1s 43ms/step - loss: 0.0546 - accuracy: 0.9815 - val_loss: 4.0163 - val_accuracy: 0.54
17
Epoch 28/30
22/22 [=====] - 1s 43ms/step - loss: 0.0385 - accuracy: 0.9861 - val_loss: 1.5148 - val_accuracy: 0.83
33
Epoch 29/30
22/22 [=====] - 1s 44ms/step - loss: 0.0768 - accuracy: 0.9861 - val_loss: 1.8154 - val_accuracy: 0.87
50
Epoch 30/30
```

```
22/22 [=====] - 1s 45ms/step - loss: 0.0515 - accuracy: 0.9815 - val_loss: 0.7634 - val_accuracy: 0.91
67
```

```
Out[ ]: <tensorflow.python.keras.callbacks.History at 0x7f7631c37cd0>
```

```
In [ ]:
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plot
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image
from tensorflow.keras.optimizers import RMSprop, Adam
import os
import PIL

dir_path= 'test/'

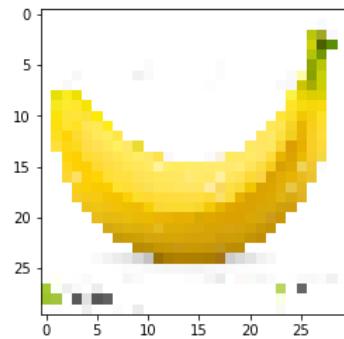
data = np.asarray(['apple','banana','mixed','orange'])
new_array= np.zeros((1,4))
#Instantiates an empty numpy array
total = len(os.listdir(dir_path))
count = 0

for filename in os.listdir(dir_path):
    img = image.load_img(dir_path + filename, target_size=(30,30))
    img_array = image.img_to_array(img)
    img_batch = np.expand_dims(img_array, axis=0)
    prediction = model.predict(img_batch)
    pred = prediction[0]

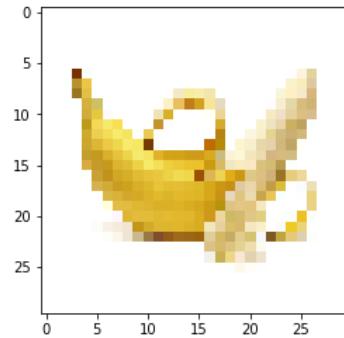
    idx, = np.where(pred==max(pred))
    #
    # Recording test set as 2D array
    new_array = np.vstack([new_array,pred])

    # Display + keep track of no. of correct predictions
    if len(idx) >1:
        plot.imshow(img)
        plot.show()
        print(f"{filename:s} is unknown by model, error in prediction")
    else:
        j = idx[0]
        plot.imshow(img)
        plot.show()
        print(f"{filename:s} is {data[j]}")
        if data[j] in filename:
            count += 1

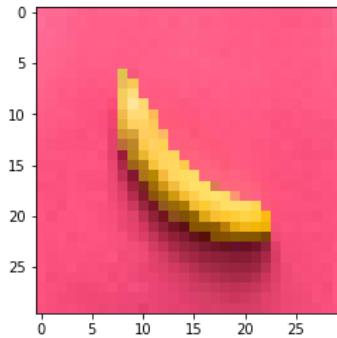
print(f"Accuracy of test set is {count/total:0.3f}")
# print(new_array)
```



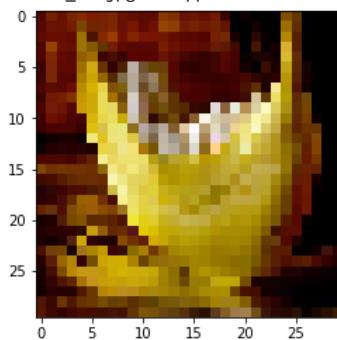
banana_79.jpg is banana



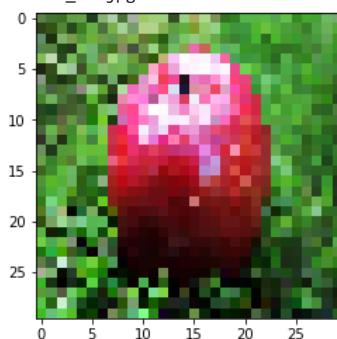
banana_82.jpg is banana



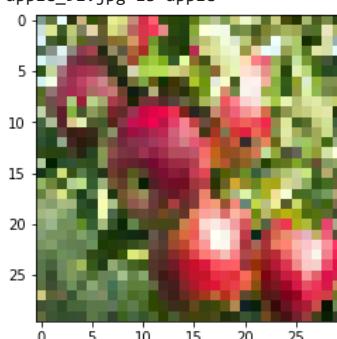
banana_88.jpg is apple



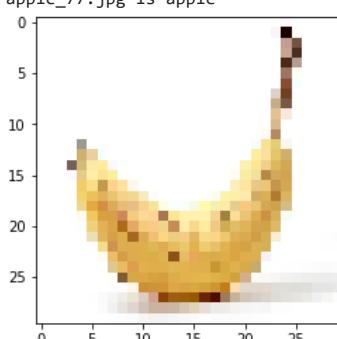
banana_83.jpg is banana



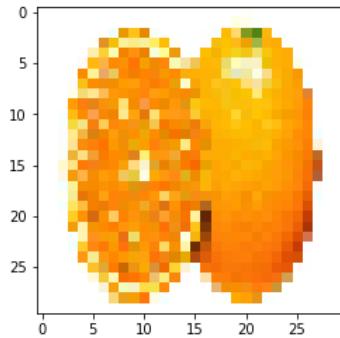
apple_91.jpg is apple



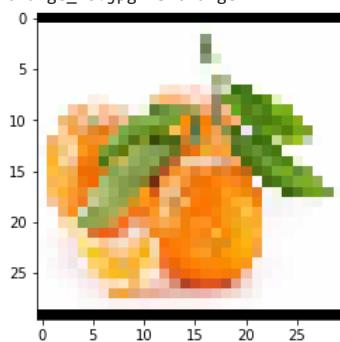
apple_77.jpg is apple



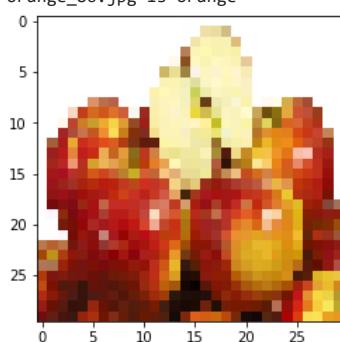
banana_84.jpg is banana



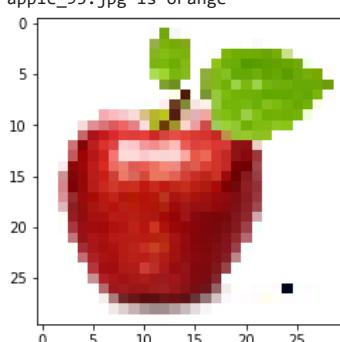
orange_78.jpg is orange



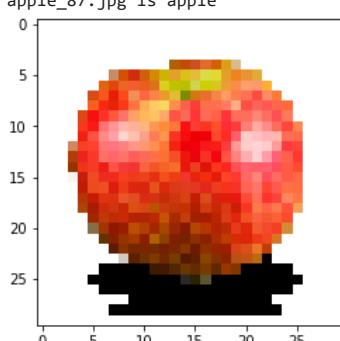
orange_86.jpg is orange



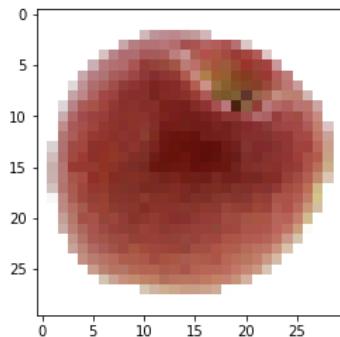
apple_95.jpg is orange



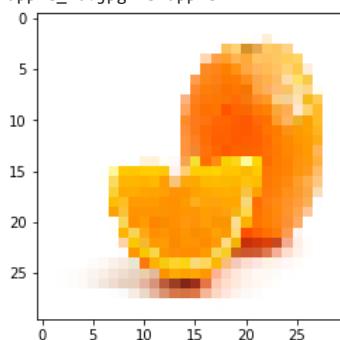
apple_87.jpg is apple



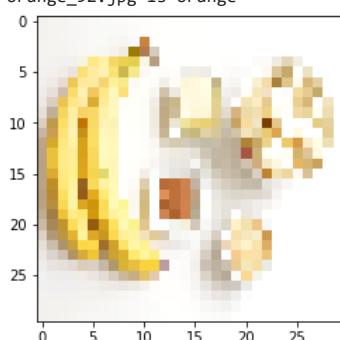
apple_92.jpg is apple



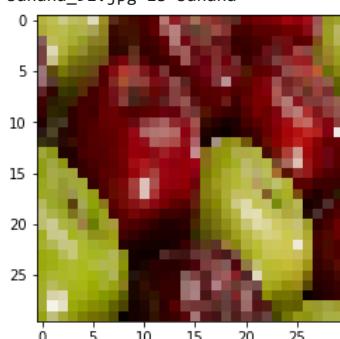
apple_90.jpg is apple



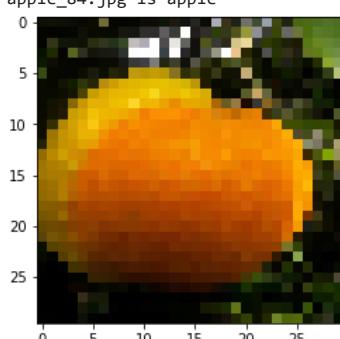
orange_92.jpg is orange



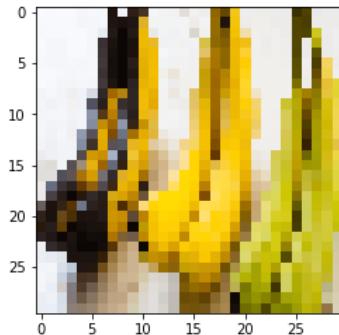
banana_91.jpg is banana



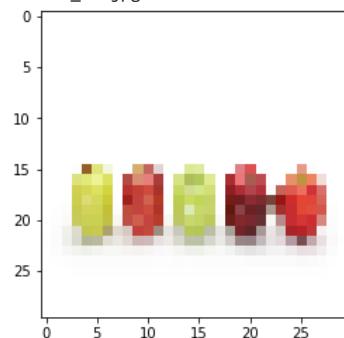
apple_84.jpg is apple



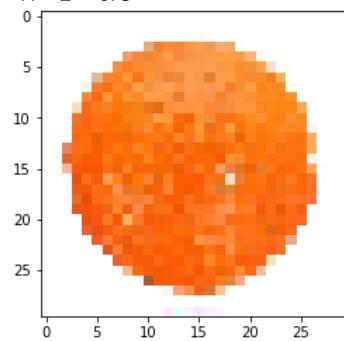
orange_85.jpg is orange



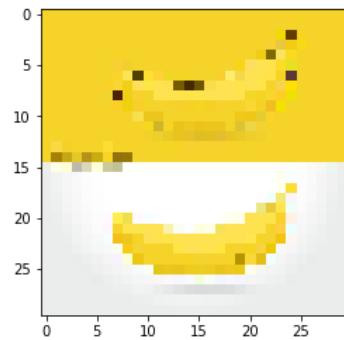
banana_87.jpg is banana



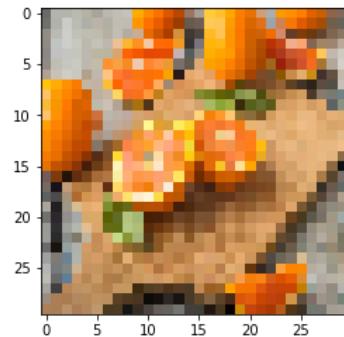
apple_86.jpg is banana



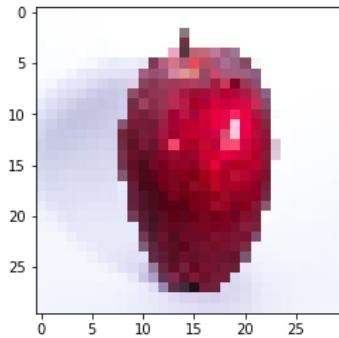
orange_83.jpg is orange



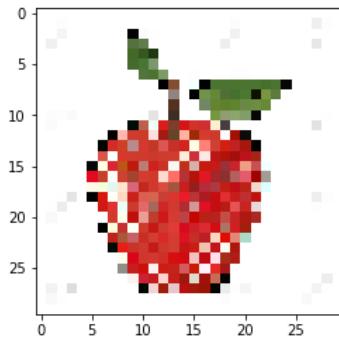
banana_93.jpg is banana



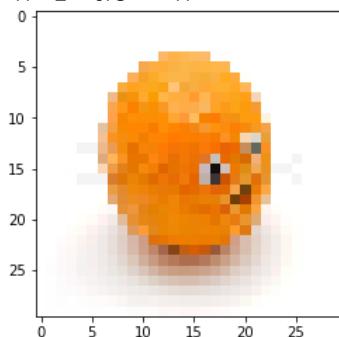
orange_77.jpg is banana



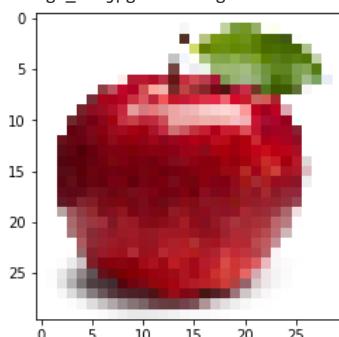
apple_93.jpg is apple



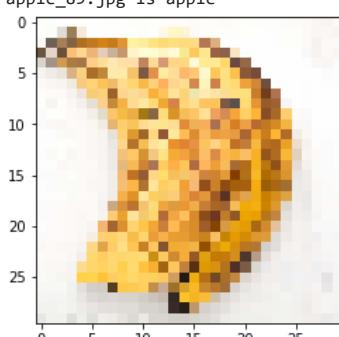
apple_88.jpg is apple



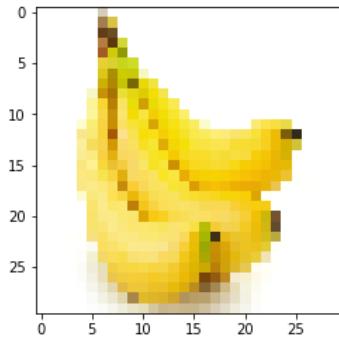
orange_91.jpg is orange



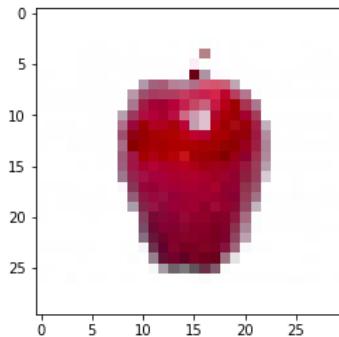
apple_89.jpg is apple



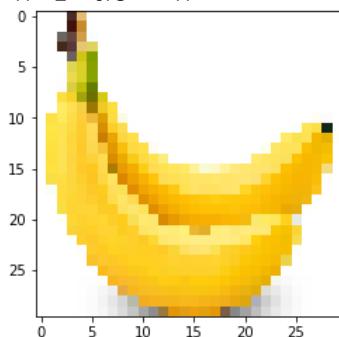
banana_86.jpg is orange



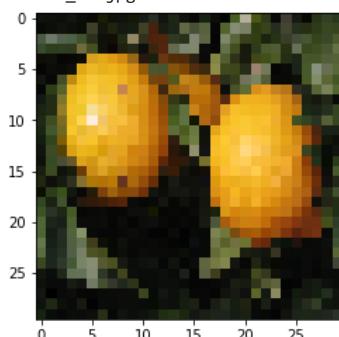
banana_90.jpg is banana



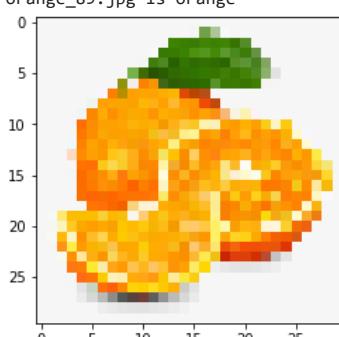
apple_80.jpg is apple



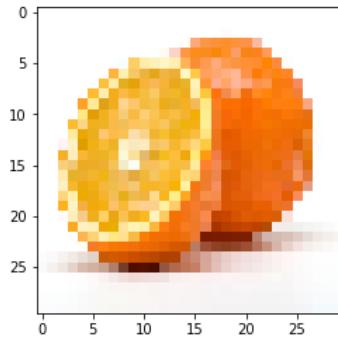
banana_81.jpg is banana



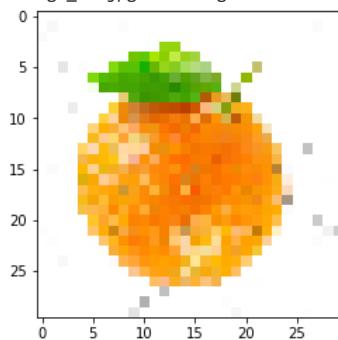
orange_89.jpg is orange



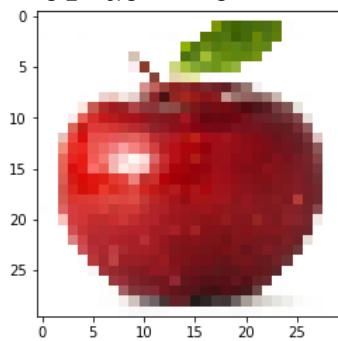
orange_82.jpg is orange



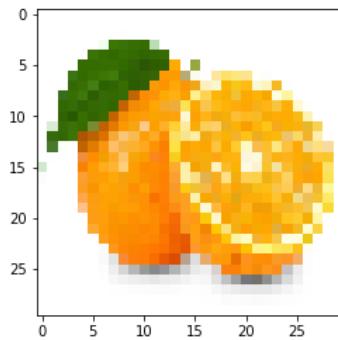
orange_84.jpg is orange



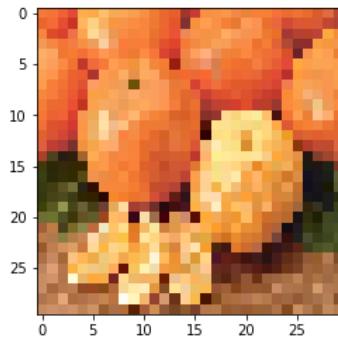
orange_95.jpg is orange



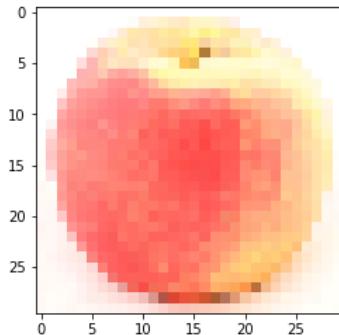
apple_81.jpg is apple



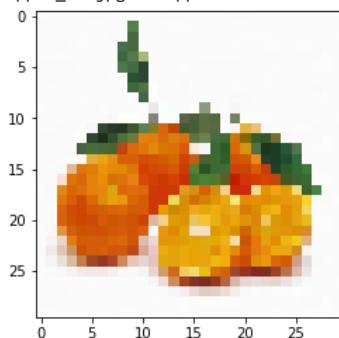
orange_80.jpg is orange



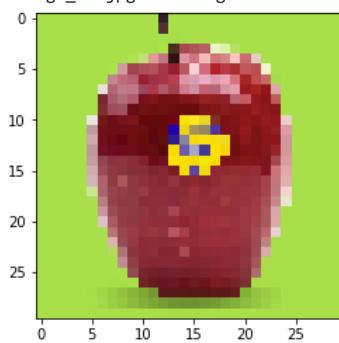
orange_90.jpg is banana



apple_78.jpg is apple



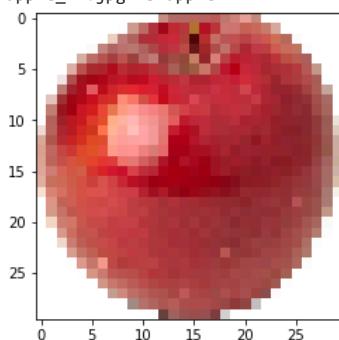
orange_87.jpg is orange



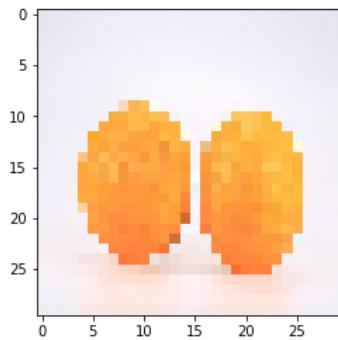
apple_85.jpg is apple



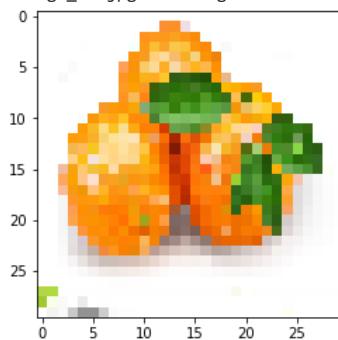
apple_94.jpg is apple



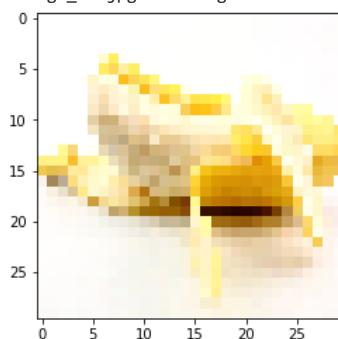
apple_83.jpg is apple



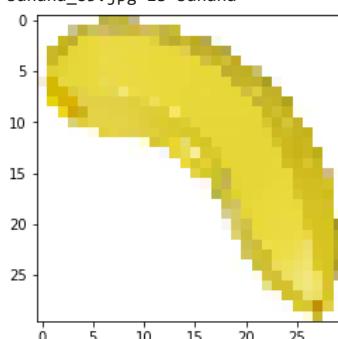
orange_93.jpg is orange



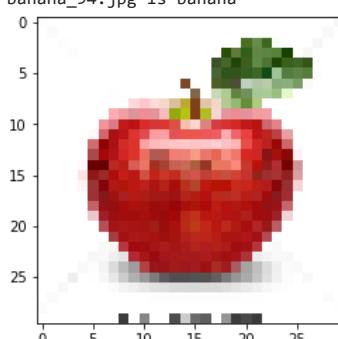
orange_81.jpg is orange



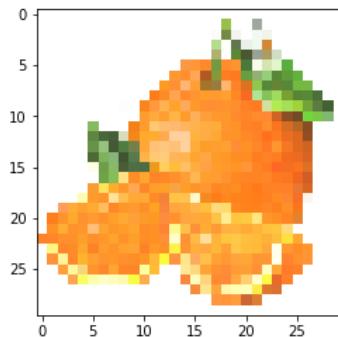
banana_85.jpg is banana



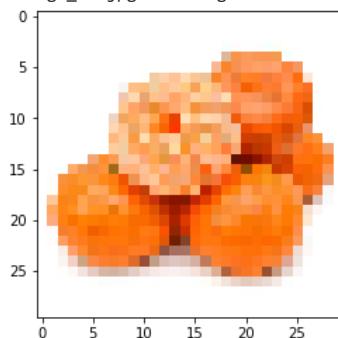
banana_94.jpg is banana



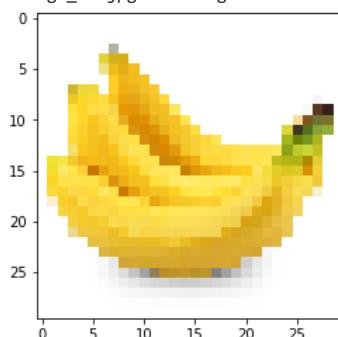
apple_82.jpg is apple



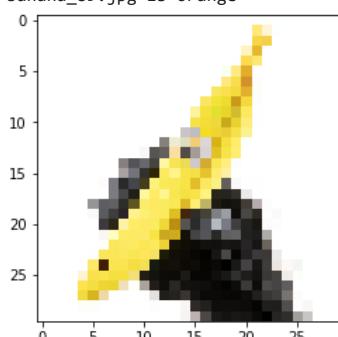
orange_94.jpg is orange



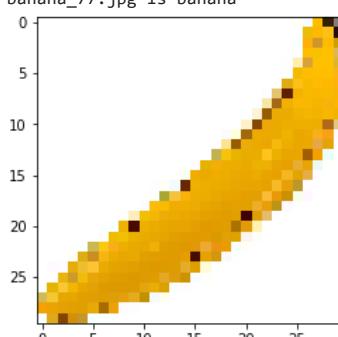
orange_79.jpg is orange



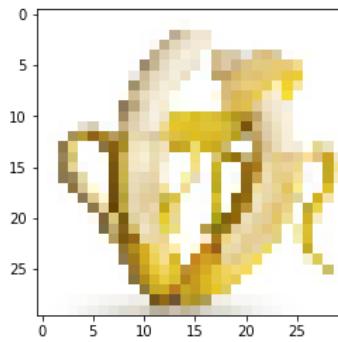
banana_89.jpg is orange



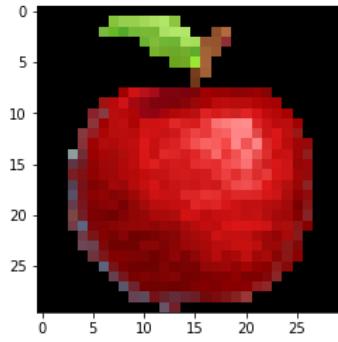
banana_77.jpg is banana



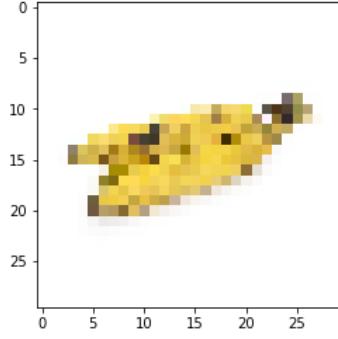
banana_92.jpg is banana



banana_78.jpg is banana



apple_79.jpg is apple



banana_80.jpg is banana

Accuracy of test set is 0.873

```
In [ ]:
from zipfile import ZipFile
file_name = 'test.zip'

with ZipFile(file_name, 'r') as zip:
    zip.extractall()
    print('Done extracting test.zip')

Done extracting test.zip
```

```
In [ ]:
data=[]
data1=[]
for i in range(77,96):
    img=Image.open("test/apple_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("apple")
for i in range(77,95):
    img=Image.open("test/banana_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("banana")

for i in range(77,88):
    img=Image.open("test/orange_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("orange")
for i in range(89,96):
    img=Image.open("test/orange_{0}.jpg".format (i)).convert("RGB")
    img_re=img.resize((30,30))
    array = np.array(img_re)
    data.append(array)
    data1.append("orange")
feature=np.array(data)
label=np.array(data1)
```

```
In [ ]: x_test=np.reshape(feature,(feature.shape[0],30,30,3))
x_test=x_test/255
```

```
In [ ]: encoder=LabelEncoder()
encoder.fit(label)
labels=encoder.transform(label)
y_test=tf.keras.utils.to_categorical(labels)
```

```
In [ ]: loss, accuracy=model.evaluate(x=x_test, y=y_test)

2/2 [=====] - 0s 27ms/step - loss: 0.7420 - accuracy: 0.8667
```

```
In [ ]: print(loss,accuracy)
```

```
0.7420070171356201 0.8666666746139526
```

Model 2b: Adam and RMSprop optimization algorithms; 200 x 200 px

```
In [ ]: import numpy as np
from PIL import Image
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout, Flatten, Dense
```

```
In [ ]: categories =['apple','banana','mixed','orange']

def process_img(file,numlist,features,label):
    for category in categories:

        for i in numlist:
            try:
                img= Image.open('%s/%s_%d.jpg' % (file,category,i)).convert('RGB')
                img=img.resize((200,200))
                img_array=np.array(img)
                features.append(img_array)
                label.append(category)

            except Exception as e:
                pass

        continue
```

```
In [ ]: #set up train & test data
x_train=[]
y_train=[]
x_test=[]
y_test=[]

process_img('train1',range(1,77),x_train,y_train)
process_img('test',range(21,96),x_test,y_test)
```

```
/usr/local/lib/python3.7/dist-packages/PIL/Image.py:960: UserWarning: Palette images with Transparency expressed in bytes should be converted to RGBA images
  "Palette images with Transparency expressed in bytes should be "
```

```
In [ ]: #convert to numpy array
x_train=np.array(x_train)
y_train=np.array(y_train)
x_test=np.array(x_test)
y_test=np.array(y_test)
```

```
In [ ]: x_train=np.reshape(x_train,(x_train.shape[0],200,200,3))
x_test=np.reshape(x_test,(x_test.shape[0],200,200,3))

x_train=x_train/255
x_test=x_test/255
```

```
In [ ]: #one-hot encoding
encoder=LabelEncoder()
train=encoder.fit_transform(y_train)
test=encoder.fit_transform(y_test)

y_train=tf.keras.utils.to_categorical(train,4)
y_test=tf.keras.utils.to_categorical(test,4)
```

```
In [ ]: model=Sequential()
model.add(Conv2D(64,(3,3),activation='relu',input_shape=(200,200,3)))
model.add(Conv2D(32,(3,3),activation='relu'))
```

```

model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(4,activation='softmax'))
model.compile(loss='categorical_crossentropy', optimizer='RMSprop',metrics=[ 'accuracy' ])
model.summary()

```

Model: "sequential_9"

Layer (type)	Output Shape	Param #
conv2d_18 (Conv2D)	(None, 198, 198, 64)	1792
conv2d_19 (Conv2D)	(None, 196, 196, 32)	18464
max_pooling2d_9 (MaxPooling2D)	(None, 98, 98, 32)	0
dropout_11 (Dropout)	(None, 98, 98, 32)	0
flatten_9 (Flatten)	(None, 307328)	0
dense_18 (Dense)	(None, 128)	39338112
dropout_12 (Dropout)	(None, 128)	0
dense_19 (Dense)	(None, 4)	516

Total params: 39,358,884
Trainable params: 39,358,884
Non-trainable params: 0

In []:

```

model=Sequential()
model.add(Conv2D(64,(3,3),activation='relu',input_shape=(200,200,3)))
model.add(Conv2D(32,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(4,activation='softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam',metrics=[ 'accuracy' ])
model.summary()

#Actual accuracy of test set is 0.945

```

Model: "sequential_7"

Layer (type)	Output Shape	Param #
conv2d_14 (Conv2D)	(None, 198, 198, 64)	1792
conv2d_15 (Conv2D)	(None, 196, 196, 32)	18464
max_pooling2d_7 (MaxPooling2D)	(None, 98, 98, 32)	0
dropout_7 (Dropout)	(None, 98, 98, 32)	0
flatten_7 (Flatten)	(None, 307328)	0
dense_14 (Dense)	(None, 128)	39338112
dropout_8 (Dropout)	(None, 128)	0
dense_15 (Dense)	(None, 4)	516

Total params: 39,358,884
Trainable params: 39,358,884
Non-trainable params: 0

In []:

```
model.fit(x_train,y_train,epochs=30,validation_split=0.1)
```

```

Epoch 1/30
7/7 [=====] - 41s 6s/step - loss: 22.1578 - accuracy: 0.2870 - val_loss: 1.2297 - val_accuracy: 0.6667
Epoch 2/30
7/7 [=====] - 39s 6s/step - loss: 1.3141 - accuracy: 0.3935 - val_loss: 1.0759 - val_accuracy: 0.5000
Epoch 3/30
7/7 [=====] - 39s 6s/step - loss: 1.1933 - accuracy: 0.5741 - val_loss: 2.9888 - val_accuracy: 0.0000e+00
Epoch 4/30
7/7 [=====] - 39s 6s/step - loss: 1.3289 - accuracy: 0.5741 - val_loss: 8.2266 - val_accuracy: 0.0000e+00
Epoch 5/30
7/7 [=====] - 39s 6s/step - loss: 1.2484 - accuracy: 0.6435 - val_loss: 0.7581 - val_accuracy: 0.8750
Epoch 6/30
7/7 [=====] - 39s 6s/step - loss: 0.8748 - accuracy: 0.7176 - val_loss: 2.4010 - val_accuracy: 0.5000
Epoch 7/30
7/7 [=====] - 39s 6s/step - loss: 1.7339 - accuracy: 0.6343 - val_loss: 1.2332 - val_accuracy: 0.6250
Epoch 8/30
7/7 [=====] - 39s 6s/step - loss: 0.4744 - accuracy: 0.8380 - val_loss: 1.3553 - val_accuracy: 0.7083
Epoch 9/30
7/7 [=====] - 39s 6s/step - loss: 0.3017 - accuracy: 0.8704 - val_loss: 0.4281 - val_accuracy: 0.9167
Epoch 10/30

```

```

7/7 [=====] - 39s 6s/step - loss: 0.2850 - accuracy: 0.9120 - val_loss: 2.7000 - val_accuracy: 0.4167
Epoch 11/30
7/7 [=====] - 39s 6s/step - loss: 0.3160 - accuracy: 0.8935 - val_loss: 1.4529 - val_accuracy: 0.8333
Epoch 12/30
7/7 [=====] - 39s 6s/step - loss: 0.1503 - accuracy: 0.9444 - val_loss: 3.3697 - val_accuracy: 0.5833
Epoch 13/30
7/7 [=====] - 39s 6s/step - loss: 1.1601 - accuracy: 0.7824 - val_loss: 1.5009 - val_accuracy: 0.7917
Epoch 14/30
7/7 [=====] - 39s 6s/step - loss: 0.2286 - accuracy: 0.9398 - val_loss: 4.2406 - val_accuracy: 0.3750
Epoch 15/30
7/7 [=====] - 39s 6s/step - loss: 0.4991 - accuracy: 0.8657 - val_loss: 2.7280 - val_accuracy: 0.7500
Epoch 16/30
7/7 [=====] - 39s 6s/step - loss: 0.9907 - accuracy: 0.8380 - val_loss: 1.6086 - val_accuracy: 0.5417
Epoch 17/30
7/7 [=====] - 39s 6s/step - loss: 0.2549 - accuracy: 0.9213 - val_loss: 2.2039 - val_accuracy: 0.7500
Epoch 18/30
7/7 [=====] - 39s 6s/step - loss: 0.1624 - accuracy: 0.9352 - val_loss: 1.5132 - val_accuracy: 0.8750
Epoch 19/30
7/7 [=====] - 39s 6s/step - loss: 0.0603 - accuracy: 0.9815 - val_loss: 2.3174 - val_accuracy: 0.7917
Epoch 20/30
7/7 [=====] - 39s 6s/step - loss: 0.0310 - accuracy: 0.9954 - val_loss: 3.2380 - val_accuracy: 0.7083
Epoch 21/30
7/7 [=====] - 39s 6s/step - loss: 1.1582 - accuracy: 0.8981 - val_loss: 0.7867 - val_accuracy: 0.9167
Epoch 22/30
7/7 [=====] - 39s 6s/step - loss: 2.3235 - accuracy: 0.7870 - val_loss: 1.5924 - val_accuracy: 0.7917
Epoch 23/30
7/7 [=====] - 39s 6s/step - loss: 0.1956 - accuracy: 0.9167 - val_loss: 1.6880 - val_accuracy: 0.8333
Epoch 24/30
7/7 [=====] - 39s 6s/step - loss: 0.0583 - accuracy: 0.9815 - val_loss: 1.5276 - val_accuracy: 0.8333
Epoch 25/30
7/7 [=====] - 39s 6s/step - loss: 0.0359 - accuracy: 0.9861 - val_loss: 1.9324 - val_accuracy: 0.7917
Epoch 26/30
7/7 [=====] - 39s 6s/step - loss: 0.0293 - accuracy: 0.9954 - val_loss: 1.8174 - val_accuracy: 0.8333
Epoch 27/30
7/7 [=====] - 39s 6s/step - loss: 0.0575 - accuracy: 0.9815 - val_loss: 1.9868 - val_accuracy: 0.8333
Epoch 28/30
7/7 [=====] - 39s 6s/step - loss: 0.5784 - accuracy: 0.8843 - val_loss: 0.3095 - val_accuracy: 0.9583
Epoch 29/30
7/7 [=====] - 39s 6s/step - loss: 0.0678 - accuracy: 0.9907 - val_loss: 1.0882 - val_accuracy: 0.8750
Epoch 30/30
7/7 [=====] - 39s 6s/step - loss: 0.0585 - accuracy: 0.9907 - val_loss: 1.5175 - val_accuracy: 0.8333

```

Out[]: <tensorflow.python.keras.callbacks.History at 0x7f7632519f10>

In []:

```
score=model.evaluate(x_test,y_test)
print('score=',score)
```

```
2/2 [=====] - 2s 1s/step - loss: 1.0362 - accuracy: 0.8000
score= [1.0362112522125244, 0.800000011920929]
```

In []:

```
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plot
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image
from tensorflow.keras.optimizers import RMSprop, Adam
import os
import PIL

dir_path= 'test/'

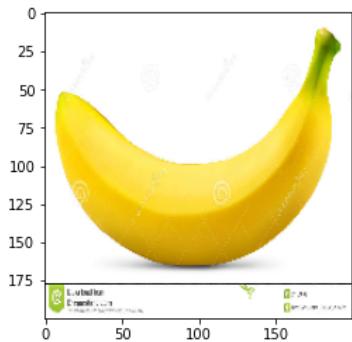
data = np.asarray(['apple','banana','mixed','orange'])
new_array= np.zeros((1,4))
#Instantiates an empty numpy array
total = len(os.listdir(dir_path))
count = 0

for filename in os.listdir(dir_path):
    img = image.load_img(dir_path + filename, target_size=(200,200))
    img_array = image.img_to_array(img)
    img_batch = np.expand_dims(img_array, axis=0)
    prediction = model.predict(img_batch)
    pred = prediction[0]

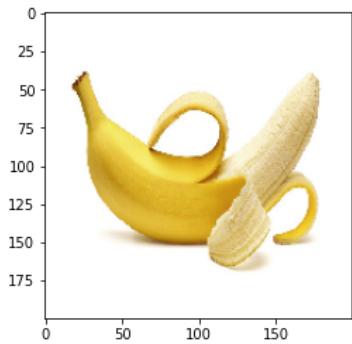
    idx, = np.where(pred==max(pred))
    #
    # Recording test set as 2D array
    new_array = np.vstack([new_array,pred])

    # Display + keep track of no. of correct predictions
    if len(idx) >1:
        plot.imshow(img)
        plot.show()
        print(f"{filename:s} is unknown by model, error in prediction")
    else:
        j = idx[0]
        plot.imshow(img)
        plot.show()
        print(f"{filename:s} is {data[j]}")
        if data[j] in filename:
            count += 1
```

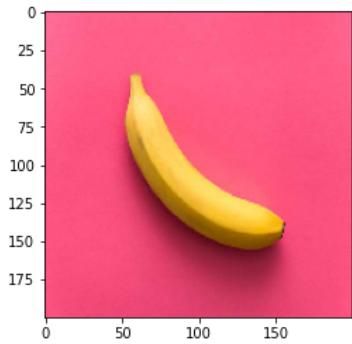
```
print(f"Accuracy of test set is {count/total:0.3f}")
# print(new_array)
```



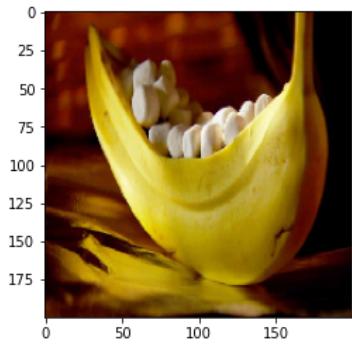
banana_79.jpg is banana



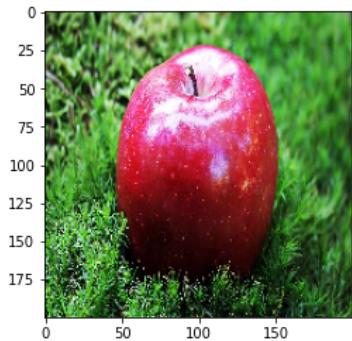
banana_82.jpg is banana



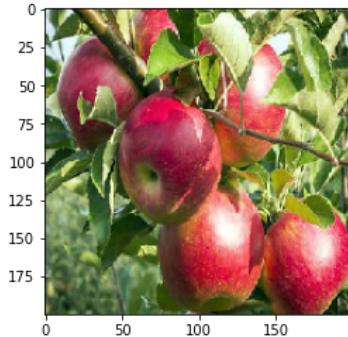
banana_88.jpg is apple



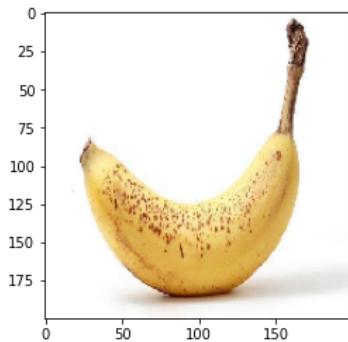
banana_83.jpg is banana



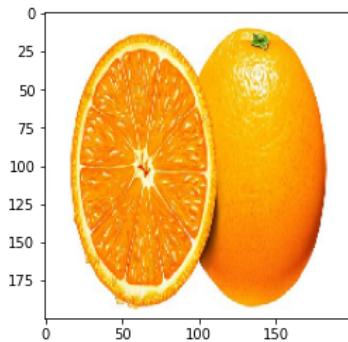
apple_91.jpg is apple



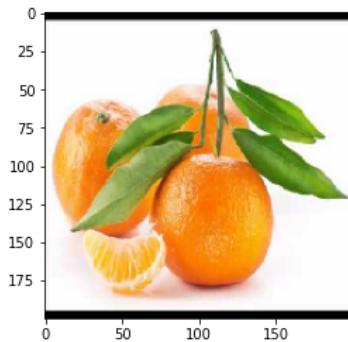
apple_77.jpg is apple



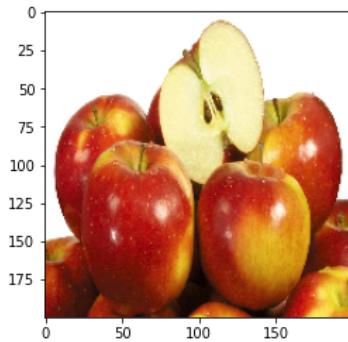
banana_84.jpg is banana



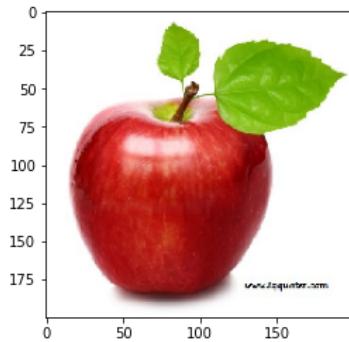
orange_78.jpg is orange



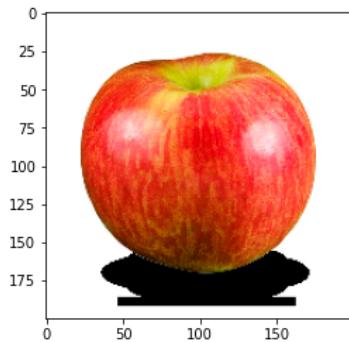
orange_86.jpg is banana



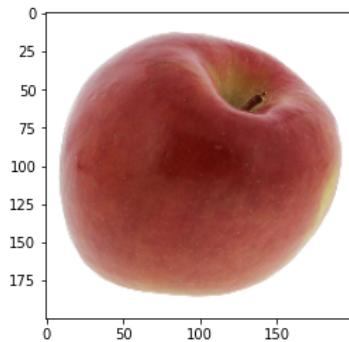
apple_95.jpg is apple



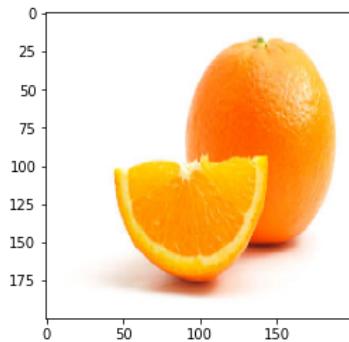
apple_87.jpg is apple



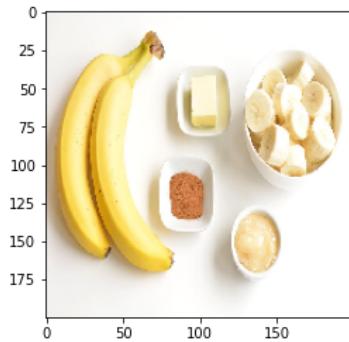
apple_92.jpg is apple



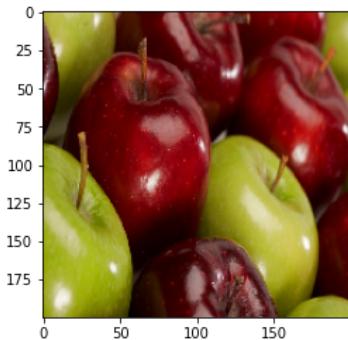
apple_90.jpg is apple



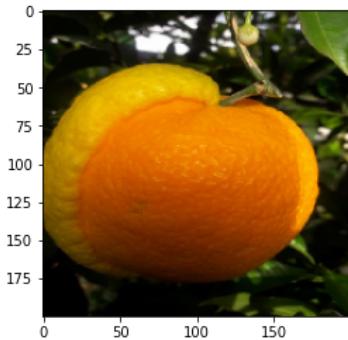
orange_92.jpg is orange



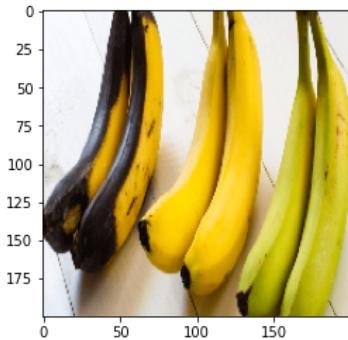
banana_91.jpg is banana



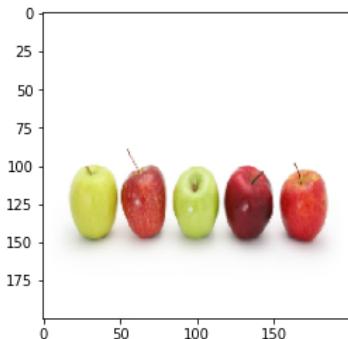
apple_84.jpg is apple



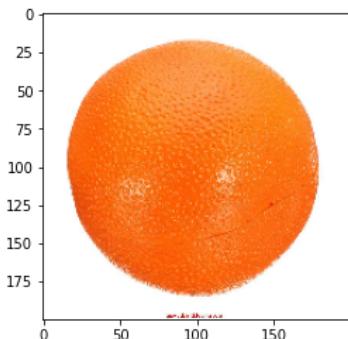
orange_85.jpg is orange



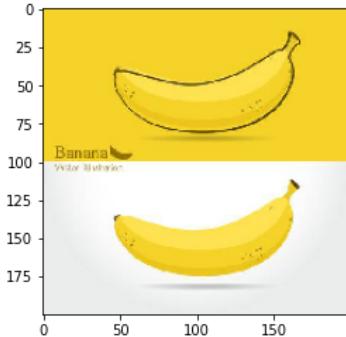
banana_87.jpg is banana



apple_86.jpg is apple



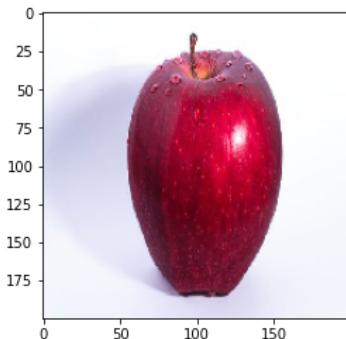
orange_83.jpg is orange



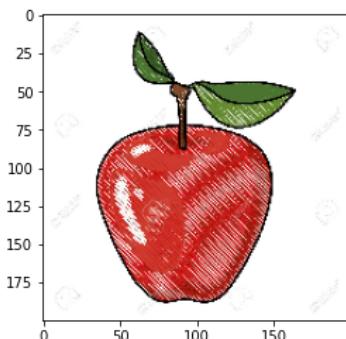
banana_93.jpg is banana



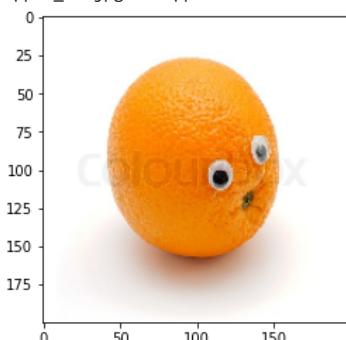
orange_77.jpg is banana



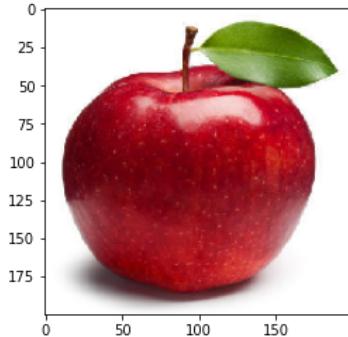
apple_93.jpg is apple



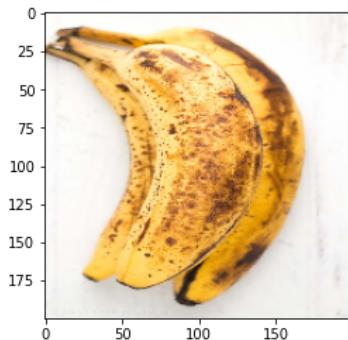
apple_88.jpg is apple



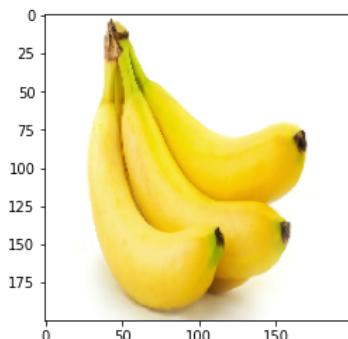
orange_91.jpg is orange



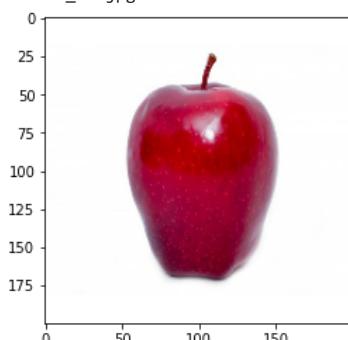
apple_89.jpg is apple



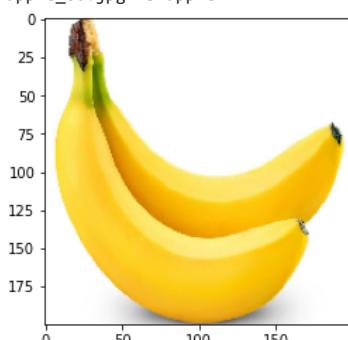
banana_86.jpg is banana



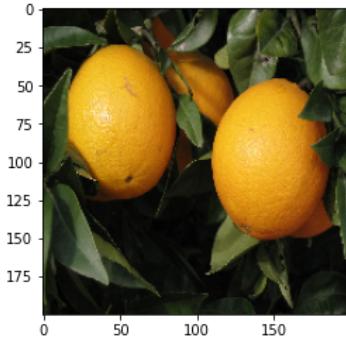
banana_90.jpg is banana



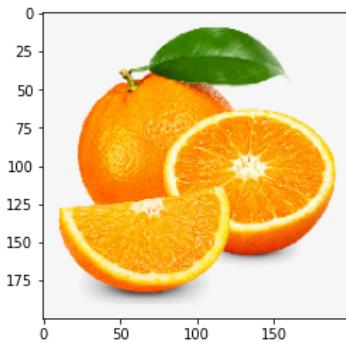
apple_80.jpg is apple



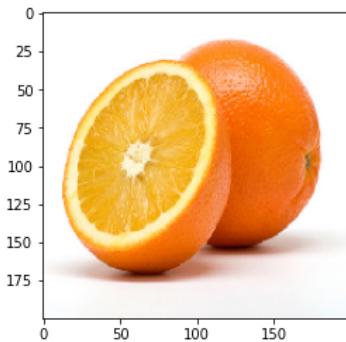
banana_81.jpg is banana



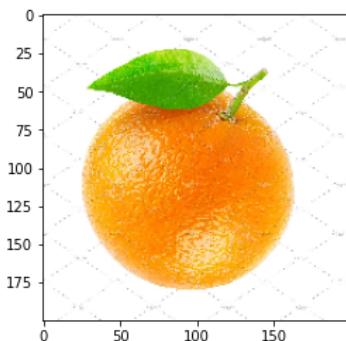
orange_89.jpg is orange



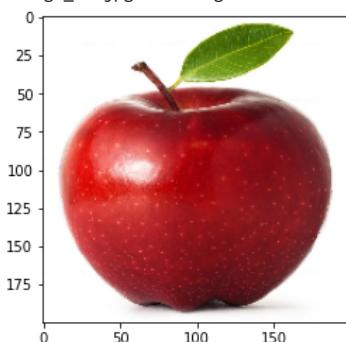
orange_82.jpg is orange



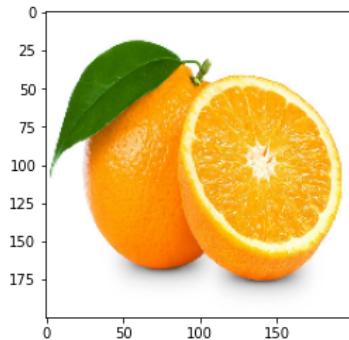
orange_84.jpg is orange



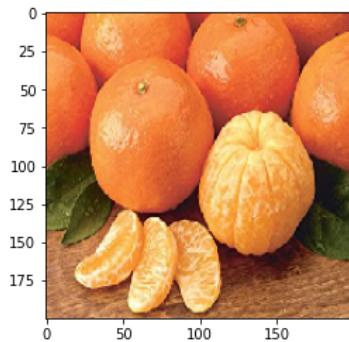
orange_95.jpg is orange



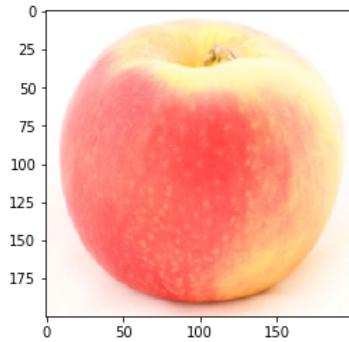
apple_81.jpg is apple



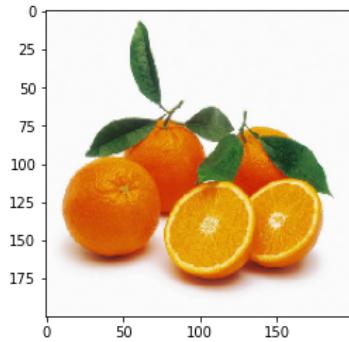
orange_80.jpg is orange



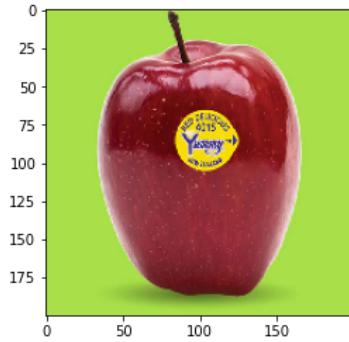
orange_90.jpg is orange



apple_78.jpg is apple



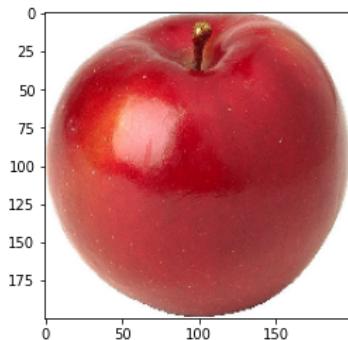
orange_87.jpg is orange



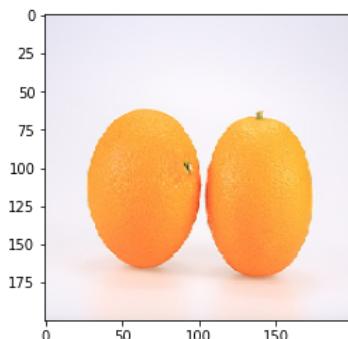
apple_85.jpg is apple



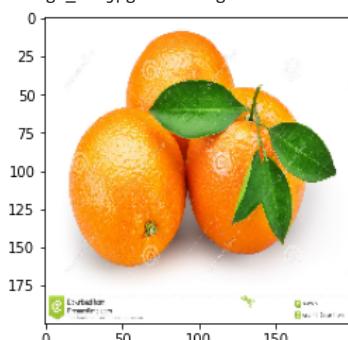
apple_94.jpg is apple



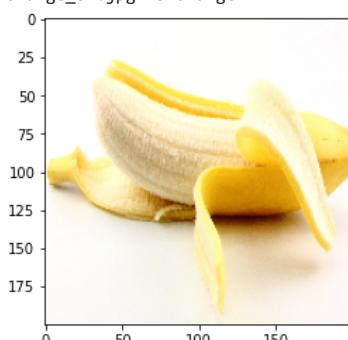
apple_83.jpg is apple



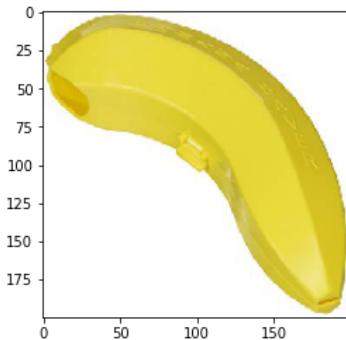
orange_93.jpg is orange



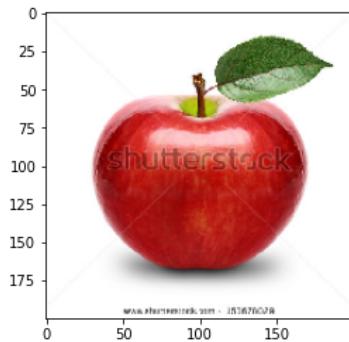
orange_81.jpg is orange



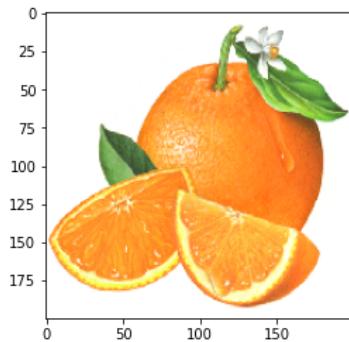
banana_85.jpg is banana



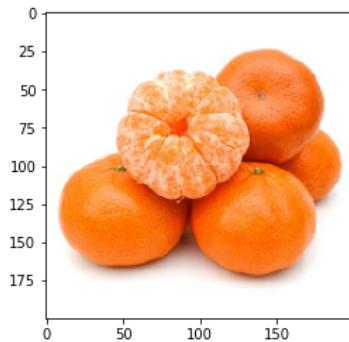
banana_94.jpg is banana



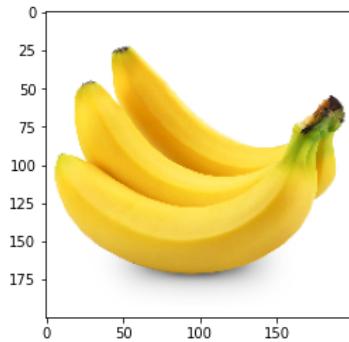
apple_82.jpg is apple



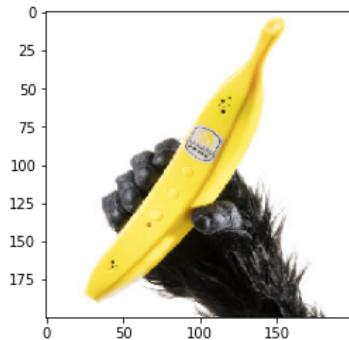
orange_94.jpg is orange



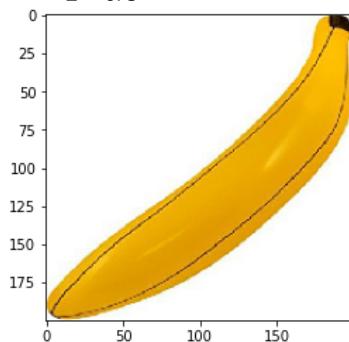
orange_79.jpg is orange



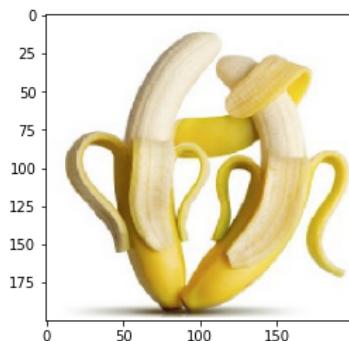
banana_89.jpg is banana



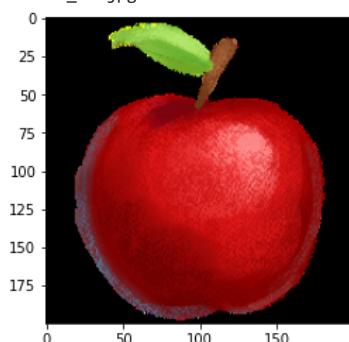
banana_77.jpg is banana



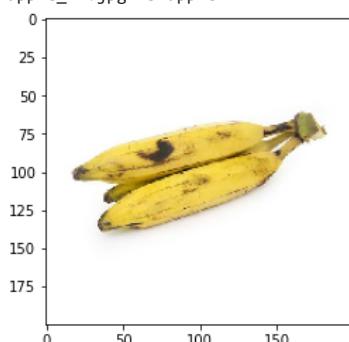
banana_92.jpg is banana



banana_78.jpg is banana



apple_79.jpg is apple



banana_80.jpg is banana

Accuracy of test set is 0.945