In [1]:
```
#Uploading the images to jupyter notebook
import zipfile as zf
files = zf.ZipFile("images.zip", 'r')
files.extractall()
```

In [13]:
```
#Load in the needed packages for the analysis
import matplotlib.pyplot as plt
import seaborn as sns
import keras
from keras.models import Sequential
from keras.layers import Dense, Conv2D , MaxPool2D , Flatten , Dropout
from keras.preprocessing.image import ImageDataGenerator
from keras.optimizers import Adam
from sklearn.metrics import classification_report,confusion_matrix
import tensorflow as tf
import cv2
import os
import numpy as np
```

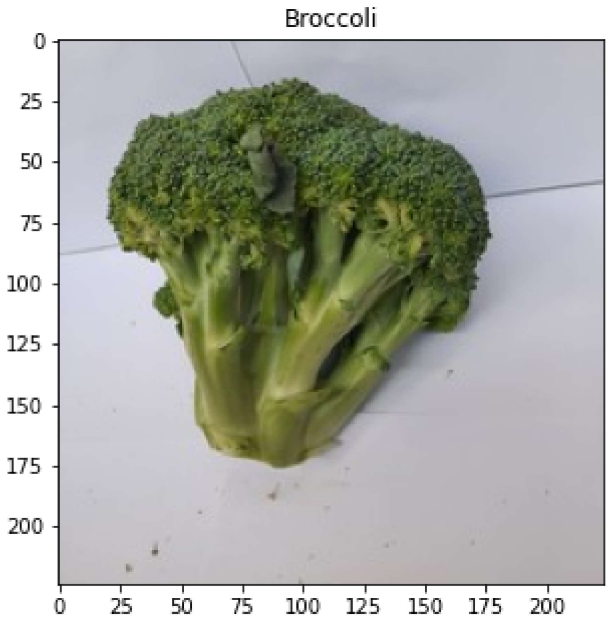
In [3]:
```
#creating a function to label the data and indexing the data
labels = ['Broccoli', 'Carrot', 'Pumpkin', 'Tomato']
img_size = 224
def get_data(data_dir):
    data = []
    for label in labels:
        path = os.path.join(data_dir, label)
        class_num = labels.index(label)
        for img in os.listdir(path):
            try:
                img_arr = cv2.imread(os.path.join(path, img))[...,::-1] #convert BGR to
                resized_arr = cv2.resize(img_arr, (img_size, img_size)) # Reshaping ima
                data.append([resized_arr, class_num])
            except Exception as e:
                print(e)
    return np.array(data)
```

In [4]:
```
#using the function on the training and validation data sets
train = get_data('Vegetable Images/train')
val = get_data('Vegetable Images/test')
```

```
C:\Users\oriri\AppData\Local\Temp/ipykernel_5836/126599425.py:15: VisibleDeprecationWarn
ing: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists
-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to
do this, you must specify 'dtype=object' when creating the ndarray.
  return np.array(data)
```

In [5]:
```
#Checking the data sets to make sure everything is correct
plt.figure(figsize = (5,5))
plt.imshow(train[1][0])
plt.title(labels[train[0][1]])
```

Out[5]:
```
Text(0.5, 1.0, 'Broccoli')
```



In [6]:

```
#Normalizing and reshaping the data
x_train = []
y_train = []
x_val = []
y_val = []

for feature, label in train:
  x_train.append(feature)
  y_train.append(label)

for feature, label in val:
  x_val.append(feature)
  y_val.append(label)

# Normalize the data
x_train = np.array(x_train) / 255
x_val = np.array(x_val) / 255

x_train.reshape(-1, img_size, img_size, 1)
y_train = np.array(y_train)

x_val.reshape(-1, img_size, img_size, 1)
y_val = np.array(y_val)
```

In [7]:

```
datagen = ImageDataGenerator(
        featurewise_center=False,  # set input mean to 0 over the dataset
        samplewise_center=False,  # set each sample mean to 0
        featurewise_std_normalization=False,  # divide inputs by std of the dataset
        samplewise_std_normalization=False,  # divide each input by its std
        zca_whitening=False,  # apply ZCA whitening
        rotation_range = 30,  # randomly rotate images in the range (degrees, 0 to 180)
        zoom_range = 0.2, # Randomly zoom image
        width_shift_range=0.1,  # randomly shift images horizontally (fraction of total
        height_shift_range=0.1,  # randomly shift images vertically (fraction of total
        horizontal_flip = True,  # randomly flip images
        vertical_flip=False)  # randomly flip images
```

```
datagen.fit(x_train)
```

In [8]:

```
#Building the Neural Network model
model = Sequential()
model.add(Conv2D(32,3,padding="same", activation="relu", input_shape=(224,224,3)))
model.add(MaxPool2D())

model.add(Conv2D(32, 3, padding="same", activation="relu"))
model.add(MaxPool2D())

model.add(Conv2D(64, 3, padding="same", activation="relu"))
model.add(MaxPool2D())
model.add(Dropout(0.4))

model.add(Flatten())
model.add(Dense(128,activation="relu"))
model.add(Dense(4, activation="softmax"))

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 224, 224, 32)      896       
                                                                 
 max_pooling2d (MaxPooling2D  (None, 112, 112, 32)     0         
 )                                                               
                                                                 
 conv2d_1 (Conv2D)           (None, 112, 112, 32)      9248      
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 56, 56, 32)       0         
 2D)                                                             
                                                                 
 conv2d_2 (Conv2D)           (None, 56, 56, 64)        18496     
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 28, 28, 64)       0         
 2D)                                                             
                                                                 
 dropout (Dropout)           (None, 28, 28, 64)        0         
                                                                 
 flatten (Flatten)           (None, 50176)             0         
                                                                 
 dense (Dense)               (None, 128)               6422656   
                                                                 
 dense_1 (Dense)             (None, 4)                 516       
                                                                 
=================================================================
Total params: 6,451,812
Trainable params: 6,451,812
Non-trainable params: 0
_________________________________________________________________
```

In [9]:

```
#Compiling the model
opt = Adam(lr=0.000001)
model.compile(optimizer = opt , loss = tf.keras.losses.SparseCategoricalCrossentropy(fr
```

```
C:\Users\oriri\anaconda3\lib\site-packages\keras\optimizers\optimizer_v2\adam.py:110: Us
erWarning: The `lr` argument is deprecated, use `learning_rate` instead.
  super(Adam, self).__init__(name, **kwargs)
```

In [10]:

```
#Fitting the model
history = model.fit(x_train,y_train,epochs = 200, validation_data = (x_val, y_val))
```

```
Epoch 1/200
C:\Users\oriri\anaconda3\lib\site-packages\tensorflow\python\util\dispatch.py:1082: User
Warning: "`sparse_categorical_crossentropy` received `from_logits=True`, but the `output
` argument was produced by a sigmoid or softmax activation and thus does not represent l
ogits. Was this intended?"
  return dispatch_target(*args, **kwargs)
125/125 [==============================] - 95s 755ms/step - loss: 1.3692 - accuracy: 0.2
707 - val_loss: 1.3399 - val_accuracy: 0.3137
Epoch 2/200
125/125 [==============================] - 98s 784ms/step - loss: 1.3266 - accuracy: 0.3
733 - val_loss: 1.2944 - val_accuracy: 0.4737
Epoch 3/200
125/125 [==============================] - 94s 752ms/step - loss: 1.2737 - accuracy: 0.5
045 - val_loss: 1.2338 - val_accuracy: 0.5113
Epoch 4/200
125/125 [==============================] - 98s 780ms/step - loss: 1.2050 - accuracy: 0.5
590 - val_loss: 1.1581 - val_accuracy: 0.5362
Epoch 5/200
125/125 [==============================] - 106s 849ms/step - loss: 1.1315 - accuracy: 0.
5920 - val_loss: 1.0903 - val_accuracy: 0.5700
Epoch 6/200
125/125 [==============================] - 98s 780ms/step - loss: 1.0594 - accuracy: 0.6
320 - val_loss: 1.0256 - val_accuracy: 0.6600
Epoch 7/200
125/125 [==============================] - 96s 767ms/step - loss: 0.9996 - accuracy: 0.6
752 - val_loss: 0.9730 - val_accuracy: 0.6687
Epoch 8/200
125/125 [==============================] - 95s 764ms/step - loss: 0.9466 - accuracy: 0.6
970 - val_loss: 0.9293 - val_accuracy: 0.6938
Epoch 9/200
125/125 [==============================] - 95s 756ms/step - loss: 0.9030 - accuracy: 0.7
207 - val_loss: 0.8922 - val_accuracy: 0.6925
Epoch 10/200
125/125 [==============================] - 95s 756ms/step - loss: 0.8638 - accuracy: 0.7
368 - val_loss: 0.8592 - val_accuracy: 0.7200
Epoch 11/200
125/125 [==============================] - 95s 757ms/step - loss: 0.8277 - accuracy: 0.7
533 - val_loss: 0.8299 - val_accuracy: 0.7175
Epoch 12/200
125/125 [==============================] - 95s 756ms/step - loss: 0.7944 - accuracy: 0.7
635 - val_loss: 0.8012 - val_accuracy: 0.7312
Epoch 13/200
125/125 [==============================] - 95s 758ms/step - loss: 0.7675 - accuracy: 0.7
732 - val_loss: 0.7746 - val_accuracy: 0.7362
Epoch 14/200
125/125 [==============================] - 95s 758ms/step - loss: 0.7379 - accuracy: 0.7
770 - val_loss: 0.7552 - val_accuracy: 0.7325
Epoch 15/200
125/125 [==============================] - 95s 760ms/step - loss: 0.7130 - accuracy: 0.7
845 - val_loss: 0.7293 - val_accuracy: 0.7437
Epoch 16/200
125/125 [==============================] - 96s 771ms/step - loss: 0.6916 - accuracy: 0.7
```

```
908 - val_loss: 0.7107 - val_accuracy: 0.7550
Epoch 17/200
125/125 [==============================] - 95s 758ms/step - loss: 0.6701 - accuracy: 0.7
878 - val_loss: 0.6919 - val_accuracy: 0.7563
Epoch 18/200
125/125 [==============================] - 96s 766ms/step - loss: 0.6507 - accuracy: 0.7
968 - val_loss: 0.6752 - val_accuracy: 0.7575
Epoch 19/200
125/125 [==============================] - 95s 760ms/step - loss: 0.6333 - accuracy: 0.8
025 - val_loss: 0.6612 - val_accuracy: 0.7613
Epoch 20/200
125/125 [==============================] - 95s 761ms/step - loss: 0.6155 - accuracy: 0.8
110 - val_loss: 0.6434 - val_accuracy: 0.7725
Epoch 21/200
125/125 [==============================] - 95s 760ms/step - loss: 0.5991 - accuracy: 0.8
133 - val_loss: 0.6295 - val_accuracy: 0.7750
Epoch 22/200
125/125 [==============================] - 95s 762ms/step - loss: 0.5858 - accuracy: 0.8
130 - val_loss: 0.6157 - val_accuracy: 0.7812
Epoch 23/200
125/125 [==============================] - 95s 760ms/step - loss: 0.5678 - accuracy: 0.8
213 - val_loss: 0.6020 - val_accuracy: 0.7887
Epoch 24/200
125/125 [==============================] - 95s 763ms/step - loss: 0.5539 - accuracy: 0.8
225 - val_loss: 0.5911 - val_accuracy: 0.7812
Epoch 25/200
125/125 [==============================] - 96s 770ms/step - loss: 0.5425 - accuracy: 0.8
245 - val_loss: 0.5778 - val_accuracy: 0.7950
Epoch 26/200
125/125 [==============================] - 95s 760ms/step - loss: 0.5289 - accuracy: 0.8
278 - val_loss: 0.5649 - val_accuracy: 0.8025
Epoch 27/200
125/125 [==============================] - 95s 758ms/step - loss: 0.5175 - accuracy: 0.8
350 - val_loss: 0.5562 - val_accuracy: 0.8012
Epoch 28/200
125/125 [==============================] - 95s 761ms/step - loss: 0.5051 - accuracy: 0.8
413 - val_loss: 0.5435 - val_accuracy: 0.8163
Epoch 29/200
125/125 [==============================] - 95s 760ms/step - loss: 0.4951 - accuracy: 0.8
447 - val_loss: 0.5359 - val_accuracy: 0.8213
Epoch 30/200
125/125 [==============================] - 95s 760ms/step - loss: 0.4839 - accuracy: 0.8
520 - val_loss: 0.5231 - val_accuracy: 0.8313
Epoch 31/200
125/125 [==============================] - 95s 760ms/step - loss: 0.4729 - accuracy: 0.8
565 - val_loss: 0.5162 - val_accuracy: 0.8250
Epoch 32/200
125/125 [==============================] - 95s 762ms/step - loss: 0.4621 - accuracy: 0.8
575 - val_loss: 0.5090 - val_accuracy: 0.8300
Epoch 33/200
125/125 [==============================] - 95s 761ms/step - loss: 0.4547 - accuracy: 0.8
605 - val_loss: 0.4963 - val_accuracy: 0.8462
Epoch 34/200
125/125 [==============================] - 95s 763ms/step - loss: 0.4461 - accuracy: 0.8
625 - val_loss: 0.4892 - val_accuracy: 0.8388
Epoch 35/200
125/125 [==============================] - 96s 771ms/step - loss: 0.4375 - accuracy: 0.8
660 - val_loss: 0.4821 - val_accuracy: 0.8400
Epoch 36/200
125/125 [==============================] - 95s 762ms/step - loss: 0.4269 - accuracy: 0.8
```

```
737 - val_loss: 0.4726 - val_accuracy: 0.8525
Epoch 37/200
125/125 [==============================] - 95s 760ms/step - loss: 0.4207 - accuracy: 0.8
720 - val_loss: 0.4665 - val_accuracy: 0.8537
Epoch 38/200
125/125 [==============================] - 95s 759ms/step - loss: 0.4123 - accuracy: 0.8
827 - val_loss: 0.4576 - val_accuracy: 0.8550
Epoch 39/200
125/125 [==============================] - 95s 760ms/step - loss: 0.4048 - accuracy: 0.8
820 - val_loss: 0.4514 - val_accuracy: 0.8575
Epoch 40/200
125/125 [==============================] - 95s 759ms/step - loss: 0.3945 - accuracy: 0.8
865 - val_loss: 0.4417 - val_accuracy: 0.8675
Epoch 41/200
125/125 [==============================] - 95s 760ms/step - loss: 0.3902 - accuracy: 0.8
873 - val_loss: 0.4354 - val_accuracy: 0.8725
Epoch 42/200
125/125 [==============================] - 96s 764ms/step - loss: 0.3811 - accuracy: 0.8
903 - val_loss: 0.4297 - val_accuracy: 0.8775
Epoch 43/200
125/125 [==============================] - 96s 766ms/step - loss: 0.3755 - accuracy: 0.8
955 - val_loss: 0.4231 - val_accuracy: 0.8800
Epoch 44/200
125/125 [==============================] - 96s 768ms/step - loss: 0.3683 - accuracy: 0.8
982 - val_loss: 0.4167 - val_accuracy: 0.8875
Epoch 45/200
125/125 [==============================] - 95s 762ms/step - loss: 0.3637 - accuracy: 0.8
967 - val_loss: 0.4151 - val_accuracy: 0.8825
Epoch 46/200
125/125 [==============================] - 95s 761ms/step - loss: 0.3572 - accuracy: 0.8
992 - val_loss: 0.4055 - val_accuracy: 0.8863
Epoch 47/200
125/125 [==============================] - 95s 760ms/step - loss: 0.3534 - accuracy: 0.9
028 - val_loss: 0.4047 - val_accuracy: 0.8900
Epoch 48/200
125/125 [==============================] - 95s 760ms/step - loss: 0.3461 - accuracy: 0.9
053 - val_loss: 0.3948 - val_accuracy: 0.8975
Epoch 49/200
125/125 [==============================] - 95s 759ms/step - loss: 0.3411 - accuracy: 0.9
068 - val_loss: 0.3915 - val_accuracy: 0.8988
Epoch 50/200
125/125 [==============================] - 95s 759ms/step - loss: 0.3350 - accuracy: 0.9
087 - val_loss: 0.3842 - val_accuracy: 0.8963
Epoch 51/200
125/125 [==============================] - 95s 760ms/step - loss: 0.3313 - accuracy: 0.9
135 - val_loss: 0.3846 - val_accuracy: 0.8975
Epoch 52/200
125/125 [==============================] - 95s 762ms/step - loss: 0.3262 - accuracy: 0.9
105 - val_loss: 0.3756 - val_accuracy: 0.8950
Epoch 53/200
125/125 [==============================] - 96s 764ms/step - loss: 0.3221 - accuracy: 0.9
105 - val_loss: 0.3769 - val_accuracy: 0.8950
Epoch 54/200
125/125 [==============================] - 97s 772ms/step - loss: 0.3165 - accuracy: 0.9
137 - val_loss: 0.3674 - val_accuracy: 0.9050
Epoch 55/200
125/125 [==============================] - 95s 760ms/step - loss: 0.3116 - accuracy: 0.9
158 - val_loss: 0.3632 - val_accuracy: 0.9050
Epoch 56/200
125/125 [==============================] - 97s 778ms/step - loss: 0.3090 - accuracy: 0.9
```

```
162 - val_loss: 0.3596 - val_accuracy: 0.9013
Epoch 57/200
125/125 [==============================] - 95s 758ms/step - loss: 0.3041 - accuracy: 0.9
172 - val_loss: 0.3573 - val_accuracy: 0.9087
Epoch 58/200
125/125 [==============================] - 95s 760ms/step - loss: 0.3004 - accuracy: 0.9
170 - val_loss: 0.3548 - val_accuracy: 0.9025
Epoch 59/200
125/125 [==============================] - 95s 759ms/step - loss: 0.2959 - accuracy: 0.9
160 - val_loss: 0.3513 - val_accuracy: 0.9025
Epoch 60/200
125/125 [==============================] - 95s 760ms/step - loss: 0.2934 - accuracy: 0.9
195 - val_loss: 0.3450 - val_accuracy: 0.9050
Epoch 61/200
125/125 [==============================] - 95s 760ms/step - loss: 0.2893 - accuracy: 0.9
202 - val_loss: 0.3415 - val_accuracy: 0.9050
Epoch 62/200
125/125 [==============================] - 95s 762ms/step - loss: 0.2852 - accuracy: 0.9
205 - val_loss: 0.3409 - val_accuracy: 0.9087
Epoch 63/200
125/125 [==============================] - 95s 763ms/step - loss: 0.2839 - accuracy: 0.9
233 - val_loss: 0.3370 - val_accuracy: 0.9137
Epoch 64/200
125/125 [==============================] - 96s 768ms/step - loss: 0.2782 - accuracy: 0.9
262 - val_loss: 0.3312 - val_accuracy: 0.9025
Epoch 65/200
125/125 [==============================] - 95s 758ms/step - loss: 0.2762 - accuracy: 0.9
262 - val_loss: 0.3280 - val_accuracy: 0.9087
Epoch 66/200
125/125 [==============================] - 95s 762ms/step - loss: 0.2740 - accuracy: 0.9
262 - val_loss: 0.3275 - val_accuracy: 0.9125
Epoch 67/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2707 - accuracy: 0.9
258 - val_loss: 0.3255 - val_accuracy: 0.9162
Epoch 68/200
125/125 [==============================] - 95s 760ms/step - loss: 0.2664 - accuracy: 0.9
293 - val_loss: 0.3220 - val_accuracy: 0.9137
Epoch 69/200
125/125 [==============================] - 95s 760ms/step - loss: 0.2633 - accuracy: 0.9
283 - val_loss: 0.3163 - val_accuracy: 0.9087
Epoch 70/200
125/125 [==============================] - 95s 759ms/step - loss: 0.2616 - accuracy: 0.9
280 - val_loss: 0.3140 - val_accuracy: 0.9200
Epoch 71/200
125/125 [==============================] - 95s 759ms/step - loss: 0.2587 - accuracy: 0.9
258 - val_loss: 0.3127 - val_accuracy: 0.9162
Epoch 72/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2556 - accuracy: 0.9
308 - val_loss: 0.3101 - val_accuracy: 0.9112
Epoch 73/200
125/125 [==============================] - 97s 775ms/step - loss: 0.2514 - accuracy: 0.9
330 - val_loss: 0.3066 - val_accuracy: 0.9087
Epoch 74/200
125/125 [==============================] - 96s 765ms/step - loss: 0.2500 - accuracy: 0.9
315 - val_loss: 0.3045 - val_accuracy: 0.9225
Epoch 75/200
125/125 [==============================] - 95s 762ms/step - loss: 0.2478 - accuracy: 0.9
323 - val_loss: 0.3021 - val_accuracy: 0.9212
Epoch 76/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2445 - accuracy: 0.9
```

```
340 - val_loss: 0.2990 - val_accuracy: 0.9187
Epoch 77/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2429 - accuracy: 0.9
325 - val_loss: 0.2991 - val_accuracy: 0.9175
Epoch 78/200
125/125 [==============================] - 95s 762ms/step - loss: 0.2401 - accuracy: 0.9
365 - val_loss: 0.2960 - val_accuracy: 0.9225
Epoch 79/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2387 - accuracy: 0.9
375 - val_loss: 0.2932 - val_accuracy: 0.9225
Epoch 80/200
125/125 [==============================] - 95s 764ms/step - loss: 0.2361 - accuracy: 0.9
352 - val_loss: 0.2926 - val_accuracy: 0.9175
Epoch 81/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2337 - accuracy: 0.9
337 - val_loss: 0.2883 - val_accuracy: 0.9237
Epoch 82/200
125/125 [==============================] - 95s 763ms/step - loss: 0.2300 - accuracy: 0.9
358 - val_loss: 0.2871 - val_accuracy: 0.9262
Epoch 83/200
125/125 [==============================] - 97s 777ms/step - loss: 0.2301 - accuracy: 0.9
380 - val_loss: 0.2851 - val_accuracy: 0.9262
Epoch 84/200
125/125 [==============================] - 96s 765ms/step - loss: 0.2266 - accuracy: 0.9
373 - val_loss: 0.2843 - val_accuracy: 0.9225
Epoch 85/200
125/125 [==============================] - 95s 763ms/step - loss: 0.2219 - accuracy: 0.9
392 - val_loss: 0.2786 - val_accuracy: 0.9225
Epoch 86/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2216 - accuracy: 0.9
367 - val_loss: 0.2796 - val_accuracy: 0.9287
Epoch 87/200
125/125 [==============================] - 95s 762ms/step - loss: 0.2181 - accuracy: 0.9
395 - val_loss: 0.2759 - val_accuracy: 0.9300
Epoch 88/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2170 - accuracy: 0.9
417 - val_loss: 0.2733 - val_accuracy: 0.9275
Epoch 89/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2155 - accuracy: 0.9
408 - val_loss: 0.2715 - val_accuracy: 0.9287
Epoch 90/200
125/125 [==============================] - 96s 765ms/step - loss: 0.2146 - accuracy: 0.9
415 - val_loss: 0.2699 - val_accuracy: 0.9312
Epoch 91/200
125/125 [==============================] - 96s 768ms/step - loss: 0.2113 - accuracy: 0.9
427 - val_loss: 0.2672 - val_accuracy: 0.9275
Epoch 92/200
125/125 [==============================] - 97s 773ms/step - loss: 0.2092 - accuracy: 0.9
427 - val_loss: 0.2709 - val_accuracy: 0.9275
Epoch 93/200
125/125 [==============================] - 95s 761ms/step - loss: 0.2072 - accuracy: 0.9
425 - val_loss: 0.2654 - val_accuracy: 0.9300
Epoch 94/200
125/125 [==============================] - 96s 766ms/step - loss: 0.2071 - accuracy: 0.9
448 - val_loss: 0.2637 - val_accuracy: 0.9312
Epoch 95/200
125/125 [==============================] - 95s 763ms/step - loss: 0.2042 - accuracy: 0.9
430 - val_loss: 0.2621 - val_accuracy: 0.9287
Epoch 96/200
125/125 [==============================] - 95s 762ms/step - loss: 0.2029 - accuracy: 0.9
```

```
433 - val_loss: 0.2609 - val_accuracy: 0.9312
Epoch 97/200
125/125 [==============================] - 95s 761ms/step - loss: 0.1994 - accuracy: 0.9
465 - val_loss: 0.2588 - val_accuracy: 0.9300
Epoch 98/200
125/125 [==============================] - 96s 766ms/step - loss: 0.1988 - accuracy: 0.9
480 - val_loss: 0.2568 - val_accuracy: 0.9325
Epoch 99/200
125/125 [==============================] - 95s 763ms/step - loss: 0.1974 - accuracy: 0.9
482 - val_loss: 0.2563 - val_accuracy: 0.9312
Epoch 100/200
125/125 [==============================] - 96s 764ms/step - loss: 0.1946 - accuracy: 0.9
470 - val_loss: 0.2539 - val_accuracy: 0.9300
Epoch 101/200
125/125 [==============================] - 96s 764ms/step - loss: 0.1943 - accuracy: 0.9
495 - val_loss: 0.2517 - val_accuracy: 0.9337
Epoch 102/200
125/125 [==============================] - 97s 773ms/step - loss: 0.1923 - accuracy: 0.9
482 - val_loss: 0.2482 - val_accuracy: 0.9312
Epoch 103/200
125/125 [==============================] - 95s 763ms/step - loss: 0.1900 - accuracy: 0.9
500 - val_loss: 0.2497 - val_accuracy: 0.9325
Epoch 104/200
125/125 [==============================] - 96s 767ms/step - loss: 0.1899 - accuracy: 0.9
495 - val_loss: 0.2465 - val_accuracy: 0.9287
Epoch 105/200
125/125 [==============================] - 96s 764ms/step - loss: 0.1874 - accuracy: 0.9
480 - val_loss: 0.2451 - val_accuracy: 0.9337
Epoch 106/200
125/125 [==============================] - 96s 766ms/step - loss: 0.1855 - accuracy: 0.9
530 - val_loss: 0.2429 - val_accuracy: 0.9325
Epoch 107/200
125/125 [==============================] - 96s 768ms/step - loss: 0.1846 - accuracy: 0.9
515 - val_loss: 0.2428 - val_accuracy: 0.9325
Epoch 108/200
125/125 [==============================] - 107s 860ms/step - loss: 0.1811 - accuracy: 0.
9530 - val_loss: 0.2432 - val_accuracy: 0.9350
Epoch 109/200
125/125 [==============================] - 99s 792ms/step - loss: 0.1814 - accuracy: 0.9
520 - val_loss: 0.2399 - val_accuracy: 0.9325
Epoch 110/200
125/125 [==============================] - 101s 807ms/step - loss: 0.1794 - accuracy: 0.
9532 - val_loss: 0.2377 - val_accuracy: 0.9325
Epoch 111/200
125/125 [==============================] - 101s 806ms/step - loss: 0.1778 - accuracy: 0.
9523 - val_loss: 0.2372 - val_accuracy: 0.9325
Epoch 112/200
125/125 [==============================] - 98s 786ms/step - loss: 0.1774 - accuracy: 0.9
517 - val_loss: 0.2354 - val_accuracy: 0.9350
Epoch 113/200
125/125 [==============================] - 96s 770ms/step - loss: 0.1733 - accuracy: 0.9
535 - val_loss: 0.2350 - val_accuracy: 0.9337
Epoch 114/200
125/125 [==============================] - 96s 770ms/step - loss: 0.1734 - accuracy: 0.9
565 - val_loss: 0.2314 - val_accuracy: 0.9337
Epoch 115/200
125/125 [==============================] - 97s 776ms/step - loss: 0.1727 - accuracy: 0.9
540 - val_loss: 0.2316 - val_accuracy: 0.9362
Epoch 116/200
125/125 [==============================] - 98s 787ms/step - loss: 0.1720 - accuracy: 0.9
```

```
555 - val_loss: 0.2306 - val_accuracy: 0.9388
Epoch 117/200
125/125 [==============================] - 99s 791ms/step - loss: 0.1695 - accuracy: 0.9
550 - val_loss: 0.2309 - val_accuracy: 0.9375
Epoch 118/200
125/125 [==============================] - 98s 783ms/step - loss: 0.1688 - accuracy: 0.9
590 - val_loss: 0.2297 - val_accuracy: 0.9388
Epoch 119/200
125/125 [==============================] - 98s 784ms/step - loss: 0.1666 - accuracy: 0.9
572 - val_loss: 0.2262 - val_accuracy: 0.9362
Epoch 120/200
125/125 [==============================] - 103s 828ms/step - loss: 0.1665 - accuracy: 0.
9548 - val_loss: 0.2252 - val_accuracy: 0.9388
Epoch 121/200
125/125 [==============================] - 100s 801ms/step - loss: 0.1634 - accuracy: 0.
9588 - val_loss: 0.2244 - val_accuracy: 0.9400
Epoch 122/200
125/125 [==============================] - 101s 810ms/step - loss: 0.1622 - accuracy: 0.
9597 - val_loss: 0.2214 - val_accuracy: 0.9388
Epoch 123/200
125/125 [==============================] - 108s 862ms/step - loss: 0.1616 - accuracy: 0.
9590 - val_loss: 0.2223 - val_accuracy: 0.9400
Epoch 124/200
125/125 [==============================] - 113s 902ms/step - loss: 0.1585 - accuracy: 0.
9603 - val_loss: 0.2223 - val_accuracy: 0.9400
Epoch 125/200
125/125 [==============================] - 101s 806ms/step - loss: 0.1584 - accuracy: 0.
9588 - val_loss: 0.2213 - val_accuracy: 0.9400
Epoch 126/200
125/125 [==============================] - 100s 798ms/step - loss: 0.1574 - accuracy: 0.
9607 - val_loss: 0.2169 - val_accuracy: 0.9388
Epoch 127/200
125/125 [==============================] - 98s 785ms/step - loss: 0.1571 - accuracy: 0.9
615 - val_loss: 0.2173 - val_accuracy: 0.9400
Epoch 128/200
125/125 [==============================] - 98s 788ms/step - loss: 0.1558 - accuracy: 0.9
597 - val_loss: 0.2149 - val_accuracy: 0.9413
Epoch 129/200
125/125 [==============================] - 102s 818ms/step - loss: 0.1541 - accuracy: 0.
9622 - val_loss: 0.2149 - val_accuracy: 0.9425
Epoch 130/200
125/125 [==============================] - 109s 869ms/step - loss: 0.1545 - accuracy: 0.
9620 - val_loss: 0.2160 - val_accuracy: 0.9388
Epoch 131/200
125/125 [==============================] - 119s 955ms/step - loss: 0.1510 - accuracy: 0.
9638 - val_loss: 0.2161 - val_accuracy: 0.9388
Epoch 132/200
125/125 [==============================] - 115s 920ms/step - loss: 0.1508 - accuracy: 0.
9615 - val_loss: 0.2122 - val_accuracy: 0.9388
Epoch 133/200
125/125 [==============================] - 114s 912ms/step - loss: 0.1489 - accuracy: 0.
9628 - val_loss: 0.2119 - val_accuracy: 0.9400
Epoch 134/200
125/125 [==============================] - 114s 911ms/step - loss: 0.1482 - accuracy: 0.
9630 - val_loss: 0.2099 - val_accuracy: 0.9400
Epoch 135/200
125/125 [==============================] - 115s 923ms/step - loss: 0.1479 - accuracy: 0.
9653 - val_loss: 0.2099 - val_accuracy: 0.9400
Epoch 136/200
125/125 [==============================] - 119s 953ms/step - loss: 0.1467 - accuracy: 0.
```

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9620 - val_loss: 0.2089 - val_accuracy: 0.9425
Epoch 137/200
125/125 [==============================] - 123s 985ms/step - loss: 0.1449 - accuracy: 0.
9655 - val_loss: 0.2072 - val_accuracy: 0.9388
Epoch 138/200
125/125 [==============================] - 129s 1s/step - loss: 0.1438 - accuracy: 0.962
5 - val_loss: 0.2045 - val_accuracy: 0.9425
Epoch 139/200
125/125 [==============================] - 147s 1s/step - loss: 0.1436 - accuracy: 0.964
3 - val_loss: 0.2043 - val_accuracy: 0.9400
Epoch 140/200
125/125 [==============================] - 113s 900ms/step - loss: 0.1423 - accuracy: 0.
9660 - val_loss: 0.2044 - val_accuracy: 0.9388
Epoch 141/200
125/125 [==============================] - 110s 883ms/step - loss: 0.1407 - accuracy: 0.
9675 - val_loss: 0.2033 - val_accuracy: 0.9400
Epoch 142/200
125/125 [==============================] - 110s 879ms/step - loss: 0.1392 - accuracy: 0.
9647 - val_loss: 0.2009 - val_accuracy: 0.9413
Epoch 143/200
125/125 [==============================] - 110s 879ms/step - loss: 0.1386 - accuracy: 0.
9670 - val_loss: 0.2016 - val_accuracy: 0.9413
Epoch 144/200
125/125 [==============================] - 109s 872ms/step - loss: 0.1390 - accuracy: 0.
9647 - val_loss: 0.2002 - val_accuracy: 0.9388
Epoch 145/200
125/125 [==============================] - 110s 879ms/step - loss: 0.1384 - accuracy: 0.
9653 - val_loss: 0.2014 - val_accuracy: 0.9400
Epoch 146/200
125/125 [==============================] - 109s 870ms/step - loss: 0.1348 - accuracy: 0.
9695 - val_loss: 0.2034 - val_accuracy: 0.9438
Epoch 147/200
125/125 [==============================] - 109s 875ms/step - loss: 0.1355 - accuracy: 0.
9685 - val_loss: 0.1989 - val_accuracy: 0.9425
Epoch 148/200
125/125 [==============================] - 115s 919ms/step - loss: 0.1341 - accuracy: 0.
9688 - val_loss: 0.1970 - val_accuracy: 0.9463
Epoch 149/200
125/125 [==============================] - 109s 873ms/step - loss: 0.1328 - accuracy: 0.
9685 - val_loss: 0.1968 - val_accuracy: 0.9400
Epoch 150/200
125/125 [==============================] - 111s 889ms/step - loss: 0.1307 - accuracy: 0.
9685 - val_loss: 0.1934 - val_accuracy: 0.9463
Epoch 151/200
125/125 [==============================] - 116s 925ms/step - loss: 0.1323 - accuracy: 0.
9697 - val_loss: 0.1960 - val_accuracy: 0.9413
Epoch 152/200
125/125 [==============================] - 112s 893ms/step - loss: 0.1311 - accuracy: 0.
9680 - val_loss: 0.1940 - val_accuracy: 0.9438
Epoch 153/200
125/125 [==============================] - 113s 903ms/step - loss: 0.1312 - accuracy: 0.
9670 - val_loss: 0.1931 - val_accuracy: 0.9425
Epoch 154/200
125/125 [==============================] - 107s 859ms/step - loss: 0.1283 - accuracy: 0.
9678 - val_loss: 0.1925 - val_accuracy: 0.9450
Epoch 155/200
125/125 [==============================] - 107s 857ms/step - loss: 0.1290 - accuracy: 0.
9670 - val_loss: 0.1894 - val_accuracy: 0.9475
Epoch 156/200
125/125 [==============================] - 108s 866ms/step - loss: 0.1263 - accuracy: 0.
```

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9720 - val_loss: 0.1889 - val_accuracy: 0.9463
Epoch 157/200
125/125 [==============================] - 113s 902ms/step - loss: 0.1268 - accuracy: 0.
9712 - val_loss: 0.1899 - val_accuracy: 0.9463
Epoch 158/200
125/125 [==============================] - 111s 892ms/step - loss: 0.1256 - accuracy: 0.
9700 - val_loss: 0.1887 - val_accuracy: 0.9438
Epoch 159/200
125/125 [==============================] - 108s 867ms/step - loss: 0.1244 - accuracy: 0.
9703 - val_loss: 0.1861 - val_accuracy: 0.9488
Epoch 160/200
125/125 [==============================] - 126s 1s/step - loss: 0.1238 - accuracy: 0.972
8 - val_loss: 0.1854 - val_accuracy: 0.9463
Epoch 161/200
125/125 [==============================] - 120s 964ms/step - loss: 0.1236 - accuracy: 0.
9693 - val_loss: 0.1860 - val_accuracy: 0.9450
Epoch 162/200
125/125 [==============================] - 98s 782ms/step - loss: 0.1229 - accuracy: 0.9
695 - val_loss: 0.1838 - val_accuracy: 0.9475
Epoch 163/200
125/125 [==============================] - 98s 784ms/step - loss: 0.1222 - accuracy: 0.9
700 - val_loss: 0.1869 - val_accuracy: 0.9463
Epoch 164/200
125/125 [==============================] - 98s 783ms/step - loss: 0.1210 - accuracy: 0.9
722 - val_loss: 0.1830 - val_accuracy: 0.9488
Epoch 165/200
125/125 [==============================] - 98s 783ms/step - loss: 0.1193 - accuracy: 0.9
720 - val_loss: 0.1831 - val_accuracy: 0.9450
Epoch 166/200
125/125 [==============================] - 98s 781ms/step - loss: 0.1172 - accuracy: 0.9
743 - val_loss: 0.1812 - val_accuracy: 0.9488
Epoch 167/200
125/125 [==============================] - 98s 782ms/step - loss: 0.1180 - accuracy: 0.9
725 - val_loss: 0.1829 - val_accuracy: 0.9463
Epoch 168/200
125/125 [==============================] - 98s 783ms/step - loss: 0.1174 - accuracy: 0.9
730 - val_loss: 0.1798 - val_accuracy: 0.9463
Epoch 169/200
125/125 [==============================] - 98s 783ms/step - loss: 0.1149 - accuracy: 0.9
735 - val_loss: 0.1820 - val_accuracy: 0.9463
Epoch 170/200
125/125 [==============================] - 100s 796ms/step - loss: 0.1153 - accuracy: 0.
9755 - val_loss: 0.1781 - val_accuracy: 0.9463
Epoch 171/200
125/125 [==============================] - 98s 786ms/step - loss: 0.1155 - accuracy: 0.9
720 - val_loss: 0.1778 - val_accuracy: 0.9463
Epoch 172/200
125/125 [==============================] - 98s 781ms/step - loss: 0.1157 - accuracy: 0.9
728 - val_loss: 0.1779 - val_accuracy: 0.9463
Epoch 173/200
125/125 [==============================] - 98s 781ms/step - loss: 0.1138 - accuracy: 0.9
737 - val_loss: 0.1784 - val_accuracy: 0.9475
Epoch 174/200
125/125 [==============================] - 98s 781ms/step - loss: 0.1138 - accuracy: 0.9
750 - val_loss: 0.1764 - val_accuracy: 0.9488
Epoch 175/200
125/125 [==============================] - 98s 780ms/step - loss: 0.1116 - accuracy: 0.9
743 - val_loss: 0.1740 - val_accuracy: 0.9500
Epoch 176/200
125/125 [==============================] - 99s 790ms/step - loss: 0.1121 - accuracy: 0.9
```

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735 - val_loss: 0.1760 - val_accuracy: 0.9463
Epoch 177/200
125/125 [==============================] - 98s 780ms/step - loss: 0.1097 - accuracy: 0.9
753 - val_loss: 0.1756 - val_accuracy: 0.9450
Epoch 178/200
125/125 [==============================] - 101s 809ms/step - loss: 0.1108 - accuracy: 0.
9750 - val_loss: 0.1750 - val_accuracy: 0.9450
Epoch 179/200
125/125 [==============================] - 97s 780ms/step - loss: 0.1103 - accuracy: 0.9
737 - val_loss: 0.1733 - val_accuracy: 0.9463
Epoch 180/200
125/125 [==============================] - 100s 798ms/step - loss: 0.1074 - accuracy: 0.
9760 - val_loss: 0.1748 - val_accuracy: 0.9488
Epoch 181/200
125/125 [==============================] - 98s 785ms/step - loss: 0.1079 - accuracy: 0.9
765 - val_loss: 0.1720 - val_accuracy: 0.9488
Epoch 182/200
125/125 [==============================] - 98s 781ms/step - loss: 0.1071 - accuracy: 0.9
755 - val_loss: 0.1720 - val_accuracy: 0.9488
Epoch 183/200
125/125 [==============================] - 98s 781ms/step - loss: 0.1073 - accuracy: 0.9
758 - val_loss: 0.1717 - val_accuracy: 0.9463
Epoch 184/200
125/125 [==============================] - 98s 783ms/step - loss: 0.1063 - accuracy: 0.9
765 - val_loss: 0.1711 - val_accuracy: 0.9463
Epoch 185/200
125/125 [==============================] - 98s 780ms/step - loss: 0.1056 - accuracy: 0.9
755 - val_loss: 0.1691 - val_accuracy: 0.9525
Epoch 186/200
125/125 [==============================] - 98s 780ms/step - loss: 0.1035 - accuracy: 0.9
775 - val_loss: 0.1690 - val_accuracy: 0.9463
Epoch 187/200
125/125 [==============================] - 98s 782ms/step - loss: 0.1023 - accuracy: 0.9
795 - val_loss: 0.1673 - val_accuracy: 0.9538
Epoch 188/200
125/125 [==============================] - 98s 781ms/step - loss: 0.1050 - accuracy: 0.9
765 - val_loss: 0.1674 - val_accuracy: 0.9475
Epoch 189/200
125/125 [==============================] - 100s 799ms/step - loss: 0.1026 - accuracy: 0.
9772 - val_loss: 0.1667 - val_accuracy: 0.9475
Epoch 190/200
125/125 [==============================] - 98s 781ms/step - loss: 0.1023 - accuracy: 0.9
772 - val_loss: 0.1669 - val_accuracy: 0.9513
Epoch 191/200
125/125 [==============================] - 98s 781ms/step - loss: 0.1016 - accuracy: 0.9
770 - val_loss: 0.1648 - val_accuracy: 0.9513
Epoch 192/200
125/125 [==============================] - 97s 780ms/step - loss: 0.1012 - accuracy: 0.9
780 - val_loss: 0.1650 - val_accuracy: 0.9488
Epoch 193/200
125/125 [==============================] - 98s 784ms/step - loss: 0.0993 - accuracy: 0.9
775 - val_loss: 0.1648 - val_accuracy: 0.9488
Epoch 194/200
125/125 [==============================] - 98s 781ms/step - loss: 0.0989 - accuracy: 0.9
778 - val_loss: 0.1631 - val_accuracy: 0.9550
Epoch 195/200
125/125 [==============================] - 98s 783ms/step - loss: 0.0986 - accuracy: 0.9
797 - val_loss: 0.1655 - val_accuracy: 0.9488
Epoch 196/200
125/125 [==============================] - 98s 781ms/step - loss: 0.0994 - accuracy: 0.9
```

```
790 - val_loss: 0.1622 - val_accuracy: 0.9538
Epoch 197/200
125/125 [==============================] - 98s 784ms/step - loss: 0.0988 - accuracy: 0.9
785 - val_loss: 0.1637 - val_accuracy: 0.9513
Epoch 198/200
125/125 [==============================] - 100s 800ms/step - loss: 0.0975 - accuracy: 0.
9785 - val_loss: 0.1611 - val_accuracy: 0.9538
Epoch 199/200
125/125 [==============================] - 98s 783ms/step - loss: 0.0962 - accuracy: 0.9
795 - val_loss: 0.1609 - val_accuracy: 0.9563
Epoch 200/200
125/125 [==============================] - 98s 780ms/step - loss: 0.0956 - accuracy: 0.9
793 - val_loss: 0.1618 - val_accuracy: 0.9513
```

In [11]:

```
#Visualizaing the model accuracy and loss for the training and validation data sets
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(200)

plt.figure(figsize=(15, 15))
plt.subplot(2, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(2, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```