Vellore Institute of Technology

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CSE4019 - Image Processing

Food Recognition and Calorie Estimation using CNN and Image Processing Techniques

By : -

P Bhargav Reddy - 19BCE1342

Lingam V V S N Datta Sai - 19BCE1373

B Jivitesh - 19BCE1275

Submitted to:-

Dr. Geetha S

Abstract:

Nowadays, regular intake of nutritious foods is important for maintaining a healthy eating routine and avoiding obesity within the physical body .. during this paper, a completely unique framework hooked into AI that naturally performs exact grouping of food pictures and gauges food credits. within the preparation section of the model system, it proposes a profound learning model that has a convolutional neural organization that orders food into explicit classifications. The principle reason for the proposed technique is to enhance the exactness of the pre-preparing model. The paper plans a model framework hooked into the customer worker model. The customer sends an image location solicitation and cycles it on the worker side. Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolution Neural Network (CNN) are the three classifiers that are modified to research the framework's enhanced precision. Exploring various avenues a few sorts of food groups, each with an outsized number of images, using AI (AI) to realize higher grouping precision.

Problem Statement:

The problem can be simply stated as, given a set of food images with calibration object thumb with the food name and an unlabeled set of food images from the same group of food, identify food and estimate food volume and calories intake.

Introduction:

Accurate and passive acquisition of dietary data from patients is important for a far better understanding of the etiology of obesity and development of effective weight management programs. Self-reporting is currently the most method for such data acquisition. However, studies have shown that data obtained by self-reporting seriously underestimate food intake and thus don't accurately reflect the important habitual behavior of people . Computer food recognition programs haven't yet been developed. during this paper, we present a study for recognizing foods from videos of eating, which are directly recorded in restaurants by an internet camera. From recognition results, our method then estimates food calories of intake.

The advantage of recognizing items, rather than the entire meal, is that the system are often trained with only single item food images. At the training stage, we first use region proposal algorithms to get candidate regions and extract the convolutional neural network (CNN) features of all regions. Second, we perform region mining to pick positive regions for every food category using maximum cover by our proposed submodular optimization method. At the testing stage, we first generate a group of candidate regions. for every region, a classification score is computed supported its extracted CNN features and predicted food names of the chosen regions

Dataset:

For a single food portion, we took several pairs of images by using smart phones; each group of images contains a top view and a side view of this food. For each image, there will be a plate and a finger pointing towards the object and no more than two foods in it. There shouldn't be two foods in the same image.

Methodology:

Calorie estimation method based on deep learning:

we use deep learning algorithms to recognize the types of food and apply image segmentation to identify the food’s contour in the photos. So as the side view. then, the volumes of each food is calculated based on the calibration objects in the images. In the end, the calorie of each food is obtained by searching the density table and a nutrition table.

Objection detection With Deep Learning Methods

We do not use semantic segmentation methods such as Fully Convolutional Networks (FCN) but choose to use Faster R-CNN. Faster R-CNN is a framework based on deep convolutional networks. It includes a Region Proposal Network (RPN) and an Object Detection Network. When we put an image with RGB channels as input, we will get a series of bounding boxes.

Volume Estimation And Calorie Calculation

According to the contours detected in the top view, the true size of a pixel is known. Similarly, we know the actual size of a pixel in the side view. Then we use different formulas to estimate the volume of each food.

Result and Discussion:

```
#image_segment
import cv2
import numpy as np
import os

def getAreaOfFood(img1):
    data=os.path.join(os.getcwd(),"images")
    if os.path.exists(data):
        print('folder exist for images at ',data)
    else:
        os.mkdir(data)
        print('folder created for images at ',data)

    cv2.imwrite('{}\\1 original image.jpg'.format(data),img1)
    img = cv2.cvtColor(img1, cv2.COLOR_BGR2GRAY)
    cv2.imwrite('{}\\2 original image BGR2GRAY.jpg'.format(data),img)
    img_filt = cv2.medianBlur( img, 5)
    cv2.imwrite('{}\\3 img_filt.jpg'.format(data),img_filt)
```

```
    img_th =
cv2.adaptiveThreshold(img_filt,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,cv2
.THRESH_BINARY,21,2)
    cv2.imwrite('{}\\4 img_th.jpg'.format(data),img_th)
    contours, hierarchy = cv2.findContours(img_th, cv2.RETR_LIST,
cv2.CHAIN_APPROX_SIMPLE) #make change here


  # find contours. sort. and find the biggest contour. the biggest
contour corresponds to the plate and fruit.
    mask = np.zeros(img.shape, np.uint8)
    largest_areas = sorted(contours, key=cv2.contourArea)
    cv2.drawContours(mask, [largest_areas[-1]], 0, (255,255,255,255),
-1)
    cv2.imwrite('{}\\5 mask.jpg'.format(data),mask)
    img_bigcontour = cv2.bitwise_and(img1,img1,mask = mask)
    cv2.imwrite('{}\\6
img_bigcontour.jpg'.format(data),img_bigcontour)

  # convert to hsv. otsu threshold in s to remove plate
    hsv_img = cv2.cvtColor(img_bigcontour, cv2.COLOR_BGR2HSV)
    cv2.imwrite('{}\\7 hsv_img.jpg'.format(data),hsv_img)
    h,s,v = cv2.split(hsv_img)
    mask_plate = cv2.inRange(hsv_img, np.array([0,0,50]),
np.array([200,90,250]))
    cv2.imwrite('{}\\8 mask_plate.jpg'.format(data),mask_plate)
    mask_not_plate = cv2.bitwise_not(mask_plate)
    cv2.imwrite('{}\\9
mask_not_plate.jpg'.format(data),mask_not_plate)
    fruit_skin = cv2.bitwise_and(img_bigcontour,img_bigcontour,mask =
mask_not_plate)
    cv2.imwrite('{}\\10 fruit_skin.jpg'.format(data),fruit_skin)

  #convert to hsv to detect and remove skin pixels
    hsv_img = cv2.cvtColor(fruit_skin, cv2.COLOR_BGR2HSV)
    cv2.imwrite('{}\\11 hsv_img.jpg'.format(data),hsv_img)
    skin = cv2.inRange(hsv_img, np.array([0,10,60]),
np.array([10,160,255])) #Scalar(0, 10, 60), Scalar(20, 150, 255)
    cv2.imwrite('{}\\12 skin.jpg'.format(data),skin)
    not_skin = cv2.bitwise_not(skin); #invert skin and black
    cv2.imwrite('{}\\13 not_skin.jpg'.format(data),not_skin)
    fruit = cv2.bitwise_and(fruit_skin,fruit_skin,mask = not_skin)
#get only fruit pixels
```

```
    cv2.imwrite('{}\\14 fruit.jpg'.format(data),fruit)

    fruit_bw = cv2.cvtColor(fruit, cv2.COLOR_BGR2GRAY)
    cv2.imwrite('{}\\15 fruit_bw.jpg'.format(data),fruit_bw)
    fruit_bin = cv2.inRange(fruit_bw, 10, 255) #binary of fruit
    cv2.imwrite('{}\\16 fruit_bw.jpg'.format(data),fruit_bin)

  #erode before finding contours
    kernel = cv2.getStructuringElement(cv2.MORPH_ELLIPSE,(5,5))
    erode_fruit = cv2.erode(fruit_bin,kernel,iterations = 1)
    cv2.imwrite('{}\\17 erode_fruit.jpg'.format(data),erode_fruit)

  #find largest contour since that will be the fruit
    img_th =
cv2.adaptiveThreshold(erode_fruit,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,
cv2.THRESH_BINARY,11,2)
    cv2.imwrite('{}\\18 img_th.jpg'.format(data),img_th)
    contours, hierarchy = cv2.findContours(img_th, cv2.RETR_LIST,
cv2.CHAIN_APPROX_SIMPLE)
    mask_fruit = np.zeros(fruit_bin.shape, np.uint8)
    largest_areas = sorted(contours, key=cv2.contourArea)
    cv2.drawContours(mask_fruit, [largest_areas[-2]], 0,
(255,255,255), -1)
    cv2.imwrite('{}\\19 mask_fruit.jpg'.format(data),mask_fruit)

  #dilate now
    kernel2 = cv2.getStructuringElement(cv2.MORPH_ELLIPSE,(5,5))
    mask_fruit2 = cv2.dilate(mask_fruit,kernel2,iterations = 1)
    cv2.imwrite('{}\\20 mask_fruit2.jpg'.format(data),mask_fruit2)
    fruit_final = cv2.bitwise_and(img1,img1,mask = mask_fruit2)
    cv2.imwrite('{}\\21 fruit_final.jpg'.format(data),fruit_final)

  #find area of fruit
    img_th =
cv2.adaptiveThreshold(mask_fruit2,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,
cv2.THRESH_BINARY,11,2)
    cv2.imwrite('{}\\22 img_th.jpg'.format(data),img_th)
    contours, hierarchy = cv2.findContours(img_th, cv2.RETR_LIST,
cv2.CHAIN_APPROX_SIMPLE)
    largest_areas = sorted(contours, key=cv2.contourArea)
    fruit_contour = largest_areas[-2]
    fruit_area = cv2.contourArea(fruit_contour)
```

```
  #finding the area of skin. find area of biggest contour
    skin2 = skin - mask_fruit2
    cv2.imwrite('{}\\23 skin2.jpg'.format(data),skin2)
  #erode before finding contours
    kernel = cv2.getStructuringElement(cv2.MORPH_ELLIPSE,(5,5))
    skin_e = cv2.erode(skin2,kernel,iterations = 1)
    cv2.imwrite('{}\\24 skin_e .jpg'.format(data),skin_e )
    img_th =
cv2.adaptiveThreshold(skin_e,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,cv2.T
HRESH_BINARY,11,2)
    cv2.imwrite('{}\\25 img_th.jpg'.format(data),img_th)
    contours, hierarchy = cv2.findContours(img_th, cv2.RETR_LIST,
cv2.CHAIN_APPROX_SIMPLE)
    mask_skin = np.zeros(skin.shape, np.uint8)
    largest_areas = sorted(contours, key=cv2.contourArea)
    cv2.drawContours(mask_skin, [largest_areas[-2]], 0,
(255,255,255), -1)
    cv2.imwrite('{}\\26 mask_skin.jpg'.format(data),mask_skin)


    skin_rect = cv2.minAreaRect(largest_areas[-2])
    box = cv2.boxPoints(skin_rect)
    box = np.int0(box)
    mask_skin2 = np.zeros(skin.shape, np.uint8)
    cv2.drawContours(mask_skin2,[box],0,(255,255,255), -1)
    cv2.imwrite('{}\\27 mask_skin2.jpg'.format(data),mask_skin2)

    pix_height = max(skin_rect[1])
    pix_to_cm_multiplier = 5.0/pix_height
    skin_area = cv2.contourArea(box)


    return fruit_area,fruit_bin ,fruit_final,skin_area,
fruit_contour, pix_to_cm_multiplier
```

```
#caleries
import cv2
import numpy as np
#density - gram / cm^3
density_dict = { 1:0.609, 2:0.94, 3:0.641,  4:0.641,5:0.513,
6:0.482,7:0.481}
```

```
#kcal
calorie_dict = { 1:52, 2:89,  3:41,4:16,5:40,6:47,7:18 }
#skin of photo to real multiplier
skin_multiplier = 5*2.3

def getCalorie(label, volume): #volume in cm^3
  calorie = calorie_dict[int(label)]
  density = density_dict[int(label)]
  mass = volume*density*1.0
  calorie_tot = (calorie/100.0)*mass
  return mass, calorie_tot, calorie #calorie per 100 grams

def getVolume(label, area, skin_area, pix_to_cm_multiplier,
fruit_contour):
  area_fruit = (area/skin_area)*skin_multiplier #area in cm^2
  label = int(label)
  volume = 100
  if label == 1 or label == 5 or label == 7 or label == 6 :
#sphere-apple,tomato,orange,kiwi,onion
    radius = np.sqrt(area_fruit/np.pi)
    volume = (4/3)*np.pi*radius*radius*radius
    #print (area_fruit, radius, volume, skin_area)

  if label == 2 or label == 4 or (label == 3 and area_fruit > 30):
#cylinder like banana, cucumber, carrot
    fruit_rect = cv2.minAreaRect(fruit_contour)
    height = max(fruit_rect[1])*pix_to_cm_multiplier
    radius = area_fruit/(2.0*height)
    volume = np.pi*radius*radius*height

  if (label==4 and area_fruit < 30) : # carrot
    volume = area_fruit*0.5 #assuming width = 0.5 cm

  return volume

def calories(result,img):
    img_path =img # "C:/Users/M
Sc-2/Desktop/dataset/FooD/"+str(j)+"_"+str(i)+".jpg"
    fruit_areas,final_f,areaod,skin_areas, fruit_contours, pix_cm =
getAreaOfFood(img_path)
    volume = getVolume(result, fruit_areas, skin_areas, pix_cm,
fruit_contours)
    mass, cal, cal_100 = getCalorie(result, volume)
```

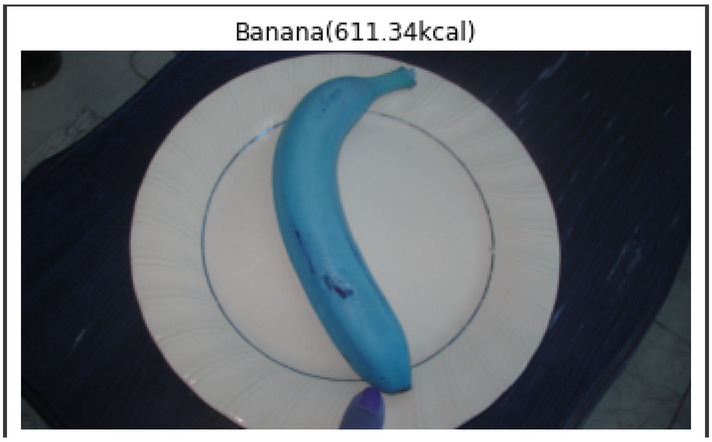
```
    fruit_volumes=volume
    fruit_calories=cal
    fruit_calories_100grams=cal_100
    fruit_mass=mass

#print("\nfruit_volumes",fruit_volumes,"\nfruit_calories",fruit_calor
ies,"\nruit_calories_100grams",fruit_calories_100grams,"\nfruit_mass"
,fruit_mass)
    return fruit_calories
```

```
#cnn_model
import tflearn
from tflearn.layers.conv import conv_2d, max_pool_2d
from tflearn.layers.core import input_data, dropout, fully_connected
from tflearn.layers.estimator import regression
import tensorflow as tf

def get_model(IMG_SIZE,no_of_fruits,LR):
  try:
    tf.reset_default_graph()
  except:
    print("tensorflow")
  convnet = input_data(shape=[None, IMG_SIZE, IMG_SIZE, 3],
name='input')

  convnet = conv_2d(convnet, 32, 5, activation='relu')

  convnet = max_pool_2d(convnet, 5)

  convnet = conv_2d(convnet, 64, 5, activation='relu')

  convnet = max_pool_2d(convnet, 5)

  convnet = conv_2d(convnet, 128, 5, activation='relu')
  convnet = max_pool_2d(convnet, 5)

  convnet = conv_2d(convnet, 64, 5, activation='relu')
  convnet = max_pool_2d(convnet, 5)



  convnet = conv_2d(convnet, 32, 5, activation='relu')
  convnet = max_pool_2d(convnet, 5)
```

```
  convnet = fully_connected(convnet, 1024, activation='relu')
  convnet = dropout(convnet, 0.8)

  convnet = fully_connected(convnet, no_of_fruits,
activation='softmax')
  convnet = regression(convnet, optimizer='adam', learning_rate=LR,
loss='categorical_crossentropy', name='targets')

  model = tflearn.DNN(convnet, tensorboard_dir='log')

  return model
```

```
import os
import cv2
import numpy as np

IMG_SIZE = 400
LR = 1e-3
no_of_fruits=7

MODEL_NAME =
'/content/drive/MyDrive/dip/model/Fruits_dectector-0.001-5conv-basic.
model'

model_save_at=os.path.join("/content/drive/MyDrive/dip/model",MODEL_N
AME)

model=get_model(IMG_SIZE,no_of_fruits,LR)

model.load(model_save_at)
labels=list(np.load('/content/drive/MyDrive/dip/labels.npy'))

# test_data='/content/drive/MyDrive/dip/test_image.JPG'
test_data='/content/drive/MyDrive/dip/orange.png'
img=cv2.imread(test_data)
img1=cv2.resize(img,(IMG_SIZE,IMG_SIZE))
model_out=model.predict([img1])
result=np.argmax(model_out)
name=labels[result]
cal=round(calories(result+1,img),2)
```

```python
import matplotlib.pyplot as plt
plt.imshow(img)
plt.title('{}({}kcal)'.format(name,cal))
plt.axis('off')
plt.show()
```



Conclusion:

In practice, the traditional models in machine learning are not attaining much accuracy when it comes to image classification. In this project, the CNN model is applied in image recognition. Much data augmentation and segmentation have to be performed as well and clean pixel values are not necessary for CNN as it on its own learn the generalized pattern required to identify and recognize new images. So using the CNN model, the accuracy is comparatively a lot higher than all other traditional models.

References:

[1] https://arxiv.org/pdf/1705.07632.pdf

[2] https://mm.cs.uec.ac.jp/e/pub/conf17/171127ege_0.pdf

[3] https://www.researchgate.net/profile/Keiji-Yanai/publication/309128551_An_Automatic_Calorie_Estimation_System_of_Food_Images_on_a_Smartphone/links/605807a6458515e8345ff678/An-Automatic-Calorie-Estimation-System-of-Food-Images-on-a-Smartphone.pdf

[4] http://img.cs.uec.ac.jp/pub/conf17/171024ege_0.pdf