Deep Learning on Food Nutrition and Calories

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***Abstract*—Calculating the amount of nutrition and calories in a given food item is now a common task. We provide service to predict the amount of nutrition and calories from food images. We do not require any input from the user, except from a single image of the food item. There are two phases in our approach to realizing our service. First, we train 300 kinds of common dishes with 300 images of each kind to set up our classifier in order to identify food types. Second, we build a list of food nutrition and calories of those food based on common recipes. Finally, we input a food image and the nutrition and calories information is given back. Our service has a good performance on food identifying in top-5 matching.**

***Index Terms*—Image Identification, Deep Learning**

I. Introduction

HAVING a good diet plays an important role in our life. In fact, more people tends to have a strict diet which has precise limitations on all kinds of nutrition and calories. A traditional way to track the amount of nutrition and calories consumed is to keep a food journal and do hundreds of thousands calculations, which is a complicated process.

Recently, people prefer newly-born automatic ways to estimate their nutrition and calories. There are many applications that provide such kind of service. However, many of them ask the user to enter the ingredients and the amount information about the meal had. These tools typically take the user input and run it against a database of food items to calculate the nutrition and calories of the given food item. Therefore, an easier way to provide nutrition and calories information is urgently needed.

In this paper, we introduce a more user-friendly way to answer the query of the food nutrition and calories information. Users are no longer asked to enter the detailed ingredients information but to provide a single image of the dish. This is particularly useful when the dish has many kinds of seasonings such as salt and sugar which are unlikely to be taken into consideration in traditional estimation. Our food identification also provides labels for other work such as calories prediction by food volume. Our method works as follows. In the first part, we train the classifier based on a dataset which has 300 kinds of dishes and each dish has 300 images. Our work includes dataset clean up, traditional classifier applying and deep learning methods. We compare the result between different methods and choose the method with the highest top-5 matching accuracy to identify food types. In the second part, we build a list of food nutrition and calories for 500 grams of different kinds of dishes based on common recipes.

Our main contributions can be summarized as follows:

-We provide food identification function

-We build a nutrition list of foods

II. Food identification

Dataset Our dataset consists of 300 kinds of food with 300 images of each kind. All images are in size of 256 * 256 pixels. However, there are some invalid images. Therefore, we delete the bad images and the repeated images in use of the MD5 code. We randomly selected 10 images of each dish as test subset. The remaining 290 images are used as train set.

Traditional Classifiers Firstly, we tried traditional classifiers as the referenced paper [1] provided. We resized the image to 64*64 and transferred the images into RGB vectors. Every three parameters in the array refers to the RGB values of one pixel. Therefore, each processed image has 12,288 features.

Then we do data compression to guarantee good generalization of the learnt models and reduce the training time. To do feature reduction, we use the Principal Component Analysis (PCA) method. After using PCA, we represent an image with a vector consists of 6,000 features. Then we pass the vector to a random forest and get the food classification. However, the result is worse than we imagined. We only have 3% accuracy for top-1 matching and 8% accuracy for top-5 matching. Then we tried Bayes classifier and we got 6% top-1 matching accuracy and 14% top-5 matching accuracy. The accurate rate was still low. Therefore, we turned to deep learning methods.

Resnet34 As we failed in using traditionial classifiers, we consider to use deep learning methods to do food type classification. We first apply resnet34 in Pytorchvision to train our classifier. We do not apply PCA this time because our RGB information for each pixel are not combined, which means in extreme cases, all blue values in the RGB vector would be abandoned. We still resized the images into 64*64 to reduce training time. Due to hardware limits, we set the batch size as 10 and epoch as 3. We use cross-entropy as our lost function. The result seems better—we have 18% accuracy on top-1 matching and 34% on top-5 matching. However, this is too low to provide good service. What limited us most was the hardware. We applied cuda acceleration but failed, and it was not enough for resnet34 to train only 3 epochs.

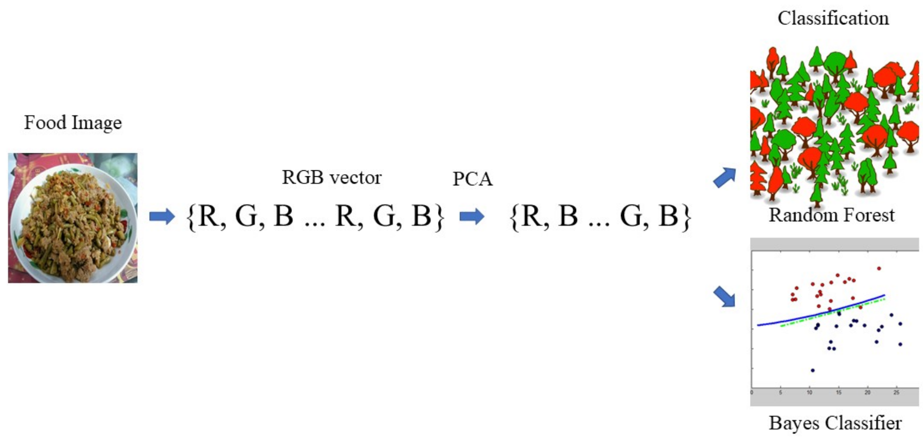

Fig. 1: Traditional Classifiers

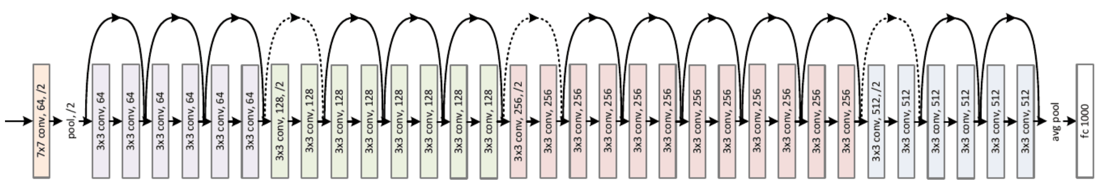

Fig. 2: Resnet34

Our Convolutional Neural Networks (CNN) Resnet34 has too many layers so that it is extremely time consuming for CPU. As a result, we consider to build our CNN to reduce training time. Our CNN consists of 3 convolutional layers, 3 pooling layers and 1 fully-connected layer. At first, we set the batch size as 10 and epoch as 6. We use cross-entropy as the loss function and adam as the optimizer. We resized the images to 64*64 again. Our CNN trained faster and we got a better result. We have 34% accuracy on top-1 matching and 55% accuracy on top-5 matching. Then we further optimized our model by adjusting the parameters. We increase the epoch to 10 and resize the images to 80*80. It took more time to training but we got better accuracy—36% for top-1 and 68% for top-5. To get better accuracy, we finally did not do resizing and agjust epoch to 30. We got 37% accuracy fot top-1 and 75% for top-5.

III. Nutrition anf Calories List

Our service provide nutrition and calories information based on common recipes. At first we have two tables: one is common recipe, another is nutrition of ingredients. What we do is combining these two tables into one list, where the dish name and its nutrition content per 500 grams are given. The combined table allows us to easily show the user the nutrition and calories.

Firstly, we renamed and integrated the ingredients. For example, we renamed “raw ginger” as “ginger” as there is no ingredient named “raw ginger” in the ingredient table. Then, we calculate the nutrition and generate the list.

IV. Results

To test our system, we did several queries. For example, we input an image of “spicy crayfish”, and the classifier gives us top-5 matchings. Then we pick the right one, and its nutrition and calorie per 500 grams is given.

V. Work Distribution

Jiacheng Dai: image processing, resnet34, CNN, nutrition list

Shuangqi Zhu: image processing, random forest, bayes classifier, resnet34, CNN

References

[1] C. Manal and E. Shady, “Calories prediction from food images,” *Innovative Applications of Artificial Intelligence*, 2017.

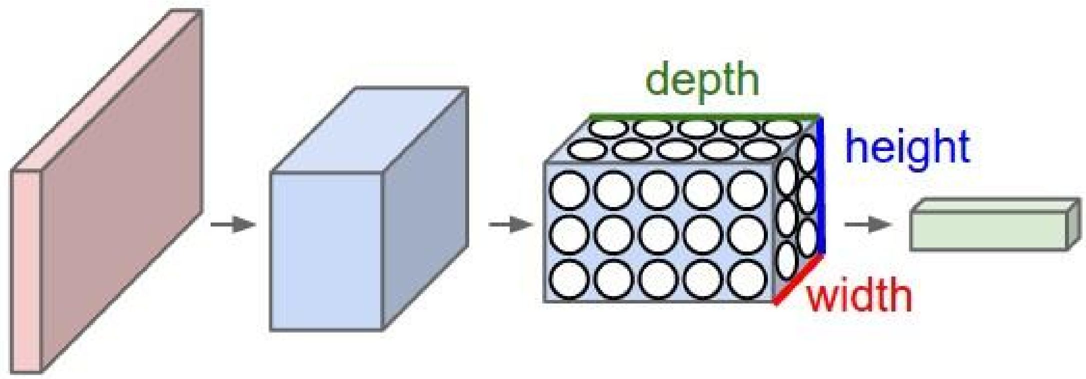

Fig. 3: Our CNN

	A	E	F
1	红烧肉	带皮五花肉	1000g
2		香葱	50g
3		生姜	50g
4		生抽，老抽	35g
5		单晶冰糖	20g
6		食盐	5g
7		纯正红糖（非赤砂糖）	50g
8		料酒，黄酒	20g
9		纯净水	500g

	A	B	C	D	E	F	G	H	I	J
1	名称	可食部分	能量	水分	蛋白质	脂肪	膳食纤维	碳水化物	视黄醇当量	硫胺素(VB1)
290	姜（子姜，嫩姜）	82	19	94.5	0.7	0.6	0.9	2.8		
291	菠菜（赤根菜）	89	24	91.2	2.6	0.3	1.7	2.8	487	0.04
292	火鸡胸脯肉	100	103	73.6	22.4	0.2		2.8		0.04
293	鸡肝	100	121	74.4	16.6	4.8		2.8	10414	0.33
294	盐水鸭（熟）	81	312	51.7	16.6	26.1		2.8	35	0.07
295	鹅蛋	87	196	69.3	11.1	15.6		2.8	192	0.08
296	对虾	61	93	76.5	18.6	0.8		2.8	15	0.01
297	落葵（木耳菜软浆叶）	76	20	92.8	1.6	0.3	1.5	2.8	337	0.06
298	乌菜（塌菜，塌棵菜）	89	25	91.8	2.6	0.4	1.4	2.8	168	0.06
299	苋菜（青，绿苋菜）	74	25	90.2	2.8	0.3	2.2	2.8	352	0.03

	A	B	C	D
1	名称	蛋白质	脂肪	胆固醇
2	红烧肉	71	175	418

Fig. 4: Nutrition tables

Fig. 5: Results