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Food Calorie Measurement Using Deep Learning Neural Network

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***Abstract*—Accurate methods to measure food and energy intake are crucial for the battle against obesity. Providing users/patients with convenient and intelligent solutions that help them measure their food intake and collect dietary information are the most valuable insights toward long-term prevention and successful treatment programs. In this paper, we propose an assistive calorie measurement system to help patients and doctors succeed in their fight against diet-related health conditions. Our proposed system runs on smartphones, which allow the user to take a picture of the food and measure the amount of calorie intake automatically. In order to identify the food accurately in the system, we use deep convolutional neural networks to classify 10000 high-resolution food images for system training. Our results show that the accuracy of our method for food recognition of single food portions is 99%. The analysis and implementation of the proposed system are also described in this paper.**

Keywords—calorie measurement, food recognition, segmentation, graph cut, deep neural network.

I. INTRODUCTION

Obesity in adults and children is considered a global epidemic [1]. The main cause of obesity is a combination of excessive food consumption and lack of physical activities [2]. Therefore, the need to accurately measure diet becomes important. Preliminary studies among adolescents suggest that innovative use of technology may improve the accuracy of dietary information of young people [3]. Also as people are becoming used to sedentary life style, they are involuntarily carried away from being aware of their food energy intake. There is overwhelming evidence that metabolic complications, which are caused by obesity, increase the risks for developing adverse health consequences such as diabetes, blood pressure, dyslipidaemia and hypertension [1]. People in general understand the links between diet and health. In fact, there is a wide spread of nutritional information and guidelines that are available to users at their fingertips. However, such information alone has not prevented diet-related illnesses or helped patients to eat healthily. In most cases, people find it difficult to examine all of the information about nutrition and dietary choices. Furthermore, people are oblivious about measuring or controlling their daily calorie intake due to the lack of nutritional knowledge, irregular eating patterns or lack of self-control. Empowering patients with an effective long-term solution requires novel mechanisms that help them make permanent changes to their dietary quality and calorie intake.

Results in [4] show mobile phone food record is important among both adolescents and adults. Also more accurate methods of dietary assessment will help strengthen the ability of researchers to identify diet–disease and diet–gene relationships. For above reasons, many researchers have been proposing assistive calorie measurement systems that run on smartphones and allow the user to take a picture of the food and measure the calorie intake automatically. In our previous work [5] -[8] , we have introduced a semi-automatic system that assists dieticians to measure calories and daily nutrient intake for the treatment of obese and overweight patients. The system enables the user/patient to obtain the measurement results of the food intake from the application, which simulates the calculation procedure performed by the dietician.

In this paper, we study the application of deep learning for food classification and recognition. Deep learning is an emerging approach from machine learning, and has been proposed in recent years to move machine learning systems towards the discovery of multiple levels of representation. We show that deep learning can be a powerful method to significantly increase the accuracy of food classification and recognition. Our proposed system makes two main contributions to the state of the art, as follows:

- We propose the use of deep learning neural networks as a means of improving the accuracy of food classification and calorie measurement systems. Experimental results of combination of different segmentation method such as color, texture, graph-cut segmentation and deep learning neural network combination show a 99% accuracy of food recognition in single food portions.
- We propose a model, which integrates our mobile calorie measurement application to the deep neural network. Our proposed Convolutional Neural Network (CNN) serves as a backbone of the application and handles the training and testing requests at the top layers, without affecting the central layers. We customize the top layer of the deep neural network presented in [12]. This allows us to embed the functionality of the application easily and retain the top levels of the network to spot the relevant food images even in low powered mobile devices.

The rest of the paper is organized as follows: In section II we present the related work. Section III gives our proposed system. In section IV, we describe the experimental results.

Finally, in section V, we conclude and provide direction for future work.

II. Related Work

In this section, we present some of the most common food intake measuring methods that have been developed in the last few years. The objective here is to describe the main advantages and drawbacks of these methods, in order to demonstrate the novelty and contribution of our proposed system. One of the first clinical works in this area is the 24-Hour Dietary Recall (24HR) [13]- [14]. This procedure lists the daily food intake using a special format for a period of 24 hours. The patient is expected to recall all the foods and beverages consumed the previous day on 24 hours prior to the interview. In this method, estimation of food portion size is made using standardized cups and spoons. The record of food amounts are converted into nutrient intakes amounts using food composition tables. Another method is the Food Frequency Questionnaire (FFQ), which uses an external verification based on double labeled water and urinary nitrogen [15]. FFQ focuses on describing dietary patterns or food habits, but not calorie intake. The main disadvantage of the 24HR and FFQ are: the delay of reporting the eaten food, the underreporting of the size of food portions, relying on memory, requiring skilled interviewers who can guess how much calories and nutrient the person has taken, not quantifying usual dietary intake, and needing complex calculations to estimate frequencies. In other methods, such as [16][17], the food is weighted before and after eating and a modified set of kitchen appliances containing an internal scale evaluates the plate and the portions before and after the food intake. But, those kinds of approaches generate inconvenience to the users, increasing underreporting generated by the proneness of the user to forget or the unwillingness of the patient to use these kinds of procedures.

To address the aforementioned issues, researchers have been looking into easier and as automated as possible ways to analyze food content, see, e.g.[19] [18]-[25[[25]. In [18], a web-based application is proposed which detects whether the user has habits considered as risk factors for obesity. The application acquires and registers data about diet, exercise, sleep, and fat mass, by using a web application and health information sensors. The major drawback of such systems is its inconvenience and its difficult learning process for the user. In [19] the authors propose a system that utilizes food images that are captured and stored by multiple users in a public Web service called FoodLog. Then, a dictionary dataset of 6512 images is formed including calorie estimation. The images in the dictionary are used for dietary assessment, but with only 6512 images, the accuracy of such approach is low. In [20], a new 3D/2D model-to-image registration framework is presented for estimating food volume from a single-view 2D image containing a reference object. In this system, the food is segmented from the background image using morphological operations while the size of the food is estimated based on user-selected 3D shape model. In [23], a set of pictures is taken for before and after food consumption in order to recognize and classify the food and determine its size. In such method, the existence of a premeasured and predefined measurement pattern is used inside the images to translate the size in pixels of each portion. All these conditions can generate difficulties, which has been addressed by [27], which proposes a system that captures the images and sends them to a research facility where the analysis and the extraction are performed. The major disadvantage of such a system is that it does not provide information to the users in real-time. There is a considerable delay in providing the information due to the offline processing of images. In [24] the authors ,propose a method to automatically identify and locate food in a variety of images. Two concepts were combined in their algorithm. First, a set of segmented objects partitioned into similar object classes based on their features, for solving the idea they have applied different segmentation method. Second, automatic segmented regions were classified using a multichannel feature classification system. They have used SVM as their classifier. The final decision is obtained by combining class decisions from individual features. In [26], author is used computer vision methods for volume estimation which can be computed from 3D models obtained using multi-view geometry. In our system, we also use food images taken with the built-in camera of a smartphone. But, we go one step further by implementing graph cut segmentation and deep learning algorithms as a means of improving the accuracy of our food classification and recognition system. Furthermore, the processing of the images and the calorie measurement results are provided to the user instantly. This means that our system is convenient to use and well suited to be a long-term solution for users. Furthermore, our system uses cloud-based virtualization where an emulation of the smartphone environment allows the application to run virtually on the remote server in the cloud. This is rather significant to overcome the limited capability of smartphones to run intensive machine learning algorithms similar to those presented in this paper. Next, we present the details of the proposed solution.

III. Proposed System

In this section, we discuss our proposed system in more details. In subsection A, we introduce the reader to our previously proposed graph cut segmentation method see [7] followed by deep learning neural network mechanism analysis in subsection B and details about calorie and time processing measurement is introduced in subsection C.

A. *Graph Cut Segmentation*

Before performing the segmentation on the image, the user captures the picture of the food with her thumb on a suitable position on the dish so that the picture will not only contain the food item, but also the user's thumb is used for size calibration. To use graph cut segmentation, it is important to determine the features of a good graph that will be extracted from an image. The following three properties capture the most important features of our graph cut based food image segmentation method: First, it should be robust; i.e., if the image is somewhat distorted, the graph should not be deeply changed. In graph cut, each pixel of the image is mapped onto a vertex in a graph. Neighboring pixels are connected by weighted edges where the weight is determined based on a predefined energy function. In the normalized cut approach, the cut cost is determined by the fraction of the total edge connections to all the vertices in the graph. Second, it should also have good algorithmic properties. This means that the graph, when drawn, is actually a symbolic representation of the image; for instance, the boundaries between the regions should match with the edges of the graph. Third, we would like to be able to rebuild an image from the graph and for this new image to be a good compression of the initial image. In other terms, the loss due to the extraction process should be minimal. We provide the details of our graph cut food image segmentation method in [7],[9].

B. *Deep Learning Neural Network*

In this section, we provide the details of the deep neural network method used in our system. The first step in our approach is to generate a pre-trained model file with the help of CNN network. This is performed by initially capturing a set of images of one particular class (e.g. 50 images of apple class) and then labeling them with object name-set (object being apple). These images will be considered as the set of relevant (positive) images and are used to train the system. In the second step of the training, we re-train the system with the set of negative images (images that do not contain the relevant object). In our case, we trained the system with the background images, so it does not categorize them as part of the apple class. Once the model file is generated from the training, we load it into the application and test it against the images captured and submitted by the user. The system then performs the image recognition process and generates a list of probabilities against the label name. The label with the highest probability is prompted to the user in the dialog box, to confirm the object name. Once the object name is confirmed, the system performs the calorie computation part by calculating the size of the food item with respect to the finger in the frame. It finally prints the output to the user with the required calorie. Figure 1, illustrates the above mentioned process. We trained the system using the deep neural network model by [12], with various classes of food samples and useful hints from [9]-[11].

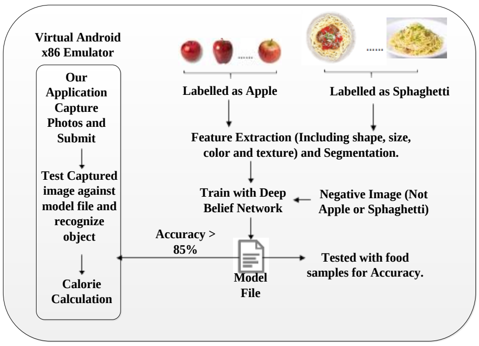


FIGURE 1 IMPLEMENTATION OF DEEP BELIEF NETWORK IN THE ANDROID APPLICATION

From technical view, a neural network which we have applied, computes a differentiable function of its input. For example, our application computes the probability of the match of the input image with the corresponding label set,

$$p(\text{label} \mid \text{an input image}) \quad (1)$$

The standard way to model a neuron's output f as an activation function of its input x is either a hyperbolic function or sigmoid function

$$\tanh(x) = (e^x - e^{-x})/(e^x + e^{-x}) \quad (2)$$

$$\text{sigmoid}(x) = 1/(1 + e^{-x})$$

But we use the term rectified linear unit (ReLU) to refer to a unit in a neural net that use the activation function $\max(0; x)$. In other words, we want to find a set of weights and biases which makes the cost as small as possible. To achieve that, we use an algorithm known as stochastic gradient descent. By using a smooth cost function like the quadratic cost it turns out to be easy to figure out how to make small changes in the weights and biases so as to get an improvement in the cost [28][29]. Hence we will be able to manipulate the weights and bias to get the output closer to the desired outcome, during the learning phase. Our goal is to train the neural network to find weights and biases which minimize the quadratic cost function C (w,b).

The idea is to use gradient descent to find the weights w_k and biases b_l which minimize the cost C. The gradient vector ∇C has corresponding components $\partial C/\partial w_k$ and $\partial C/b_l$. The stochastic gradient descent can be used to speed up learning by estimating the gradient ∇C by computing ∇C_x for a small sample of randomly chosen training inputs. By averaging over this small sample it turns out that we can quickly get a good estimate of the true gradient ∇C, and this helps speed up gradient descent, and thus learning.

For example, this algorithm will help us to tweak the weights (w) and bias (b) during the learning phase, in a way we can finally determine the output as one of the two (Apple or Cherry), without affecting the rest of the food classes. Delta changes in either the weights or the bias will change the result from one food class to another. As shown in the below diagram, considering we have taken the color feature into account, any change in the weight w_1 or bias b would alter the final result, which in this case deciding between apple and cherry. If the probability of the image p>0.5 towards Apple, it would be classified as Apple and same is the case with any other food type. An example is shown in Figure 2.

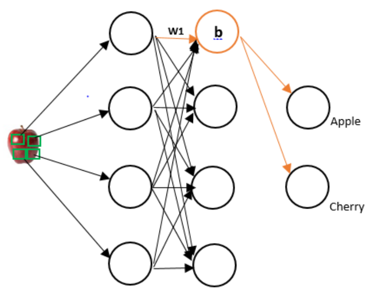


FIGURE 2 AN EXAMPLE SHOWING IMPLEMENTATION OF STOCHASTIC GRADIENT DESCENT

Algorithm implementing stochastic gradient descent [29].

Input a set of training examples

- For each training example x: Set the corresponding input activation all, and perform the following steps:
- Feedforward: For each $l = 2,3,\ldots,L$ compute

  $z^l = w^l a^{l-1} + b^l$ and $a^l = \sigma(z^l)$.
- Output error, δ^l: Compute the vector $\delta^l = \nabla_a^C \odot \sigma'(z^l)$.
- Backpropagate the error: For each $l = L-1, L-2, \ldots, 2$ compute
- $\delta^l = ((w^{l+1})^T \delta^{l+1}) \odot \sigma'(z^l)$.
- Gradient descent: For each l=L, L-1…2, update the weight according to [29].

* Where L denoting the layer number, δ^l being the output error, bl being the bias, w^l being the weight and C being the cost.

C. *Calorie and Time Processing Measurement*

- *Calorie Measurement:*

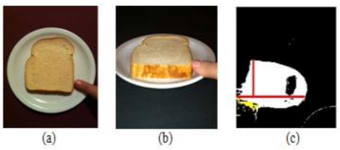
The calorie measurement procedure in our approach is as follows:

After classifying the food object the system then calculates the total amount of food portion on the plate in order to estimate the calorie value. The constraint here is that the calorie estimation is calculated based on the food image captured by the user which is the only known variable. The challenge here is in determining the dimension of the food portion based on the image captured, since the food size in the image is relative to the distance from which the photo was captured. Hence, food images captured from closer range had larger food dimension and vice versa led to an inaccurate estimation of calorie. To address this issue it is necessary to determine the reference object in the image, which would also be dependent on each food category. We proposed two such approaches, which would be able to estimate the calorie of the recognized food portion in the plate:

1) Finger Based Calorie Measurement.

2) Calorie Measurement using Distance Estimation.

Both these calorie measurement methods make use of reference object: Finger is used as reference object in first method whereas calculated distance is used as a reference object in the latter.



Finger Based Calorie Measurement [5]

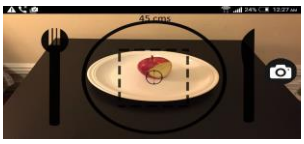

Calorie Measurement using Distance Estimation **Error! Reference source not found.**

FIGURE 3 CALORIE MEASUREMENT METHOD

1) Finger Based Calorie Measurement: As shown in the Figure 3 (Finger Based Calorie Measurement), food image is captured for bread, where the user's finger is placed next to the food object in the plate. Since the dimension of the user's finger is known, the system can compute the corresponding dimension of the food object (bread), when captured from top view and side view. These dimensions are then used in calculating the volume of the food object, which is further mapped to the corresponding calorie value of the food object.

2) On the other hand as shown in the Figure 3 (Calorie Measurement using Distance Estimation), the distance between the food image and the mobile device is calculated using the mobile sensors, accelerometer and magnetic field sensors. The values computed from these sensors, enable the system to compute the angle at which the person is positioning his device, which along with the person's height. This known value is used in computing the distance between the food object and the mobile device. Hence the captured image along with the distance computed is then processed in the system, in order to determine the block dimensions which would further be used to compute the area of the food portion. Although, both these methods make use of different methodologies they are fundamentally based on the concept of the reference object. Table 1 shows the uncertainty measurement calculations for each of these methods:

TABLE 1 UNCERTAINTY MEASUREMENT FOR CALORIE MEASUREMENT USING DISTANCE ESTIMATION

Food Item	Finger Based Calorie Measurement	Calorie Measurement using Distance Estimation	Uncertainty difference between the two methods
Bread	139.018	138.276	0.742
Apple	95	93.4	1.6
Banana	105.21	99.3	5.91

- *Time Processing Measurement:*

The overall time taken for processing the food image, recognizing the food object and calorie computation has improved with every iteration. We have applied different methods which are shown in the chart below, we observed that MapReduce SVM for food recognition and calorie computation took 163.5 seconds overall. The cause for significant large time was due to allocation and deallocation of cloud resources while implementing the SVM on runtime. With the use of deep learning algorithm we were able to achieve an improvement in overall time consumption with 26.96 seconds. This was still considered significantly large time considering wait time for user to process the food image request. Using the cloud virtualization along with deep learning we were able to reduce the time for processing 14.64, which were further able to improve by using decision mechanism.

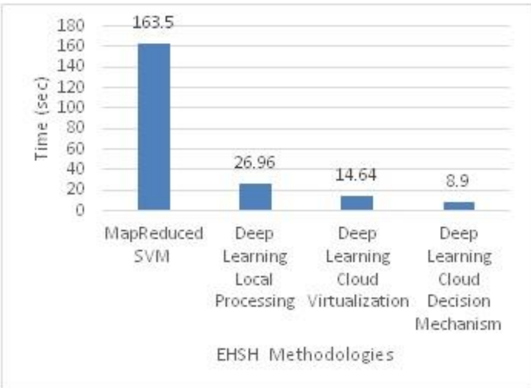


FIGURE 4 TIME PROCESSING WITH DIFFERENT ALGORITHM

IV. EXPERIMENTAL RESULTS

This section presents the experimental results of our system. In this work, we have combined Graph cut segmentation and deep neural network. The combination of these two methods allow us to improve the accuracy of our food classification and recognition significant compared to our previous work in [12]. By recognizing the food portions by these two models and also by having the size and shape of the food portions from graph cut algorithm, we will have a chance to calculate the whole food portions calorie. Before the implementation of the image recognition algorithm in the Android application, the first step in our approach is to generate a pre-trained model file with the help of CNN network. We performed this step by initially capturing a set of images of one particular class (For e.g. 50 images of apple class) and then labeling them with object name-set (object being apple). These images are considered the set of relevant (positive) images. After the image-sets are captured, the system is trained with these images. Then, the system is re-trained with the set of negative images (images that do not contain the relevant objects). In our case, we trained the system with the background images, so it does not recognize them or categorize them as part of the image class. Once the model file is generated from the training, we load it into the Android Application and test it against the images captured and submitted by the user. The label with the highest probability is prompted to the user in the dialog box, to confirm the object name. The dialog box will prompt the user to confirm the food type. If the food type suggested by the application is correct, the user would then click "Yes", if not, the user clicks on "No" button. If the user clicks "Yes", the application will then display the estimated calorie value of the food type. If user clicks "No", then the application will prompt the user to enter the correct food type and would further display the estimated calorie value based on user's entered information. In this paper, our data set comprises of 30 different categories of food and fruits. These food and fruit images are divided into training and testing sets, where around 50% of the fruit images from each group are used to train the system and the remaining images serve as the testing set. As Figure 5 and Table 3 show, by applying graph cut segmentation and Deep Neural Network algorithm, we have better recognition. Our system could recognize the food portions very accurately in 3 seconds. The results of table I show that we have 99% accuracy in our single food portions. Furthermore, we have the measurement method in our work which includes: One way to increase the confidence in experimental data is to repeat the same measurement many times and to better estimate uncertainties by checking how reproducible the measurements are. When dealing with repeated measurements, there are important statistical quantities: average or mean (estimate of the "true" value of the measurement), standard deviation (a measure of the "spread" in the data), and standard error (estimate in the uncertainty in the average of the measurements). Each category contains more than 100 images. When dealing with repeated measurements, there are two important f quantities: average (or mean) and standard error. These are summarized in Table 2.

TABLE 2 REPEATED UNCERTAINTY OF MEASUREMENT

Food items	**Real Calories**	**Average Calories**	**Standard Error**
Red Apple	80	80	0
Orange	71	70	0
Tomato	30	30	0.01
Carrot	30	28	0.1
Bread	68	68	0.5
Pasta	280	276	0.3
Egg	17	17	0
Banana	10	10	0
Cucumber	30	30	0.25
Green Pepper	16	16	0.04
Strawberry	53	52	0.5

Results shows the average calories are so close to the real one and also the small range of standard error also shows the accuracy of the system. The overall accuracy of the system with both methods is shown in Table 3.

TABLE 3 FOOD RECOGNITION ACCURACY FOR SINGLE FOOD

	Recognition Rate (%)			
	Food items	**Using color-texture segmentation**	**Using graph-cut, color-texture segmentation**	**Using Deep Neural Network Method**
1	Red Apple	97.64	100	100
2	Orange	95.59	97.5	99
3	Corn	94.85	96	99.5
4	Tomato	89.56	95	100
5	Carrot	99.79	100	100
6	Bread	98.39	99	99
7	Pasta	94.75	98	100
8	Sauce	88.78	92	98
9	Chicken	86.55	89	100
10	Egg	77.53	83	100
11	Cheese	97.47	97	100
12	Meat	95.73	96	100
13	Onion	89.99	93	99.4
14	Beans	98.68	98	100
15	Fish	77.7	85	100
16	Banana	97.65	97	100
17	Green Apple	97.99	97	99
18	Cucumber	97.65	98	100
19	Lettuce	77.55	85	100
20	Grapes	95.7	95	98
21	Potato	88.56	89	100
22	Tangerine	97.59	99	100
23	Chocolate Cake	88.19	85	100
24	Caramel Cake	85.29	85	100
25	Rice	94.85	94	100
26	Green Pepper	97.99	98	100
27	Strawberry	83.47	98	99
28	Cooked Vegetable	92.62	96	100
29	Cabbage	77.55	100	100
30	Blueberry	83.47	95	100
Total average		92.21	95	99

V. CONCLUSION

Our aim in this paper is to empower the user by a convenient, intelligent and accurate system that helps them become sensible about their calorie intake. We employed a rather unique combination of graph cut segmentation and deep learning neural networks as a means of accurately classifying and recognizing food items. We showed that the combination of those two methods provides a powerful instrument to attain a 100 % accuracy of food recognition in our system. We presented the implementation of the virtualization approach of the application which allows us to benefit from cloud based resources. Our plan for future work is to increase our database of images and use the approach presented in this paper to test mixed food portions.

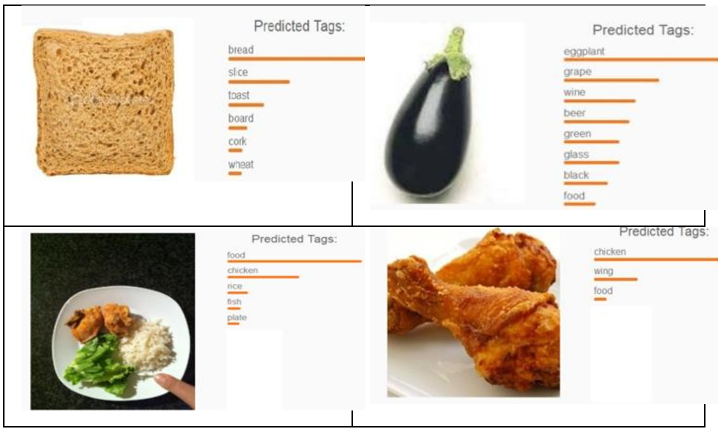


FIGURE 5 RESULT OF FOOD RECOGNITION

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