Food Item Recognition and Intake Measurement Techniques

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ABSTRACT

High-calorie intake can be harmful and result in numerous diseases. Standard intake of a number of calories is fundamental for keeping the right balance of calories in the human body. Currently, some techniques allow users to estimate the calorie count of their food. The latest applications developed to solve under description topic enabled the user to identify calorie part of a food item by taking its photograph. The photograph then passes some pre-processing steps, and after successful segmentation, many physical features are examined such as shape and size etc. Also, dimensions of the food object are determined. The concluding step is then recognition along with calorie estimation. In this paper, different calorie estimation techniques are reviewed. Every method has negative and positive features as well. We also throw light on the deficits of these techniques and some ideas to improve those deficits. The main aim of this review paper is to do a critical analysis of recent studies on accurate calorie estimation and food item recognition. We contribute to building a system that provides tools to monitor calorie intake by estimating calories based on food item recognition and accurate volume calculation.

CCS Concepts

• Computing methodologies→Transfer learning • Computing methodologies→Supervised learning by classification • Computing methodologies→Machine learning algorithms • Computing methodologies→Machine learning • Computing methodologies→Neural networks • Applied computing →Health care information.

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Keywords

Calorie Measurement; Food Recognition; Food Intake Measurement; Food Item Classification

1. INTRODUCTION

High-calorie intake can be harmful and result in numerous diseases. As reported by world health organization, more than $1/10^{th}$ of the adult population in the world is obese. A calorie is the unit of energy. It indicates energy acquired from eating and drinking, and energy burn through physical movement. For example, an apple contains eighty calories, while about a hundred calories are used with a one-mile walk. Formally, a food calorie is the amount of energy needed to increase the temperature of 1000 gram of water by 1 degree Celsius at a pressure of 1 atmosphere [1]. The number of calories in food reveals how much potential energy the food contains. The need to measure food calories is increasing day by day as people are more keen to consume healthy meals to stay away from obesity. Obesity in adults is increasing at an alarming rate. The primary source of obesity is the inequality between the amount of meal intake and the energy burnt through physical activity. Breast, colon, and prostate cancers are caused by high calorie intake [2]. A grown-up obese person is categorized as having a body mass index (BMI) equal to or greater than 30. Moreover, the WHO stated that the rate of obesity around the world had surpassed two billion which is about thirty percent of the world population [3]. Obesity treatment has been the focus of an extensive number of recent studies, and the outcomes demonstrate that the absence of balance for energy consumed is the primary explanation behind the growing obesity rates. There are many techniques to measure the ratio of obesity, but BMI is the WHO's recommendation. Other methods include waist circumference (WC), waist-to-hip ratio (WHR) and skinfold thickness. To measure BMI, weight as well as the height of the person are key factors.

$$BMI = \frac{\text{Weight}}{\text{Height}}$$

The measurement of daily meal intake is essential to maintain a healthy lifestyle — methods for measuring food intake range from manual dietary assessment to automatic sensing ones. The manual methods require the user to manually input the food details along with the portion sizes and is tedious and time-consuming, resulting in users refraining from using these approached for very long. Thus, recent approaches have focused on automated methods. Smart devices have become ubiquitous, and their importance in daily life routine cannot be ignored. Researchers use smart devices assisted with the techniques from computer vision, image processing and artificial intelligence to build novel methods for food intake measurement. The objective of this review paper is to do a critical analysis of recent studies on accurate calorie estimation and food item recognition.

Section 1 has given the brief Introduction, which included the necessity of the system, and a brief idea about the intention of the paper. The arrangement of the remaining paper is as follows. Motivation is covered in Section 2 whereas Section 3 represents the Literature Survey. Section 4 is the section of Evaluation and Comparative Results. Section 5 shows Improvements and Future Work. The final section represents the Conclusion.

2. MOTIVATION

As been said earlier, a person must have the perfect balance between the daily meal intake and the energy utilized. If the amount of meal intake is higher than the energy utilization then it concluded that the person is becoming obese. So, it reflects that the measurement of daily meal intake is quite essential to lose weight as well as to preserve the healthy weight for ordinary people. To accomplish this task, a mechanism is required that empowers the patients with a long-term solution and also guide them to achieve constant and lasting changes to their dietary quality and calorie intake. Many approaches, details of which come later in this review paper, are developed. The objective of this review paper is also to discuss the advantages and drawbacks of all those techniques. We analyzed the techniques in detail and found some worth sharing the pros and cons of each detail. Some common factors lacking in all techniques pushed us to highlight the principal reasons which result in a less effective and short-term solution. Here we throw light on those factors.

2.1 Non-or Semi-automatic System

Manual calorie measurement is too tedious and cumbersome. Existing systems somehow require user input for correct recognition of food items. Some techniques are obsolete and require too much effort while others still require some input from users. None of the recent approaches is entirely automatic. So, there is the basic need of the highly accurate and efficient automatic system.

2.2 Cost Effective and Approachable Solution

The cost regarding computation and time is one of the critical aspects of any algorithm. If an algorithm is not precise enough to lower the computation cost, then another algorithm will outdate it shortly. The economic cost of a solution to a problem also has an adverse effect. If we consider the traditional and manual approaches, monetary cost is the most disturbing factor. Many approaches involve the analysis of an expert dietician, who may charge a very high amount. An automatic system utilizing smart devices may offer that analysis free of cost.

2.3 Limited Dataset

The dataset is the backbone of every computer vision-based solution. The dataset defines and controls the applicability of a solution over the test data. The validity and effectiveness of a solution are wholly addressed by the underlying dataset. As far as we have reviewed the existing and recently adapted approaches, we clinched the fact that only one or two datasets are repeatedly used. So, the vacant space must be filled with other datasets to increase the usefulness of current approaches.

2.4 Assumptions

The solution loses its effectiveness by adding assumptions. It can impact any solution across some variables [4]. It increases the risks and lessens the strength of a solution since it is possible that they will turn out to be false. Removing those assumptions might elevate the existing solutions towards high accuracy and efficiency.

2.5 Time Efficiency

We have already debated on cost regarding time, which is the critical factor in measuring the efficiency of an algorithm. A solution with less time consumption is considered to be the more effective. The efficiency of an algorithm can be computed by determining the number of resources it consumes. Time is one of the primary resources that an algorithm consumes. So, time efficiency is one of the significant factors which needs to be controlled in an existing approaches.

3. LITERATURE SURVEY

In this section, we review significant food intake calculation and measurement techniques. We will review techniques spanning from old manual dietary assessment to modern image-based approaches.

3.1 Manual Approaches

The manual methods require the user to manually record food details along with the proportion sizes. In Twenty-Four Hour, Dietary recall (24HR) [5] is based on keeping track or record of all the eating activity in the last 24 hours. The person under examination is inspected by a dietitian or an expert for consumed food. Another approach which shares the same methodology with 24HR is Food Frequency Questionnaire Method (FFQ) [6]. This approach uses a list of food items. For each food item, the user enters the number of time that food has been consumed in a given time frame (e.g. one year). To calculate the nutrition value of the food consumed, food portion sizes must be known. Therefore, 24HR and FFQ also attempt to collect food portion sizes. To avoid underreporting of portion sizes, techniques have been designed to improve the portion size estimation [7].

The general drawbacks of traditional manual approaches are misreporting, data management and time consumption. Also, the user has to fill in the forms and, in some methods, preserve the data every day.

There are also existing smartphone-based applications (e.g. MyFitnessPal [8], SHealth [9]) that help users to keep track of the food they take. The applications assist users in achieving dietary goals such as weight gain/loss, food allergies or maintaining a healthy diet. However, these require users to manually input the food details along with the portion sizes. This can be very tedious and time-consuming, resulting in users refraining from using these apps for very long. Furthermore, naive users rely on self-reports of calorie intakes which often are misleading. Similarly, [10] relies on expert nutritionists to analyze images every day.

3.2 Automated Approaches

Automated systems include Nutrition Evaluation Scale System (NESSY), which consists of an electronic bar code reader with bar-coded food identification catalogue. The system can be used for automated nutrition evaluation [11]. The use of sensors was extended further in Automatic Dietary Monitoring (ADM). This idea used a chewing sound sensor which comprised of a wrist-worn acceleration sensor and a microphone in the external ear canal to record chewing sounds [12]. The sound chewing sensor monitors the weight of consumed bites via recording chewing cycles using described sensors and food types. This approach uses expensive equipment, however, which limits its usability. The use of smartphones for indirectly measuring the calorie expenditure was explored in [13]. A smartphone equipped with a built-in accelerometer (3-axis) estimated the energy expenditure, measured in metabolic equivalents (METs) by guessing the posture using acceleration values of the mobile device. The calculated METs value differs for different behaviour, e.g. sitting, standing, walking and running.

3.2.1 Image-based automated methods

Image-based automated methods for calorie measurement can be broadly divided into two groups. Algorithms in the first group [14,15,16,17], start by recognizing the food category, followed by food portion size/volume estimation and finally calorie estimation using standard nutritional fact tables.

Some methods [14], [18], [19] in the first approach, take two photos of the food item, one from the top and another from the side. The photo from the top was used for segmentation, and the side photo was used for measuring depth. The photos also contained a reference object for scale estimation. Reference objects were different in different approaches, e.g. thumb, coin, a piece of paper of known area. Information from both the photos was used to measure volume or portion size. The next common step is the pre-processing of images which is a necessary step for efficient and accurate segmentation. Pre-processing covers a variety of methods which includes resizing of images, lightening factor consideration and noise removal etc. After successful pre-processing segmentation is done. Method of segmentation varies with the adapted approach. Some of the adapted techniques are colour and texture segmentation. Some approaches have used more than four or five segmentation techniques. Feature extraction is also one of the critical steps toward better classification. Different features are extracted depending upon approach used. Some features are size, shape, colour and texture. Extracted features served as the input to classification step. Classification done has usually followed the Support Vector Machine (SVM) approach. SVM took features as input and classified the input image. Some approaches also used Deep Neural Network (DNN). Now comes the final step, i.e. calorie measurement. Information from segmentation gives the area and depth of the food item, which helps in calculation of volume. Density and calculated volume help in determining the mass. In the end, mass is compared to a standard table containing values of calories for the standard amount of different food items. After classification, calories in leftover food were measured. Images of leftover food were taken, and the whole process was repeated for calorie calculation. Results were compiled and displayed to the user.

Pouladzadeh et al. [14] proposed a system that involves capturing an image of the food and processing it through predefined steps, which follow a pipeline architecture. These steps/blocks include food image segmentation and food portion recognition. Calorie measurement is done using the nutritional fact tables. The classification step used SVM. Segmentation of the previous method was improved in [18], which used Graph-Cut. We have seen the use of smart devices such as a smartphone. The bottleneck in the use of smart devices is lack of high processing power as compared to cloud computing servers. These servers are capable of doing millions of instructions per second. Keeping this factor in mind, the authors in [19] improved the time efficiency by introducing the concept of mobile cloud computing in calorie measurement.

The system often fails to detect various food portions in mixed food; it also fails to segment them properly. The area measurement technique proposed is based on error-prone depth estimation technique. The dataset consisting of food items placed in white plates with a smooth texture is considered too simplistic. Chen el at. [15] uses a depth camera such as Kinect to estimate the volume of food for calorie measurement, which makes the algorithm unsuitable for regular use. Model-based measurement of food portion size is proposed in [16]. The method consists of three stages, i.e. base plane localization, food segmentation and volume estimation. A 2D-3D model to image registration scheme is used for volume estimation. The algorithm does not perform accurately in cases of shadows, reflection, sophisticated food, ingredients and motion blurring. Im2calorie [17] estimates food categories, ingredients, the volume of each dishes and calories. However, the calorie annotated dataset used is not sufficient [20].

The primary approach for calorie estimation in [21], [22] and other methods mentioned above, is to start by recognizing the food category, followed by food portion size estimation and finally calorie estimation using standard nutritional fact tables.

3.2.2 Direct estimation methods

Algorithms in the second group directly estimate the calories from food image [23], [20]. Ege and Yanai [20] directly estimate food calories from a food photo by simultaneously learning of food categories, ingredients and cooking directions. They argue that simultaneous learning of categories, ingredients and calories will boost performance as there exists a correlation between them [22]. Various approaches have also been proposed for food recognition only. Ahmed et al. [24] propose two methods to recognize food. These methods include Speeded-up Robust Features (SURF) and Spatial Pyramid Matching (SPM). The former methods require a dictionary of code words, and histograms are generated against those code words using a linear kernel classification scheme. The latter (SPM) accounts for spatial information by dividing and subdividing the given image into increasingly smaller subregions and computing histograms in each. Kawano et al. [25] propose a real-time mobile food recognition system, which continuously acquires frames of the image from the camera device, the user draws boxes against the food items on the screen, and food recognition is carried out within the boxes.

Graph cut based segmentation algorithm Grab-Cut is used for accurate food segmentation. Recognitions is performed using the linear kernel SVM (support vector machine). Camera position and viewing direction need to be maintained to obtain more reliable SVM classifications. Convolutional neural network has also been employed for the recognition task [17], [20], [22], [26] and as a result, the recognition accuracy has improved significantly. Other methods include a total of 120 pizza images were used in [25], Qin et al. [23] used only 180 images of food, and [24] used fruits in salads.

3.2.3 Datasets

Availability of large dataset is crucial for machine learning based food recognition algorithms. Food-101 [27] is a large publicly available dataset of food images. It contains 101 classes of food items with 1,000 images for each class. Similarity, UEC Food 100 [28] contain 100 categories of food images. VIREO Food-172 [29] contains 110,241 food images from 172 categories. Each food image is manually annotated with 300 ingredients. Calorie annotated datasets include [20] and [30]. There is no publicly available dataset that contains subcontinental dishes. Therefore, a new dataset should be created containing both subcontinental and other common cuisines.

4. EVALUATION AND COMPARATIVE RESULTS

This section will show the comparative study and analysis of all the reviewed techniques. Moreover, evaluation of these techniques will also be part of this section. As we know, the topic under description comprises two main parts; Recognition and Calorie measurement. However, we will show some facts and figures regarding the accuracy of recognition and measured calories of every system in this section.

In [31] authors used data set comprising of 12 different categories of food and fruits consisting of 1636 images. They divided 50% images as training set and remaining 50% as a testing set. They have provided different accuracy results with colour, texture, size and shaped feature individually and collectively. The claimed average accuracy for recognition rate is 92.6%. However, they have not provided any figures regarding calorie measurement. In [14] the average accuracy for recognition rate using all the four features (i.e. color, texture, shape, size) was 92.21%. However, they have added three more categories to the data-set. Also, they incremented the number of images in data-setup to 3,000.

In [19] authors improved the methodology by enhancing the processing power through the introduction of mobile cloud computing. They have also trained and tested the system periodically with mobile computing only and realized that achieved accuracy was not more than 90%. After empowering the mobile computing technique with cloud computing, they achieved the accuracy of 99%. They also increased the collection of images to 3,500 and 40 single food categories.

In [21] they used Deep Learning for better feature extraction and accurate classification. They claimed the accuracy of 95% on average. As shown in Table 1, the comparison of actual with estimated calories produced a very minute difference as 0.65.

Table 1. Uncertainty in Bread Calorie Calculation

Area (Pixel)	Weight (g)	Actual Calorie	Estimated Calorie	Difference
66	188	167.32	165.642	1.7
59.66	166	147.47	154.12	-6.38
72	198	176.22	175.57	0.65
18	86	79.21	82.44	-3.23
36	140	124.6	113.63	11

Authors of [32] claimed 99% accuracy, which they attained by employing a fusion of segmentation and classification methods. The segmentation method used was the famous Graph-cut method along with DNN for classification. They used the dataset having 30 categories but with images of 10,000 in entirety. Moreover, every class or category have hundred or more images. They also used 50% as training set and remaining 50% as a test set. Their contribution is exceptional and up-to-date in the way that they have measured the uncertainty between finger based and distance-based calorie measurement as shown in Table 2.

Table 2. Uncertainty Calculation in Finger Vs Distance Based Calorie Measurement Methods

Nutrition Item	Finger-Based Calorie Measurement	Distance-Based Calorie Measurement	Difference
Apple	95.000	93.400	1.600
Bread	139.018	138.276	0.742
Banana	105.210	99.300	5.910

They also gave a comparison of different calorie estimation techniques based on processing time as shown in Table 3. We can observe that time consumption in processing for Map Reduced SVM is 163.5 Sec. Most of the time was utilized in assigning resources and taking them back when the job is done. However, Deep Learning implementation caused it to reduce up to a figure of 26.96 seconds. The processing time reduced to 14.64 seconds by utilizing cloud virtualization and a decision mechanism was used to reduce the processing time further.

A comparative analysis of all the reviewed techniques is given in Table 4. It presents different classification methodologies used in all of the reviewed techniques. Segmentation type represents the technique used to segment the food item portion and feature extraction as well. Some papers measured the surface area based on reference object, e.g. thumb, coin or card etc. whereas others have used distance measurement technique as shown in the last column of Table 4. Also, it presents the accuracy comparison. We can conclude that use of Deep Learning has outperformed other methods regarding accuracy and overall time taken for pre-processing, recognition and calorie computation.

5. IMPROVEMENTS AND FUTURE WORK

From our comparative study, it can be seen easily that all the reviewed techniques were orderly progressive, i.e. later techniques were better than the former. Every technique contained some deficiencies, which was removed by the forthcoming technique. In this section, we will discuss the deficiencies still existing in the system and try to suggest some improvements as future work.

Table 3. Time Processing with Different Algorithms

Methodology	Time (Sec)
Map Reduced SVM	163.5
Deep Learning Local Processing	29.96
Deep Learning Cloud Virtualization	14.64
Deep Learning Cloud Decision Mechanism	8.9

5.1 Recognition and Detection of Mixed Food

Most of the techniques emphasized on recognition of single food images. Recognition of mixed food images still needs much enhancement by enlightening the proper segmentation technique.

Graph-cut segmentation is the best-suited technique for this scenario because it can find super matching pixels or contour of an item in an image. However, the limitation is that this technique may fail where the objects in images have rambling edges, or the same kind of objects very near to each other. Integration of figure priors inside this framework solved these issues. A Graph-Cut algorithm will be the best for collaborative segmentation which unites shape priors.

5.2 Recognition and Detection of Cooked and Liquid Food

None of the techniques explicitly covered cooked foods, liquid foods and complex foods like salads and sandwiches as part of their study. In future, calories of cooked or liquid food can be obtained by inspecting ingredients. An additional step of calorie measurement for ingredients can be introduced after successful recognition of cooked or liquid food items. Calorie measurement of ingredients will contain the same steps, i.e. segmentation, feature extraction and nutritional information retrieval.

5.3 Enrichment of the Dataset

Most of the reviewed techniques used the Food dataset in [33]. To incorporate more diversity of cookeries around the world, a considerable dataset is required other than the traditional dataset. It should also consist of different parameters like different lightning conditions, camera angles, different backgrounds etc. Also, no publicly available data set contains subcontinental dishes. Therefore, a new dataset should be created containing both subcontinental and other familiar cuisines.

5.4 Transfer Learning Approach

[32] used deep learning neural network for classification purposes. We know that a massive volume of data is needed to train a Convolutional Neural Network (CNN) because it has to learn many weights from an ordinary image. A simple method to train a CNN from scratch is the usage of the related model to extract structures from a new dataset robotically . This method is called Transfer Learning, it is a suitable way of deep learning techniques without using the large dataset and it does not take a long time. Using the described technique, i.e. Transfer Learning, we can achieve high accuracy in a very time efficient manner.

5.5 Nutrition Aware Calorie Measurement System

Based on existing application, an extension can be made by introducing a new feature of nutrition aware calorie measurement. The application will inform the user about some specific nutritious elements, e.g. sodium chloride, glucose etc. This feature can help patients who experience the ill effects of chronic diseases, for example, adult-onset diabetes or hypertension.

Table 4. Summary of Different Food Item Recognition and Calorie Measurement Techniques

Technique	Classification Methodology	Segmentation Type	Image Categories	Total Images	Calorie Measurement
[31]	SVM	Color, Texture, Size, Shape	12	1636	Reference Based
[14]	SVM	Color, Texture, Size, Shape	15	3000	Reference Based
[18]	SVM with RBF Kernel	Color, Texture, Size, Shape, Graph-cut	30	-	Reference Based
[19]	Map Reduced SVM	Color, Texture, Size, Shape, Graph-cut	40	3500	Reference Based
[18]	Deep Learning Cloud Virtualization	Color, Texture, Size, Shape, Graph-cut	30	-	Reference Based
[32]	Deep Learning Cloud Decision Mechanism	Color, Texture, Size, Shape, Graph-cut	30	10000	Both Reference and Distance-Based

5.6 Background Independent Recognition of Food Images

None of the reviewed technique proposed the independent background recognition for food images. They all used specific textured plates, i.e. white colour plates. This might mitigate the usability and effectiveness of the system. So, there is a need of recognition system which can recognize the food item even with different backgrounds. Many approaches can be devised based on Deep Learning. A latest and most appropriate technique is Faster R-CNN towards real-time object detection with region proposal networks advances in Neural Information. Utilizing the above described technique, we can achieve the desired task of background independence.

6. CONCLUSION

Currently, obesity is the major issue in human life. Curiosity is found among people to measure their heaviness and healthy eating in order to avoid obesity. So, there is a need of a system which can measure calories of daily intake of diet. The calorie measurement system can help nutritionist for physical and medical treatment of overweight persons; ordinary people can also get the benefit of this system by controlling their diet more closely without worrying about being fat. The paper presents discussion at different calorie estimation techniques. Every technique has negative and positive features as well. We also throw light on the deficits of these methods. Critical analysis of recent studies on accurate calorie estimation and food item recognition is the primary objective of the paper being presented. Based on this, we now conclude that food calorie measurement is a hot topic in computer vision research currently. By all counts, and with comparative results, this study unveiled that recent methods have scope for improvement, as this remains an open research problem. Also, the strengths and weaknesses of all the reviewed techniques are revealed. It is clear from the presented review that the presented topic has the potential to turn into a more beneficial and effective application by eradicating the described deficits of these techniques. We have also described possible improvements and future work to enhance the usability and accuracy of the system.

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