Measuring Food Volume and Nutritional Values from Food Images

By

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Abstract

Obesity and being overweight have become growing concerns due to their association with many diseases, such as type II diabetes, several types of cancer and heart disease. Thus, obesity treatments have been the focus of a large number of recent studies. Because of these studies, researchers have found that the treatment of obesity and being overweight requires constant monitoring of the patient's diet. Therefore, measuring food intake each day is considered an important step in the success of a healthy diet. Measuring daily food consumption for obese patients is one of the challenges in obesity management studies. Countless recent studies have suggested that using technology like smartphones may enhance the under-reporting issue in dietary intake consumption. In this thesis, we propose a Food Recognition System (FRS) for calories and nutrient values assumption. The user employs the built-in camera of the smartphone to take a picture of any food before and after eating. The system then processes and classifies the images to detect the type of food and portion size, then uses the information to estimate the number of calories in the food. The estimation and calculation of the food volume and amount of calories in the image is an essential step in our system. Via special approaches, the FRS can estimate the food volume and the existing calories with a high level of accuracy. Our experiment shows high reliability and accuracy of this approach, with less than 15% error.

Acknowledgements

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Finally, I dedicate this work to my family.

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List of Acronyms and Definitions

2D	Two-Dimensional Space
3D	Three-Dimensional Space
AMA	American Medical Association
BLOB	Binary Large OBject
BMI	Body Mass Index
Cal	Calorie
DLW	Doubly Labeled Water
P	Density
FFQ	Food Frequency Questionnaire
FRS	Food Recognition System
M	Mass
V	Volume
RFID	Radio-frequency identification
ROI	Region of Interest
ROI	Region of Interest
SVM	Support Vector Machine
WC	Waist circumference
WHR	Waist-to-Hip ratio
WHO	World Health Organisation
YCrCb	Digital Video signal for Luminance and dimensional color distribution over Cr and Cb

Chapter 1 - Introduction

The idea presented in this thesis is driven by the growing apprehensions regarding health problems related to obesity and being overweight. In addition, the involvement of new technologies such as smartphones and tablets in the health-care field motivated us to find an assistant solution to link technology with treating health problems such as obesity. In this thesis, a semi-automatic device is proposed to reduce and decrease the misreporting problems in weight management. In this chapter, we will define the obesity problem and how we can categorise it, and we will also explain our proposed solution in general.

1.1 Motivation

Recently, the spread of obesity and being overweight has been globally significant and is considered as one of the major public health issue. According to the World Health Organisation (WHO), in 2008, more than one in ten of the world's adult population was obese [1]. Moreover, the WHO stated that the rate of obesity around the world has surpassed one billion; they predicted that this number might increase to 1.5 billion in 2015 [2]. Obesity is defined as a medical condition that causes abnormal accumulation of fat in the body [3]. In 2013, the American Medical Association (AMA) officially classified obesity as a disease that requires medical treatments and has dangerous health consequences [4]. Generally, obesity is defined as the increasing number of fat cells in a person's body [3]. Therefore, obesity and being overweight are notably linked to many chronic diseases such as type II diabetes, sleep apnea, high cholesterol, ischemic stroke, risks of coronary heart diseases, kidney and gall bladder and breast and colon cancer. Strong evidence shows that obesity is caused by the increased intake of high-calorie foods that are high in sugars, fat and salt but include a low amount of vitamins, minerals and other micronutrients. Obesity treatment has been the focus of a large number of recent studies, and the results show that the lack of balance for energy consumed with the energy intake is the main reason for the increasing rate of obesity [1]. There are many techniques to measure and classify the rate of fat in the human body such as the Body Mass Index (BMI), waist circumference, waist-to-hip ratio, and skinfold thickness. The following is an explanation of those techniques.

1.1.1 Body Mass Index (BMI)

Body Mass Index (BMI) is the WHO's recommended measurement tool for measuring total body fat. This technique depends on two values, which are the weight and height of the individual. In other words, BMI is calculated by isolating weight by height. The estimated results will be in (kg)/(m2). Depending on the given results, the obesity level can be classified as per the following table [5]. The BMI is likely the same for both males and females, but it might be different for some individuals such as athletes and elderly people.

Table 1: BMI Classification of Obesity and Overweight.

BMI kg/m2	Classification
<18.5	Underweight
18.5 - 24.9	Normal range
25 - 29.9	Overweight
30 - 34.9	Obesity I
35 - 39.9	Obesity II
≥40	Obesity III

1.1.2 Waist Circumference and Waist-to-Hip Ratio

Waist circumference (WC) and the waist-to-hip ratio are important methods in measuring the rate of fat in the human body. The WC tool has been chosen as a better measuring method than the BMI [6]. This technique relies on using a tape measure placed in a suitable position at the waistline. The waist-to-hip ratio (WHR) is likewise used to measure the fat in the belly. It is calculated by measuring the waist and the hip and then dividing the waist measurement by the hip size.

1.1.3 Skinfold Thickness

In this technique, specialists use a caliper at several regions of the body to measure the thickness of the skin and its accumulated fat [7]. After that, they calculate the percentage of body fat based on the measurements.

1.2 The Proposed Solution

From all of the above, it is clear that, for obese individuals to lose weight healthfully and for normal people to maintain a healthful weight, the daily food consumption must be measured [8]. Thus, obesity treatment requires the patient to have healthy food and decrease daily food intake. But in most obesity cases, it is not easy for the patients to measure or control their daily eating due to the lack of nutrition education, self-control and denial of the negative effects of obesity. Therefore, using a monitoring food system will assist the patient as an effective option for obesity treatment. Nowadays, new technologies like computers and smartphones are involved in the medical treatment of different types of diseases and obesity is considered one of these common diseases. Much evidence shows that behavioral treatment and changing lifestyle habits is very effective in managing weight loss [9]. In this research, we developed and implemented a system that measures and detects the daily food intake for an individual who is overweight or obese or even wants to monitor the food he or she consumes daily. To reach this goal, we propose a Food Recognition System (FRS) to measure calorie and nutrient intake values by using a smartphone or any other mobile device with a built-in camera. We will explain in detail the importance of our system and how it is different from other dietary intake applications. We will also describe in detail how the results of the image are transitioned to the nutritional tables of food with the least possible error, which is our main goal. The user must take a picture of the selected food with his or her smartphone before and after eating to compare the sizes of the portions before and after the food intake, in case the user does not finish the meal). The system will then process the food images to detect different types of food and their particular portion sizes. Figure 1 shows the overall diagram of the proposed system that we will discuss later. In fact, this thesis will mostly cover the idea of how to estimate food volume from an image in the FRS.

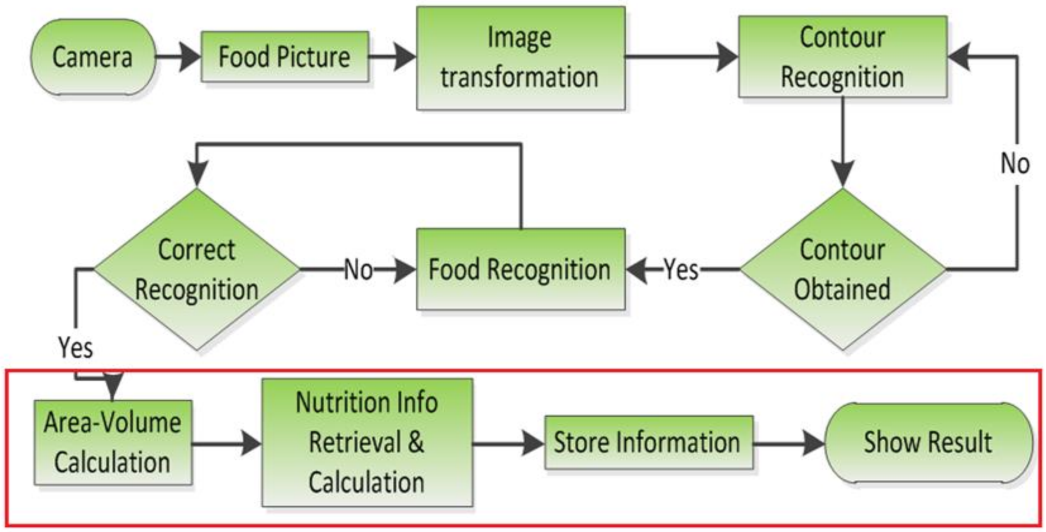

Figure 1: Diagram of the Food Recognition System

In other words, this thesis introduces a new food intake measuring system called the FRS. The idea behind these semi-automatic dietary intake assessments is to help and improve the treatment and management of obesity and overweight and take advantage of new technologies in the field of public health. By uploading the FRS application on their mobile phones, obese and overweight patients will have the opportunity to monitor their daily food intake without making any misreporting errors. Moreover, people with healthy weights can also use this system to watch their daily intake, which will assist them in avoiding obesity and becoming overweight. In addition, dietitians also can use this device to treat obese patients. A high-level block diagram illustrating the steps and the general architecture of the proposed FRS in this research is shown in Figure 2.

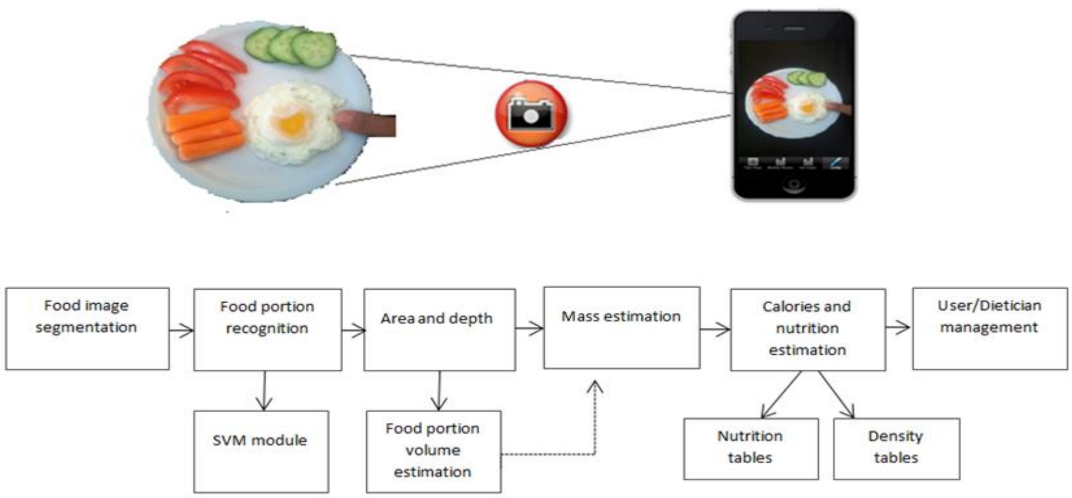

Figure 2: The general architecture of the food recognition system (FRS)

The first step of the FRS is capturing an image of any food in a special way that we will review later. Using image segmentation methods, the food portion area and all dimensions will be extracted from the photo. After that, the Support Vector Machine (SVM) technique will classify and identify the type of food. This will allow the system to extract the food volume from the image in an exclusive approach that will give the system the ability to calculate the mass of the food. Finally, the system will obtain all the nutrition facts by the adoption and the usage of food and density nutrient fact tables. The FRS is the combination of several phases, and the output of each phase is the input for the following stage.

1.3 Accuracy Level

Before addressing any technical issues, it is very important to know the expected accuracy level of the proposed system. To figure this, we must first determine the level of accuracy provided by similar systems, whether clinical methods done by experts or electronic devices. Regarding the clinical methods, if we ask a dietitian to figure the amount of calories in a dish with food by looking to the dish or measuring it manually, he or she will not be able to give an exact or accurate number of calories in the food due to the difficulties in realizing the food's ingredients and how much fat and salt have been used in preparing the food, which may greatly affect its nutritional value. Moreover, some parts of the food are not displayed on the surface of the dish, like pieces of chicken in salad or soup.

Regarding the use of electronic devices, there are many mobile applications available on the market to measure and recognize the nutrition values for any meal, but most of these applications require high commitment and interaction each time they are used. Moreover, most of these programs require Internet connection, because they cannot measure any food that is not stored in the data. Therefore, it is crucial to know that a high level of accuracy is not a key demand of our system, because it is impossible to estimate the exact amount of calories in any dish by just looking at it or even by use any electronic device. Knowing the expected accuracy level of our system is very important in terms of defining our goals with this system.

1.4 Limitations

There are some limitations with our system. For example, mixed and liquid food cannot be measured. Similarly, our system will also miss obstructed or buried food items. Moreover, by multiplying area and depth, we are assuming that the food portion's shape is uniform throughout its height, which is not necessarily true. However, these limitations exist in all existing systems, whether manual or automatic, and are not specific to our system.

1.5 Thesis Goal

This project aims to find solutions to eliminate the problem of misreporting and the inability to estimate the dietary intake for people who suffer from obesity and being overweight by employing modern technology and benefit from its advantages, such as ease of use and suitability for all ages. Thus, the aim of this thesis is to design an application that runs on smartphones containing a camera to measure the amount of calories in food intake with the assurance that the main objective is not high accuracy in measurement, but to reach the results with the lowest possible error, as mentioned previously.

1.6 Contribution of This Thesis

The FRS allows obese patients and users with healthy weights to monitor the amount of calories in their food intake by taking a picture of the food before and after eating. Subsequently, the system performs calculations after the image analysis process. By taking advantage of image segmentation, classification with the SVM, and area and volume estimation, the FRS will reduce the problem of underreporting daily food intake. In this thesis, therefore, we make the following contributions:

- Design of system workflow from all viewpoints: the user, the dietitian, and the system to create an effective system.

- Design and implementation of a method to calculate the volume of the food from the SVM-classified image and the thumb as a reference.

- Proposal and design of an approach to estimate the amount of calories and the nutrient values of any food inside the image. Noticing that, the approach for image processing and SVM classification was implemented by other students working in this project.

-Proof-of-concept and performance evaluation and analysis.

1.7 Research Publications

[1] P. Pouladzadeh, G. Villalobos, **R. Almaghrabi**, S. Shirmohammadi, "A Novel SVM Based Food Recognition Method for Calorie Measurement Applications" IEEE International Conference on Multimedia and Expo Workshops (ICMEW), pp. 495–498, 2012.

[2] G. Villalobos, **R. Almaghrabi**, P. Pouladzadeh, S. Shirmohammadi, "An Image Processing Approach for Calorie Intake Measurement," IEEE International Conference on Medical Measurement and Applications (MeMeA), pp.71–75, 2012.

[3] **R. Almaghrabi**, G. Villalobos, P. Pouladzadeh, S. Shirmohammadi, "A Novel Method for Measuring Nutrition Intake Based on Food Image," IEEE International Instrumentation and Measurement Technology Conference (I2MTC), pp. 366–370, 2012.

[4] G. Villalobos, **R. Almaghrabi**, B. Hariri, and S. Shirmohammadi, "A Personal Assistive System for Nutrient Intake Monitoring," in International ACM Workshop on Ubiquitous Meta User Interfaces, 2011, pp.17-22.

1.8 Summary

In this chapter, we stated and defined the problem of obesity and being overweight and the phenomena's highly alarming increase around the world. In addition, we generally explain the idea behind our project; we also demonstrated our goal and the contributions that make this system different from other systems. In the next chapter, we will define other works related to the idea of our system, and we will exemplify the pros and cons for each to demonstrate the FRS's strong abilities.

1.9 Thesis Organisation

The majority of this thesis presents the design, evaluation, and volume and calories estimation of a food in an FRS-based image. Thus, the remainder of this thesis is structured as follows:

Chapter 2 - Related Work discusses and classifies some of the existing dietary intake assessment methods.

Chapter 3 – System Components discusses the structure of the proposed system and its main components.

Chapter 4 - System Workflow and Description specifies the design of the proposed system from all perspectives.

Chapter 5 – Proposed Methodology discusses in details all the methods used in the proposed system.

Chapter 6 - Evaluation and Performance Analysis presents the evaluation results and analysis from the above chapter.

Chapter 7 - Conclusion and Future Work Summarises and concludes the thesis, and what to expect from future work.

Chapter 2 - Related Work

Commonly, dietary intake measurement methods can be classified into traditional and electronic approaches. Use of the traditional methods has been well-known for decades, whether in hospitals or through research studies. Electronic methods have started to appear recently due to the widespread use of technology globally. In this chapter, we will present a number of the most common dietary intake measuring methods. As well, we will define the drawbacks of those methods to demonstrate the strength of our proposed monitoring system, which can be used for people with healthy weights and for medical purposes to improve the treatment methods related to misreporting for people who suffer from serious medical conditions, such as obesity and overweight. The following is a description of different methodologies behind food measuring systems.

2.1 Traditional Dietary Assessment Approaches

In this subsection, we will review some of the traditional and standard methods in dietary intake assessments:

2.1.1 Doubly Labeled Water Method

The doubly labeled water (DLW) method was developed in the early 1950s by Lifson and McClintock in 1966 [10]. DLW was widely used for a long time in measurement issues related to dietary intake studies to estimate energy expenditure; in fact, it is considered the gold standard method for measuring total energy expenditure. This approach is to give a subject (say, a human or animal) a dose of heavy Oxygen O^{18} and Hydrogen H such as deuterium in a certain quantity, and then collect samples of urine or saliva in consecutive periods (i.e., several days or weeks) and measure the concentration of some of the elements [11,12]. Despite its global popularity, DLW is one of the most expensive measuring intake methods because it requires costly equipment to estimate the concentrations of the isotopes that need to be measured. It also takes a long time to get the measurement results. Furthermore, DLW does not give the opportunity to measure the amount and type of food consumed.

2.1.2 Twenty-Four-Hour Dietary Recall

This method basically means an interview. It requires a dietitian or even a trained interviewer to ask the respondent to remember and record in detail all the food and drink he or she consumed during a period of time in the recent past (typically the previous 24 hours) [13]. The interview can occur either by meeting with the patient or via phone [14]; the interviewer should be familiar with nutritional habits and cooking methods to complete and control the data collection format. Moreover, the interview itself is restricted specifically to help the patient remember all the needed information, which is not sufficient for overweight patients. Researchers in [15] illustrate that the interviewer's probing minimises the chance of underreporting or forgetting by 25%. This means that self-monitoring and lack of communication with the interviewer leads to negative results in this approach. Additionally, it is quite difficult for a person to remember the contents and amount of one's daily food intake, especially for obese patients. In most cases, they cannot estimate the amount of their food intake, and if the recall is unannounced, the diet is not changed. Thus, the main disadvantage of the 24-hour dietary recall is the delay and inaccuracy of reporting the eaten food due several factors, such as age, gender, education, credibility and obesity. Moreover, this method requires only short-term memory and an expert interviewer, which makes it an expensive method.

2.1.3 Food Record Method

This method is based on the processing of consumer food dairy lists created by an expert nutritionist for a certain period of time. These lists contain the type and quantity of food to reduce the error rate; mostly, these lists are sent to a group of selected individuals. After a while, the nutritionist receives the completed dairy lists. The nutrition specialist analyses, evaluates and compares the received data with typical data, so the error rate is reduced. The main advantage of this method is that it does not rely on memory like the previous method, as long as the data is recorded at the same time to eat and the food intake weight is measured. However, one of the biggest disadvantages of this method is that it does not measure the eating behavior, which may significantly affect obese patients.

2.1.4 Food Frequency Questionnaire Approach

The food frequency questionnaire (FFQ) method is a dietary assessment tool used especially for nutritional surveys in large groups. Moreover, this method was developed to use with adolescents. Essentially, FFQs contain a list of foods and an assortment of options relating to the frequency of consumption of each of the foods listed. Each region has their own questionnaire with the popular food in that area for example, Chinese food, Mexican food, Indian food or American food. In this technique, the patient must record all the daily food consumed on a list containing several types of foods for a specific period of time. This method also requires a meeting with an interviewer [16]. This methodology does not require a highly experienced interviewer, and like the 24-hour dietary intake method, the meeting can be face-to-face, over the phone [17] or via self-adoption of patients, so the food intake can measure in different ways [18]. In general, FFQs were designed to evaluate eating habits, not the food intake amount [19]. Numerous studies to develop this tool were done between the 1960s and 1970s [20, 21, and 22]. Thus, the FFQ tool is officially recommended as one of the dietary intake assessment methods in the American Public Health Association's Manual of Nutritional Assessment in Health Programs [23].

2.1.5 Portion Size Estimation

The main goal of the portion size estimation method is to train people to improve their intake assumptions. Portion size estimation may be one contributor to underreporting problem. In [24], it was found that 45 minutes of training in portion-size estimation among second- and third grade children in Arizona and New Mexico significantly improved estimates for solid foods such as bread, sugar or cereal, which were measured by dimensions(length and width), cups, or tablespoons. Liquids such as milk and soup were estimated by cups or by label analysis. Amorphous foods such as pretzels were estimated least accurately even after training, and some foods still exhibited an error rate of more than 100%. Thus, training can improve portion size estimation; however, more than one session may be needed. Accuracy may be unattainable.

2.1.6 General Drawbacks of the Food Dietary Recall

There is a crucial need to study and recognise the disadvantages of the previously mentioned existing measuring methods to understand the incentive behind this project. Two main objectives are behind the usage of the dietary intake assessment, which are figuring if any society's population is taking enough nutrients like carbs, proteins, sodium or calcium or discovering if any person is taking more than he or she needs [25]. Generally, the dietary assessment recall causes an underestimation of energy intake [26]. In addition, the incidence of underreporting is too high due to data collection methods [27]. The main advantage of the 24-hour dietary recall is that a professional interviewer will complete the food list, but this method is expensive. Moreover, the collected data does not affect the subject's behavior, but simultaneously, many disadvantages appear, such as the misreporting of the food whether it is related to the amount or preparing method [28]. Furthermore, there are several drawbacks related to data storage. For instance, the subject must be sufficiently educated to preserve the data every day, which is impossible for most obesity patients. There will also be a need to store the collected data into large software with the help of computer experts. This will waste time and be very costly.

2.2 Early Electronic Dietary Assessment Approaches

Electronic devices for food intake measurement have been modestly developed since the 1980s. The Portable Electronic Tape Recording Automated (PETRA) scale was one of the earliest systems, developed by Cherlyn Electronics, Cambridge, to measure food intake and overcome all the negative aspects related to the traditional approach [29]. The idea behind this device is to use cassettes to record both food portions and ingredients. Several studies show that it is very difficult to use the PETRA scale in poorly educated societies [30].

A system similar to PETRA but more sophisticated has appeared, called the Nutrition Evaluation Scale System (NESSy). The development of this system was the first breakthrough to the idea of using a computer with measuring devices. This system is considered the first fully automated food recognition system [31]. In fact, using a computer for direct analysis in food measuring systems is considered a drawback, which we will explain in detail in the next section. A Personal Digital Assistant (PDA) is considered one of the most common devices in the field of food intake measurement. The use of a PDA is much better than the traditional methods previously mentioned. A PDA records the food the user consumes, and each individual can store all the food kinds from the nutrition fact tables without having to type them manually or calculate the totals of consumed food [32]. Besides, this device gives the user immediate feedback whenever he or she wants. In addition, it allows the nutritionist or the user to store data by connecting the device to the computer and the Internet. However, Beasley's study shows that the results of portion estimation part can have an error, and it can take a long time for the user to record the information [33]. In another study, researchers asked a group of overweight and obese adults to self- monitor their daily food intake (including habits and food consumed) in a period of 24-week behavioral weight control program by using a PDA and the result was that the use of PDA did not increase the validity of food intake reporting [34].

2.3 Recent Electronic Dietary Assessment Approaches

As a substitute for the old dietary intake methods, researchers developed devices for measuring food intake linked to computers. Consequently, the usage of technological devices in the diaries assessment method became extensive in health care for data collection purposes. For examples, diaries have been used to measure several categories, such as physical activities, sleep, pain, heart rate, medication taken, food intake and energy expenditure [35]. Thus, much food intake measuring software has been developed such as Calorie Counter, Meal Snap and Veggie Vision.

In addition, some researchers have applied methods related to neural networks, intelligent systems, sensors, and recently, image processing and pattern recognition approaches. Researchers in [36] developed Automatic Dietary Monitoring (ADM) to predict the weight of individual bites taken to reduce the self-reporting burden for any subject participating in diet programs. The idea behind ADM is to use the body's sensors to monitor the weight of the user's bites of food through recording chewing cycles and food types, thus providing continuous data from a chewing sound sensor. Specifically, the system received the intake signals via a wrist-worn acceleration sensor, a microphone in the external ear canal to record chewing sounds (This area provides a loud chewing signal without environmental sounds), and an electromyography (EMG) sensor at the throat to measure swallows.

Nishimura and Kuroda advanced a wearable sensor system by using a microphone integrated into a Bluetooth headset. The system recorded chewing sounds to figure the type of food, crunchy or not, to help the user remember the type of food eaten [37]. However, these methods can be used only in laboratory experiments, as they do not provide accurate results. Moreover, it is actually uncomfortable for the user to wear a microphone in the ear canal or a sensor in the throat area. Different types of food can give the same chewing sounds, such as broccoli, sweet peppers and carrots. On the other hand, because of applying intelligent technologies in the dietary intake assessments, researchers in [38] created a dietary-aware dining table for diary intake consumption. They used radio-frequency identification (RFID) as a surface sensor to gauge the type of food eaten and integrated existing scales on a dining table to measure food weight. But there are many drawbacks related to this technique, including the difficulty in using it in several locations and the complexity of attaching the RFID tag to each served food.

In the following sections, we will explain some of the food intake measuring methods that are categorised depending on image processing approaches and volume estimation. This will certify the importance of our system.

2.3.1 Image-Based Dietary Assessment Approaches

Recently, food intake measuring systems that rely on image capture and analysis became commonly used all over the world due to the great advances in cell-phone camera resolutions, computer programs, network connectivity and image processing analysis. To recognise food consumption, the user captured an image of the food and sent this image to websites to learn the type and amount of calories.

Sometimes, the captured image is compared to an image stored in the data of the device [39]. In this case, researchers applied the nutrition data to a health-aware HTC smartphone system. Users captured an image for the selected food. Then, these images are compared to the image with all the nutrition facts stored in the phone data. This data consists of some food images and information from restaurants or homemade food. The main weaknesses in this device is that users do not have the opportunity to measure different types of food rather than the types stored in the database. Moreover, the HTC device does not count the amount of food intake which might be different from the amount of food already stored in the data.

Wu and Yang created a computer program method to identify fast-food intake from video of eating by using a wearable camera [40]. In this method, numbers of captured images from a fast-food restaurant are compared to images stored in a computer database. Researchers applied the camera in three different locations with 101 food types. They achieved a 73% recognition rate, but there were several drawbacks to this approach, such as the accuracy level being subject to change with lighting and unseen food objects.

Different investigations have been done to extract food intake from an image. Researchers in [41] used the Neural Network (NN) to develop a method to extract food intake from an image; in this approach, they captured a photo of several dishes in a tray before and after eating. Particularly, an image of the whole tray is captured first. Then this image will be converted to a binary image by using threshold values, and a small image of the food will be extracted from the tray image. Due to the previous procedures, the system will identify all information related to the image such as length, width and shape. All previous information will transfer to the NN. After getting the results, researchers applied them to a computer simulation program to compare the information and analyse the results. This method is also difficult for the user to follow. The user must capture the photo in a tray to extract the shape of the food. Moreover, the food image needs to be analysed by the computer, which is impractical for everyday usage.

Martin and others proposed an approach depends on image processing [42]. In this approach, the user captured food photos before and after consumption. After that, images were sent to a research center via Internet connection. An expert dietitian evaluated the images to estimate the amount of the food intake. This method has drawbacks, like the impossibility of using this method without a network connection.

With the Wellnavi device [43], users can capture video images at a 45° angle of the selected food and then write the description of the food on the screen. Users must then send the information plus the image via Internet to a data center for a nutritionist to extract the results. Actually, the use of this system is limited due to how the image is captured and the complexity of writing the food description on the screen.

The idea of the smart kitchen has also appeared [44]. In this approach, researchers designed a smart kitchen called the Calorie-Aware Kitchen with Ubiquitous Computing technology, including cameras to increase the awareness of choosing healthy food and the amount of calories in prepared food. The kitchen includes a camera overhead to capture images of the food preparation process, while there are sensors connected to the counter and stove to measure all the ingredients and cover most of the places inside the kitchen. This will result in immediate feedback for the user with a suggestion for the suitable amount of calories intake. The major downsides to this approach are the limited usage, the smart kitchen being linked to a certain place and the inability for the smart kitchen to be used outside the home. In addition, movement is restricted in the space provided for food preparation, which is undesirable for most people. Moreover, some configuration mistakes could happen, such as mistaking the types of cooking oil or meat due to the similarity between food categories.

Regarding digital photography, there is a method called the Remote Food Photography Method (RFPM) [45]. In RFPM, users captured a photo of the selected food with a cell phone and sent this image to an investigator via a cellular network. To avoid misreporting, they sent reminders via email or phone to alert users to take and send the image to the researchers. Researchers will compare the received images with a standard image stored in the system's data to estimate the portion size correctly and resend the result to the user. As previously mentioned, these kinds of systems have limitations regarding data and the need to have a constant wireless connection.

Puri and others [46] designed the Food Intake Visual and Voice Recogniser (FIVR) system. The idea behind this system is to use both voice and images to estimate caloric amounts. The user must take three pictures of the selected food and certify the type of the food by speech. This input data is then sent to an isolated server through the wireless communication. After all the image and speech analysis, the result will be returned to the user as a text message. There are two negatives to this system. It is inconvenient when users enter data through speech because they may be in places where it is difficult for them to talk or they might hesitate to speak in front of others and In addition, users with speech problems will not be allowed to use the system. Moreover, the device will be admitted to recognize only one language which is not effective for deferent users.

2.3.2 Volume Estimation in Image-Based Diary Assessment Approaches

Since volume estimation is considered a complex challenge in image-based food dietary intake methods, we focus on volume estimation part in the FRS. Thus, this subcategory will define some of the previous work in this area to show the differences and the validity of our novel method for volume estimation, from image to the final stage of the image-processing analysis. The most recent studies in the field of food image recognition illustrated that there is a strong need to use a reference in the pictures to fix the viewpoint and distance of the camera. Notably, this reference could be any item that has the same size with every occurrence. Hence, in some methods, like the RFPM [45], the user should place a special card beside the selected food before taking the picture. The system also asks the user to identify the type of food and its amount in the photo; however, it is impossible for any user to estimate the portion size for any type of food, as mentioned earlier. In our system, we will overcome this drawback.

Using a different approach, researchers [47] proposed a system to estimate food volume from a single image relying on virtual reality (VR) technology. In this method, a number of 3D wireframe objects built in a virtual environment simulate specific food items in a real digital image. Binary cameras must be used to capture the image, one for the real-life environment and the other for the virtual world. Both images are taken with a checkerboard as reference. Actually, the validity of this approach is only inside the measurements laboratory and experimentation which is insufficient for daily use. An eating plate is used as a reference for a single image [48], while another study suggested using any reference with a circular shape such as a plate, coin or bowl [49]. They established an algorithm to estimate the volume of regular-shaped food on the circular object. Unfortunately, the authors experimented with just three food items, which is not quite enough to take the approach as a standard. Moreover, it is sometimes difficult for the user to find a circular plate.

Sun and others have determined a method to measure the volume of any food consumption [50]. In this approach, a picture of the selected food must be taken with a calibration card placed near the food as a reference object. Later, the pictures are uploaded onto a computer, and the user is responsible for entering all the information related to the picture such as the type of food and all the geometric values such as length and width by clicking on the image. Finally, the program will calculate the volume of the food and provide all the nutrition facts to the user. Definitely the result will be close to the real life sizes because the measurements were uploaded manually, but this method has shortcomings because, for example, the card must always be in the photo when the user needs the system. Actually, the system cannot adapt to the user without the card, so if it is lost or forgotten, the system will be inoperative. Besides, as mentioned before, it is impractical to upload the image onto the computer and manually enter all the data into the system.

Most of the aforementioned methods can only be used within the laboratory or in certain places. In fact, to build our FRS, we will take advantage of the existing methods and overcome all their drawbacks. Our FRS aims to use cell-phone technology to allow the user to take a picture of the selected food at any time and any place with the thumb as a reference or tool to measure the dimensions inside the image to estimate the amount of food from the captured photo. This unique method will provide more accurate results than other methods.

2.4 Summary

In this chapter, we discussed the history of food dietary intake assessment in detail. Moreover, this review demonstrates the advantages and disadvantages, generally and specifically, for each device. In fact, the old methods of food assessment showed several weaknesses that made them completely unsatisfactory when used. While new measuring instruments showed—especially image-based analysis—very satisfactory results, even they have drawbacks. It is possible to overcome the drawbacks and improve those systems. It is obvious now that using electronic devices to assess food intake is a real option for both users and dietitians because it is superior to paper-based dietary assessment methods. Moreover, it is now clear that the developing image-processing methods and volume-estimation approaches will aid in the improvement of these devices' quality.

Chapter 3 - System Components

The structure of the food database is the main point for building and testing our system [51]. This chapter presents the technical and scientific aspects that we took into consideration when we built the system. Those aspects are the usage of calories and nutrition tables, food density tables, image processing, shape recognition as a part of image processing, and classification with the SVM.

3.1 Calories' Definition and Nutritional Tables

A calorie (Cal.) is a typical measuring unit defined as the amount of heat energy needed to raise the temperature of 1 gram of water 1 degree [52]. This unit is used to measure the overall amount of energy necessary for life processes in any food portion that consists of the main food components, which are carbohydrates, proteins and fat. Each element has a standard amount of calorie per gram. The number of existing calories in carbohydrates and proteins is 4 kcal/g, while in fat, the number of calories is 9 kcal/g. Besides grams, calories are adopted in nutritional facts tables.

Calorie intake must rely mostly on the weight of the individual, his or her daily activity, age and gender. Each person should daily consume a certain amount of calories. If the amount of calories expenditure is increased, it will lead to weight gain and, therefore, the risk of obesity. Thus, all nutrient facts tables should include the number of calories plus other facts for any food categories or any food item. In our system, we will use the nutrient fact tables and the amount of calories for each type of food as a basic criterion, and this will allow us to find the amount of calories in a food image. In fact, the FRS relies on the already established nutrient fact tables as a reference to estimate the number of calories from any selected food photo. These data are stored in the system database in tables. Table 2 shows a sample set of nutrient facts for some types of food from Health Canada nutrient guidelines [53].

Table 2: Image of Nutrient Table Sample

Food name	Measure	Weight (g)	Energy (Kcal)	Protein (g)	Carbohydrate (g)	Fat (g)
Apple with skin	1	138	72	N/A	19	N/A
Potato	1	135	116	2	27	N/A
Chicken, ground	75	75	135	16	0	9
Orange	1	131	62	1	15	N/A
Peach	1	98	38	1	9	N/A
Bread, white,	1	35	93	3	18	1
Zucchini	125	95	15	1	4	tr
Steak	75	75	181	23	0	10
Chicken breast	75	75	142	19	0	7
Cheddar cheese	50	50	202	12	1	17

3.2 Food Density

The term of density, ρ, is described as the mass of any material per volume. Alternatively, it is defined as the ratio of any food element's component to the calorie. In the case of foods, there are many different types of density depending on the relationship between volume and mass. Those types are true density, solid density, subdivision density, apparent density, and bulk density [54]. In particular, true density represents the density of pure elements that result from the calculation of the food component densities with preservation of mass and volume. Solid density represents the elements divided into very small parts to make sure no pores appear. Subdivision density is known as the density of material that has not been changed in it is internal construction and includes the density of the internal pore without taking into account the external pore. To calculate the density in apparent density, all internal and external pores must be considered. Bulk density is defined as the total density of the material if packed or the mass in the total volume occupied.

Bulk density is considered the suitable type of density to use with the image-processing approach. The pictures that were used for food volume estimations were captured by a digital camera or cell phone camera, which indicates that the food volumes were measured with the internal and external pores included. Food density tables can be found online or in the Health Canada food guide. Food density can also be obtained from readily available tables [55].

3.3 Image Processing

Image processing is a form of signal processing in which an image, picture or frame from a video is processed to produce another image or a set of information, parameters or specific data obtained from the characteristics of the initial image to be analysed. In our case, we used image processing to analyse the two-dimensional signals inside the data of the image to define the contours of the food in the image, perform a segmentation and a measurement of the objects to obtain an approximation of the real-life size of the portions, and finally allow the nutritional facts calculations with the information obtained from the image processing procedure.

An image or a set of images is used as input of the FRS (re-image) plus the objects present inside each photo (the thumb). These images are analysed by signal processing, and the outcome of the image processing is another image, images, or a set of features extracted from the original images. The pre-processing action comprises colour, texture features and, size and shape. Many tests and trials should be done to achieve the desired result image processing requires. To get satisfactory results for any digital image, each image contains a set of elements or pixels, namely x and y. Each pixel has it is own value that show its location in the image.

3.4 Shape Recognition as a Part of Image Processing

Shape recognition is a sub-area of image processing focused on the definition of different type of characteristics achieved from each object present inside an image. Among others, the most common characteristics obtained are area; edge; size; Euler number (E), where E is defined by the number of connected components (C) and the number of object holes (H); and H is given by E=C-H and the geometric attributes shown by the shape if the silhouette of the object is closely related to a standard geometrical form, like regular shapes such as a circle, square or triangle. From probability theory, the (m, n) moment of the probability density given by f(x, y) and applied in Hu's seven moments for visual pattern recognition can also be calculated for a specific object. Its shape will define the numbers gained by this calculation. This subset of results will define results exclusively related to each shape [56].

3.5 Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a widely used computer algorithm to assign labels to any objects via training diverse of cases. Moreover, it is also used to estimate the resulted error performance to increase classification accuracy. Alternatively, it is used to identify food items after the segmentation level. The SVM method is noticeably successful in pattern recognition, especially in the recognition area [57]. In other words, the SVM is a classification device that uses machine learning theory to increase accuracy assumption to automatically appropriate the stored data into the best group. Compared with the neural network uses in the same area of recognition such as in [58] the SVM will give more accurate results to our FRS in the classification stage.

3.6 Summary

The FRS is an application that relies on several techniques. By applying all the previously mentioned aspects, we can reach our main goal, which is estimating the amount of calories from any image of food. The available nutrient facts table, food density table, and segmentation and classification with the SVM will improve the level of accuracy in our system. In the following chapter, we will start to explain the first phase of applying those aspects to build the FRS.

Chapter 4 - System Workflow and Description

Regarding the FRS workflow and description, we will use a mobile device with camera that supports a wireless connection to store the nutrient data in a centralised database connected with a hospital database with the help of image processing and shape recognition. The wireless connection will not be used in the image processing analysis part, like previous methods mentioned in the related work part. Moreover, beside the ease of use and many features, using mobile phones in our method will excite and encourage the user. In this chapter, we will explain the behavior of each component in our system and the interaction scenario between the user and the system and the system itself.

4.1 System Environment and Components

The environment of the FRS has three main components, which are the user, the dietitian and the system itself. The following is a detailed explanation of each component.

4.1.1 System User (Patient)

The user starts by placing his or her thumb near the dish. Then, the user captures a photo of the prepared food item to be used in the measuring procedure. The measuring technique based on using the thumb in a photo capture is significant in our system. As mentioned before, the thumb is considered a typical standard for estimating the size of the selected food item. Compared to previous measuring methods such as PDAs and the calibration card, the thumb is a more flexible, controllable and stable standard because our system is designed to store the patient thumb since the first use to be recognised during system deployment. Note that, in the case of the inability to use the thumb, the system user can use a coin instead of the thumb when he or she takes the photo.

Moreover, the user is responsible for selecting the type of food from the installed data in the mobile. This step will make the identification of the food more accurate. For example, if the user captured a photo of a dish containing chicken, the user will be responsible for notifying the system about what type of meat it is by choosing from the stored data. Figure 3 shows the user (patient) interaction in the system.

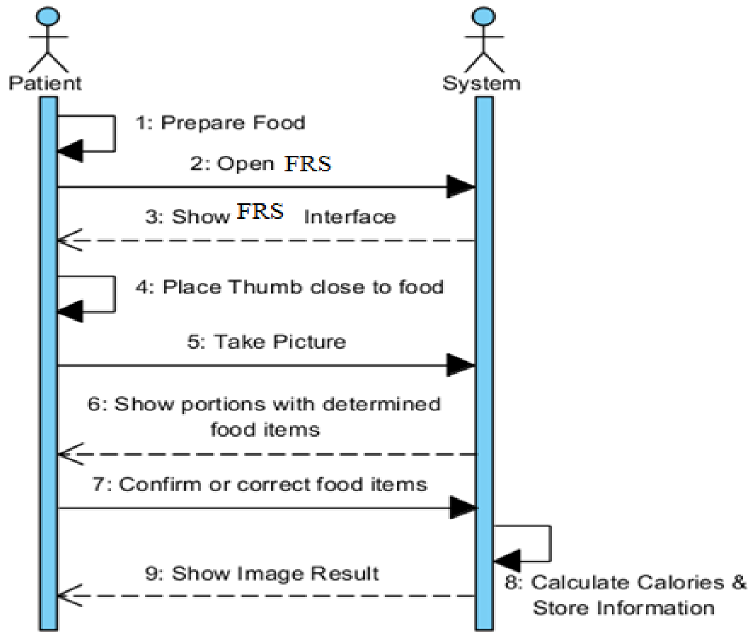

Figure 3: User interaction with the FRS [59]

4.1.2 The Dietitian

Our system will allow the dietitian to enter and store the therapeutic food plan for the user and request the daily caloric intake, so the system will notify the user if he or she exceeds the daily calorie limit. Also, the dietitian can regularly monitor the user's food intake and verify that caloric consumption has not been violated. Figure 4 illustrates the interaction between the doctor, the user and the FRS.

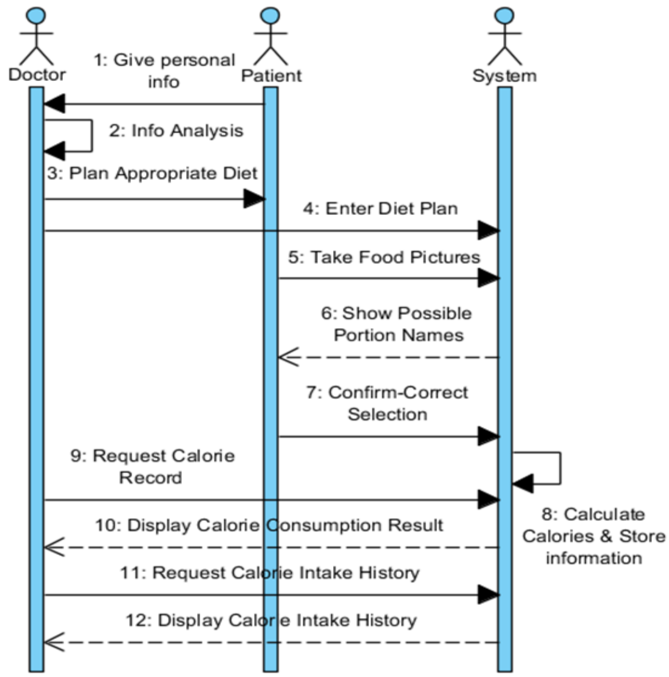

Figure 4: The interaction between the doctor, the user and the FRS [59]

4.1.3 The Food Recognition System

The FRS can be represented as an application that has a user-friendly graphical user interface in a mobile device that contains a camera. Generally, the function of our method is to capture a photo for the selected food by using the patient's thumb as a measurement reference to calculate the amount of calories and nutrient values with the help of nutrition fact tables as a database. The FRS is a combination of colour segmentation scheme, which only engages mean-shift colour segmentation, with a thumb measurement method. For a more accurate food intake measurement system, we engaged texture segmentation and the SVM classification scheme [62]. All the previous procedures must take place before the volume estimation part.

Our system is generally considered a liaison between the patient and nutrition specialist. Figure 5 illustrates how the FRS links the user and the doctors.

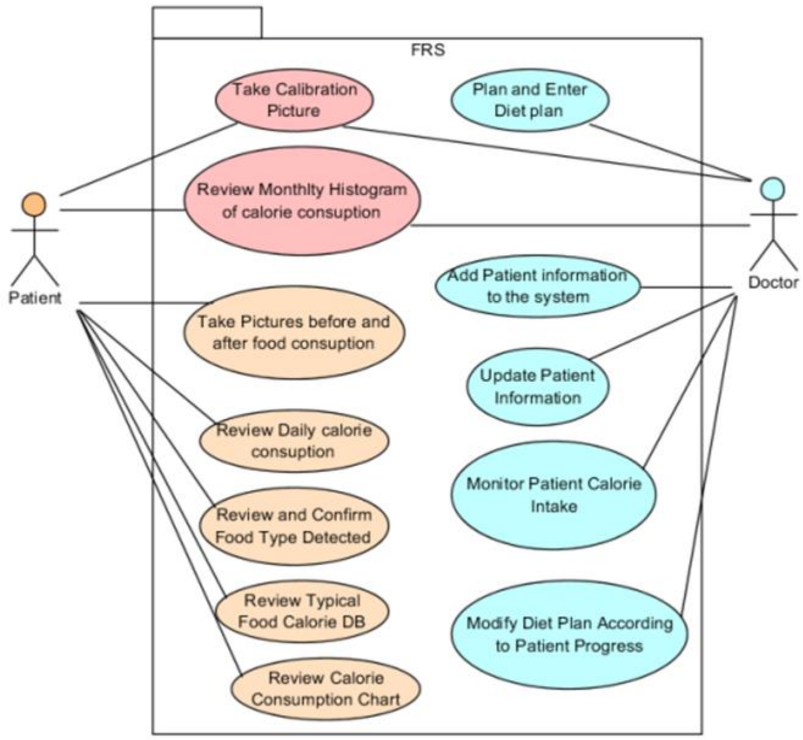

Figure 5: The FRS links between the user and the doctor [59]

4.2 User Interface of the FRS

Early [58], we developed the Graphical User Interface (GUI) of the FRS in IOS SDK, which is the user interface of the standard software development kit for iPhone applications released by Apple Inc. Figure 6 shows a snapshot of the user interface of the system. The use of the FRS starts with a dietitian; he or she must upload the patient information, such as the file number, name, weight, starting date, the weight target or goal, information regarding the diet plan of the patient, and the allowed calorie consumption for every day. Figure 7 displays the interface where the dietitian inputs the patient information.

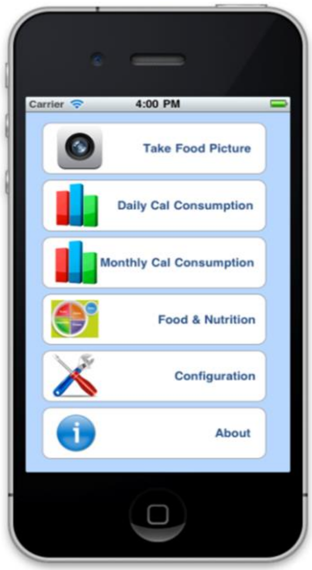

Figure 6: The user interface of the system [59]

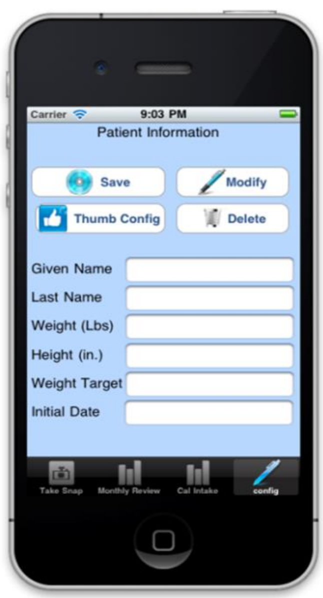

Figure 7: The GUI, where the dietitian can upload patient information [59]

After that, the patient should take a picture for his or her thumb separately to store the size of the thumb as a reference, and this feature or proposed method will give us more accurate results for calculating the dimensions of food portions. Moreover, the user or the patient also will have the choice to present the scopes of the thumb in centimeters or inches, to perform the corresponding size translation. Our proposed system depends on the first-time calibration by entering the thumb dimensions as shown in Figure 8.

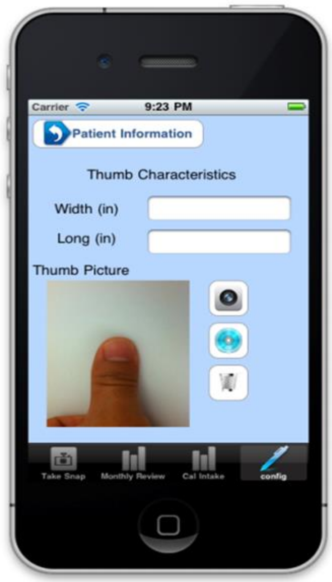

Figure 8: Thumb calibration [59]

After the previous step, users can start utilising the system. (The previous step can be done by the user himself or herself. Before eating any meal, the user captures a photo of the food with his or her thumb in a suitable position near the dish [59]. As mentioned before, the user must capture two images from the top and side. Figure 9 shows the technique of the photo capture by using the thumb.

Figure 9: A snapshot of the FRS GUI showing the food with the thumb [59]

Overall, after the picture is taken, the FRS starts to process the image to detect the plate and segments several types of food on the dish based on different colours and features on the plate. In the first stage, the system will ask the user to identify the type of food after comparing the food items in the image with the stored data that contains types of food with colour features, as in Figure 10. This step will appear in the case of misclassification only. With every use, the SVM will classify the data. The system can display the results in different formats as requested by the user. Figure 11 shows a pie chart and value chart of the nutrition intake during a specified interval [59].

Figure 10: The system allows the user to define the type of food with default values.

Figure 11: calories daily consumptions and the allowed intake values [59]

4.3 Summary

In this chapter, we presented the design of the FRS and its components. Thus, we clarify in details the GUI for our system after first-time usage and the adaptation methods between both the system and user (either patient or dietitian). Designing a simple and clear GUI will encourage the user to use the system regularly and will maximise all the advantages of such a system.

Chapter 5 - Proposed Methodologies

In this chapter, we will discuss all the methodologies used in the construction of the FRS. Meanwhile, we will deeply explain each principle we applied to build the system. We will define a method to estimate the number of calories from an image by taking the advantages of some concepts that we explained previously. First, we will go through the references that we applied to our system to extract the measurements in an easy, unique way. We will explain the correct techniques to use this method to get the best results. Then we will explain how we used the result from the first analysis stage to estimate volume so we can continue our calculation correctly. A full block diagram of the general proposed method is shown in Figure 12.

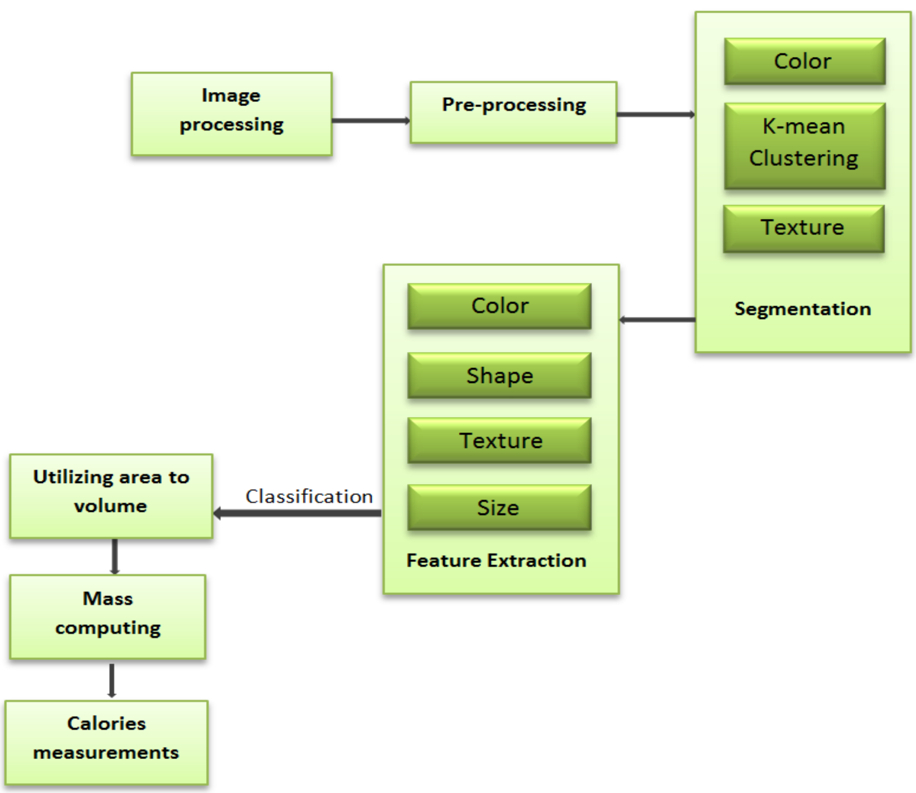

Figure 12: Overall architecture of the FRS procedure

5.1 Image Processing

Once the picture of the food is captured by the user, the image is transformed and prepared for the next step, which we will explain in the following subsection.

5.2 Pre-Processing

In the beginning, a simple conversion must be performed on the image to change the image size into a standard format for precise results for system segmentation. Thus, the size of each image will be compared with standard size categories. We have defined one size category as a standard, which are 970 × 720 pixels for simplicity. Larger images will be reduced to this size before accomplishment of any image-processing technique [61].

5.3 Image Segmentation and Feature Extraction[1]

The segmentation phase starts immediately after analysing the pre-processing step. This part will operate with four different features: colour, texture, shape and size, on which we are mainly concentrating in this project. These parts also include the calculation in pixels of the thumb and its size in pixels by using a Gaussian edge detection filter and then the skin detection scheme. The extracted size will be used in transforming the pixel size of food portions to actual, real-life size. In addition, the colour feature will be extracted by using the colour histogram, while the size feature will be extracted by including the pixels in the Region of Interest (ROI) for each food portion. Moreover, this will give us the shape feature which will be used in our calculating method.

5.4 Classification by SVM[1]

Classification with the Support Vector Machine has been done. The extracted features previously mentioned will be fed into the SVM classifier so that the classifier returns the food name as its output. For each feature, there will be training and testing phase. In fact, the aim of using the SVM in the FRS is to produce a system that can predict or guess the board value of data cases in the testing set, which are just given by their characteristics. To

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[1] Parisa Pouladzadeh performed this work.

increase accuracy and reduce misclassification, the system can interact with the user to verify the kind of food portions, and the user can then settle or alter the food type as mentioned before. The use of SVM method in this model contains five texture features, ten colour features, three shape features, and six size features. All the features of each food item are extracted during the segmentation phase. At the same time, it will be used as training vectors for the SVM. This step is essential for the FRS to calculate the amount of calories. Classification with the SVM provides the system with the type of food [62].

5.5 Using the Thumb as a Reference[2]

The FRS is based on a new measuring technique, which involves the user's thumb in the captured photo. This technique has an important contribution in our system. Besides the ease of use and availability everywhere, the thumb is considered a typical standard to analyse the dimensions of the selected food item in our system. Actually, placing the thumb in the selected image will permit us to calculate the amount of calories by converting the 2D image to a 3D image. The user will identify the thumb from the first-time usage (one-time calibration), and the size of thumb will be a standard measurement that will be compared to all the extracted food sizes entering the system. In details, the extracted food area will be compared to the thumb including all features, such as colour and size.

The calculation will start by finding the binary large object corresponding to the thumb blob, and consequently, the number of pixels can be extracted, noting that, with each image, we have defined the ROI to get more accurate calculation results of the thumb inside the image. Figure 13 shows the method of calculating the dimensions of the thumb; the resulted dimensions of the thumb and the plate will be in pixels. Therefore, we need to convert the size extracted from the image to real-life size to have the right calculation results and consequently provide the user with appropriate outcomes

[2] Gregorio Villalobos performed this work.

In the following subsection, we will explain the method of image capture by using the thumb as a reference.

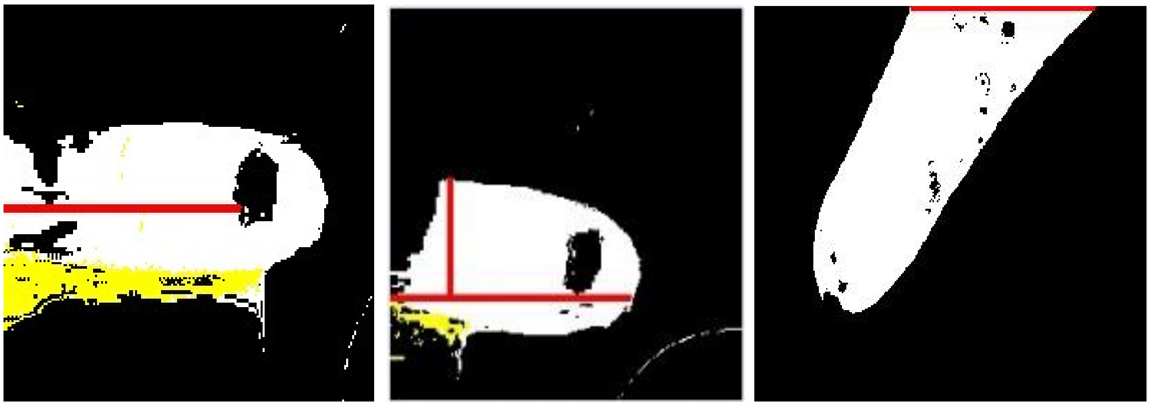

Figure 13: The method of calculating the dimensions of the thumb

5.6 Technique of Image Capturing

As mentioned in the previous section, a person's thumb can be used to calibrate the image and analyse the dimensions of the selected food item.. First, the user will capture two photos of the selected food, one from the top and the other from one side of the dish, with his or her thumb placed in the photo. Figure 14 shows a captured food image with the position of the thumb. The application, which already has the dimensions of the user's thumb as mentioned before, analyses the pixels of both the thumb and the food from the first photo (top view). Then this area will be used with the other dimensions of the food from the second photo (side photo) to generate the volume. We presented the concept of using the thumb for calibration instead of using a card [47]. As well as its implementation and evaluation in [59] and [60], we will explain in detail how to obtain volume from the selected image in the following section.

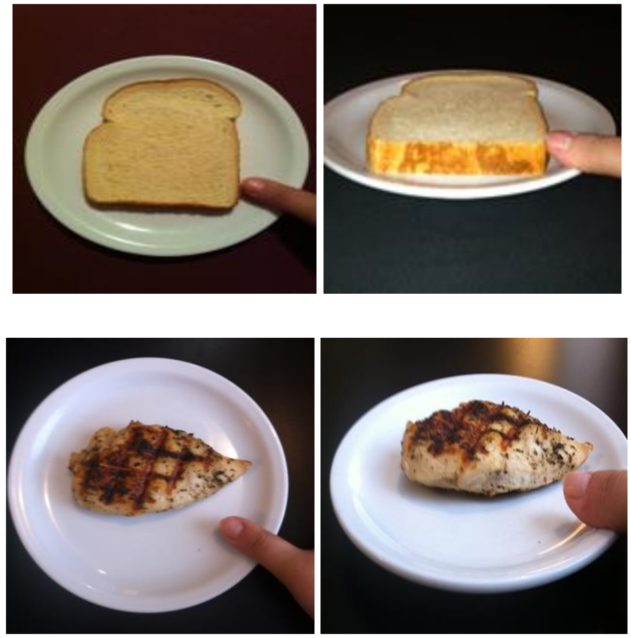

Figure 14: A captured food images with the correct position of the thumb

5.7 Obtaining Volume by Utilising Area Size

The estimation of food volume through an image is a major challenge in dietary intake assessment applications. In this section, we will examine the methodology of obtaining the volume of any food image by utilising the area size that has been extracted from the photo after the image analysis and the shape recognition process. As soon as the photos of the selected food are captured, the application starts to analyse the pixels of both thumb and meal from the first photo (top view). The main resulting value from this calculation is the area size (height and length) in pixels, which will be used with the other dimensions of the food item from the second photo (side photo) to generate the volume (width). Finding the volume of the photo leads us to easily calculate the amount of the calories in the selected food via a special algorithm that depends on the nutritional tables stored inside our application. In the next subsections, we will elucidate in detail how we calculate volume in irregular and regular shapes.

5.8 Volume Calculation of Irregularly Shaped Food from an Image

Of course, the vast majority of food can be classified as having an irregular shape. To calculate the surface area and the depth for a food portion, we overlay a network of squares into the image segment (grid) so that each square contains an equal number of pixels and, consequently, equal area size. There are two reasons behind the usage of the grid in the image segmentation: First, compared to other volume estimation approaches, involving the grid will make the calculation more easily match either regular or irregular food shapes, such as toast, a chicken leg, steak or a piece of cheese. Obviously, there will be some estimation errors as mentioned earlier, but these errors can be reduced by making the grid finer. Second, having the grid in the image can affect performance in binary ways:

- Late but more accurate recognition and response to the user in the condition of having an admirable network shape or
- A faster but less accurate response in the condition of having a rougher network shape.

All this is due to the capacity of smartphone data storage. Figure 15 illustrates an example with an actual food portion. The total area (TA) of the food portion is calculated as the sum of the sub areas (Ti) for each square (i) in the grid, as shown in the following equation:

$$TA = \sum_{i=1}^{n} T_i \qquad (1)$$

Where n is the total number of squares in the food portion's area. After that, and by using the photo from the side view, the system will extract the depth of the food, d, to calculate the volume, V, using the following equation:

$$V = TA * d \qquad (2)$$

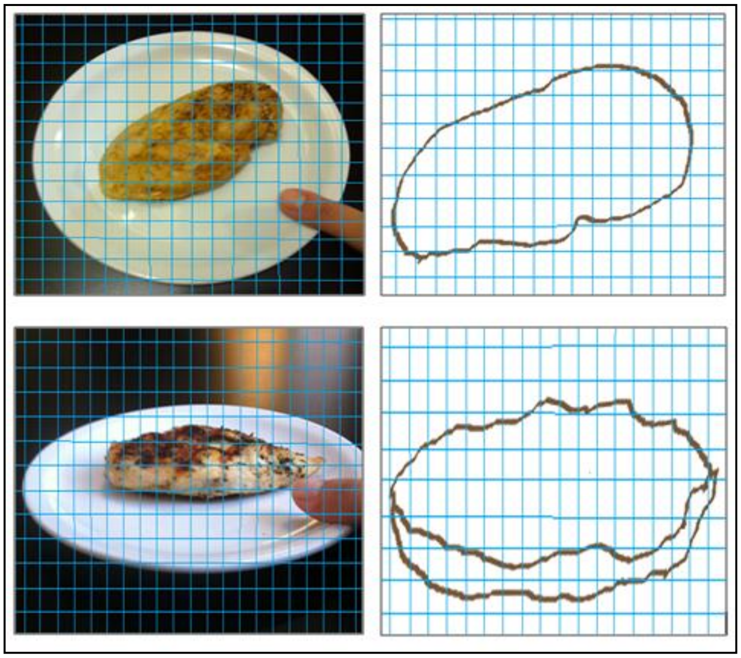

Figure 15: Method for food portion area and volume measurement in irregular shapes.

5.9 Volume Calculation of Regular-Shaped Food from an Image

Some types of food have regular shapes such as sliced cheese or toast. In case of regular shapes such as a square, circle, triangle etc., we can use linear formulas to calculate their area, instead of using a grid. This, however, requires an additional module that can recognise regular shapes. Figure 16 illustrates some sample calculations for regular shapes in a set of different food images.

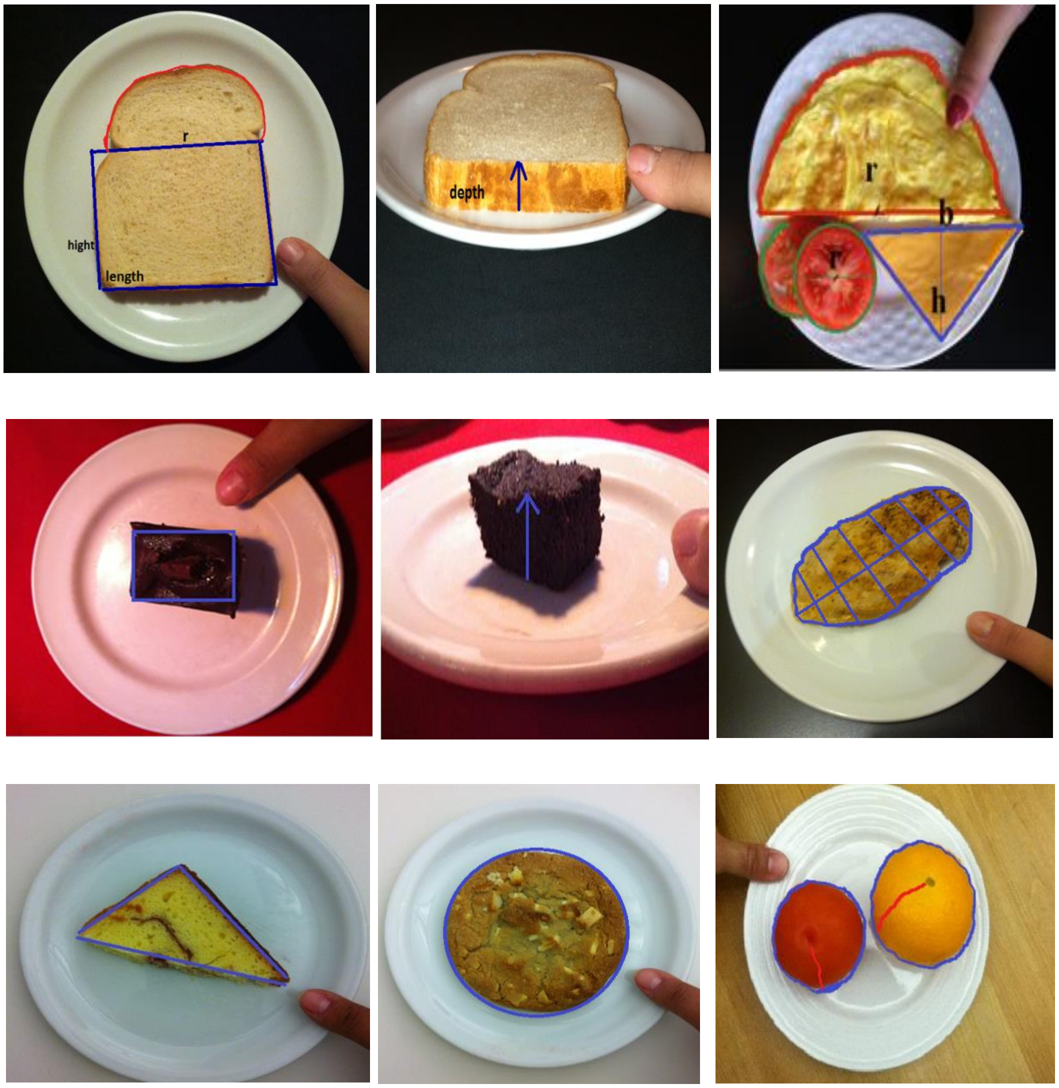

Figure 16: Calculating area and volume of regular shapes in food images [59]

The calculation of area and volume in the food image is just the first step that will allow the FRS to compute the mass of the food and consequently calculate the amount of calories through the food image. We will explain in detail the method of calculating mass in the following sections.

5.10 Computing Mass

Measuring the mass of food in the picture is the interval step that will lead us to finding the amount of calories since each type of food has a specific amount of calories depending on its weight. For example, if an apple's weight is 138 grams, the amount of calories is approximately 70 calories. If the apple weighs 90 grams, the amount of calories will be about 35 calories. Additionally, all the nutrition tables that we rely on in our FRS as a standard are based on the mass of food. The knowledge of the food dimensions inside the image, as mentioned before, will give the system the ability to calculate the mass of the food in the image through applying the following general mathematical equation.

$$M=\rho V \tag{3}$$

Where M is the mass of the food portion, ρ is the food density, and V is the food volume extracted before from the image, plus the user's thumb inside the photo. (Note that thumb size is always fixed in the picture). After all the previously stated procedures (pre-processing, image processing, shape recognition and SVM classification), the FRS can easily estimate the mass of any food inside the image. The measuring unit will be in grams, like the tables in real life.

5.11 Calories' Measurements and Estimation

The main objective of the FRS is to estimate the amount of calories and nutrition values for any food type from an image. Thus, caloric estimation is the main, final stage for our system. In fact, the importance of using the already stored nutrient fact tables will also appear in this stage. In general, the system starts to calculate the calories by comparing the inputs from the image (mass) with the inputs from the nutrient tables (mass measured by gram and calorie amount, which is measured by calories), which are already stored in the application's database. We propose a novel method to measure and estimate the amount of calories in any image. As mentioned before, this method depends on the association between the standard stored variables in the nutrient fact tables such as calories, food weight and nutrient values with the known variables extracted from the image to calculate the unknown variables, which are mass and calories. After image processing, pre-processing, SVM classification, and volume and mass calculation, we can apply the following proposed method:

$$\textbf{Calorie in the photo} = \frac{Calorie\ from\ nutrient\ table * mass\ in\ the\ photo}{Mass\ from\ nutrient\ table} \qquad (4)$$

By applying that equation, the FRS can straightforwardly identify the amount of the calories in an image containing food. It is vital to notice that, in some cases, the user will not finish all the food on the dish. Thus, a third picture must be taken to have a better assumption of the amount of calories. In this stage, the user must take a picture of the dish, including the leftover food, from the top. All the previously mentioned procedures will be occurring in this step. Last, the system will compare the final results with the extracted result from the general stage. The differences in calories will be calculated and given to the user as the final result. In the following chapter, we will evaluate our method and show the high accuracy of our results.

5.12 Summary

In this chapter, we have presented the methodologies and techniques of volume estimation and calculation from any image containing food in any shape after image processing and classification. In our FRS, we innovate a new method to extract volume from a photo. This method relies on a new technique, which is using the thumb as a reference object. Users placed their thumb beside the selected food before taking the picture. The picture will be taken twice from different sides, one from the top and the other from the side. The resulting data (area, depth) which will be in pixels and must be converted to the suitable measuring unit will be used to calculate the volume of the food. In addition, in the calculation part, we suggested two methods, which are calculating volume for irregular shapes and calculating volume for regular shapes. Moreover, we presented the implementation of each of the concepts that we used to build the FRS. Our main goal in this part of the project was finding a method to fill the gap between image processing, the classification by SVM and the food portion estimation. We suggested a method to estimate the mass of the food inside any image; in fact, calculating the mass of the food portion led us to propose a method to calculate the amount of calories and nutrient values with the assistance of nutrition fact tables.

Chapter 6 - Evaluation and Performance Analysis

To evaluate and test our proposed methods, we started our experiments by taking a real photo of dishes containing food by using the iPhone 4 or any similar device. Hence, we started testing the images with a thumb one by one to estimate the colour and the size of the food. Several approaches have been adapted in our system to recognise the thumb inside the image and the food itself. We use the colour space YCbCr approach to recognise the pixels related to the thumb inside the image, no matter where the thumb was[2]. In addition, we combined two approaches, the k-mean colour clustering method and the mean-shift segmentation method, to get more accurate results in the colour segmentation phase[2]. Then we applied counter-detection to extract the food portions and identify each part of the food by its colour. To get more accurate results, we used Gabor filters to measure texture segmentation. Simultaneously, we used SVM classification to identify the type of food [63], regarding which we proposed a method that contains several vector features, including texture, colour, shape and size. In fact, this training method will help the FRS to measure and estimate the volume and the amount of calories for any food portions inside the image. Figure 17 illustrates the entire procedure of image analysis, segmentation and colour texture for different food images. After all the aforementioned processes, the system will be ready to identify and calculate the volume and the amount of calories of the selected image. In fact, in this thesis, our main restriction is how to extract size from an image and how we find the amount of calories in the food image through volume extraction.

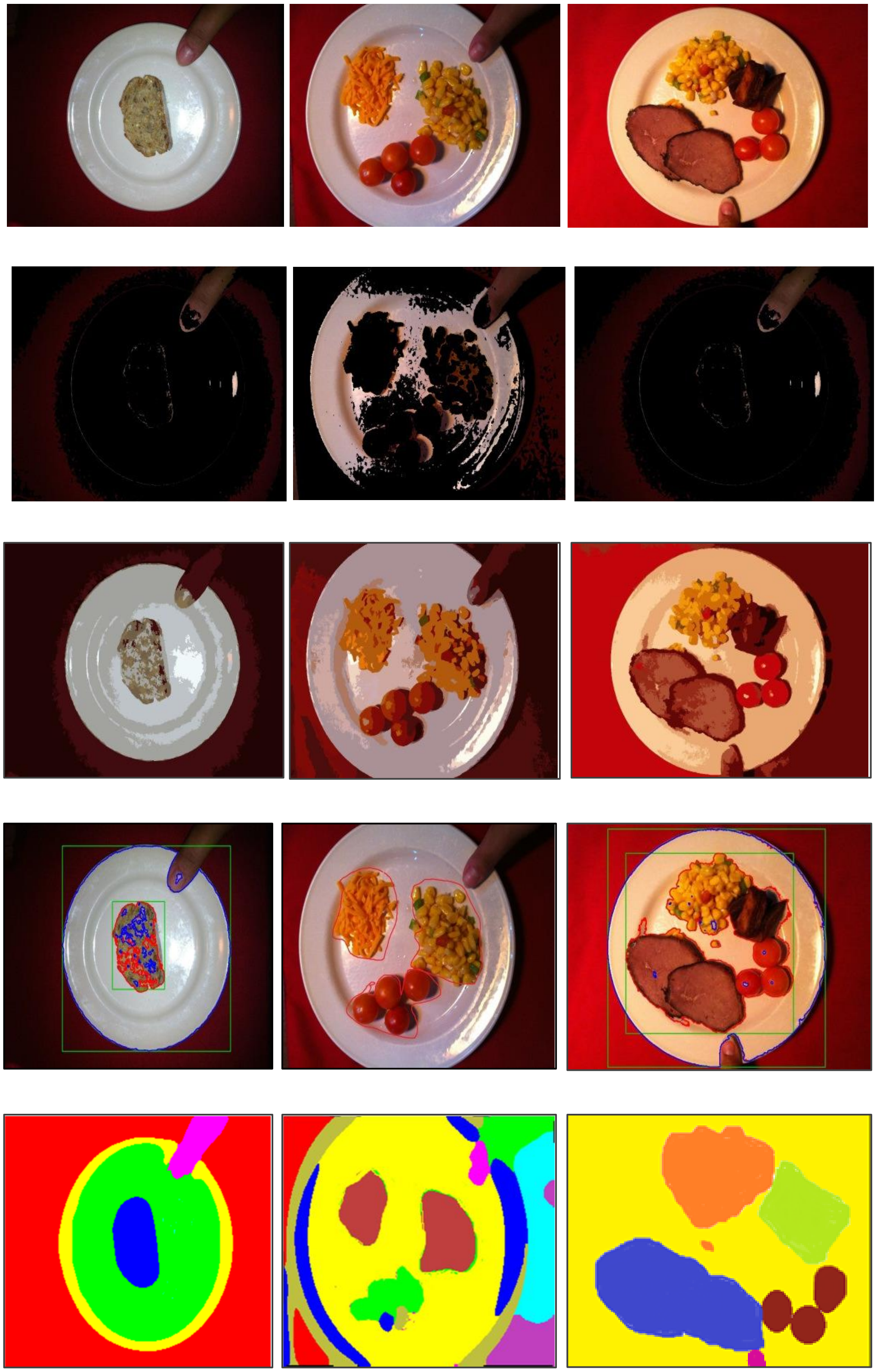

Figure 17: The procedure of image analysis, segmentation and color texture for different food images

For our experiment, we tested the proposed method in two ways. At the beginning, we created special software, and we tested more than 100 kinds of simple food. We applied the proposed method after the end of the image processing and classification phases. But before this, we measured every type of food manually to verify the validity of the results given by the proposed method.

After image processing and classification, we started to estimate the volume of the food from the image. As mentioned in Chapter 5, the system will provide us with the colour, textures and size features. It is also will provide us with height, length and depth for each portion, including the shape of the food. We applied all the mathematical formats and equation related to volume calculation for any geometric shape such as cube, sphere and so on.

In addition, we applied our proposed method to calculate the volume for irregular shapes, so we separate the shapes into regular shapes by drawing grids. In other words, the system will deal with irregular shapes by splitting them into small squares, calculating the area of each part separately and calculating the integration of all the squares. As stated previously, the given measurement unit will be in pixels, and we must convert the measurements to centimetres or Quebec centimetres to convert the pixels to real-life size. We can also take a fixed image containing the same number of pixels, considering one pixel equal to 1 cm. Table 3 shows the results of calculating the volume of different types of simple food.

Table 3: The results of calculating the volume of different types of simple food

No.	Food item	Volume	No.	Food item	Volume
1	Bread	42.9	**16**	Fish (filet)	23.2
2	Apple	44.6	**17**	Chicken breast	18.6
3	Orange	85.6	**18**	Cheese (slice)	81.1
4	Steak	12	**19**	Sauce	20.6
5	Bread/toast	8	**20**	Pasta	50.2
6	Brown bread	7.3	**21**	Red Beans	22
7	Cake	4.6	**22**	Corn	14.31
8	Spaghetti	55	**23**	Green Pepper	34.7
9	Cookies	14	**24**	Chocolate Cookies	10.5
10	Omelet	18	**25**	Marble cake	8.24
11	Carrot	2.2	**26**	Rice	18.7
12	Cucumber	2.1	**27**	Cabbage	202.4
13	Potato	13	**28**	Lettuce	8.3
14	Banana	6.9	**29**	Fish (filet)	16.9
15	Tomato	34	**30**	Chicken breast	304.2

After calculating the size, we started applying the proposed method to compute the mass of the food inside the image. Thus, we used the known variables, which are volume and food density, to calculate the mass. We also measured and weighed all the selected food manually to ensure the validity of the proposed method at the same time. Thus, finding the mass of the selected food allowed us to calculate the amount of the calories and this is simply by applying our proposed equation that allowed us to compare the amount of calories and mass in the standard tables with the estimated results. We noticed that, by applying this method, we reached a reasonable error percentage of less than 15% comparing with amount of calories in the standard nutrition fact tables. The following Table 4 contains a variety of food for which we estimate the amount of the calories from an image by applying our novel method.

Table 4: The results of calculating the calories of different types of simple food

No.	Food item	Error percentage (%)	No.	Food item	Error percentage (%)
1	Bread	1.8	**17**	Carrot	10.23
2	Apple	11.37	**18**	Tomato	12.5
3	Orange	14.5	**19**	Fish (filet)	3.9
4	Steak	9.11	**20**	Chicken breast	8.3
5	Bread toast	1.6	**21**	Cheese (slice)	2.4
6	bread	4.22	**22**	Sauce	7.2
7	White Cake	2.30	**23**	Pasta	12.8
8	Spaghetti	-3.07	**24**	Red Beans	1.1
9	Cookies	0.50	**5**	Corn	4.9
10	Omelet	10.5	**26**	Green pepper	4.78
11	Carrot slices	2.3	**27**	Chocolate cookies	2.3
12	Cucumber	2.01	**28**	Marble cake	8.4
13	Potato	11.72	**29**	Rice	13.3
14	Banana	11.45	**30**	Cabbage	11.2
15	Doughnuts	6.1	**31**	Bread (multigrain)	7.1
16	Tomato	12.67	**32**	Lettuce	3.2

6.1 Performance Analysis

The aim of this subsection is to analyse and evaluate the results from our experiments. Our experiments show that the accuracy level varied from one type of food to another. Based on this, the level of accuracy results can be divided based on the outcomes we extracted from our measuring method to high, regular or medium, and low accuracy. Figure18 shows a graph of each accuracy level. In the following, we will talk in detail about each type of accuracy.

6.2 Food with High Accuracy Results

After calorie estimation, we found that some types of food gave high accuracy results with less than 5% error, including bread, cookies, fish and some food cut into small parts, such as carrot slices, cheese, a cucumber and a piece of cake. We noticed that those types of food are more likely in regular and simple shapes, or they can be divided into parts as regular shapes such as a square, circle or triangle. Moreover, foods that have almost no depth provided a highly accurate result, better than other types with large depth.

6.2.1 Food with Medium Accuracy Results

The experiment showed that some types of food, such as steak, multigrain bread and doughnuts with chocolate on the top, provided results that can be categorised as medium accuracy; the margin of error ranged between 5% to 10%. We noticed that those types of food most likely have a regular shape or can be divided into parts regularly and with reasonable depth. Additionally, those types of foods cast a shadow on the plate, which increases the error when calculating the area.

6.2.2 Food with Low Accuracy Results

Other types of foods, such as apples, oranges, tomatoes and potatoes, showed a weak response and low accuracy results. The error rate ranged from 10% to less than 15%. We found that the high error rate is due to several reasons, including the food shapes, such as foods that take spherical or conical forms where the aspect ratio is very large. This will affect the expanse of the area. As well, some types of foods, such as rice and cabbage, yielded low accuracy results due to the colour feature, which is quite similar to the colour of the dish. Furthermore, some types of food may have great size, but occupy a small space.

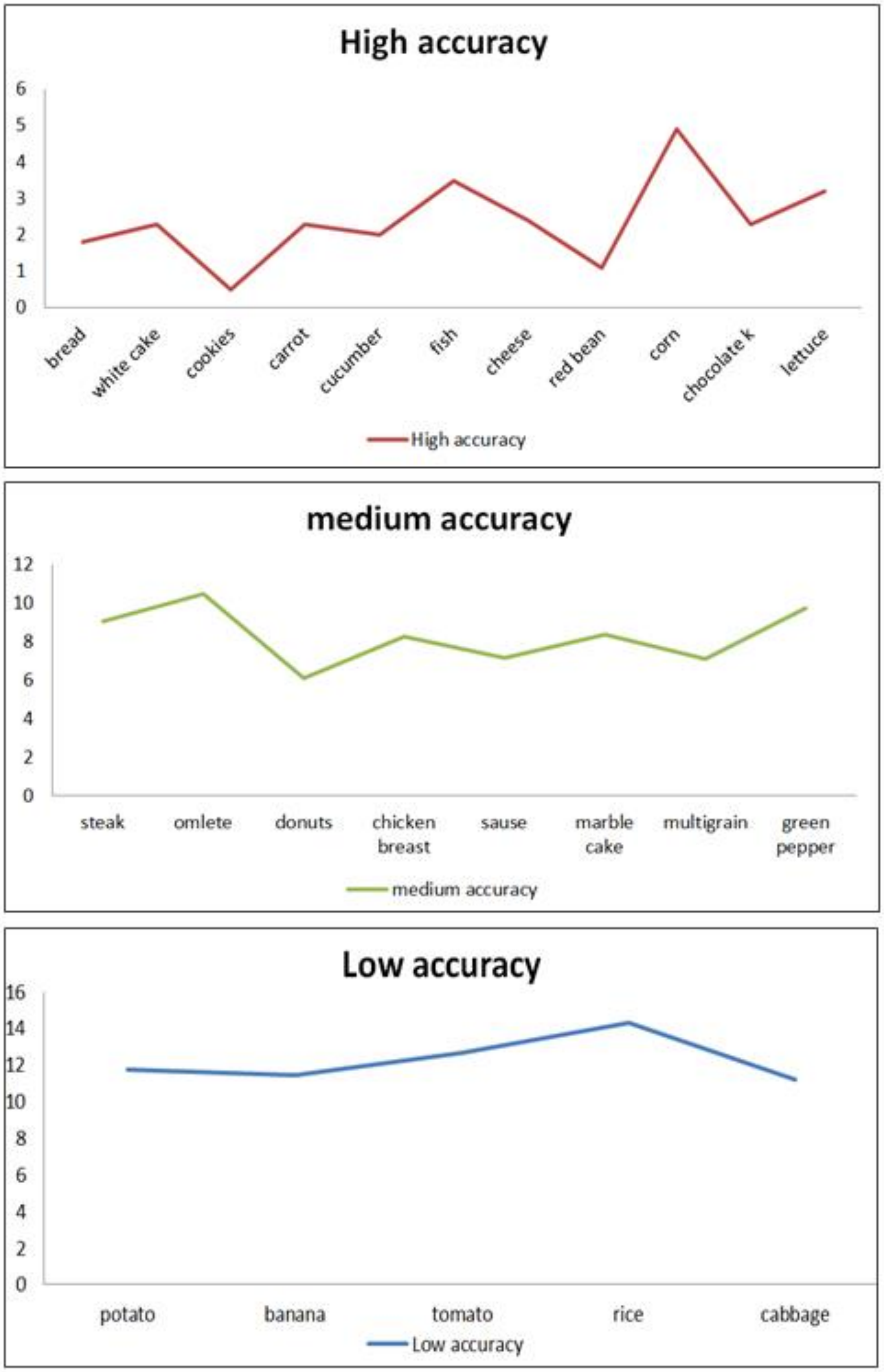

Figure 18: Graph illustrating the three accuracy levels

6.3 Summary

In this chapter, we aim to evaluate and test all the proposed methods that we used to build the FRS. By applying all the approaches starting with image processing, classification by SVM, volume, mass and caloric estimation, we calculated the amount of calories in different types of food images with a reasonable error percentage. Finally, we categorised the level of accuracy depending on the results we extracted.

Chapter 7 - Conclusion and Future Work

The FRS is an application directly related to the dietary intake assessment applications that take advantage of image processing and pattern recognition to calculate the volume of the food in any selected image and thus estimate the amount of calories and nutrient values. In this chapter, we will conclude the work in this thesis and review its contributions. Then we will propose probable directions for future work.

7.1 Discussion

The need to have a system that measures daily food intake is crucial due to the increase of obesity rates around the world and to solve the problem of under-reporting in dietary intake assessments. In addition, estimating food volume and caloric assumptions are considered challenges when designing any dietary intake applications. Therefore, in this thesis, we proposed a measurement method to estimate the amount of calories from any food images through measuring the volume of the food portions inside the image. To reach our goal, we designed the FRS application, which can be used on mobile devices and tablets.

To use the system, the user must take two images containing the selected food plus the measurement reference, which is the person's thumb: one from the top view and one from the side. Then the system will start analysing the image by using several concepts, which are image processing, re-processing, shape recognition, image segmentation and SVM classification. Our main focus in this thesis was in utilising the volume from the estimated area by image analysis, and after that, calculating the mass of the food to find the amount of calories. We proposed a method to calculate the volume for different food shapes, and we continued to calculate the mass and the calories with another proposed method. To have a result that is more accurate and to ensure the validity of our method, we measured the food in two ways: manually and after image processing.

We have verified that our proposed measurement pattern method is practical, controllable with the use of nutrient fact tables as standard data, and our extracted results can increase the optimistic potentials of the FRS. All this will encourage the user to employ the system. Consequently, this will increase the amount of food reported by the patient and will generate more historical data to the dietitian to analyse and control a diet. Moreover, by using the FRS in any smartphone, the problem of under-reporting will be reduced, and the patient will have the ability to create an effective diet plan. Our results showed reasonable accuracy of our method in area measurement, and successively, volume and caloric measurement. We reached reasonable accuracy results with less than 15% error. Our experiment gave us the ability to classify the accuracy level into high, medium and low, depending on the estimated results.

7.2 Future Work

Even though we have reached satisfactory accuracy results from our proposed method for measuring volume and calories in a food image the system needs to training and it is still possible to work on improving the idea to include more aspects, such as liquid, mixed and more complex food such as salads and sandwiches. Moreover, we can cover more food types from a variety of cuisines around the world by storing more types of food and data from restaurants that provide the amount of calories and the nutrition facts for their menus.

Conversely, the limitations of the mobile device data storage can be overcome by asking the user to send a group of images that are already analysed to a server to be stored or even to iCloud computing in any open-source device. This can be done after every visit to the dietitian or even for a specific time. For some types of food that do not have a density amount, we can propose a method to measure the mass for a food type. Thus, we can calculate food density. As another step, we can include the user's eating behaviours and physical activities in the system. This will give the opportunity for both patient and doctor to control the recommended diet and make sure the person will follow the plan.

Another idea that we can apply to our system is the usage of an online gaming idea. By using virtual reality, users can adapt some games relying on physical activities. To encourage them to finish the game, we can calculate the amount of energy expenditure in the playing time.

For patients who suffer from chronic diseases such as diabetes or high blood pressure, the system will has the ability to give a recommendation of how much glucose or sodium chloride they can consume per day.

As a future step for our proposed system, we can avoid the problem of long-time responding by simply storing all the information of any consumed food starting with image processing until caloric estimation. If the user consumes the same type of food, the system can just calculate the difference of the area between the previous and the present consumed food.

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