DESIGN AND DEVELOPMENT OF COMPUTER VISION SYSTEM FOR CALORIE AND NUTRITION MEASUREMENT

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DECLARATION

I, **Manisha**, hereby declare that the dissertation entitled **"Design and Development of Computer Vision System for Calorie and Nutrition Measurement"** is an authentic record of my study carried out towards the partial fulfilment as requirement for the award of degree of Master of Engineering in Electronics and Communication at Thapar University, Patiala, under the supervision of **Dr. Vinay Kumar**, Assistant Professor, Electronics and Communication Engineering Department. The matter presented in this dissertation has not been submitted to any other University/Institute for the award of any other degree.

Date: 10/7/2017

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It is certified that the above statement made by the candidate is correct to the best of my knowledge and belief.

Date: 10/07/2017

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ABSTRACT

Obesity in children and adults has almost doubled since 1980 due to their association with various diseases, such as heart disease, type II diabetes and various types of cancer. Obesity and being overweight is considered to be fifth primary risks for the worldwide deaths. The main reason of obesity is consumption of high calorie foods and absence of physical activities.

In 2008, one-tenth of the world's population was obese and figure is increased to one-sixth in 2012. As a result it is impetrating that we should fight collectively hand in hand against this huge problem before it poses a threat to our health system. Thus, treatments of obesity have been the centre of a huge number of current studies. Because of these studies, researchers have observed that obesity treatment needs consistently monitoring of the patient's daily diet. However, measuring daily intake of fruits and vegetables is considered a significant step in the success of a good diet.

Measuring daily intake of fruits and vegetables for obese patients is one of the most challenging tasks in obesity control studies. Numerous studies have recommended that using modern technology like smart phones may improve the under-reporting problem in daily diet intake consumption.

In this thesis, we present a system that helps in calculating the amount of nutrients; we get from fruits and vegetables in daily diet. Our system uses image processing and classification methods to recognize the food and measures the calories and intimates the user about daily/weekly/monthly deficiencies. The evaluation and computation of the fruits and vegetables volume and total calories in the picture is an important step in our system. Our experiment results shows high reliability and accuracy of this method, with less than or equal to 25% error.

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LIST OF ABBREVIATIONS

WHO	World Health Organization
HBSC	Health Behavior in School-aged Children
BM1	Body Mass Index
WC	Waist Circumference
WHR	Waist-to Hip Ratio
CHD	Coronary Heart Disease
DLW	Doubly Labeled Water
FFQ	Food Frequency Questionnaire
PDA	Personal Digital Assistance
ADM	Automatic Dietary Monitoring
RFID	Radio Frequency Identification Technique
RFPM	Remote Food Photography Method
FIVR	Food Intake Visual and Voice Recognizer
GLCM	Gray Level Co-occurrence Matrix
ASM	Angular Second Moment
IDM	Inverse Difference Moment
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
DT	Decision Tree

RF	Random Forest
GLM	Generalized Linear Model

CHAPTER 1

INTRODUCTION

The idea discussed in this thesis is navigated by the growing uneasiness regarding health issues related to obesity and malnutrition. In addition, the implication of recent technologies such as tablets and smart phones in the health-maintenance field motivated us to search an assistant solution to connect technology with treating health issues such as overweight. In this thesis, a system is designed to manage the weight as well as malnutrition problem. In this chapter, we will discuss the obesity and under nutrition problem and how we can classify it and we will also demonstrate our presented solution in general.

1.1 MOTIVATION

Obesity in children and adults has almost doubled since 1980 and is considered to be fifth primary risks for the worldwide deaths. The main reason of obesity is consumption of high calorie foods and absence of physical activities. In 2008, one-tenth of the world's population was obese and figure is increased to one-sixth in 2012. According to the 1996 report by United Nation World Health Organization (WHO), in developing countries along with obesity, malnutrition also became more challenging tasks than starvation [1]. WHO evaluates that approximately 1.7 million or 2.8% of deaths are due to consumption of too few fruits and vegetables. Further, it estimates that inadequate use of fruits and vegetables in daily diet causes approximately 11% of ischemic heart diseases deaths, 14% gastrointestinal cancer death and 9% of stroke deaths [2]. The Health Behavior in School-aged Children (HBSC) study 2001/2002, which was organized in 33 European and North American countries for the students between the age of 13 to 15, reported that less than 50% of all young people taking vegetables and fruits in their daily diet [3]. Deficiency of nutrients in diet results in raised chance of various diseases; such as, cardiovascular disease, obesity, scurvy, diabetes or osteoporosis in addition to behavioral and psychological problems. Strong evidence proves that obesity is caused by the surplus intake of high-calorie foods that are rich source of fat, salts and sugars but poor in vitamins, fiber, minerals and other nutrients [4]. Recent studies show that the main reason for the rise in the rate of obesity is imbalance between the energy consumed and energy intake. There is large number of methods to calculate and classify the quantity of fat in human body such as

Body Mass Index (BMI), waist-to-hip ratio; waist circumference and skin fold thickness. The explanation of above mentioned terms is demonstrated below.

1.1.1 Body Mass Index (BMI)

Body Mass Index (BMI) is the WHO's suggested measurement device for calculating total body fat. This system depends on two values, .i.e. the weight and height of the person. In other words, BMI is measured by dividing weight by height. The expected outcome will be in (kg)/(m^2). Depending on the known results, the obesity level can be categorized as per the table given below [5]. The BMI is probably the identical for both males and females, but it might be different for a few persons such as athletes and aged people.

BMI kg/m^2	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

Table 1.1 BMI Classifications of Obesity and Overweight.

1.1.2 Waist-to-Hip Ratio and Waist Circumference

Waist-to-hip ratio and waist circumference (WC) are main methods in calculating the fat in the human being. The WC tool has been selected as a better estimating method than the BMI [6]. This technique depends on using a tape measure located in an appropriate place at the waistline. The waist-to-hip ratio (WHR) is similarly used to calculate the fat in the belly. It is evaluated by measuring the waist and the hip and then isolating the waist measurement by the hip size.

1.1.3 Skin fold Thickness

In this method, specialists apply a caliper at a number of regions of the body to calculate the thickness of the skin and its stored fat [7]. After that, they compute the percentage of fat in body on the basis of measurements.

1.2 THE PROPOSED SOLUTION

From entire of the above discussion, it is understandable that, for obese persons to lose weight healthfully and for average people to sustain a healthy weight, the daily consumption of fruits and vegetables must be calculated [8]. Research has shown that eating fruits and vegetables reduces the risk of obesity thus lowering the risk of insulin resistance and diabetes as well as make people satisfy with low fat food [9]. Experts have advised to take at least 600g of fruits and vegetables daily [10]. Therefore, development of an automatic measurement system is required that not only measures the daily amount of calories and nutrition but also intimates if we are lagging behind.

According to the 2000 report by the United States Department of Agriculture making fruits and vegetables as a part of daily diet supply 16% of magnesium, 19% of iron and 9% of the calories. It is estimated that consumption of fruit and vegetable contribute to 91% of vitamin C, 15% of niacin, 48% of vitamin A, 30% of folate, 17%of thiamine and 27% of vitamin B6 [11,12]. In 2000, study conducted in European countries on human, reported that carotenoid-rich fruits and vegetables such as spinach, broccoli offers a better protection in lowering the DNA damage, increasing LDL oxidation resistance than taking the supplements of carotenoid dietary [13, 14].

According to He et al. (2006) study increase in consumption of fruits and vegetables results in decreasing the risk of obesity by 24%. Further, study carried out by He et al. (2006) shows that consumption of 600 grams of fruits and vegetables per day decrease the stroke by 19%, Coronary heart disease (CHD) by 31%, reduce blood pressure, lower the risk of type-2 diabetes and maintain the level of blood glucose [15]. It also helps in removing the toxics from the body as well as decreases the loss of urinary calcium and reduces the bone resorption. But in most cases, it is not easy for the patients to calculate or manage their daily consumption due to the absence of nutrition education.

So, the measurement system is required that measure the amount of calories and nutrition we intake in routine. Nowadays, recent technologies like smart phones are included in the medical therapy of various types of diseases and obesity is examined as one of the common disease. Many facts prove that behavioral treatment and improving lifestyle behavior is very helpful in managing weight loss [16].

In this thesis, we constructed and implemented a system that computes and detects the daily intake of fruits and vegetables for a person who is fat or obese or even wants to observe the consumption of fruits and vegetables in daily diet. To accomplish this goal, we construct a system that helps in calculating the amount of nutrients, we get from fruit and vegetables in daily diet through IoT based intelligent calorie measure. We will demonstrate in detail the significance of our system and how it is distinct from other dietary intake systems. We will also discuss in detail how the outcomes of the image are transformed to the nutritional tables of eatables with the least feasible error, which is our major goal. Figure 1.1 presents the overall design of the proposed calorie measurement system that will discuss later.

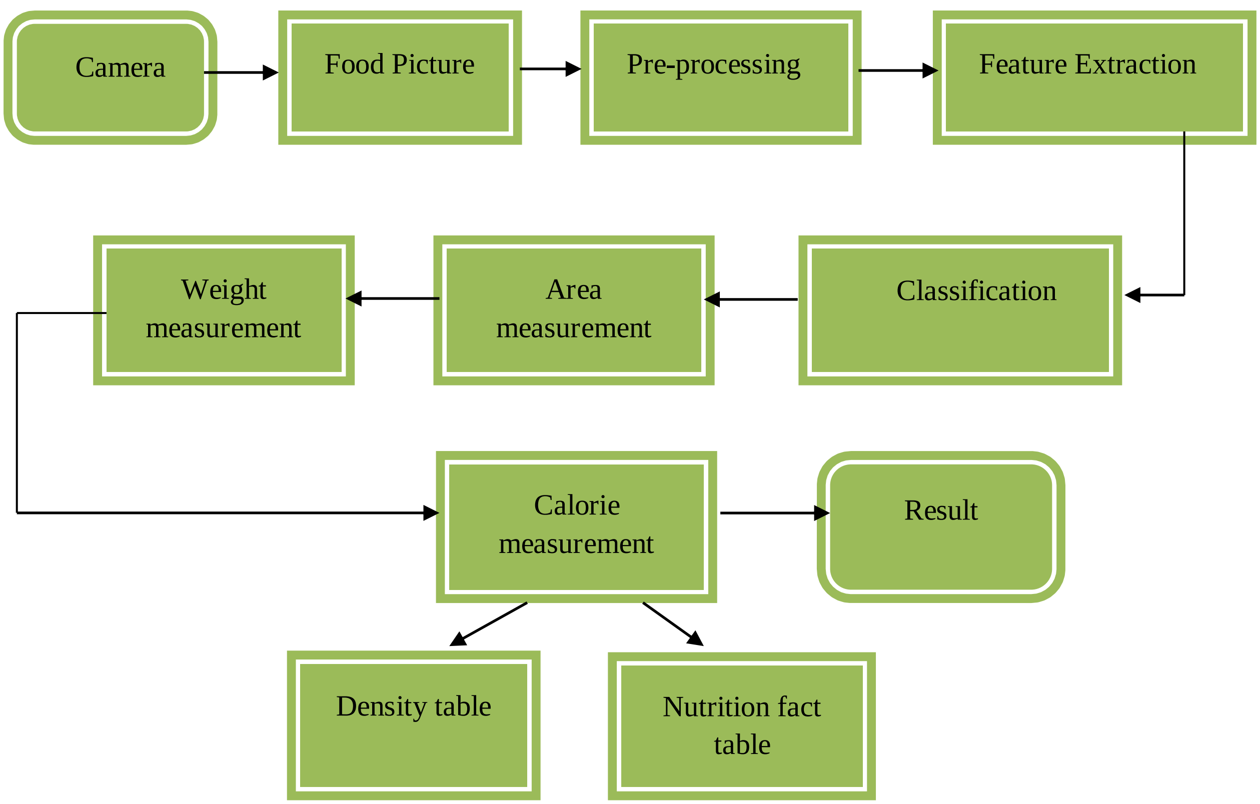


Figure 1.1 Overall system design

In other words, this thesis establishes a food intake measuring system. The thought behind the system is to help and enhance the treatment and management of obesity and utilize the new technologies in the field of public health. By using this system obese people will have the opportunity to observe their daily intake of fruits and vegetables. Furthermore, person with healthy weights can also use this system to observe their daily intake, which will help them in avoiding obesity.

1.3 ACCURACY LEVEL

It is very important to know the expected accuracy level of the designed system. To infer this, we must first conclude the level of accuracy given by related systems, whether clinical methods prepared by experts or electronic devices. Concerning clinical methods, if we ask a dietitian to compute the total calories in a dish with food manually, he or she will not be able to find the exact number of calories in the food due to the difficulties in memorizing the food's ingredients and amount of fat and salt have been used in making the food, which may really affect its nutritional value.

Concerning electronic devices, there are number of mobile applications existing in the market to estimate and identify the nutrition values for any food, but most of the applications need high commitment and interaction every time when they are used. Moreover, most of these applications want Internet connection, because they cannot determine the food that is not a part of pre-defined dataset. Therefore, it is important to know that it is not a key demand of our system to give high level of accuracy, because it is not easy to compute the exact number of calories in any food by just observing at it or by using any electronic device. So, in defining our goals towards the system it is important to know the accuracy level of proposed system.

1.4 LIMITATIONS

There are some disadvantages of our system. For example, mixed fruits and vegetables cannot be recognized correctly by the system. However, these types of disadvantages exist in all present systems, whether manual or automatic, and are not particular to our system.

1.5 THESIS GOAL

The aim of this project is to find solutions to get rid of the problem of inability to approximate the daily intake of low-calorie fruits and vegetables for person who is suffering from the problem of obesity with the help of modern technology. Thus, the purpose of this thesis is to compute the total amount of calories we take from fruits and vegetables in daily diet. Our main purpose is not to get high accuracy in measurement, but to get the results with the lowest feasible error, as discussed previously.

1.6 THESIS ORGANIZATION

The thesis work has been organized in the following chapters:

Chapter 2 Related Work: Discusses some of the existing daily intake estimation techniques.

Chapter 3 Proposed Methodology: Proposal and design of a system to calculate the amount of calories in fruits and vegetables inside the image and implementation of a technique to estimate the volume of the fruits and vegetables from the best classifier classified image and the coin as a reference.

Chapter 4 Evaluation and Performance Analysis: The estimated calories are then compared with the nutritional fact table given by international or national health Organization. At last performance of the method is discussed.

Chapter 5- Conclusion and Future scope: The observed results of the thesis are concluded here in this chapter and also the future work in this field is also suggested.

CHAPTER 2

RELATED WORK

Normally, dietary intake estimation strategies can be classified into conventional and electronic methodologies. Use of the conventional strategies has been well-known for quite a long time, regardless of whether in hospitals or in research examines. Due to improvement in the technologies the electronic strategies becomes more in demand. In this part, we will show some of the most widely recognized dietary intake measuring techniques. As well, we will define the disadvantages of those techniques to illustrate the strength of our proposed system, which can be use by the individuals with healthy weights and for medical purposes to enhance the treatment strategies for the person who is suffering from obesity. The following is the illustration of various techniques behind food measuring systems.

2.1 CONVENTIONAL DIETARY INTAKE METHODS

In this part, we will discuss some of the conventional and standard techniques of dietary intake estimation.

2.1.1 Doubly Labeled Watery Technique

The doubly labeled water (DLW) technique was developed in the mid 1950s by Lifson and McClintock in 1966 [17]. This technique was used for a long time to compute the energy consumption from daily intake; in fact, it is viewed as the gold standard technique for calculating total energy consumption. This method is to give a subject (say, a human or animal) a heavy dose of Oxygen O18 and Hydrogen H such as deuterium in a specific amount, and afterwards gather samples of urine or saliva in continuous periods (i.e., few days or weeks) and calculate the concentration of a few of the elements [18,19]. In spite of its worldwide popularity, DLW is considered as one of the most costly measuring intake technique since it requires expensive equipments to calculate the concentrations of the isotopes that should be measured. Also it takes a lot to time to give the measurement results. Moreover, it does not give the information about the quantity and category of food consumed.

2.1.2 24 Hours Dietary Recall

This technique basically implies an interview. It demands a dietitian or even a prepared interviewer to request the respondent to recall and record in detail all the eatables and drink he or she has taken in the previous 24 hours [20]. The interview can happen either by meeting with the sufferer or through phone [21]; the interviewer must be familiar with nutritional manners and cooking ways to fulfill and manage the data set format. Also, the interview itself is confined particularly to help the patient recall all the required information, which is not adequate for overweight patients. Researchers in [22] outline that the interviewer's examining limits the possibility of underreporting or overlooking by 25%. This implies that self-observing and lack of communication with the interviewer prompts negative outcomes in this approach. Moreover, it is quite tough for an individual to recall the amount of food he or she takes in previous 24 hours diet, especially for patients who is suffering from obesity. Therefore, the drawback of the 24-hour dietary recall is the postponement and error of reporting the eaten food due to various factors, such as age, sex, training, credibility and obesity. In addition, this technique needs only short-term memory and a prepared interviewer, which makes it a costly strategy.

2.1.3 Food Record Technique

This technique is based on the processing of dairy lists of consumer food prepared by a skilled nutritionist for a specific time frame. These lists consist of the type and amount of food to decrease the error rate; mainly, these lists are directed to a group of chosen individuals. After a while, the nutritionist gets the finalized dairy lists of food items taken by the individual. The nutrition expert analyses, computes and compares the finalized data with typical data, so the error rate is decreased. The benefit of this technique is that it does not depend on memory like the previous technique, information is recorded while eating and the food intake weight is calculated. However, the drawback of this technique is that it does not compute the eating behavior, which may affect the sufferer.

2.1.4 Food Frequency Questionnaire Technique

The food frequency questionnaire (FFQ) technique is a diet estimation tool used particularly for nutritional surveys in huge groups. In addition, this technique was established to use with young people. Basically, FFQs consist of list of foods and a group of options relating to the frequency of utilization of each of the listed foods. Each section has their own questionnaire with the food in that region for example, American food, Mexican food, Chinese food or Indian food. In this method, the patient must record the list of food he or she consumed in a certain period of time. This technique additionally needs an interaction with an interviewer [23]. This technique does not need a very experienced interviewer, and like the 24-hour diet intake strategy, the meeting can be eye-to-eye, via telephone [24] or through self-adoption of sufferer, so the daily intake of food can be calculated in various ways [25]. In general, FFQs were fabricated to compute the eating habits of an individual, not the amount of food he or she takes in daily diet [26]. To enhance this technique number of studies has been done between the 1960s and 1970s [27, 28, and 29]. In this manner, the FFQ method is officially suggested as one of the diet intake estimation technique in the American Public Health Association's Manual of Nutritional Assessment in Health Programs [30].

2.1.5 Portion Size Estimation Technique

The primary objective of the portion size estimation strategy is to prepare people to enhance their daily diet intake assumptions. Portion size measurement might be one contributor to underreporting issue. In [31], it was found that 45 minutes of guidance in portion-size evaluation among second- and third grade youngsters in Arizona and New Mexico considerably enhanced the evaluation for solid foods such as grain, sugar or bread, which were estimated by dimensions(length and width), glasses, or tablespoons. Liquids, for example, soup and milk were evaluated by containers or by label examination. Amorphous foods, for example, pretzels were not estimated accurately even after training, and several foods still showed an error rate of over 100%. Thus, training can enhance portion size measurement; but more than one session might be required. Accuracy might be unattainable.

2.1.6 Disadvantages of Food Dietary Recall

There is significant need to study and identify the drawbacks of the previously discussed existing measuring strategies to understand the motivating force behind this project. Two most important objectives behind the usage of the dietary intake evaluation, which are assuming if any general public population is taking an adequate amount of nutrients like proteins, calcium, carbs or sodium or discovering if any individual is taking more than he or she requires [32]. Basically, the diet recall system does a wrong estimation of energy consumption [33]. In addition, the rate of underreporting is too high because of data collection strategies [34]. The benefit of the 24-hour dietary recall is that a trained interviewer will finish the food list, but this technique is costly. In addition, the gathered information does not change the subject’s behavior, but at the same time, many drawbacks appear, such as it does not give information about the quantity or preparing strategy [35]. Moreover, there are number of disadvantages related to storage of data. For instance, the subject must be adequately educated to save the data each day, which is not possible for patients. There will likewise be a need to store the gathered information into software with the assistance of computer experts. This will dawdle and becomes very expensive.

2.2 EARLY ELECTRONIC DIET ESTIMATION TECHNIQUES

Electronic devices for measuring the daily consumption of food have been developed since the 1980s. The Portable Electronic Tape Recording Automated (PETRA) scale was developed by Cherlyn Electronics, Cambridge, to calculate the daily food intake and it enhance the results in comparison to the conventional approach [36]. In this approach a cassette is used to record the information about the size of food portion as well as ingredients present in it. Studies show that it is extremely difficult for uneducated people to use the PETRA scale [37].

The enhanced approach similar to PETRA has been developed, called the Nutrition Evaluation Scale System (NESSy). The advancement in this approach is using a personal computer with measuring equipments. It is fully computerized food recognition system [38]. A Personal Digital Assistant (PDA) is one of the widely used devices for the measuring the daily food intake. In comparison to conventional strategy, PDA gives much better results. A PDA records the information of food the person consumes, and every individual can store all the nutrition fact tables of different types of food without typing them physically or measure the quantity of food consumed [39]. In fact, the user can save the information by associating the device to the PC and the Internet. Moreover, Beasley's study demonstrates that the results of estimation of food portion can have an error, and large amount of time is required to the user to save the information [40]. In another review, researchers asked overweight and obese people to selfmonitor their daily intake of food (including type of food consumed) within a time of 24-week behavioral weight control program with the help of PDA and the outcome was that the utilization of PDA did not expand the legitimacy of food intake reporting [41].

2.3 NEW ELECTRONICS DIET ESTIMATION TECHNIQUES

In the new electronic techniques for measuring the daily food intake devices are connected with computer. Thus, the use of new technologies in diaries assessment techniques results in increasing the cost of the health care system for information gathering purposes. For examples, to calculate several categories, such as food intake, heart rate, medication taken, physical activities, energy expenditure and sleep diaries were used [42]. Therefore, various daily foods taking estimation software has been designed for example, Veggie Vision, Meal Snap and Calorie Counter.

Moreover, various researchers have applied techniques on the basis of sensors, intelligent systems, neural networks and further, image processing and pattern identification methods. Researchers in [43] designed Automatic Dietary Monitoring (ADM) to calculate the weight of food portion taken to decrease the stress of self-reporting for any individual looking for diet program. The thought behind ADM is to make use of the body's sensors to observe the weight of the food bites through recording of chewing cycles and type of food, thus gives continuous information from a chewing sound sensor. Basically, the wrist-worn acceralation sensor in the system gives the signal about the food intake, to record the sounds of chewing microphone is used a microphone, and to calculate the swallows an electromyography (EMG) sensor is used in the throat.

In [44] Nishimura and Kuroda make a wearable sensor system more superior by integrating a microphone into Bluetooth headset. In this, the system finds the type of food on the basis of chewing sounds. So, it reduces the burden to memorize the food type. Thus, these techniques give good results only in laboratory experiments, due to accuracy issues. Furthermore, it is uncomfortable for the person to put on a microphone or a sensor in the throat. Variety of foods like broccoli, carrots and sweet peppers gives the same chewing sound. Whereas in [45] radio-frequency identification (RFID) technique a sensor is used on the surface of system to identify the type of food as well as to calculate the weight of food integrated scales are used.

Disadvantage of the system is that it is not easy use at every location and it is difficult to attach the system with each served food.

In the next sections, we will discuss various food intake estimation methods that are categorized on the basis of image processing techniques and volume estimation.

2.3.1 Image-Based Diet Estimation Techniques

Lately, various new food estimation systems based on capturing of an image are used commonly used all around the world because of advancement in technologies like improvement in camera resolutions, network connectivity, computer programs, and image processing analysis. For the identification of consumption of food, image of food is captured and forwarded it to websites to identify the type of food.

Sometimes, the captured food image is compared to the stored image in the database of the system [46]. In this case, nutrition data is applied to a health-aware HTC smart phone system. Image of selected food is captured by the users. Then, the captured images are compared to the stored image along with its nutrition facts. The dataset consists of various types of food. The drawback of this system is that a person can measure the food only which is present in database. Furthermore, system does not calculate the intake of food.

In [47] Wu and Yang developed a computer program technique to recognize the intake of fast-food with the help of wearable camera. In this technique, numbers of fast-food images are captured from restaurant and then compared to the stored images in database. Researchers captured the images of 101 type of food by placing the camera in three different directions. The recognition rate achieved by the system is 73%, but there were few disadvantages of this technique, such as variation in level of accuracy when an unknown food is present.

In [48] to recognize the food from an image Neural Network (NN) is used; in this method, a photo of various types of dishes present in a tray is captured before and after meal. Initially, an picture of the full tray is captured. Then the captured image is converted into binary image with the help of thresholding, and afterwards, different types of food will be segmented from the tray. In the previous steps, the system will gives all information about the image such as shape, width and length. All the prior information will convey to the NN. After receiving the results, it is applied to a computer simulation program for the comparison and analyzing the results. This approach is also very tough for the user to follow.

Martin and others in [49] developed a technique based on image processing. In this technique, the user captured the image of food before and after taking meal. Afterwards, it is forwarded to research centre through internet connection. Their experts compute the amount of food intake with the help of delivered images. The drawback of this method is we cannot use it without internet connection.

In [50], the user extract the images of the selected food from the video at a 45° angle with the help of wellnavi device and then write the detail about it on the screen. Afterwards a user sends the description of food along with food images to data centre through network connection to extract the results. The disadvantage of the system is difficulty in capturing the image from video and writing the food detail on the screen.

In [51] smart kitchen has been made in which to enhance the awareness about selecting the healthy food and compute the calories in the prepared food camera is used. The camera is placed at some height to capture the images of the preparing food, sensor is placed near the counter and stove to watch the ingredients used in food preparation process and several cameras are placed inside the kitchen. The results are forwarded to users about the amount calories in meal. The major drawback of this smart kitchen is inability of it to be used outside home. Further, food preparation space is fixed, which is disagreeable for most people. In addition, some configuration error could take place .i.e. in selecting the cooking oil due to the similar food categories.

Concerning digital photography, technique is proposed called the Remote Food Photography Method (RFPM) [52]. In RFPM, with the help of mobile phone photo of selected food is captured and forwarded it to an investigator through a cellular network. The continuous reminder through email or phone messages to receive and forward the food images to the investigators is sent to avoid misreporting. The received images are compared with a stored image in the database to evaluate the food portion size and the results are resend to the user. As mentioned before, these types of systems have limitations .i.e. requirement of constant internet connection.

Puri and others [53] developed a system named as the Food Intake Visual and Voice Recognizer (FIVR). In this system both images and voice are used to estimate the quantity of calories in food. In this three pictures of selected food is taken from three different locations and type of food is declare through speech. This input information is then forwarded to an isolated server via. wireless communication. After the analysis of all the image and speech, the result will be forwarded to the user by a text message. There are two downsides of this system. It is not convenient to use for a person who cannot speak. In addition, system can identify only one language so it is not helpful for deferent users.

2.3.2 Volume Estimation in Image Based Techniques

It is a complex challenge to estimate the volume from the image in food intake methods. This subcategory will describe some of the earlier work in this field to demonstrate the differences and the legality of novel technique for volume estimation, from initial to the last stage of the image-processing evaluation. The recent work in this field to recognize the food is demonstrated that there is a need to specify a reference in the image to focus the viewpoint and distance of the camera. Primarily, this reference can be anything which has the similar size with each occurrence. Thus, in some approaches, like the RFPM [52], a special card is placed by the user next to the chosen food before taking the photo. Also, this system asks the person to recognize the variety of food and its quantity in the photo; moreover, it is not possible for any person to approximate the size for any kind of food, as discussed earlier.

Using several approaches, researchers [54] developed a system to compute the volume of food through single image based on virtual reality (VR) technique. In this technique, a large number of 3D wireframe things made in virtual surroundings simulate particular item of food in a real digital image. System captures the two types of image by using binary cameras, one from the real environment and other from virtual environment. Check board is taken as reference while capturing both types of images. Actually, the legality of this technique is only within the measurements laboratory and it is inadequate for daily use. For single image [55] eating plate is taken as a reference, while another techniques suggested that any circular shape for example coin, plate or bowl [56] can use as reference . They developed an algorithm to compute the volume of food which is regular-shaped from the circular object. The authors tested with just three types of food, which is not pretty enough to consider the method as a standard. Furthermore, it is sometimes tough for the person to get a circular plate.

Sun and others developed an approach to calculate the volume of food consumed [57]. In this method, an image of food is captured by placing calibration card besides the food as a reference thing. Afterwards, the images are uploaded on a computer, and it is responsibility of user to enter all the data related to image .i.e. kind of food and about the dimensions of food such as width and length. Finally, the software will compute the food volume and gives all the information about the nutrition facts of food intake to the user. The system will give results close to the actual size because of manual uploading of size, but this approach has drawbacks such as the card must be present in the picture while capturing. Actually, the user cannot use the system without the card, so the system is of no use if card is lost or forgotten.

Most of the methods which are mentioned above can be used either at certain places or in laboratory only. In fact, to make our system, we will take benefit of the already existing methods and remove their downsides up to some extent. Our system use mobile phone technology to capture the image of fruits and vegetables. The dimensions of eatables are calculated by comparing it with the stored image of eatables in database. At the end, by using the nutritional fact table nutrients present in the food are estimated. This approach will provide more accurate results in comparison to other methods.

2.4 SUMMARY

In this chapter, we illustrated the history of food dietary intake measurement in detail. Furthermore, this review discussed the pros and cons of devices specifically. In fact, the previous methods of food estimation showed a number of weaknesses that made them unsatisfactory method when used. While new measuring techniques showed very satisfactory results, even though they have drawbacks. It is feasible to improve those systems. It is clear that to estimate the food using electronic devices gives better results in comparison to paper-based estimation techniques. Furthermore, it is obvious that by improving the image-processing techniques and volume-estimation methods will improve of the system quality.

CHAPTER 3

PROPOSED METHODOLOGY

In this chapter, we will explain all the techniques used in manufacturing the system to estimate the amount of calories from a picture. Figure 3.1 demonstrates the overall system consists of five main parts: dataset collection, pre-processing, feature extraction, classification and calorie measurement.

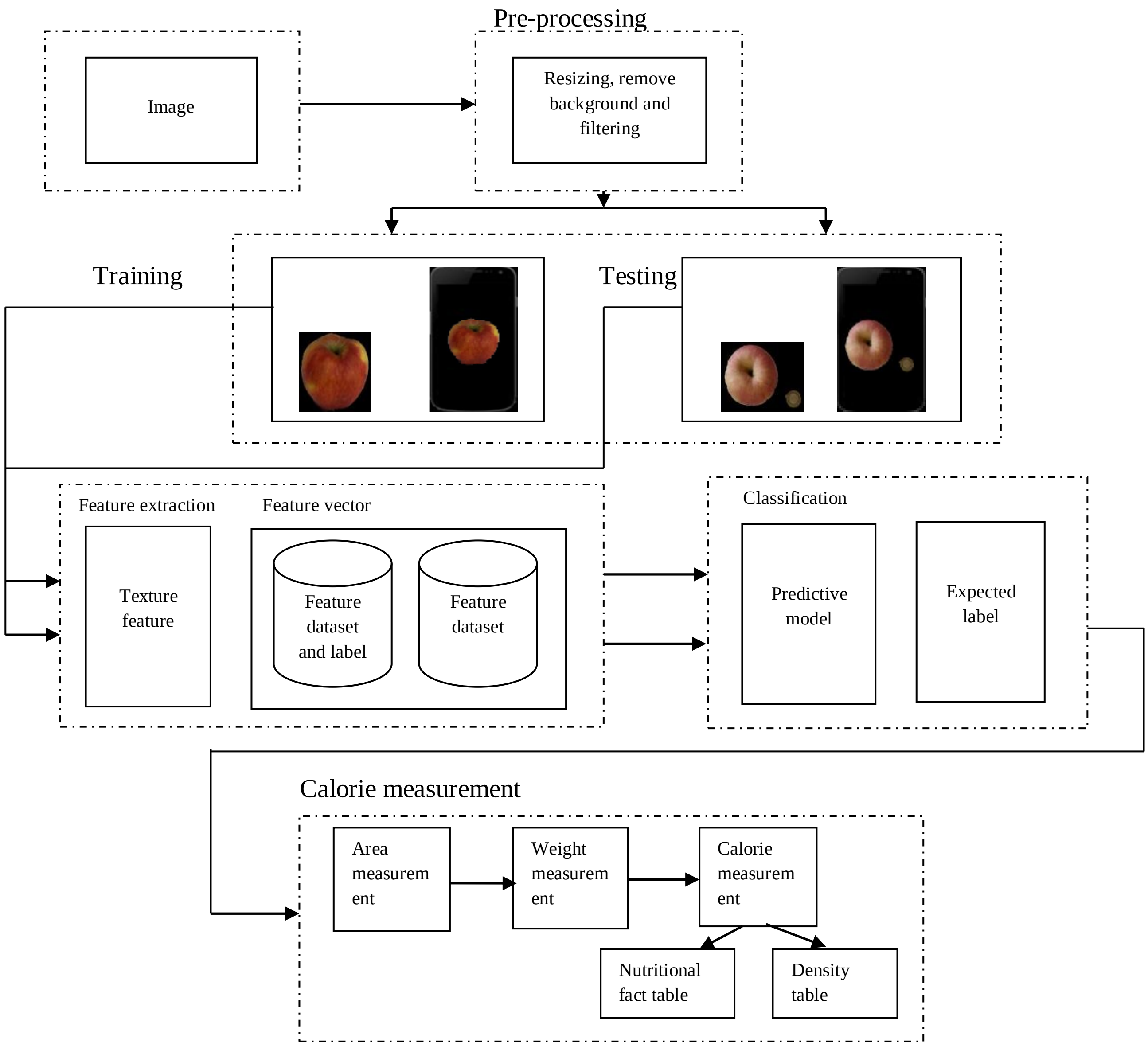


Figure 3.1 Proposed system diagram

3.1 IMAGE PROCESSING AND PRE-PROCESSING

Once the images of variety of fruits and vegetables are captured, it is transformed and forwarded to the next step. In the proposed work dataset consisting of 450 image of 9 types of fruits and vegetables such as: apple (i.e. Akane apple, Alkmene apple), orange (i.e. tangerines, Mediterranean mandarin), guava (peru), pomegranate, chikoo, watermelon, tomato, capsicum, and cucumber is developed. These images are collected from fruit vendors. All original fruit images are obtained in RGB format. The images are captured using MOTO G3 Turbo 13 mega pixel rear camera having resolution 4128 x 3096 pixels under proper lightening condition at different angles and distances to avoid fruit image virulent effect of illumination. They are resized to 160×150 with black background. Figure 3.2 represents some of captured images.

Figure 3.2 Images of fruits and vegetables with black background

Out of 450 images 356 are used for training and independent set of 94 are used as testing set to estimate the performance of different classifiers.

Data set (fruits)	Number of original images	Number of training images	Number of testing images
Apple	66	51	15
Guava	40	30	10
Pomegranate	55	45	10
Chikoo	40	30	10
Orange	52	40	12
Capsicum	60	45	15
Tomato	52	40	12
Watermelon	40	30	10
Cucumber	45	45	10

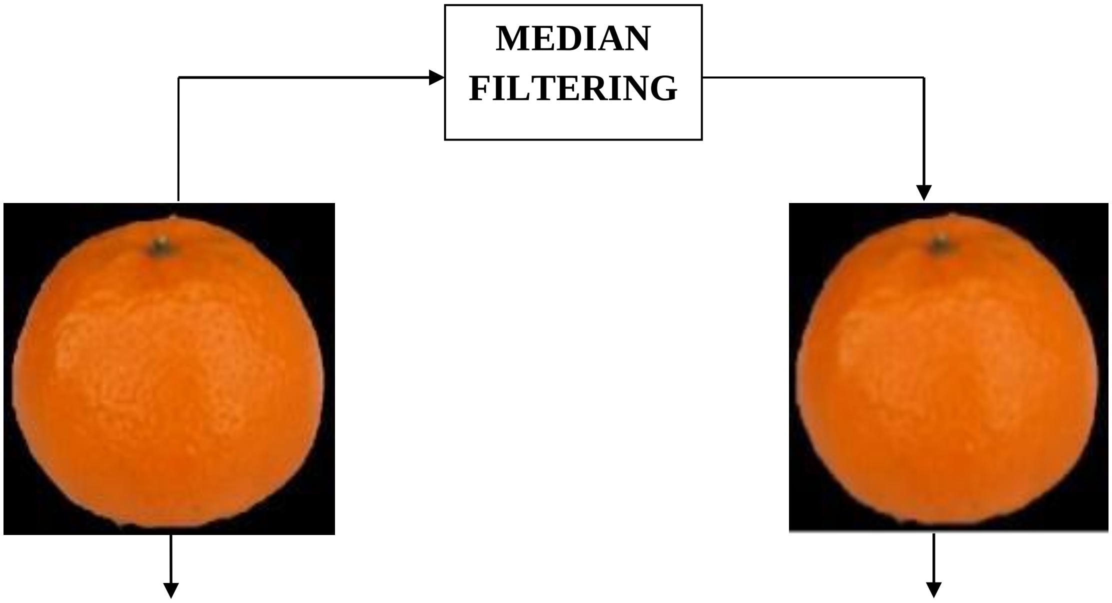
Table 3.1 Dataset specification

The aim of pre-processing is to remove the false peaks from the image and then smoothen the image by using series of filters. In this work, median filter of size 5×5 kernel is applied on an image. Median filter is well known order-statistics filter in which non-linear operation is performed to remove noise [58]. This filter is extremely effective in the existence of impulse noise like salt and pepper noise. It gives more effective results than convolution when aim is to remove simultaneously noise and preserve edges.

$$F(x, y) = \underset{(x,t)\in S_{xy}}{\text{median}} \{g(s, t)\} \tag{3.1}$$

where, x and y show the location of pixel in matrix F (.) over which median filter is applied.

In the process intensity of current pixel is replaced with the median of that pixel and its neighbors. Figure 3.3 shows the results before and after applying median filter.



$$\begin{bmatrix} 239 & 240 & 239 & 238 & 236 \\ 230 & 233 & 235 & 236 & 236 \\ 231 & 233 & 236 & 238 & 238 \\ 237 & 238 & 240 & 239 & 237 \\ 237 & 238 & 239 & 237 & 234 \end{bmatrix} \qquad \begin{bmatrix} 240 & 239 & 238 & 236 & 236 \\ 233 & 235 & 236 & 236 & 236 \\ 233 & 235 & 236 & 237 & 237 \\ 235 & 237 & 238 & 238 & 237 \\ 237 & 237 & 238 & 237 & 237 \end{bmatrix}$$

(a) (b)

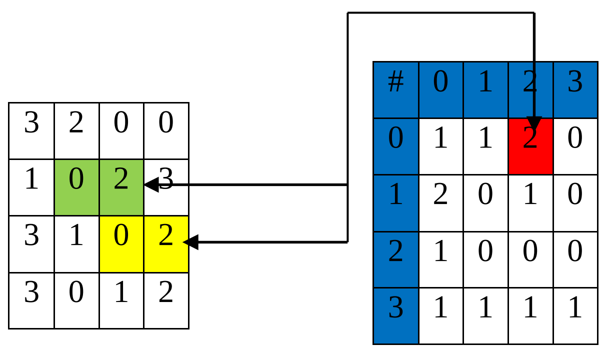
Figure 3.3 (a) Original image (b) Image after enhancement

3.2 FEATURE EXTRACTION

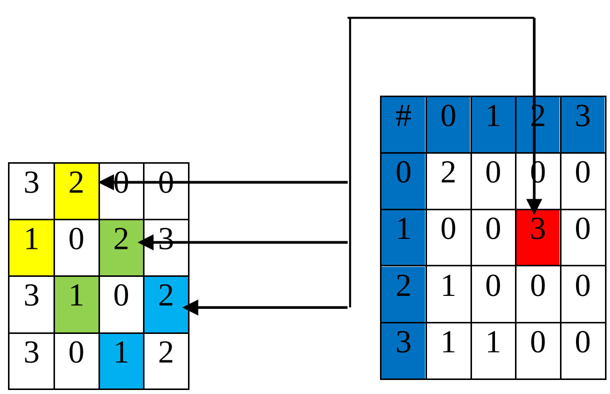
3.2.1 Texture feature

A feature is distinct information, which differentiates on entity from another. It describes the characteristics of the object. The main goal to extract the features is to get the relevant information that distinguishes each class. The relevant information which is extracted from the entity is used to make a feature vectors. Then, these feature vectors is used to identify the target output class with the help of input class. It becomes easy for classifier to distinguish between the classes by looking at these features. Feature extraction process removes the redundant data from the informative data [59]. It is conversion of input data to set of features. A characteristic of image can be defined by extracting number of features from an image like size, shape, color, and texture. In this work, texture features are extracted by this Gray Level Co-occurrence Matrix (GLCM).

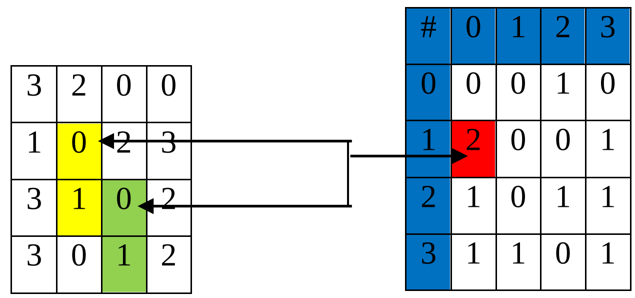
We use GLCM for extracting texture information. It generates a square matrix of size equal to the maximum intensity and created with frequency of the distinct intensities of grey in the stack [60]. The process is strongly influenced by the direction and pitch of the pixel. Element $P(i, j, d, \theta)$ in matrix represents probability of concurrence between two pixels with intensities i and j respectively and pixel pattern can exist in four orientations of θ; i.e., horizontal (0°), vertical (90°) and two diagonal directions $(45°, 135°)$ for specified d where d is gap between the pixels of interest[61]. Texture in an image is unequally distributed among its RGB components; therefore, the prominence of features is different in different RGB planes. In the proposed work, 21 texture features are extracted using GLCM for red, green and blue planes, respectively. An example of four configurations of GLCM matrixes with d=0 is demonstrated in Figure 3.4.



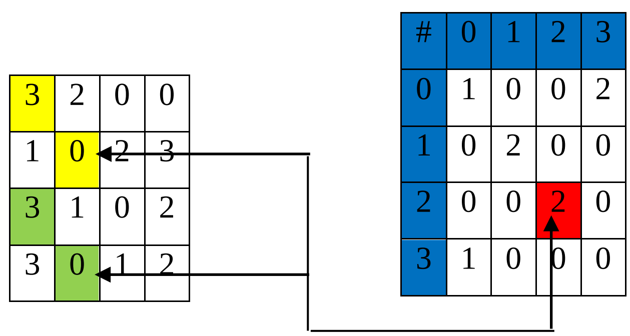
(a)



(b)



(c)



(d)

Figure 3.4 GLCM formation for (a) 0^0 (b) 45^0 (c) 90^0 (d) 135^0 with a distance d=0

In the proposed work, an input image is quantized into 8 gray levels as GLCM produces better discrimination or segmentation of textures between different fruits and vegetables. Figure 3.5 shows the GLCM matrix for several fruits and vegetables for $\theta = 0^{\circ}$ and d=0.

apple

8x8 double

	1	2	3	4	5	6	7	8
1	6963	107	39	20	0	0	0	0
2	161	2847	129	36	0	0	0	0
3	5	219	4776	247	1	0	0	0
4	0	0	304	7235	169	0	0	0
5	0	0	0	170	1351	7	0	0
6	0	0	0	0	7	11	0	0
7	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0

(a)

capsicum

8x8 double

	1	2	3	4	5	6	7	8
1	8119	233	26	0	0	0	0	0
2	234	12398	344	1	0	0	0	0
3	25	344	1599	75	0	0	0	0
4	0	2	73	182	8	0	0	0
5	0	0	1	7	9	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0

(b)

tomato

8x8 double

	1	2	3	4	5	6	7	8
1	7976	39	36	37	22	9	0	0
2	54	7	5	9	7	18	0	0
3	73	33	59	4	11	25	0	0
4	16	21	105	1214	53	37	0	0
5	0	0	0	182	3643	106	0	0
6	0	0	0	0	195	4900	149	0
7	0	0	0	0	0	149	4531	28
8	0	0	0	0	0	0	28	219

(c)

Figure 3.5 GLCM matrices for (a) Apple (b) Capsicum (c) Tomato

The GLCM can find up to 14 distinct features, however those calculated in manuscript are:

Angular Second Moment, explaining the consistence of an image. Its value will be high when image when values of pixel are similar and image has good consistency given by

$$\text{ASM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i,j)\}^2 \tag{3.2}$$

Contrast, calculate the local uniformity in the image. Its value is high when large amount of variations are present in the image defined by

$$\text{CONTRAST} = \sum_{n=0}^{G-1} n^2 \left\{\sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j)\right\} \tag{3.3}$$

Inverse Difference Moment, computing the consistency of the image. It results in low value when image is inhomogeneous represented by

$$\text{IDM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} \ P(i,j) \tag{3.4}$$

Correlation, describing the relation between the pixels and its neighbors; it can be positive or negative, given by

$$\text{CORRELATION} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \tag{3.5}$$

Inertia, calculates the intensity contrast between the pixels and its neighbor for the entire image, defined by

$$\text{INERTIA} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i-j\}^2 \times P(i,j) \tag{3.6}$$

Cluster Shade, calculates the skewness of the matrix, defined by

$$\text{SHADE} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left\{i+j-\mu_x-\mu_y\right\}^3 \times P(i,j) \tag{3.7}$$

Cluster Prominence, measure the irregularity, defined by (7)

$$\text{PROM} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\left\{i + j - \mu_x - \mu_y\right\}^4 \times P(i,j) \qquad (3.8)$$

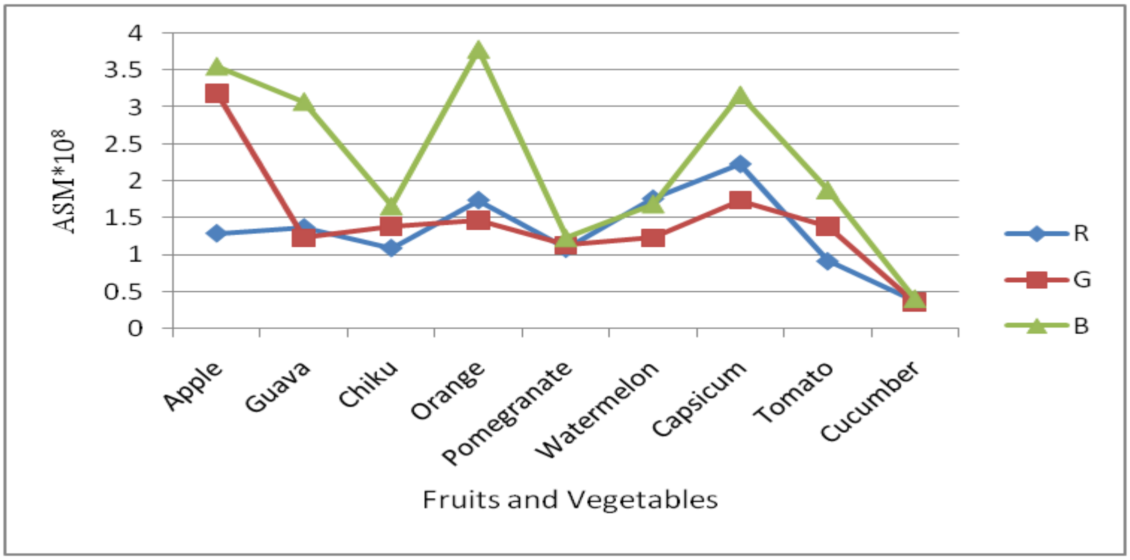
where, G is number of gray levels.

In the proposed work, 21 texture features are extracted using GLCM for red, green and blue planes, respectively. Texture in an image is unequally distributed among its RGB components. Therefore, the prominence of features is different in different RGB planes. Thus, we extract features from individual RGB plane.

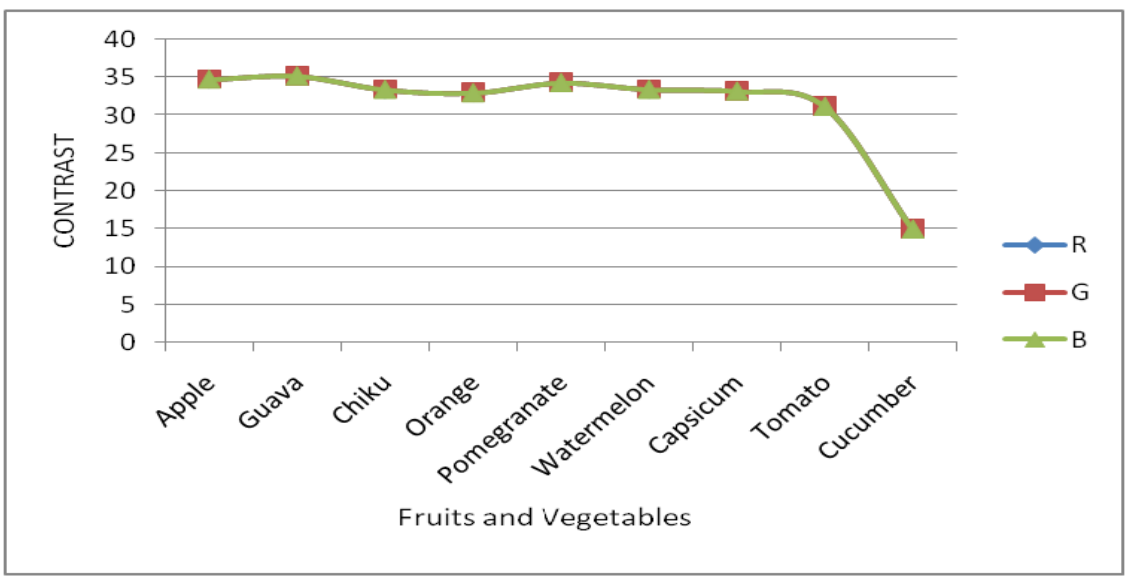
Features Fruits and Vegetables		$Asm*10^8$	$Con*10^4$	$Idm*10^3$	$-Corr*10^{-10}$	Inertia	$-Shade*10^{16}$	$Prom*10^{21}$
Apple	R	1.29	34.72	23.73	5.37	2582	1590	1380
	G	3.19	34.72	23.83	147	2096	11.1	1.83
	B	3.56	34.72	23.87	246	2042	5.15	0.656
Guava	R	1.37	35.16	23.99	3.42	5468	3180	3440
	G	1.23	35.16	23.86	2.90	5880	4060	4770
	B	3.08	35.16	23.98	77.6	4468	29.5	6.69
Chiku	R	1.09	33.37	22.83	2.88	5368	3910	4610
	G	1.39	33.37	22.89	5.40	4336	1520	1310
	B	1.66	33.37	22.81	11.9	3820	465	26.9
Orange	R	1.74	32.94	22.67	0.80	9050	26300	5870
	G	1.47	32.94	22.49	4.38	5204	2050	1960
	B	3.79	32.94	22.55	460	4132	1.92	0.17
Pomegranate	R	1.08	34.28	23.10	1.12	9794	16600	3140
	G	1.13	34.28	22.97	6.67	6332	1140	881
	B	1.23	34.28	22.83	10.0	6296	617	390
Watermelon	R	1.76	33.39	23.07	8.88	2090	720.96	483.86
	G	1.23	33.39	22.94	3.73	2664	2641.0	2732.4
	B	1.69	33.39	23.05	7.21	2464	985.03	733.56
Capsicum	R	2.23	33.15	22.97	31.10	1538	109	39.1
	G	1.74	33.15	22.84	12.10	1906	452	261
	B	3.17	33.15	22.90	218.0	1606	5.89	0.798
Tomato	R	0.91	31.13	21.42	1.82	3084	7234.2	10719
	G	1.39	31.13	21.76	13.35	1252	364.63	199.57
	B	1.88	31.13	21.640	51.86	1416	47.68	13.24
Cucumber	R	0.37	14.91	10.29	91.22	1126	9.79	2.0522
	G	0.359	14.91	10.29	56.82	1094	19.91	5.28
	B	0.404	14.91	10.32	125.06	944	6.104	1.0923

Table 3.2 Different texture features values for individual fruit and vegetable

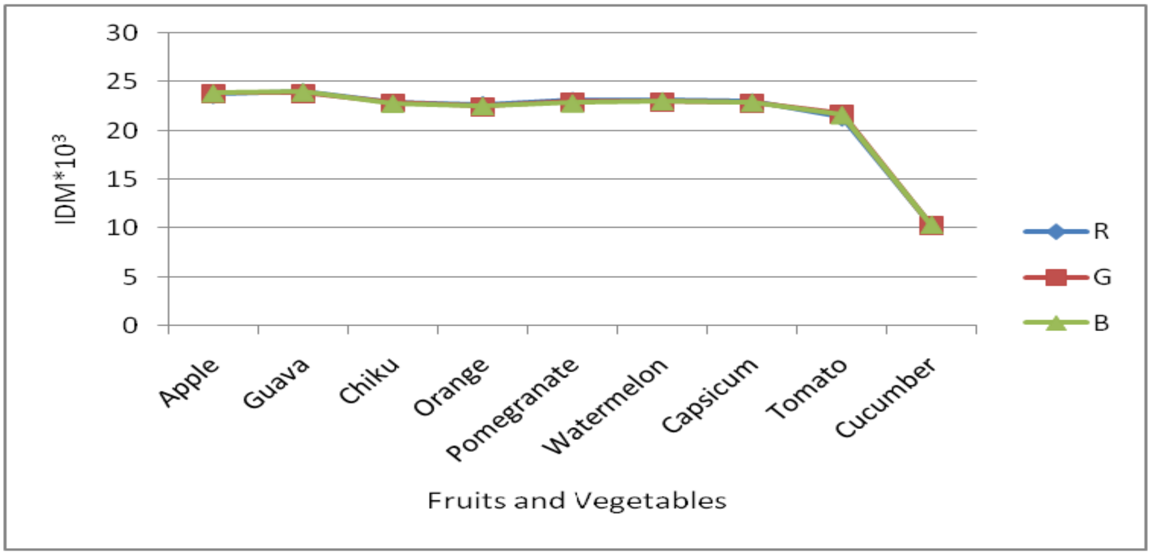
Graphical, representation of Table 3.2 is shown in Figure 3.6 in which (a) represents the variation in value of ASM for RGB component of each fruit and vegetables, (b) represents the CONTRAST value which is same for RGB component of particular fruit and vegetable, (c) represents the variation in value of IDM for RGB component of each fruit and vegetables, (d) represents the variation in CORR value for RGB component of each fruit and vegetables, (e) represents the variation in value of INERTIA for RGB component of each fruit and vegetables, (f) represents the variation in value of PROMINANCE for RGB component of each fruit and vegetables, (g) represents the variation in value of SHADE for RGB component of each fruit and vegetable.



(a)

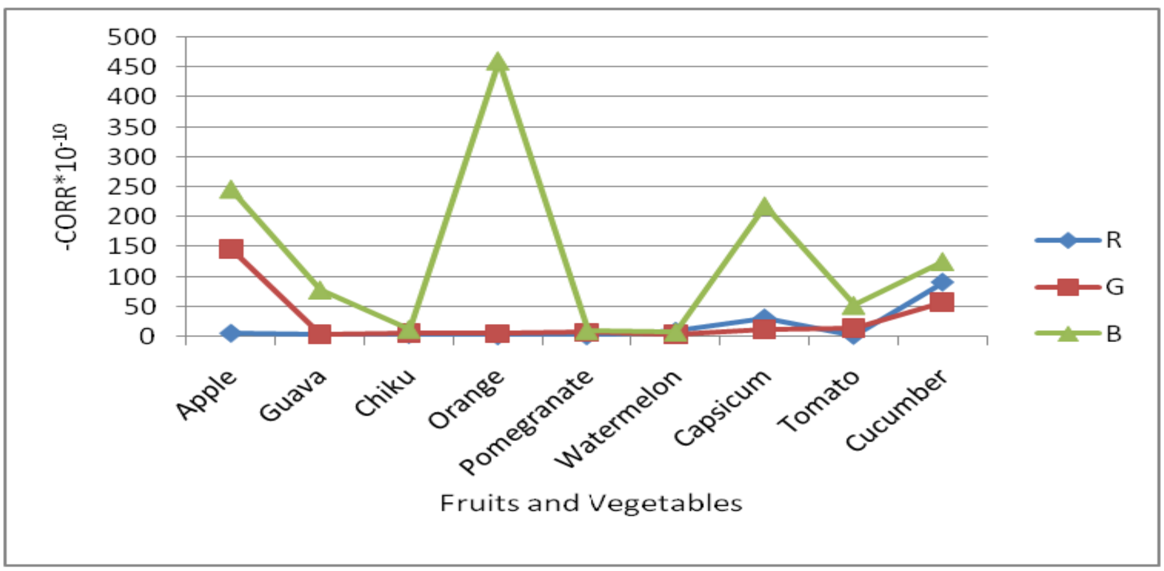


(b)



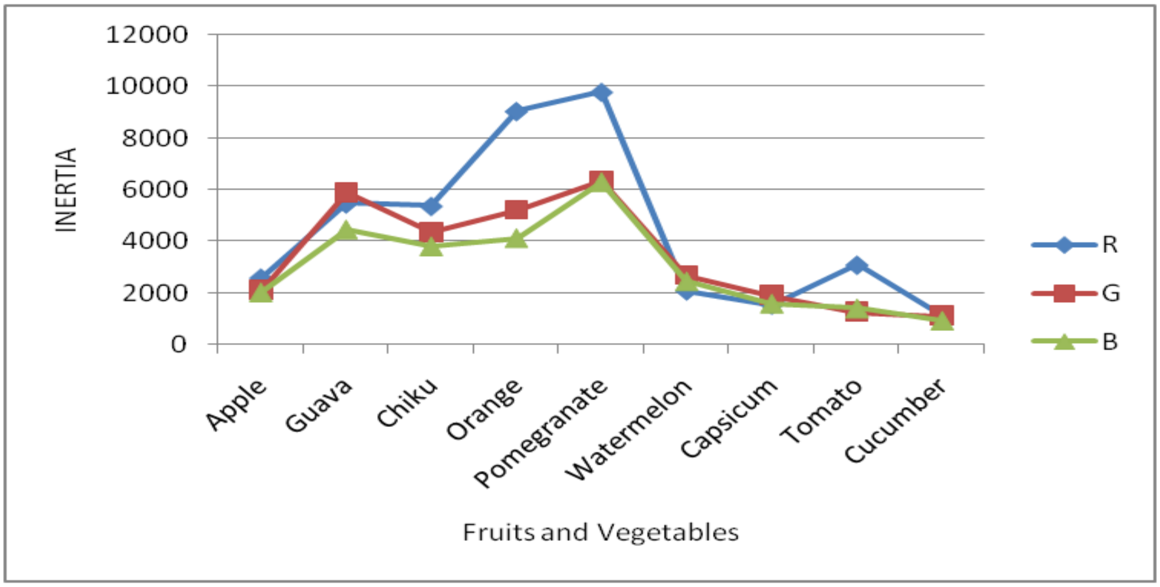
30
25
20
15
10
5
0
IDM*10^3
Apple
Guava
Chiku
Orange
Pomegranate
Watermelon
Capsicum
Tomato
Cucumber
Fruits and Vegetables
R
G
B

(c)

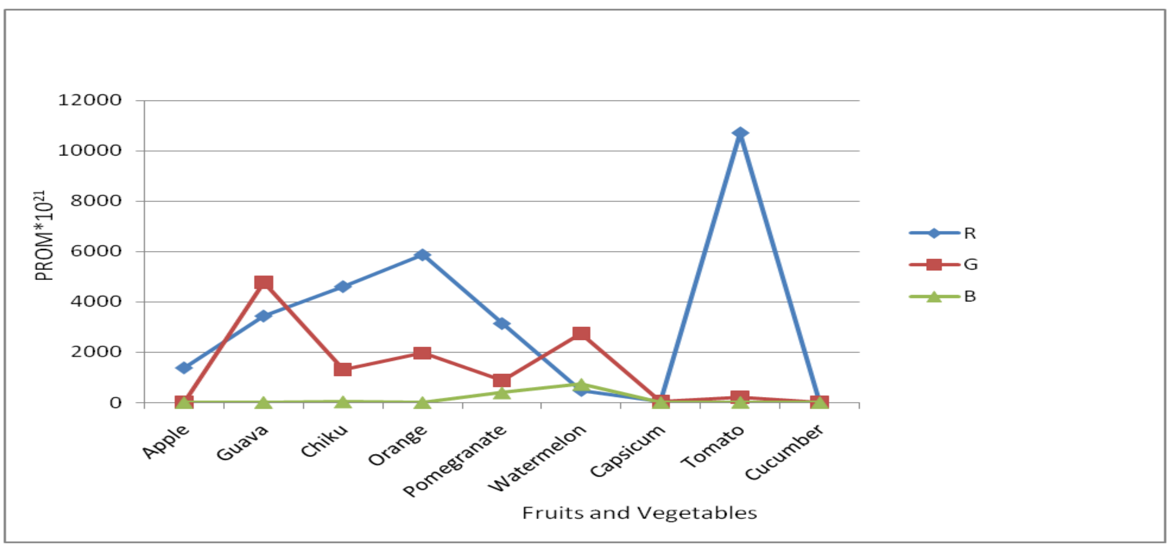


500
450
400
350
300
250
200
150
100
50
0
-CORR*10^-10
Apple
Guava
Chiku
Orange
Pomegranate
Watermelon
Capsicum
Tomato
Cucumber
Fruits and Vegetables
R
G
B

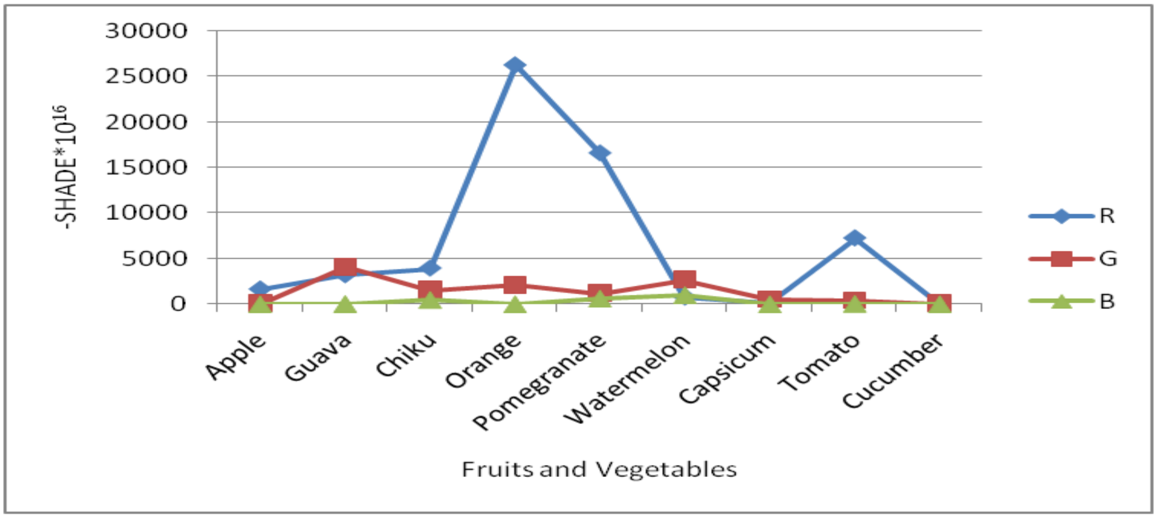
(d)


12000
10000
8000
6000
4000
2000
0
INERTIA
Apple
Guava
Chiku
Orange
Pomegranate
Watermelon
Capsicum
Tomato
Cucumber
Fruits and Vegetables
R
G
B

(e)


12000
10000
8000
6000
4000
2000
0
PROM*10^21
Apple
Guava
Chiku
Orange
Pomegranate
Watermelon
Capsicum
Tomato
Cucumber
Fruits and Vegetables
R
G
B

(f)



(g)

Figure 3.6 Illustrate the plot between the GLCM features (a) Asm (b) Contrast (c) Idm (d) Correlation (e) Inertia (f) Prom (g) Shade versus fruits and vegetables.

3.2.2 Color feature

Color is one of the most significant features of images. A specific color model or space is used to extract the color feature. There are number of color spaces such as RGB, HSV, LUV, and HMMD. Color features are extracted from an image after specifying the color space [63]. There are number of number of well-known color features have been used such as color histogram, color moments (CM), color coherence vector (CCV), and color correlogram, etc. In the proposed work color moments are extracted from fruits and vegetables.

$$\text{Mean} = \sum_{i=1}^{i=n}\sum_{j=1}^{j=m} x_{ij}/_{mn} \tag{3.9}$$

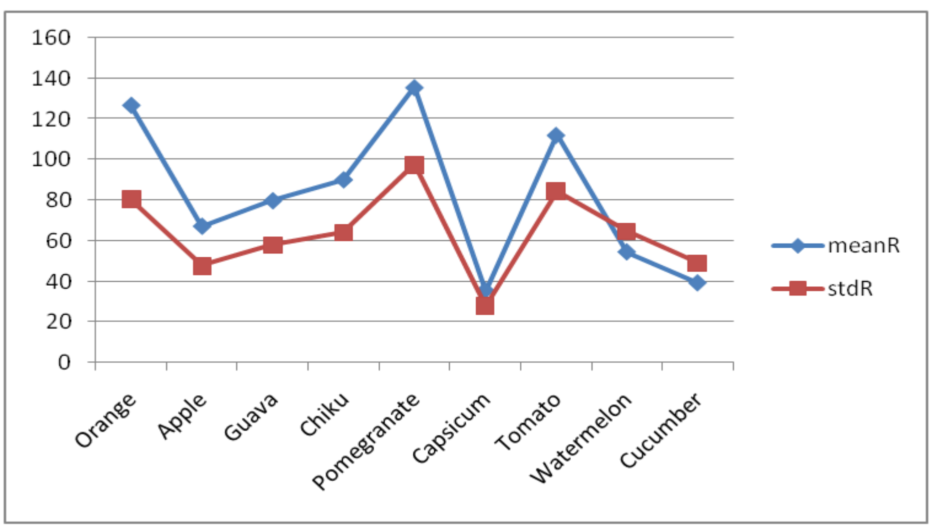
$$\text{Standard deviation} = \sqrt{variance} \tag{3.10}$$

where, variance = $\frac{1}{mn}\sum_{i=1}^{i=m}\sum_{j=1}^{j=m}(x_{ij} - mean)^2$ and x_{ij} is pixel value of i^{th} row and j^{th} column.

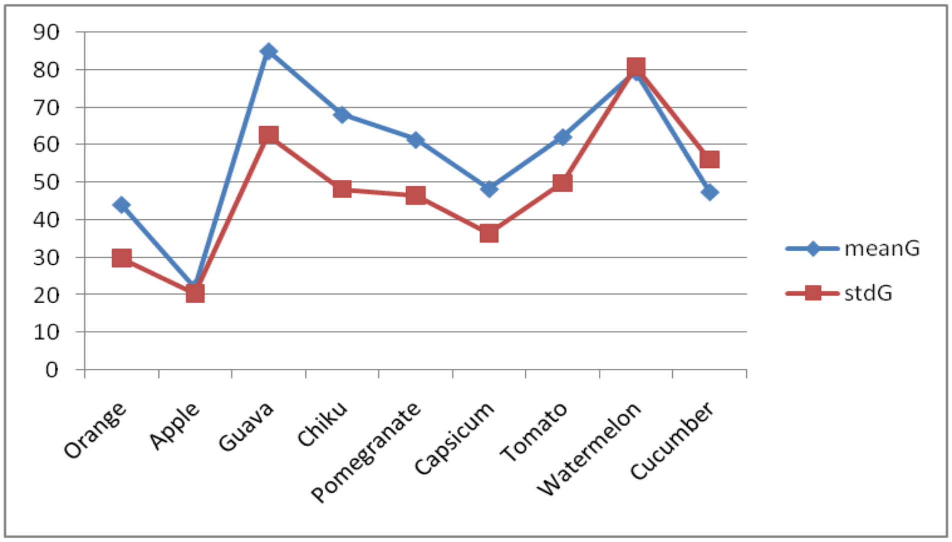
Fruit	meanR	stdR	meanG	stdG	meanB	stdB
Orange	126.95	80.53629	44.21364	29.96962	4.921069	12.08431
Apple	67.13089	47.57889	22.08442	20.42097	20.04058	17.71358
Guava	79.73331	57.79211	85.11535	62.81757	23.80249	28.71638
Chiku	90.08063	64.17347	68.17142	48.30125	50.64092	35.45427
Pomegranate	135.6643	97.6562	61.48945	46.6062	51.99663	40.40788
Capsicum	35.40206	27.67329	48.37374	36.46482	21.29362	20.10348
Tomato	112.0463	84.49108	62.225	49.96769	36.46163	30.10033
Watermelon	54.45363	64.71448	79.48808	80.96927	59.40817	64.17226
Cucumber	39.12938	48.98193	47.57528	56.16836	34.74226	44.01197

Table 3.3 Different mean and standard deviation values for individual fruits and vegetables

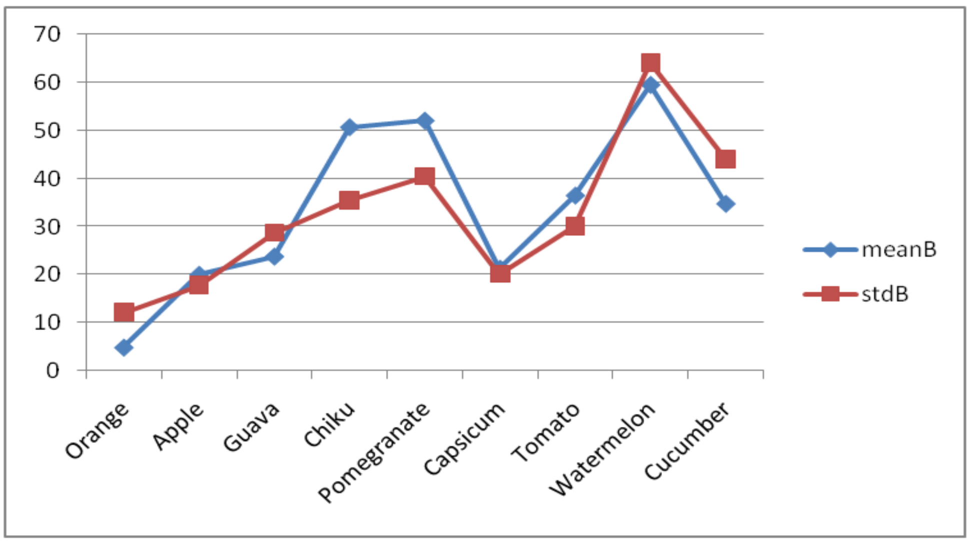
Graphical, representation of Table 3.3 is shown in Figure 3.7 in which (a) represents the variation in mean and standard deviation values in R channel, (b) represents the variation in mean and standard deviation values in G channel , (c) represents the variation in mean and standard deviation values in B channel for different fruits and vegetables.



(a)



(b)



(c)

Figure 3.7 mean and standard deviation (a) R component (b) G component (c) B component of fruits and vegetables

3.3 CLASSIFICATION

Classification is a process in which images are classified on the basis of their similarities. It is easier for human to classify the objects then machine. The rise in large capacity computers, availability of good quality cameras, and increase in demand for automatic video analysis results in increasing the interest in classification algorithm. A basic classification system comprised of camera fixed at some height from where images are captured and then processing is done. In classification system, there is a pre-defined dataset of images and pattern though which objects are classified [63]. For many applications image classification become an important and challenging task which includes biomedical imaging, biometry, video surveillance, vehicle navigation, industrial visual inspection, robot navigation, and remote sensing.

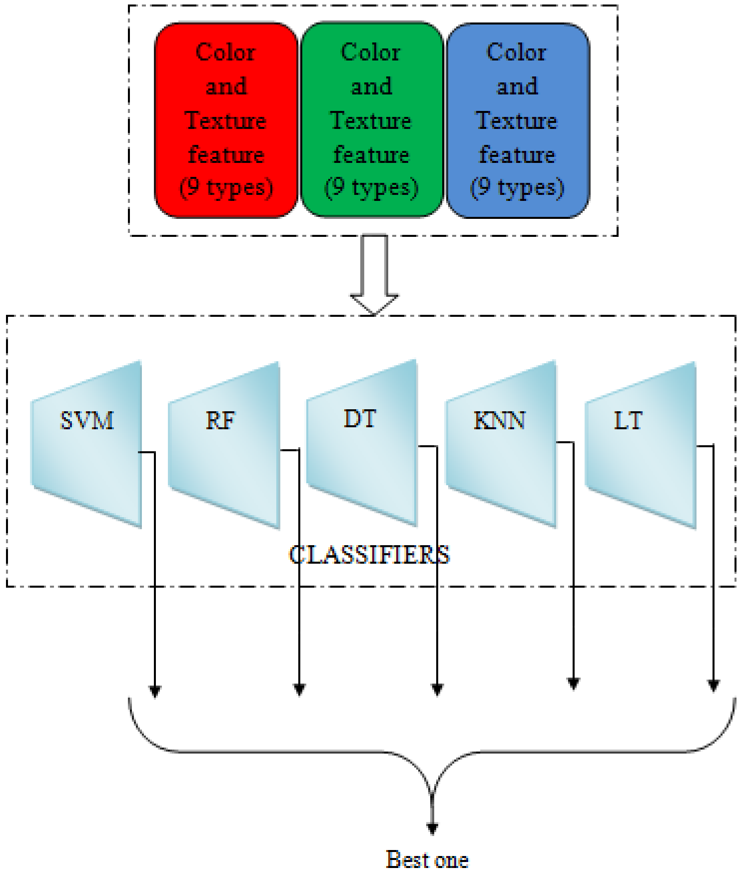


Figure 3.8 Classification model

We use 5 classifiers for statistical learning and compare classifier accuracy. The outline of the classifier models used in the present work is discussed below:

3.3.1 Support Vector Machine (SVM)

SVM classifier is derived from statistical learning theory by Vapnik and Chervonenkis [64]. In SVM classification, data points belonging to different classes are separated by dividing planes. The classification is done on the basis of margin between the separating planes. In fact, the generalized error is less if the planes have the maximum margin to the nearest training data points of any class. The testing data points are then mapped into same space and prediction is done on the basis of which side of gap the point's falls.

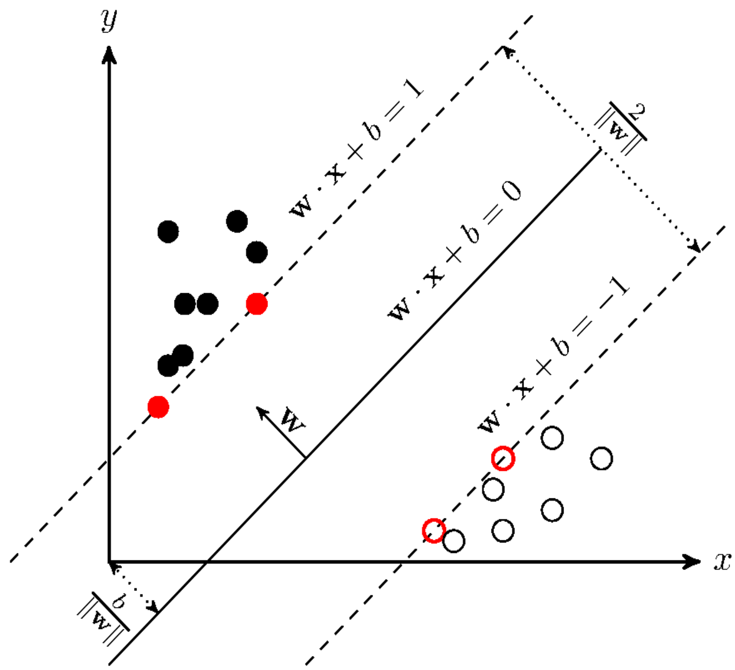


Figure 3.9 Support Vector Machine [64]

Thus, the aim of svm is [65] to discover a most favorable hyperplane that separates the two classes. Let(x_i,y_i) are the training samples, where i = 1, 2...N, $y_i \in \{-1, 1\}$ are the class labels. The two classes separated by hyperplane amounts to make sure that the x_i belongs to y_i of same sign must be on the same side of hyperplane. If such a hyperplane exists that data is considered to be a linearly separable. The hyperplanes are denoted by w and b, we require

$$y_i(w.x + b) > 0, i = 1, \dots \dots N \tag{3.11}$$

If information is linearly seperable, it is feasible to rescale w and b .i.e.

$$min_i[y_i(w.x + b)] > 1, i = 1, \dots \dots N \tag{3.12}$$

This is demonstrated in Figure 3.9. If an optimal separating hyperplane (OSH) is existed then the decision function will decide whether a new point x corresponds to y = 1 or 0 is given by

$$f(x) = sgn(\sum_i^N \alpha_i \, y_i x_i . x + b) \tag{3.13}$$

The expression inside the sgn() function is the calculation of distance from the hyperplane. Here $\alpha i \geq 0$ is the result found during training. The $\alpha i > 0$ is known as the Support Vectors. In case of non-linearly separable we establish a slack variable $\varepsilon \geq 0$ [66]

$$\mathrm{y_i(w.x + b) > 1 - \varepsilon, i = 1, \dots \dots N} \tag{3.14}$$

For wrongly classified points $\varepsilon > 1$. The general OSH solution is then to decrease

$$\frac{1}{2}\mathrm{w.w} + \mathrm{C}\sum_{\mathrm{i}}^{\mathrm{N}} \varepsilon_{\mathrm{i}} \tag{3.15}$$

The second term denotes the total number of wrongly classified points. The tradeoff between the two terms are controlled by C. Larger the value of C lower will be wrongly classified terms but the value of w should be high. Lesser the value of C would result in more wrongly classified points but a sparser result with L1 regularized w.

3.3.2 K-Nearest Neighbor (KNN)

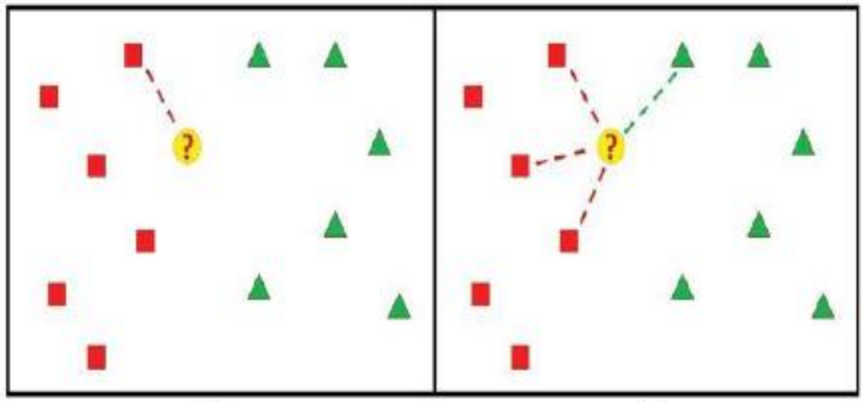
k-nearest neighbor algorithm [67,68] is used to classify objects based on the nearest training example in the feature pool. It is the simplest algorithm among all the machine learning algorithms. In this algorithm training procedure consists of feature vectors and labels of the images used in training dataset. During classification process, the unknown label point is allocated to the label of its k- nearest neighbors.

KNN is a kind of instance-based learning, or lazy learning where classification is done on the basis of majority voting of label of its k nearest neighbors. The object is classified on the basis of nearest class to the object when k=1. When two classes exist, the value k should be an odd integer. While executing multiclass classification there is still a possibility of getting k to be an odd integer. . In KNN algorithm image is converted into vector of fixed length will real values, we used the common function of KNN .i.e. Euclidean distance to find the distance; it is calculated by

$$d(x,y) = \left|\left|x,y\right|\right| = \sqrt{(x-y).(x-y)} \tag{3.16}$$

$$= \left(\sum_{i=1}^{m}((x_i - y_i)^2)\right)^{1/2} \tag{3.17}$$

where, x and y are histograms in $X = R^m$. Figure 3.10 shows the process of KNN classification.



(a) (b)

Figure 3.10 (a) Class assigned to ? is left one according to the 1-NN rule (b) as k=4, the class assigned to? is left as well according to KNN decision rule [68].

The advantage of the KNN classification is that it gives well better results with multi-classes because its decision is based on neighbors of similar types. Therefore, even if the target class is multi-class, it still gives the good accuracy. However a drawback of the KNN classification is that it takes all the features equal while computing for similarities. This may lead to errors in classification, mainly when small subset of features is used for classification.

3.3.3 Decision Tree (DT)

Decision tree [69] is examined to be the most accepted data-mining methods for information discovery. It methodically analyzes the data present in a large information source to compute valuable relationships and rules and generally it is used for the classification/prediction purpose. In comparison to several other data mining methods, it is broadly applied in different areas since it is powerful for data scaling or distributions [70, 71]. A decision tree has rooted tree structure. Each non-leaf nodes in a decision tree is consider as decision node, which shows a criterion to split the cases into two or more sub trees. Each leaf nodes show a cluster of like cases, which are allocated to a particular class. The decision tree algorithm can predicts the class for any unknown case, by moving down from the root node to a leaf, by using the rules in the nodes to choose the branch to go to.

The most important component of a decision tree classification is the process used to estimate splits at every internal node of the tree, it is named as splitting criterion. In decision tree classification ID3 algorithm is used to take decision in which Entropy is the most accepted splitting criterion.

a. Entropy

Given a node (S) that consists of attributes and class of the attributes, we can determine homogeneity (or heterogeneity) of the node on the basis of classes. If a node is pure or homogenous, it will consist of only a single class. If a node consists of several classes, then it the node is considered to be an impure or heterogeneous. To compute the level of impurity or entropy.

$$\text{Entropy(S)} = \sum -P_j \, log_2^{P_j} \tag{3.18}$$

where, S is dataset for which entropy is computed, j is set of classes, p_j is probability of number of elements in class j to the total number of elements in S

Entropy for pure node (consist of single class) is zero because its probability is 1 and log (1) = 0. Entropy reaches its highest value when the entire classes in the node have the same probability. To discover the most excellent attribute for a specific node in the tree, information gain is used. The information gain is defined as

$$\text{Gain(S)} = I(S) - \sum_j p_j * I(j) \tag{3.19}$$

where, $I(S)$ is entropy of dataset, j is subset created by splitting S, p_j is probability of number of elements in class j to the total number of elements in S, $I(j)$ is entropy of subset j.

3.3.4 Random Forest (RF)

Random forests [72] were first developed by Breiman in 2001 [73], and were derived from the bagging algorithm [74]. In a random forest, a tree does not depend on each other in the forest, so that the training and testing can be processed in parallel [75]. Given a set of training data $\{x_1, x_2, \ldots \ldots x_n\} \in R^{L\times n}$, n denotes the number of samples and L is the number of features. x_i shows the location of sample i in the space $R^{L\times n}$, while z shows the relationship between x_i and x_j, where z ∈ Z = $\{1, -1\}$. If x_i and x_j corresponds to same class, then value of z=-1, and if $x_i$and x_j corresponds to the different class, then value of z=1. A random forest is a grouping of tree-structured predictors. For the k^{th} tree, the ensemble is$f_k(x) = f(x, \vartheta_k)$, and where$f(x, \vartheta_k)$, spread along with the training set and the random vector ϑ_k , which represents the different stochastic elements of the tree. $\{\vartheta_k\}$ are independent and uniformly distributed, and each tree votes to the most approachable class at the input vector x. Probability for predicting the class z is

$$P(z|x) = \frac{1}{K}\sum_{k=1}^{K} P_k(z|x) \tag{3.20}$$

where, $P_k(z|x)$the evaluated density of the class is labels of the k^{th} tree and K is the number of trees in the forest. The decision function of the forest is defined as

$$C(x) = \underset{j \in Z}{\arg\max}\, P(j|x) \tag{3.21}$$

The margin function of the random forest is

$$ml(z, x) = P(z|x) - \underset{\substack{j \in Z \\ j \neq z}}{max} P(j|x) \tag{3.22}$$

this shows that the generalization error will merge as the number of trees grows. An upper bound for the generalization error is denoted by

$$PE^* \leq \bar{\rho}(1 - s^2)/s^2 \tag{3.23}$$

in which PE^* denotes the generalization error, $\bar{\rho}$ denotes the mean value of the relationship between the trees, and s is the power of the set of $f(x, \vartheta_k)$. Clearly, when we have sufficient number of trees in the forest, the generalization error of the random forests converges to a finite value.

3.3.5 Generalized Linear Model (GLM)

The Generalized Linear Models are expansion of linear modeling process. In other words, they expand the ideas of regression analysis to a large class of complications concerning the relationship between a response and one or more descriptive variables [76]. These models can be used for the systems which do not follow the normal distribution like chi square, binomial, Poisson, gamma and others. The link function is used when dependent variables is considered to be nonlinearly connected to the predictors. In addition, these models can also be used to estimate the responses having non-continuous distribution and non-linearly related to the predictors for dependent variables. Generalized linear models equation for link linear relationship [77] is defined as.

$$E(Y) = g(\mu) = \beta_0 + \beta_1 + \gamma + \beta_j x_j \tag{3.24}$$

The link function $g(\mu)$ is used to connect the random or stochastic components of the model, the probability distribution function of the response variable and the systematic component of the model (the linear predictor). Basically $g(\,)$ is used to convert the μ_i to a range on which they are not constrained.

3.4 CALORIE’S AND NUTRITIONAL FACT TABLE

A calorie is a measuring unit which is defined as the amount of heat energy required to raise the temperature of 1 gram of water by 1 degree [78]. This unit is used to calculate the overall amount of energy essential for life processes in any food portion that consists of the main food components, such as vitamins, carbohydrates, minerals, proteins and fat. Each component has a standard amount of calories per gram. The number of calories in carbohydrates and proteins is 4 kcal/g, while in fat, the number of calories is 9 kcal/g. Besides grams, calories are assumed in nutritional facts tables.

Calorie intake mostly depends on the weight of the person, his or her daily activity, age and gender. Each person should daily take a certain quantity of calories. If the quantity of calories dissipation is increased, it will results in increasing the weight and, therefore, the possibility of obesity. Thus, all nutrient facts tables should contain the number of calories plus additional facts related to food item or any food categories. In our proposed system, the nutrient fact tables and the quantity of calories for several types of fruits and vegetables is used as a basic criterion, and this will help us to find the quantity of calories in a food image. In fact, the system depends on the already known nutrient fact tables as a reference to compute the number of calories from any selected fruit and vegetable photo. This information is stored in the system database. Table 3.4 shows a sample set of nutrient facts for several fruits and vegetables from Health Canada nutrient guidelines [79].

Food name	Measure	Weight (g)	Energy (kcal)
Apple with skin	1	138	72
Orange	1	131	62
Guava	1	55	38
Chiku	1	170	141
Watermelon	$\frac{1}{18}$	280	90
Pomegranate	$\frac{1}{2}$	105	80
Cucumber	1	301	47
Tomato	1	123	22
Capsicum	1	140	31

Table 3.4 Nutritional fact table

3.5 DENSITY TABLE

The word density, ρ, is defined as the mass of any object per volume. Alternatively, it is defined as the proportion of any food element’s part to the calorie. In the case of food, there are variety of density depending on the connection between volume and mass. The types of densities are true density, bulk density, subdivision density, solid density and apparent density [80]. Out of all, Bulk density is considered the appropriate type of density to work with the image-processing technique. The images that were used for fruits and vegetables volume examinations were captured either by mobile camera or digital camera, which shows that the fruits and vegetables volumes were calculated with the internal and external pores included. Food density tables can get either from online or Health Canada food guide. Food density can also be acquired from easily obtainable tables [81].

In the proposed work, we use “aqua-calc” [84] to calculate the density from the estimated volume. It provides information of about 4000 types of food which includes Japanese as well as international food items.

3.6 USING THE COIN AS A REFERENCE

The system is based on a new method, which involves the coin while an image is captured. This method has an important role in our system. Besides the easiness of use, the coin is used as a size reference to calculate the real life size of fruits and vegetables. Actually, placing the coin in the image will allow us to compute the calories in fruits and vegetables by transforming the 2D image to a 3D image. We use the concept of coin for calibration purpose. The system already has the dimensions of coin, can then use it for evaluating the actual size of the eatable.

The calculation will start by capturing an image either it is used for database or of which calorie is measured from the top at the fixed distance .i.e. 15 centimeter. Then, a captured image is converted into a binary image to compute the area inside the coin and eatable. The extracted binary area of coin is compared to real-life size area of the coin to calculate the per pixel area in real-life dimensions. Then, the computed area of one pixel is used to calculate the size of fruits and vegetables in real dimensions.

3.7 METHOD OF IMAGE CAPTURING

A coin can be used to calibrate the image and examine the dimensions of the fruits and vegetables. First, the user will take a picture from the top, with the coin placed alongside the fruits and vegetables. The system, already has the dimensions of the coin as mentioned before, examine the pixels of both the coin and the fruits and vegetables in plate from the photo. Then the computed area will be used with the depth of the fruits and vegetables to estimate the volume. We presented the idea of using the coin for calibration in place of using a card [54].

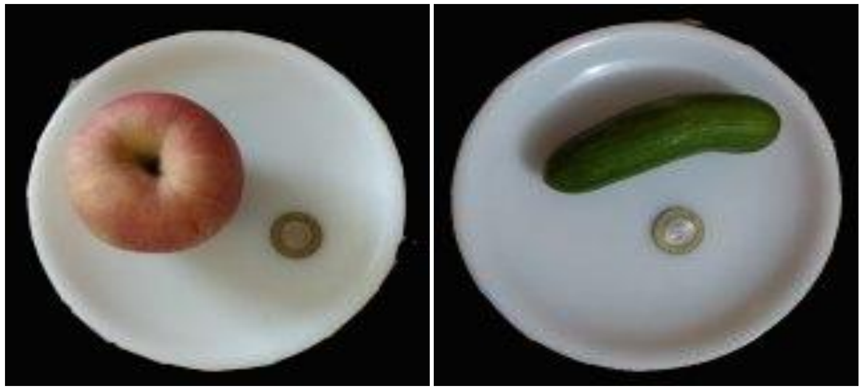


Figure 3.11: A captured images with the coin

3.8 MEASUREMENT OF CALORIE AND NUTRITION

The volume of fruits and vegetables measurement above is used to calculate the mass of the fruits and vegetables. Mass is real term which we need to calculate the calories. Once we get the mass, we can easily calculate the amount of calories by using the nutritional fact tables. The information about the nutritional values of eatables is easily available from national and international health organizations.

To calculate the mass of the eatable, the mathematical equation used is given below

$$M = \rho V \tag{3.25}$$

where, M is the mass of eatable and ρ is the density of food. In the proposed work aqua-calc [84] is used to calculate the mass from estimated volume.

After calculating the mass of the food system will calculate the calories by using the formulae given below

$$\text{Calorie in picture} = \frac{\text{Calorie from table} \times \text{Mass in the picture}}{\text{Mass from tables}} \tag{3.26}$$

CHAPTER 4

EVALUATION AND PERFORMANCE ANALYSIS

4.1 TOOLS USED

During our experiments, we use both Matlab (2015a) and R open (version 3.2.2) software tools on HP Core i3, 2.2-GHz platform.

4.2 CLASSIFICATION MODEL EVALUATION METRICS

Different evaluation parameters are used to measure the performance of the classification process, defined in Equations.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \tag{4.1}$$

$$\text{Error} = \frac{FP+FN}{TP+FN+TN+FP} \tag{4.2}$$

where, TP = True Positive, TN = True Negative, FP=False Positive, FN=False Negative

4.3 RESULT ANALYSIS, COMPARISON AND DISCUSSION

A classification performance of different machine learning approaches on fruits and vegetables dataset (1) Support Vector Machine (2) K Nearest Neighbor (3) Decision Tree (4) Linear Model (5) Random Forest using texture features shown in Figure 4.1.

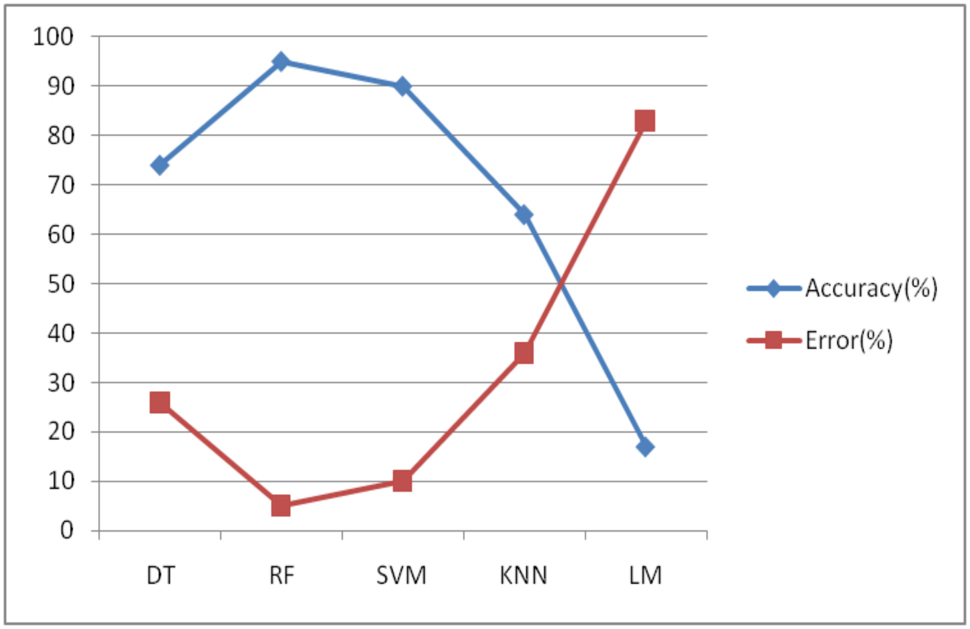


Figure 4.1 Accuracy and error rate of different classifiers

From Figure 4.1 it becomes evident that random forest gives much better accuracy in comparison to Decision tree, Support vector machine, linear tree and K-means nearest neighbor.

Furthermore, the accuracy is calculated for training-testing partition of 50-50, 60-40, 70-30 and 80-20 respectively to verify its uniformity demonstrated in Table 4.1. It shows that random forest performs well in all training-testing patterns.

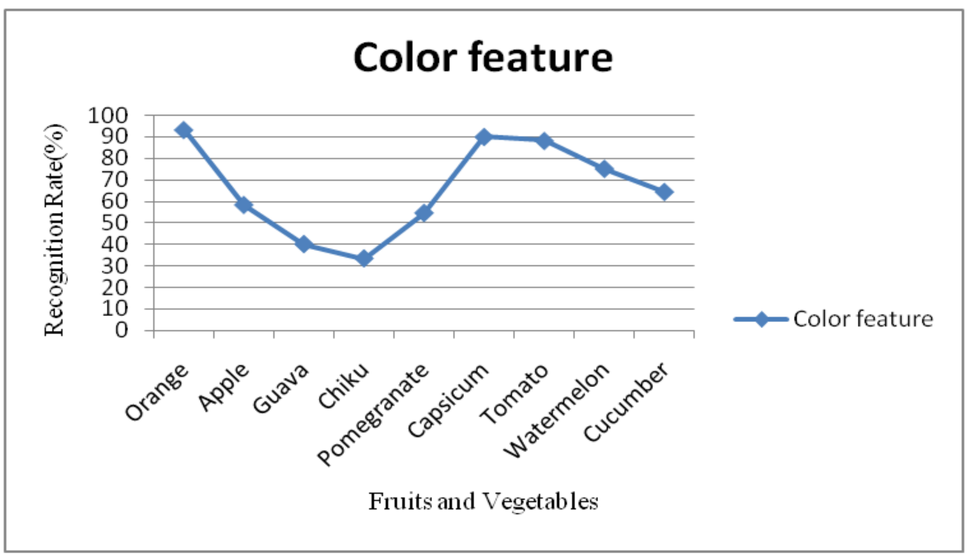
Models	Training and testing partition calculation			
	50-50%	60-40%	70-30%	80-20%
Random Forest	95%	94%	95%	92%

Table 4.1 Performance comparison on different testing-training partition

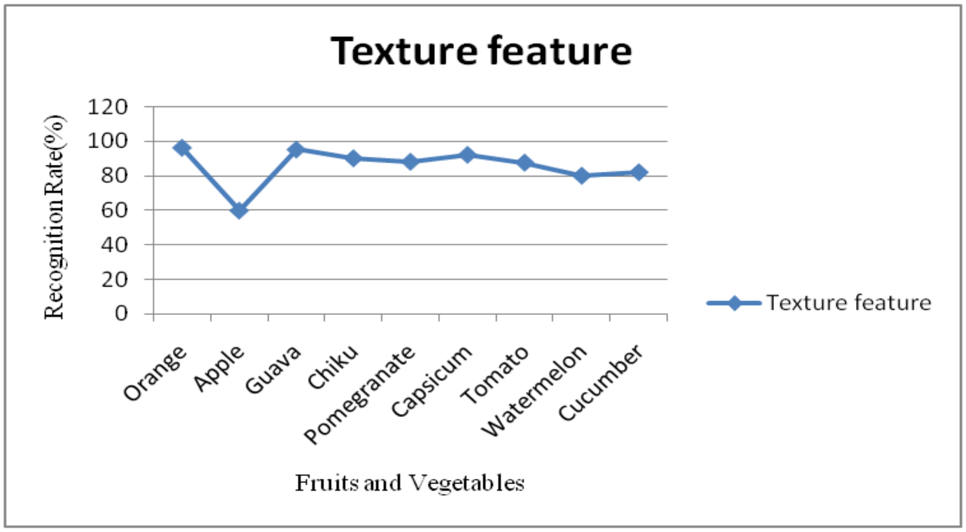
No.	Food items	Using Color Features	Using Texture Features	Using all Features
1.	Orange	93.33	96	98
2.	Apple	58.33	60	50
3.	Guava	40.01	95	95
4.	Chiku	33.33	90	88
5.	Pomegranate	54.54	88	66
6.	Capsicum	90.09	92	95
7.	Tomato	88.23	87.50	92
8.	Watermelon	75.22	80	82
9.	Cucumber	64.40	82	80
Total Average		66.38	85.61	82.88

Table 4.2 Results of Fruits and Vegetables Recognition Rate

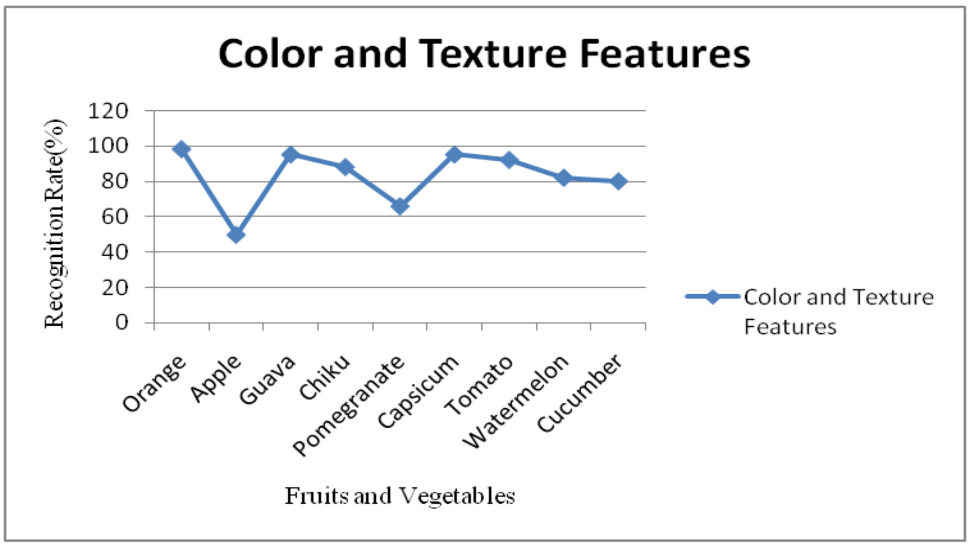
Graphical representation of Table 4.2 is shown in Figure 4.2 in which (a) represents the recognition rate of each fruit and vegetable on the basis of color features, (b) represents the recognition rate of each fruit and vegetable on the basis of texture feature, (c) represents the recognition rate of each fruit and vegetable by combining both texture and color feature.



(a)



(b)



(c)

Figure 4.2 Recognition Rate of Fruits and Vegetables through (a) Color Features (b) Texture Features (c) Both Color and Texture Features

We have calculated the mass of variety of fruits and vegetables by using the proposed technique. Our experimental results, few of which are presented in Table 4.3, show that our mass measurement technique achieves an error of about 24% in the worst case, and less than 3% in the best case.

Items	Calculated Mass(grams)	Actual Mass(grams)	Error percentage
Apple	124	140	11.4%
Pomegranate	267	282	5.31%
Tomato	18.8	25	24.8%
Cucumber	68	70	2.85%
Capsicum	71	80	11.25%
Orange	233	240	2.91%

Table 4.3 Results of calculating the mass of different types of fruits and vegetables

In order to compute the accuracy of the proposed technique, we have presented two different scenarios. In the first scenarios, technique is applied on variety of fruits and vegetables, and volume are extracted and then by using density table [82] mass is evaluated. With the help of extracted mass, calories in fruits and vegetables are computed using table given by health Canada [83]. In the second one, the real fruits and vegetables is weighted and its actual calories is computed by using table [82]. Finally, the extracted calories from two different scenarios are compared. Table 4.4 shows some of the results.

Items	Calculated Calorie	Actual Calorie	Absolute Accuracy (%)
Apple	70.85	80	88
Pomegranate	113.61	120	94
Tomato	12.03	16	75
Cucumber	20.40	21	95
Capsicum	28.40	32	88
Orange	120.30	124	90
Average Accuracy			88

Table 4.4 Accuracy of proposed technique in comparison with real values

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

The proposed system is an application related to the food intake estimation applications that take benefit of image processing to evaluate the volume of the fruits and vegetables in an image and thus calculate the amount of calories in it. In this chapter, we will conclude the work presented in this thesis and analyse its contributions.

5.1 DISCUSSION

There is a requirement of system that calculate daily intake of fruits and vegetables is essential due to the raise of obesity rates across the world. In addition, approximation of fruits and vegetables volume and caloric assumption is considered to be the biggest challenge when designing any diet control applications. Therefore, in this thesis, we presented a calorie measurement system that estimates the calories from variety of fruits and vegetables images through calculating the volume fruits and vegetables inside the image. To accomplish our goal, we designed the system application.

To use the technique, the person must take image containing the fruit or vegetable plus the measurement reference, which is the coin. Then the system will examine the image by using various concepts such as image processing, pre-processing, color and texture feature extraction, RF classification. Our main aim of the thesis is utilizing the volume from the calculated area by analyzing the image, and after that, evaluating the mass of the fruit or vegetable to get the amount of calories. To get the more accurate results and to guarantee the validity of our technique, we measured the fruit or vegetable by two methods: manually and after image processing.

We have confirmed that our measurement system is practical, convenient with the use of nutrient fact tables as standard information, and our computed results can optimize potentials of the system. All this will inspire the user to make use of the system. Our results showed reasonable accuracy of our system in volume and calorie estimation. We achieved reasonable accuracy results which are 25% in worst case and 5% in best one.

5.2 FUTURE WORK

Even though we have achieved acceptable accuracy results from our proposed system for calculating volume and calories in a fruits and vegetables image the method needs to training and it is still require to work on enhance the idea to contain more aspects i.e. more complex food items such as salads, liquid and mixed fruits and vegetables. For several types of fruits and vegetables that do not have a density amount, we can design a system to calculate the mass for a type of fruits and vegetables. Thus, we can compute the density of food. As another technique, we can cover in the system is the person's eating habits and physical activities. This will help both patient and doctor to manage the suggested diet and make sure the being will follow the diet plan.

As a future step for our proposed method, we can avoid the difficulty of long-time responding by just storing all the data of any consumed fruits and vegetables starting with image processing till estimation of calorie. If the person consumes the same type of fruits and vegetables, the system can just compute the difference of the area between the previous and the present consumed fruit or vegetable.

REFERENCES

[1] Whiting DR *et al.* (2011). IDF diabetes atlas: global estimates of the prevalence of diabetes for 2011 and 2030, *Diabetes* research *and clinical practice,* 94(3), 311-321.

[2] Hedinger C. *Histological typing of thyroid tumours*. Switzerland, SW: Williams and Sobin, 2012.

[3] Bray GA and Bouchard C. *Handbook of Obesity*, 2nd edition. New York, USA: Marcel Dekker, 2004.

[4] Chaudhry A et al. (2012). Trends in Twitter use by physicians at the American Society of Clinical Oncology annual meeting, 2010 and 2011. *Journal of Oncology Practice*, *8*(3), 173-178.

[5] World Health Organization. (2000). *Obesity: preventing and managing the global epidemic* (No. 894). World Health Organization.

[6] Ashwell M *et al.* (1996). Ratio of waist circumference to height is strong predictor of intra-abdominal fat, *British Medical Journal,* 313(7056), 559-560.

[7] Duren DL *et al.* (2008). Body composition methods: comparisons and interpretation, *Journal of Diabetes Science Technology,* 2(6), 1139–1146.

[8] Jia W *et al.* (2009). Food Portion Size Measurement System for Image-Based Dietary Assessment, *Bioengineering Conference* [35th: Boston, MA, USA: 2009], pp. 3-5.

[9] Vainio H, Miller AB (2003). Primary and secondary prevention in colorectal cancer. *Acta oncologica,* 42(8), 809-815.

[10] Clean E *et al.* Fruits and vegetables, (1992).

[11] Snetselaar L. *Nutritional counseling for lifestyle change*. CRC Press, 2006.

[12] Wargovich MJ (2000). Anticancer properties of fruits and vegetables. *HortScience*, 35(4), 573-575.

[13] Seddon J M *et al.* (1994). Dietary carotenoids, vitamins A, C, and E, and advanced age-related macular degeneration., *Jama*, 272(18), 1413-1420.

[14] Seifried HE *et al.* (2003). The antioxidant conundrum in cancer. *Cancer research*, 63(15), 4295-4298.

[15] He FJ, Nowson C A, MacGregor GA (2006). Fruit and vegetable consumption and stroke: meta-analysis of cohort studies. *The Lancet*, 367(9507), 320-326.

[16] Franz MJ et al. (2007). Weight-loss outcomes: A systematic review and meta-analysis of weight loss clinical trials with a minimum 1-year follow up, *Journal of the American Dietetic Association,* 107, 1755-1767.

[17] Shetty P (2002). Human energy requirements: Where are we now? Issues emerging from the 2001 expert consultation on energy in human nutrition, *Food, Nutrition, and Agriculture,* 30, 5-13.

[18] Schoeller DA (1988). Measurement of energy expenditure in free-living humans by using doubly labeled water, *Journal of Nutrition*, 118, 1278–1289.

[19] Schultner J *et al*. (2010). Application of the two-sample doubly labelled water method alters behaviour and affects estimates of energy expenditure in black-legged kittiwakes. *The Journal of Experimental Biology,* 213, 2958-66.

[20] Biro G *et al*. (2002). Selection of methodology to assess food intake. *European Journal of Clinical Nutrition,* 56, S25–S32.

[21] Casey PH *et al.* (1999). The use of telephone interview methodology to obtain 24-hour dietary recalls, *Journal of the American Dietetic Association,* 99, 1406–1411.

[22] Campbell VA, Dodds ML (1967). Collecting dietary information from groups of older people, *Journal of the American Dietetic Association,* 51, 29-33.

[23] Zulkifli SN, Yu SM (1992). The food frequency method for dietary assessment, *Journal of the American Dietetic Association,* 92(6), 681-685.

[24] Fox TA, Heimendinger J, Block G. The use of telephone surveys as a method for obtaining dietary information: A review, *Journal of the American Dietetic Association,* 92,729-732.

[25] Lyu *et al.* (1998). A comparison of face-to-face food frequency interviews with telephone interviews and self-administered questionnaires, *Journal of the Academy of Nutrition and Dietetics,* 98(1), 44-48.

[26] Kristal AR, Shattuck AL, Williams AE (1992). Food frequency questionnaires for diet intervention research, *In Proceedings of National Nutrient Databank Conference* [17th: Baltimore, Washington DC:1992], pp.110-125.

[27] Young CM, Trulson MF (1960). Methodology for dietary studies in epidemiological surveys. II. Strengths and weaknesses of existing methods, *American Journal of Public Health,* 50(6), 803-814.

[28] Abramson JH, Slome C, Kosovsky C (1963). Food frequency interview as an epidemiological tool, *American Journal of Public Health,* 53(7), 1093-1101.

[29] Hankin JH, Stallones RA, Messinger HB (1968). A short dietary method for epidemiologic studies. III. Development of questionnaire, *American Journal of Epidemiology,* 87(2), 285-298.

[30] Al-Maghrabi R (2013). Measuring Food Volume and Nutritional Values from Food Images. Ph.D. Thesis, University of Ottawa, Canada, 2013.

[31] Weber J *et al.* (1999). Portion-size estimation training in second and third-grade American Indian children, *American Journal of Clinical Nutrition*, 69(4), 782S–787S.

[32] Garrow J (1995). Human nutritionists' guilty secret, *Journal of Nutrition Bulletin*, 20(2), 103-108.

[33] Hambrus L (1998). Dietary assessments: How to validate primary data before conclusions can be drawn, *Scandinavian Journal of Nutritinal Näringsforskning,* 42(1), 66-68.

[34] Schoeller DA (1990). How accurate is self-reported dietary energy intake?, *Nutrition reviews*, 48(10), 373-379.

[35] Thompson FE, Subar AF (2008). Dietary assessment methodology. *Nutrition in the Prevention and Treatment of Disease*, 2, 3-39.

[36] Harbottle L, Duggan MB (1994). Use of the PETRA scale in a weighed inventory study of British Asian children: Methodological considerations, *Journal of Human Nutrition and Dietetics*, 7(4), 275-281.

[37] Bingham SA *et al.* (1994). Comparison of dietary assessment methods in nutritional epidemiology: Weighed records v. 24 h recalls, food-frequency questionnaires and estimated-diet records, *British Journal of Nutrition* 1994, 72(4),619-643.

[38] Kretsch MJ, Fong AK (1990). Validation of a new computerised technique for quantitating individual dietary intake: The Nutrition Evaluation Scale System (NESSy) vs the weighed food record, *American Journal of Clinical Nutrition*, 51(3), 477- 484.

[39] Johannes CB *et al.* (2000). Electronic versus paper instruments for daily data collection. *Annals of epidemiology*, 10(7), 457.

[40] Beasley J (2007). The pros and cons of using pdas for dietary self-monitoring, *Journal of the American Dietetic Association*, 107(5), 739-740.

[41] Beasley J (2007). The pros and cons of using pdas for dietary self-monitoring, *Journal of the American Dietetic Association*, 107(5), 739-740.

[42] Burke LE *et al*. (2005). Self-monitoring dietary intake: Current and future practices, *Journal of Renal Nutrition*, 15(3), 281–290.

[43] Amft O, Kusserow M, Tröster G (2009). Bite weight prediction from acoustic recognition of chewing, IEEE *Transactions on Biomedical Engineering*, 56(6), 1663– 1672.

[44] Nishimura J, Kuroda T (2008). Eating habits monitoring using wireless wearable in-ear microphone, *International Symposium on Wireless Pervasive Computing*, 130-133.

[45] K. Chang *et al.* (2006). The diet-aware dining table: Observing dietary behaviors over a tabletop surface, *In Proceedings of Pervasive Computing International Conference* [4th: Berlin, Heidelberg:2006] pp. 366–382.

[46] Gao C, Kong F, Tan J (2009).Healthaware: Tackling obesity with healthaware smart phone systems, *IEEE International Conference in Robotics and Biomimetics (ROBIO)*,[Guilin, China: 2009], pp. 1549 –1554.

[47] Yang J, Wu W (2009). Fast Food Recognition From Videos of Eating for Calorie Estimation, *IEEE International Conference on Multimedia and Expo*, [New York, USA: 2009] pp. 1210–1213.

[48] Takeda F *et al.* (2003). Dish extraction method with neural network for food intake measuring system on medical use, *International Symposium on Computational Intelligence for Measurement Systems and Applications*, [Lugano, Switerland: 2003] pp. 56-59.

[49] Martin CK., Kaya S, Gunturk B K. (2009). Quantification of Food Intake Using Food Image Analysis, *IEEE Conference on English Medicine and Biology Society*, [Minneapolis, USA: 2009] pp. 6869–6872.

[50] Kikunaga S *et al.* (2007). The application of a handheld personal digital assistant with camera and mobile phone card (Wellnavi) to the general population in a dietary survey, *Journal of Nutritional Science and Vitaminology*, 53(2),109 –116.

[51] Chi PY *et al*. (2008). Enabling Calorie-Aware Cooking in a Smart Kitchen, International Conference on Persuasive Technology, [3rd: Berlin, Heidelberg: 2008] pp. 116-127.

[52] Martin CK *et al.* (2009). A novel method to remotely measure food intake of free-living people in real-time: The Remote Food Photography Method (RFPM), *British Journal of Nutrition,* 101(3), 446-456.

[53] Puri M *et al.* (2009). Recognition and volume estimation of food intake using a mobile device, *IEEE Conference on Applications of Computer Vision*, [Snowbird, USA: 2009] pp. 1-8.

[54] Zhang ZN *et al.* (2011). Food Volume Estimation from a Single Image Using Virtual Reality Technology, *IEEE Conference on Bioengineering*, [37th: Troy, USA: 2011].

[55] Yang Y *et al.* (2011). Food volume calculation in different imaging scenarios, *IEEE Conference on Bioengineering*, [37th: Troy, USA: 2011] pp. 1-2.

[56] Yue Y *et al.* (2010). Food volume estimation using a circular reference in image-based dietary studies, *IEEE Conference on Bioengineering*, [35th: New York, USA: 2010].

[57] Mingui S *et al*. (2008). Determination of food portion size by image processing, *Journal of Engineering in Medicine and Biology Society,* [30th: Vancouver, Canada: 2008] pp. 871 - 874, August 2008.

[58] Gonzalez R, Woods R and Eddins S. *Digital Image Processing Using MATLAB*, 2nd edition, Tata McGraw Hill New Delhi, 2010.

[59] Lowe DG (2004).Distinctive image features from scale-invariant key points, *International journal of computer vision*, 60(2), 91-110.

[60] Ali A, Jing X and Saleem N (2011). GLCM-based fingerprint recognition algorithm, *IEEE International Conference on Broadband Network and Multimedia Technology*, [4th: Shenzhen, China: 2011] pp. 207-211.

[61] Wenbo W *et al.* (2015). Classification of SAR Image Based on Wavelet Transform and Gray Level Co-occurrence Matrix, *IEEE International Conference on Instrumentation and Measurement, Computer, Communication and Control*, [5th:Qinhuangdao, China: 2015] pp.1 04-107.

[62] Hu MK (1962). Visual pattern recognition by moment invariants, computer methods in image analysis. *IRE Transactions on Information Theory,* 8(2), 179-187.

[63] Kamavisdar P, Saluja S, Agrawal S. A survey on image classification approaches and techniques, *International Journal of Advanced Research in Computer and Communication Engineering& Applications*, 2(1), 1005-1009.

[64] Ben-Hur A *et al.* (2001). Support vector clustering, *Journal of machine learning research*, 2, 125-137.

[65] Chapelle O, Haffner P and Vapnik VN (1999). Support vector machines for histogram-based image classification, *IEEE transactions on Neural Networks*, 10(5), 1055-1064.

[66] Vapnik V N (1999). An overview of statistical learning theory, *IEEE Transactions on Neural Networks*, 10(5), 988-999.

[67] Bremner D *et al.* (2005). Output sensitive algorithms for computing nearest neighbor decision boundaries, *Discrete and Computational Geometry*, 33(4), 593–604.

[68] Cover T, Hart P (1967). Nearest-neighbor pattern classification, *IEEE Transactions on Information Theory*, 13(1), 21-27.

[69] Quinlan JR (1986). Induction of decision trees, *Machine Learning*, 1(1), 81-106.

[70] Provost F, Domingos P (2000). Well-trained PETs: Improving probability estimation trees.

[71] Cestnik B (1990). Estimating probabilities: A crucial task in machine learning, In Proceedings of European Conference on Artificial Intelligence (ECAI), [9th: Stockholm, Sweden: 1990] pp. 147-149.

[72] Amit Y, Geman D (1997). Shape quantization and recognition with randomized trees, *Neural Computational*, 9(7), 1545–1588.

[73] Breiman L (2001). Random forests, *Mach. Learn.*, 45(1), 5–32.

[74] Breiman L (1996). Bagging predictors, *Mach. Learn.*, 24(2), 123– 140.

[75] Leistner C *et al.* (2009). Semi-supervised random forests, *IEEE International Conference on Computer Vision*, [12th: Koyto, Japan: 2009] pp. 506–513.

[76] McCullagh P, Nelder JA. *Generalized Linear Models*, 2nd edition, Chapman and Hall, London, 1989.

[77] Dobson A. *An Introduction To Generalized Linear Models*, 3rd edition, Chapman and Hall, London, 1990.

[78] Hargrove JL (2006). History of the calorie in nutrition, *The Journal of nutrition*, 136(12), 2957-2961.

[79] Health Canada, Nutrient Values of some common foods. Available at http://www.hc-sc.gc.ca/fn-an/alt_formats/pdf/nutrition/fiche-nutri-data/nvscf-vnqau-eng.pdf

[80] Rahman S. *Food Properties Handbook*, 2nd edition, CRC Press, 1995.

[81] Stumbo PJ, Weiss R (2011). Using database values to determine food density, *Journal of Food Composition and Analysis*, 24(8), 1174-1176.

[82] Tremblay M S *et al.* (2011). New Canadian physical activity guidelines, *Applied Physiology, Nutrition, and Metabolism*, 36(1), 36-46.

[83] Muller K *et al.* (2001). An introduction to kernel-based learning, *IEEE Transactions on Neural Networks*, 12(2), 181–201.

[84] aqua-calc Food Volume to Weight Conversions. Available at http://www.aqua-calc.com/page/density-table

LIST OF PUBLICATIONS

1. "IoT based Computer Vision System for Nutrition Management", *ELCVIA Electronic Letters on Computer Vision and Image Analysis*- Communicated, 2017.

Thesis

ORIGINALITY REPORT

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PRIMARY SOURCES

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2	Almaghrabi, Rana, Gregorio Villalobos, Parisa Pouladzadeh, and Shervin Shirmohammadi. "A novel method for measuring nutrition intake based on food image", 2012 IEEE International Instrumentation and Measurement Technology Conference Proceedings, 2012. Publication	%1
3	mecs-press.org Internet Source	%1
4	O., O., E. J., and A. J.. "The Role of Fruit and Vegetable Consumption in Human Health and Disease Prevention", Diabetes Mellitus - Insights and Perspectives, 2013. Publication	<%1

5	www.slideshare.net Internet Source	<%1
6	Peltzer, Karl, and Supa Pengpid. "Fruits and Vegetables Consumption and Associated Factors among In-School Adolescents in Five Southeast Asian Countries", International Journal of Environmental Research and Public Health, 2012. Publication	<%1
7	www.hsph.harvard.edu Internet Source	<%1
8	www.ijarcce.com Internet Source	<%1
9	www.ijeert.org Internet Source	<%1
10	Fengqing Zhu, , Marc Bosch, Insoo Woo, SungYe Kim, Carol J Boushey, David S Ebert, and Edward J Delp. "The Use of Mobile Devices in Aiding Dietary Assessment and Evaluation", IEEE Journal of Selected Topics in Signal Processing, 2010. Publication	<%1
11	Lecture Notes in Computer Science, 2011. Publication	<%1
12	www.ias.ac.in Internet Source	<%1

13	www.eng.miami.edu Internet Source	<%1
14	Zhu, Fengqing, Anand Mariappan, Carol J. Boushey, Deb Kerr, Kyle D. Lutes, David S. Ebert, Edward J. Delp, Eric L. Miller, and Ilya Pollak. "", Computational Imaging VI, 2008. Publication	<%1
15	www.cs.uccs.edu Internet Source	<%1
16	www.cs.technion.ac.il Internet Source	<%1
17	medicine.org.hk Internet Source	<%1
18	Lecture Notes in Computer Science, 2006. Publication	<%1
19	ijarcce.com Internet Source	<%1
20	www.apostolkft.hu Internet Source	<%1
21	Q. Chen, , J. Zhao, and J. Cai. "Identification of Tea Varieties Using Computer Vision", Transactions of the ASABE, 2008. Publication	<%1
22	www.informatik.uni-freiburg.de	

Internet Source

<%1

---

23 www.mdpi.com
Internet Source
<%1

24 www.acsg.mcmaster.ca
Internet Source
<%1

25 William Wakeham. "Material Properties: Measurement and Data", Springer Handbook of Experimental Fluid Mechanics, 2007
Publication
<%1

26 thales.doa.fmph.uniba.sk
Internet Source
<%1

27 www.coursehero.com
Internet Source
<%1

28 blogs.consumerreports.org
Internet Source
<%1

29 asian-transactions.org
Internet Source
<%1

30 www.swindonjsna.co.uk
Internet Source
<%1

31 ORIOL PUJOL. International Journal of Image and Graphics, 2004
Publication
<%1