PERSONAL DIETARY ASSESSMENT USING MOBILE DEVICES

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ABSTRACT

Mariappan, Anand Raghu Kumaran M.S.E.C.E., Purdue University, December 2008. Personal Dietary Assessment using Mobile Devices. Major Professor: Edward J. Delp.

In this thesis, we investigate image segmentation and classification methods for automatically identifying food items. In this work, color and texture features are used to design the image classification method. The goal is to use these image analysis techniques to create a novel food recording method using a mobile device that will provide an accurate account of daily food and nutrient intake. We also have designed an User-Interface for a Windows Mobile Device which lets the user to "record" foods consumed by capturing the before and after images of the meal. The user-interface also lets the user label the food items.

1. INTRODUCTION

The increasing prevalence of obesity among the youth is of great concern [1] and has been linked to an increase in type 2 diabetes mellitus [2]. Accurate methods and tools to assess food and nutrient intake are essential in monitoring the nutritional status of this age group for epidemiological and clinical research on the association between diet and health. The collection of food intake and dietary information provides some of the most valuable insights into the occurrence of disease and subsequent approaches for mounting intervention programs for prevention. The assessment of food intake in adolescents has been evaluated by a food record (FR), the 24-hour dietary recall (24HR), and a food frequency questionnaire (FFQ) with external validation by doubly-labeled water (DLW) and urinary nitrogen [3–7]. Currently, there are too few validation studies in children to justify one particular method over another for any given study design.

Assessment of diet among adolescents is problematic. Early adolescents, ages 11 to 14 years, in particular, are in that period of time when the novelty and curiosity of assisting in or self-reporting of food intakes starts to wane and the assistance from parents is seen as an intrusion [3]. Dietary assessment methods need to continue to evolve to meet these challenges. There is recognition that further improvements will enhance the consistency and strength of the association of diet with disease risk, especially in light of the current obesity epidemic among this group.

Preliminary studies among adolescents suggest that innovative use of technology may improve the accuracy of diet information from young people.

Our goal is to develop, implement, and evaluate a mobile device (i.e., a PDA or mobile telephone) food record that will translate to an accurate account of daily food and nutrient intake among adolescents.

Mobile computing devices provide a unique vehicle for collecting dietary information that reduces burden on record keepers. Images of food can also be marked with a variety of input methods that link the item for image processing and analysis to estimate the amount of food. Images acquired before and after foods are eaten can estimate the amount of food consumed.

In this thesis, we describe some preliminary results from the development of such a system.

1.1 Review of Current Dietary Assessment Methods

A review of some of the most popular dietary assessment methods are provided in this section. Our objective here is to analyze the advantages and major drawbacks of these methods. This will demonstrate the significance of our mobile system which can be used for population and clinical based studies to improve the understanding of dietary exposures among adolescents.

1.1.1 24-Hour Dietary Recall

The 24-hour dietary recall (24HR) consists of a listing of foods and beverages consumed the previous day or the 24 hours prior to the recall interview. Foods and amounts are recalled from memory with the aid of an interviewer who has been trained in methods for soliciting dietary information. A brief activity history may be incorporated into the interview to facilitate probing for foods and beverages consumed. The Food Surveys Research Group (FSRG) of the United States Department of Agriculture (USDA) has devoted considerable effort to improving the accuracy of this method.

The major drawback of the 24HR is the issue of underreporting of the food consumed [8]. Factors such as obesity, gender, social desirability, restrained eating and hunger, education, literacy, perceived health status, age, and race/ethnicity have been shown to be related to underreporting [9–12]. Harnack, et al. [13] found significant underreporting of large food portions when food models showing recommended serving sizes were used as visual aids for respondents. Given that larger food portions have been observed as occurring over the past 20 to 30 years [14, 15] this may be a contributor to underreporting and methods to capture accurate portion sizes are needed. In addition, youth, in particular, are limited in their abilities to estimate portion sizes accurately [3]. The most common method of evaluating the accuracy of the 24HR with children is through observation of school lunch [16] and/or school breakfast [17] and comparing foods recalled with foods either observed as eaten or foods actually weighed. These recalls have demonstrated both under-reporting and over-reporting, and incorrect identification of foods.

1.1.2 Food Record

The 24HR is useful in population based studies; the preferred dietary assessment method for clinical studies is the food record. Depending on the primary nutrient or nutrients or foods of interest, the minimum number of food records needed is rarely less than two days. Training the subjects, telephoning with reminders for recording, reviewing the records for discrepancies, and entering the dietary information into a nutrient database can take a large amount of time and requires trained individuals [18].

The food record is especially vulnerable to underreporting due to the complexity of recording food [19, 20]. A study among 10-12 year old children found significant underreporting of total energy intake (TEI) when the intake was compared against an external marker, doubly-labeled water (DLW) [21]. As adolescents snack frequently, have unstructured eating patterns, and consume greater amounts of food away from the home, their burden of recording will be much greater compared to adults. It has been suggested that these factors, along with a combination of forgetfulness and irritation and boredom caused by having to record intake frequently may be contributing to the underreporting in this age group [22]. Dietary assessment methods perceived as less burdensome and time-consuming may improve compliance [22].

1.1.3 Portion Size Estimation

Portion size estimation may be one contributor to underreporting. In [23] it was found that 45 minutes of training in portion-size estimation among 9-10 year olds significantly improved estimates for solid foods which were measured by dimensions or cups, and liquids estimated by cups. Amorphous foods were estimated least accurately even after training and some foods still exhibited an error rate of over 100%. Thus, training can improve portion size estimation, however more than one session may be needed.

1.1.4 Evaluation of Dietary Assessment Methods

The number of days needed to estimate a particular nutrient depends on the variability of the nutrient being assessed and the degree of accuracy desired for the research question [24–27]. Most nutrients require more than four days for a reliable estimate [25, 27]. However, most individuals weary of keeping records beyond four days which may decrease the quality of the records [19].

Another challenge in evaluating dietary assessment methods is comparing the results of the dietary assessment method to some measure of "truth." This is best achieved by identifying a biomarker of a nutrient or dietary factor [20, 28]. The underlying assumption of a biomarker is that it responds to intake in a dose-dependent relationship [26]. The two methods that have widest consensus as valid biomarkers are DLW for energy [20,29] and 24-hour urinary nitrogen for protein intake [6,30,31]. A biomarker does not rely on a self-report of food intake, thus theoretically the measurement errors of the biomarker are not likely to be correlated with those of the dietary assessment method. Other biomarkers collected from urine samples include potassium and sodium [30]. Plasma or serum biomarkers that have been explored are levels of ascorbic acid for vitamin C intake [30,32], β-carotene for fruits and vegetables or antioxidants [32–34]. These latter markers are widely influenced by factors such as smoking status and supplement use, thus their interpretation to absolute intake is limited.

2. IMAGE ANALYSIS SYSTEM

2.1 Previous Work

A lot of work has been done in the field of image segmentation and automatic food recognition. A review of some of the image segmentation methods and previous work on automatic food recognition are provided in this section.

In the paper by Jimenez et.al [35] an automatic fruit recognition system, which can recognize spherical fruits in different situations such as shadows, bright areas, occlusions and overlapping fruits is reported. A three-dimensional scanner is used to scan the scene to generate five digital images. Two images represent the azimuth and elevation angles ($AZ(x, y)$ and $EL(x, y)$), the distance or range is included in $RANG(x, y)$, the attenuation is in $ATTE(x, y)$ and the reflectance image $REFL(x, y)$. The image analysis process uses the images obtained from the scanner to detect the position of the fruits by thresholding and clustering. The Circular Hough Transform is used to identify the center and radius of the fruits. This paper also gives a comprehensive study of the previous fruit detection work.

[36] proposes a robust algorithm to segment the food items from the background of color images. The image is converted to a high contrast grayscale image from an optimal linear combination of the RGB color components and then the image is segmented using a global threshold which is estimated by a statistical approach to minimize the intraclass variance. The segmented regions are subjected to a morphological process to remove small objects, to close the binary image by the dilation followed by erosion and to fill the holes in the segmented regions.

The work presented in [37] uses a stick growing and merging method to segment complex food images. The image is first pre-processed by an edge-preserving smooth-

[0]The image analysis system described in this chapter was co-developed with Fengqing Zhu.

ing technique and a large number of horizontal lines ("sticks") are built in which pixels are homogeneous by traversing the initial image. The sticks ends correspond to edge points. Once the sticks are built, then adjacent sticks are merged to form a sub region based on the stick-stick homogeneity criterion C_{2ssh}. Then the sub regions are merged if it satisfies a minimal sub region merging criterion. The regions with non-stick areas appear as noises or edges which cause less smooth boundary. Boundary modification step is used to reduce the degree of boundary roughness. This paper also presents that they were successful in segmenting many food complex food images including pizza, apple, pork and potato.

In the paper [38] proposes a snake model which is a controlled continuity spline under the influence of image forces and external constraint forces. Energy functionals are needed to make the snakes useful for vision problems. They process three different energy functionals to detect features such as lines, edges and terminations. Edges in images are detected by using a simple energy functional. The snake is used to detect contours with large image gradients by using the edge functional. This paper also explains by using the edge functional they were able to segment food items such as pear and potato.

The work presented in [39, 40] discusses the different set of features, namely color, shape and texture features, that can be used for image retrieval. [41] proposes to use color and texture features and clustering technique to segment the images. This paper also indicates that the image segmentation algorithm based on the color and texture features performed well in low-resolution and compressed images. In the paper by Dorin et.al [42], they were able to produce high quality edge image by extracting all the significant colors. In our work we extract namely the color and texture features for image identification.

2.2 Image Analysis and Visualization

Our goal is to use a mobile device with a build-in camera, integrate image analysis and visualization tools with a nutrient database, to allow an adolescent user to discretely “record” foods eaten. Mobile devices, such as PDAs and mobile telephones with cameras, are general purpose computing devices that have a great deal of computational power that can be exploited for solutions to this problem. PDAs are ideal as a field data collection device for diet assessment [43, 44]. However, there have been problems when deploying these types of devices if one does not understand the user and the environment in which the device will be deployed.

We believe that a properly designed system will make mobile devices attractive to users and can be used to measure food intake. Most mobile devices include digital cameras which make taking pictures and labeling the content of the pictures less burdensome than writing on paper. The use of a mobile device that works the way young people interact with portable devices may address many of the issues outlined as barriers to recording food intake among adolescents. Young users treat their mobile device as an extension of their personality and this needs to be considered in the design of our system.

Mobile devices have the potential to create an entire new platform for applications and services that could be used for dietary assessments. For example, some individuals may forget to record their food when eaten, in which case the record can become a cross between a recall and a record. With paper and pencil recording there is no way a researcher can check that foods were recorded at the time of the meal or that all meals were recorded at the end of the day. With a mobile device, every entry records a time stamp, thus allowing researchers to more accurately determine if data entry occurred at typical meal times (record), long after the meal, or all at once at the end of the day (an unassisted recall). The use of an image provides another dimension of verifying food intake.

The user will capture an image of his/her meal or snack both before and after eating. This reduces the burden of many aspects of recording for the users and reduces analysis for the researchers. However, in the event that a picture of a food cannot be obtained, the system needs an alternative way of determining the food consumed.

We have developed methods to automatically segment and identify food items from an image acquired from a mobile device. An example of such an image is shown in Figure 2.1. This is not an easy problem in that some foods may not be identifiable from an image. For example, the type of milk in a cup (e.g., low fat or skim milk) may not be determined from the image alone. This will require other types of "side information" be available to the system either through how the food was packaged (e.g., an image of the milk carton) or through inputs (manual or audio) from the user.

A block diagram of our image analysis system is shown in Figure 2.2. Our plans for addressing the various tasks are described below.

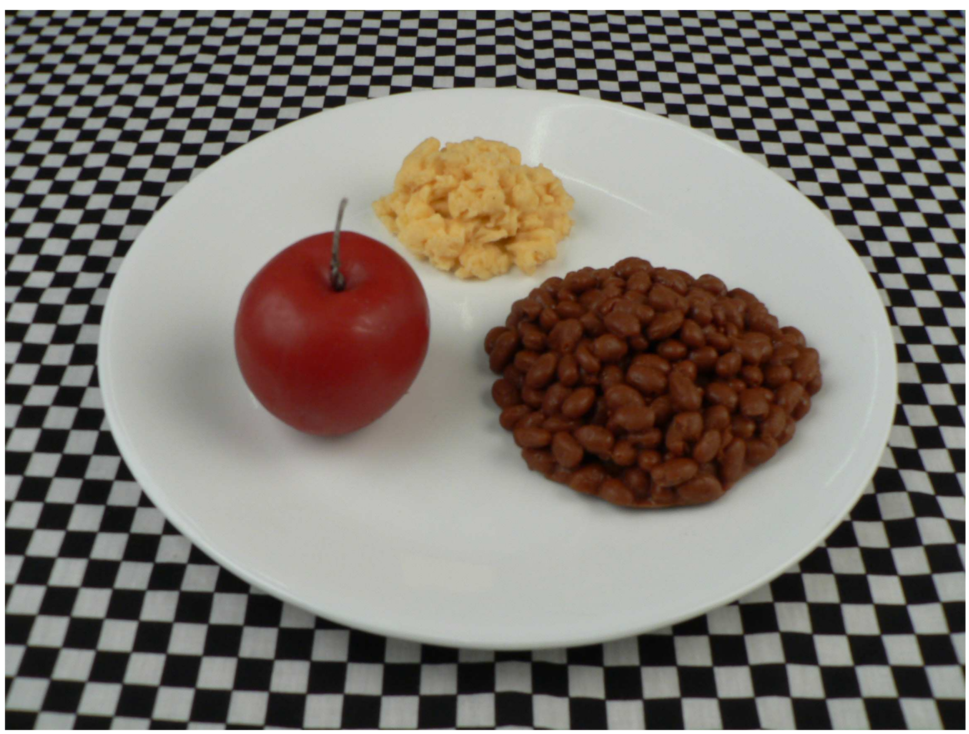


Fig. 2.1. A Typical Image of a Meal.

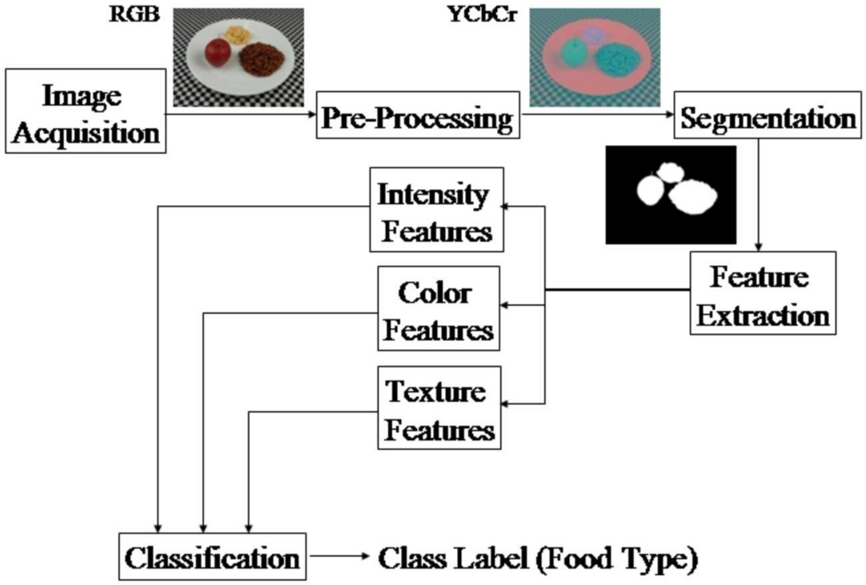


Fig. 2.2. Image Analysis System.

2.3 Image Calibration and Acquisition

Since we are interested in knowing how much food was consumed, we need to have a 3D calibrated system. This could be accomplished by having the user take the image with a known fiducial object, e.g., a pen or PDA stylus, placed next to the food so one could use this to "calibrate sizes" in the images. We might also use the known dimensions of a plate or cup in a scene. Other a priori information in the scene such as the pattern on the tablecloth (see Figure 2.1) could also be used.

For 3D or volume estimation we are also exploring the use of multiple images of the scene taken at different orientations. This will also require that calibration information be available so that depth information can be recovered.

2.4 Image Segmentation

Our goal is to automatically determine the regions in the image where a particular food is located. Once a food item is segmented, we will identify the food item Our image segmentation method is a two step process.

2.4.1 First Step of Segmentation

In the first step the image is converted to a grayscale image and then thresholded with a threshold of 127 to form a binary image. It was determined empirically that the pixel values in the binary image corresponding to the plate had values of 255. For segmenting the food items on the plate, the binary image was searched in 8-point connected neighbors for the pixel value 0. Connected segments less than 1000 pixels were ignored because they correspond to the tablecloth (see Figure 2.1). In this step we used a fixed threshold. Thus, pixels corresponding to the food items might be considered as the plate. As a result, we need a second step of segmentation. The result of the first step of segmentation is shown in Figure 2.3(a).

2.4.2 Second Step of Segmentation

In the second step, the image is first converted to the YCbCr color space. Using the chrominance components, Cb and Cr, the mean value of the histogram corresponding to the plate was found. Pixel locations which were not segmented during the first step were compared with the mean value of the color space histogram of the plate to identify potential food items. These pixels were labeled differently from that of the plate. Then 8-point connected neighbors for the labeled pixels were searched to segment the food items. An example is shown in Figure 2.3(b), the food item, i.e. scrambled egg, which was not segmented in the first step is successfully segmented in the second step using the color space.

2.5 Feature Extraction

Two types of features were extracted from each segmented food region, namely color features and texture features.

2.5.1 Color Features

For color features, the average value of the pixel intensity along with the two color components were extracted. The color components were obtained by first converting the image to the YCbCr color space

2.5.2 Texture Features

For texture features, we used Gabor filters to measure local texture properties in the frequency domain. In the literature can be found several Gabor techniques for many texture-segmentation applications [45–48]. Gabor filters describe properties related to the local power spectrum of a signal and have been used for texture features [47]. A Gabor impulse response in the spatial domain consists of a sinusoidal plane wave of some orientation and frequency, modulated by a two-dimensional Gaussian envelope and is given by:

$$h(x, y) = exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right]\cos\left(2\pi Ux + \varphi\right) \tag{2.1}$$

In our work, we used a Gabor filter-bank proposed in [45]. It is highly suitable for our use where the texture features are obtained by subjecting each image (or in our case each block) to a Gabor filtering operation in a window around each pixel and then estimate the mean and the standard deviation of the energy of the filtered image. A Gabor filter-bank consists of Gabor filters with Gaussians of several sizes modulated by sinusoidal plane waves of different orientations from the same Gabor-root filter as defined in Equation (2.1), it can be represented as:

$$g_{m,n}(x, y) = a^{-m} h(\tilde{x}, \tilde{y}), \quad a > 1 \tag{2.2}$$

where $\tilde{x} = a^{-m}(x \cos\theta + y \sin\theta)$, $\tilde{y} = a^{-m}(-x \sin\theta + y \cos\theta)$, $\theta = n\pi/K$ (K = total orientation, $n = 0, 1, ..., K - 1$, and $m = 0, 1, ..., S - 1$), and $h(\cdot, \cdot)$ is defined in Equation (2.1). Given an image $I_E(r, c)$ of size $H \times W$, the discrete Gabor filtered output is given by a 2D convolution:

$$I_{g_{m,n}}(r, c) = \sum_{s,t} I_E(r - s, c - t) {g_{m,n}}^*(s, t), \tag{2.3}$$

As a result of this convolution, the energy of the filtered image is obtained and then the mean and standard deviation are estimated and used as features. In our implementation, we divided each segmented food item in to 64×64 non-overlapped blocks and used Gabor filters on each block. We used the following parameters: 4 scales (S=4), and 6 orientations (K=6).

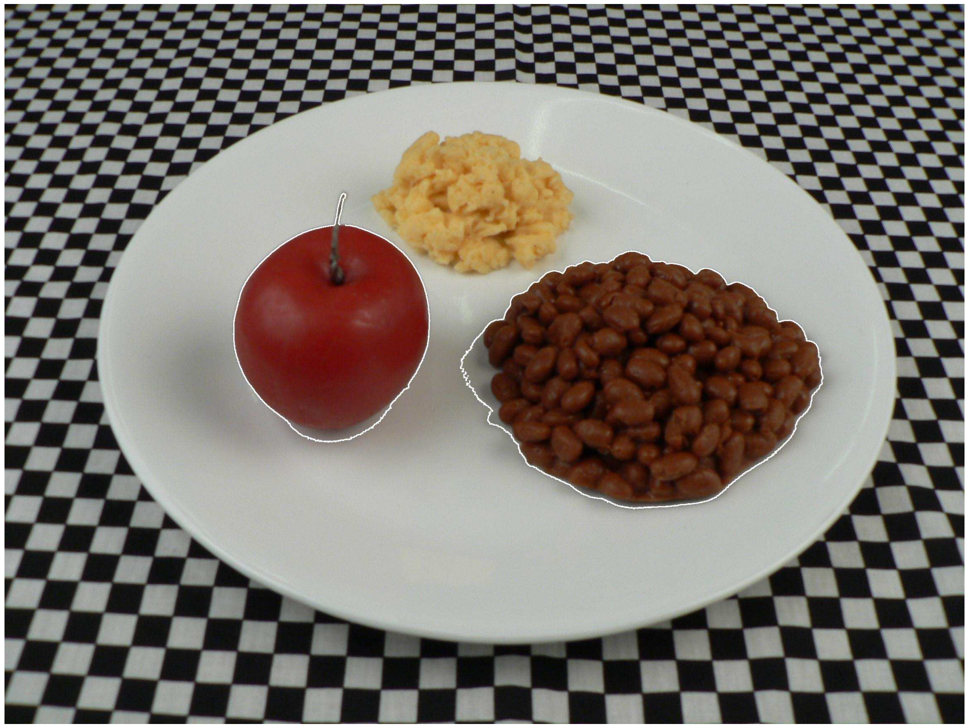
2.6 Classification

Once the food items are segmented and their features are extracted, the next step is to identify the food items using statistical pattern recognition techniques [49, 50] . For classification of the food item, we used a support vector machine (SVM) [51–53]. SVM is a technique used for data classification. A classification task usually involves with training and testing data which consist of some data instances. Each instance in the training set contains one class label and several "attributes" (features). The goal of SVM is to produce a model which predicts target value of data instances in the testing set which are given only the attributes. Given a training set of instance-label pairs $(x_i, y_i), i = 1, ..., l$, where $x_i \in R^n$ and $y \in \{1, -1\}^l$, the SVM [54, 55] requires the solution of the following optimization problem:

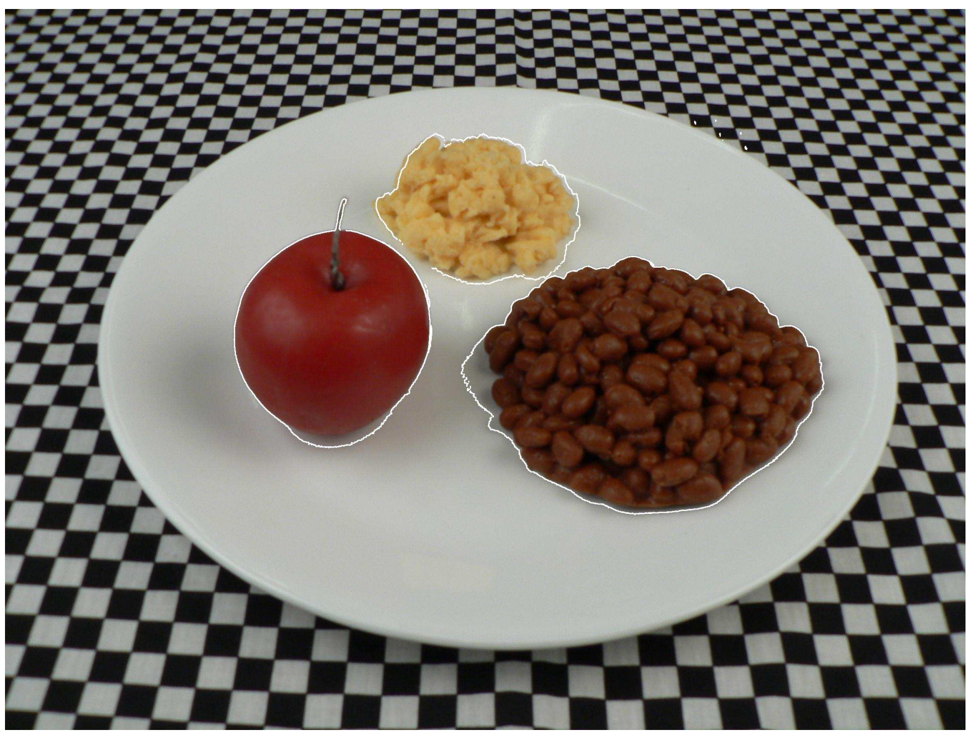
$$\min_{\omega,b,\xi} \quad \frac{1}{2}\omega^T \omega + C \sum i = 1^l \xi_i \qquad subject \quad to \quad y_i(\omega^T \Phi(x_i) + b) \geq 1 - \xi_i, \qquad \xi_i \geq 0. \tag{2.4}$$

Here training vectors x_i are mapped into a higher (maybe infinite) dimensional space by the function Φ. Then SVM finds a linear separating hyper plane with the maximal margin in this higher dimensional space. $C > 0$ is the penalty parameter of the error term. Furthermore, $K(x_i, x_j) \equiv \Phi(x_i)^T\Phi(x_j)$ is called the kernel function. We use the radial basis function (RBF): $K(x_i, x_j) = exp(-\gamma\|x_i - x_j\|^2), \gamma > 0$. The RBF kernel non-linearly maps samples into a higher dimensional space, so it, unlike the linear kernel, can handle the case when the relation between class labels and attributes is nonlinear.

The feature vectors used for the SVM contain 51 values, 48 texture features and 3 color features. The feature vectors for the training images (which contain only one food item in the image) were extracted and a training model was generated using the SVM. A set of 17 plastic food images were used as training images and each food item was given an unique label to generate a training model for plastic food. And a set of 12 real food images were used as training images to generate a training model for real food. In our work we used the LIBSVM [56] a library for support vector machines.



(a) Segmented Food Items After First Step.



(b) Segmented Food Items After Second Step.

Fig. 2.3. Example of segmented food items (a) Food Item Segmented Using a Fix Threshold (T = 127), (b) Additional Food Item Segmented Using Color Information.

3. EXPERIMENTAL RESULTS

3.1 Image Database

A database of approximately 2800 images was created using the following devices:

- Canon PowerShot SD200
- Canon PowerShot S3
- Canon PowerShot SD870
- Nikon 3700
- Nikon 7600
- Panasonic DMC-FZ4
- HTC P4351, Windows Mobile Device

3.1.1 Plastic Food

The database contains images of plastic food replicas and real food items. For the plastic food the images were acquired using specific conditions, such that the foods were placed on a white plate on a checker-board (black and white) patterned tablecloth. The tablecloth was used as a fiducial mark for estimating the dimensions and area of the food item. The white plates were used to assist the segmentation of the food items. The training images used were taken with only one food item and the testing image contained 2 or 3 food items. The database consists of 50 plastic food images, 17 images were used for training and 33 images were used for testing. The average classification results indicated a 93.745% (Table 3.1)accuracy when 17 images were used as training images and 14 images containing 32 food items were used as test images. Examples of correctly classified objects and misclassified objects are shown in Figure 3.1. More examples of segmentation and classification results are shown in Appendix A.3.

Table 3.1
Classification Accuracy.

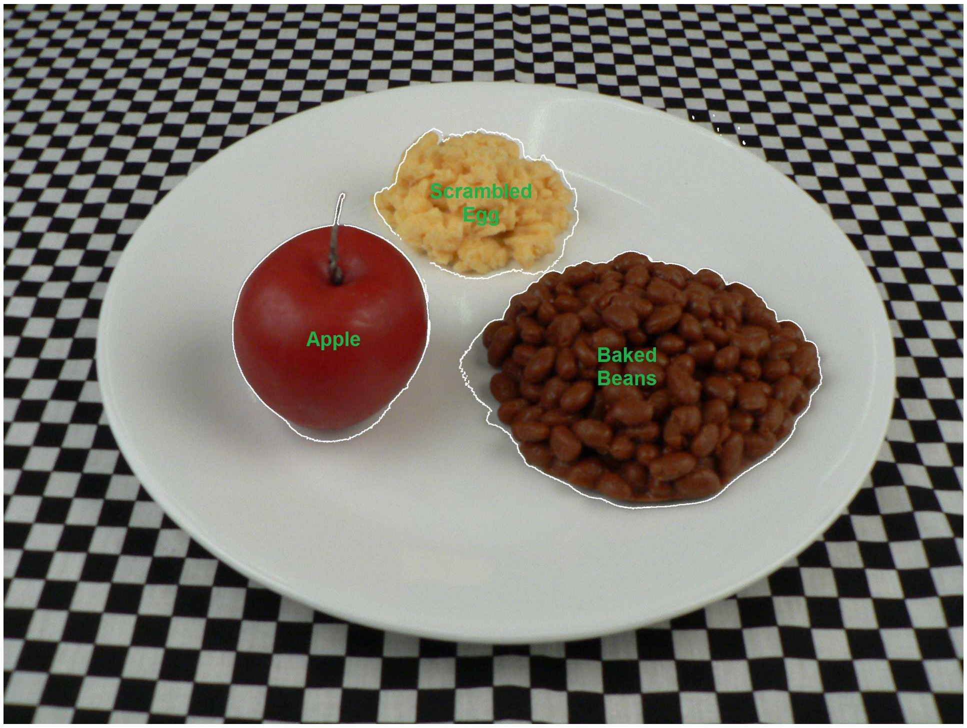
Food Type	Training Images	Testing Images	Classification Accuracy
Plastic Food	17	33	93.75%
Real Food	11	245	57.55%

3.1.2 Real Food

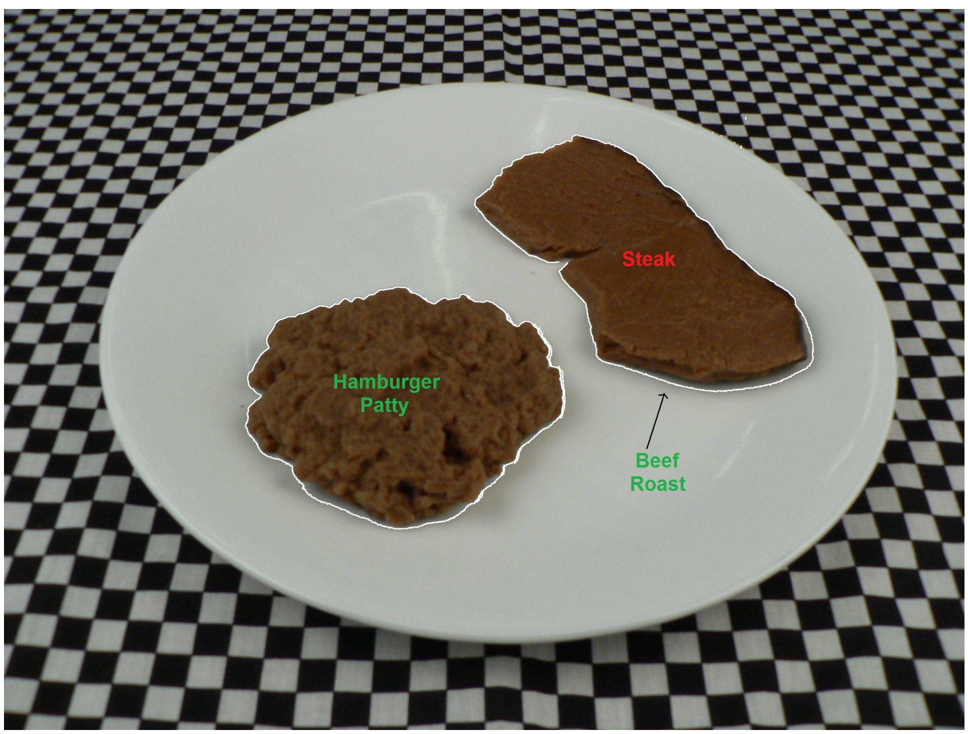
The plastic food the images were acquired using specific conditions, such that the foods were placed on a white plate on a checker-board (black and white) patterned tablecloth and also on a black tablecloth with a checker board square. The tablecloth and the checker board square were used as a fiducial mark for estimating the dimensions and area of the food item. The white plates were used to assist the segmentation of the food items. The training images used were taken with only one food item and the testing image was taken with different lighting conditions, different resolution and different orientation. The database consists of 256 real food images, 11 images were used for training and 245 images were used for testing. The average classification results indicated a 57.55% (Table 3.1) accuracy when 11 images were used as training images and 245 images containing 11 food items were used as test images. The classification accuracy for test images with similar lighting conditions as the training images were better than the test images with no or bad lighting conditions as shown in (Table 3.2). Examples of correctly classified objects and misclassified objects are shown in Figure 3.2. More examples of segmentation and classification results are shown in Appendix B.3.

Table 3.2
Classification Accuracy - Real Food.

Lighting Conditions	Training Images	Testing Images	Classification Accuracy
Good Lighting	11	116	70.68%
Bad / No Lighting	11	129	34.91%



(a) Example of Successfully Classified Food Items.



(b) Example of Misclassified Food Items.

Fig. 3.1. Example of classified food items (a) All food items are successfully classified using a SVM, (b) Some food items are misclassified by the SVM, i.e. beef roast is misclassified as steak.

(a) Example of Successfully Classified Food Items.

(b) Example of Misclassified Food Items.

Fig. 3.2. Example of classified food items (a) Food items are successfully classified using a SVM, (b) Food items are misclassified by the SVM, i.e. Mac and Cheese is misclassified as soup.

4. USER INTERFACE

In this section, a review of some of the goals of user interface design is provided along with the structure and navigation of the designed user interface for Mobile Phone Food Record (mpFR). The details of the usability tests performed on the mpFR are also discussed. Graphical user interface (GUI) is a type of user interface which allows people to interact with electronic devices like computers, hand-held devices (MP3 Players, Portable Media Players, Gaming devices), household appliances and office equipment. Graphic interfaces, with the help of images, texts and menus, try to approximate the picture the user has of a certain problem. The best known example is probably the desktop metaphor, where the screen shows a typical office desk, with files in folders, a note pad, a waste paper basket, etc. Often the actions of the user can be reduced to typing a few words and pointing to images and menus with the help of a mouse or simply a finger.

4.1 Goals of User Interfaces

Designing the visual composition and temporal behavior of GUI is an important part of software application programming. Its goal is to enhance the efficiency and ease of use for the underlying logical design of a stored program, a design discipline known as usability. Techniques of user-centered design are used to ensure that the visual language introduced in the design is well tailored to the tasks it must perform. A GUI may be designed for the rigorous requirements of a vertical market. This is known as an "application specific graphical user interface." The latest cell phones and handheld game systems also employ application specific touch screen GUIs. But

[0]The user interface described here for the mobile phone food record is an extension of work initially performed by Professor Kyle D. Lutes, Department of Computer and Information Technology, Purdue University.

the majority of user interfaces is designed to meet one or more of the following goals, even if often the goals are not made explicit.

- **Easy to use**: Someone who has little or no knowledge about the system, but knows enough about the subject domain, should be able to use the application without much training.
- **Easy to learn**: The ease of learning can be measured in various ways. One measure could be the time required to master a certain task, another could be the degree to which users feel they understand the system after some period of time.
- **Easy to maintain**: Many programs are created for extended use, which nearly always means that they have to be updated a few times. If the users themselves or another non-programmer has to do this, the interface has to provide some form of support.
- **Fast/minimal effort**: The number of keystrokes (mouse clicks, mouse travel distance) required for performing some task should be minimal. Note that this is not the same as the response time. The response time is a measure of how fast the system can respond to user events.
- **Flexible**: Some systems are meant to be used by a wide variety of users in many different situations.
- **Simple screen layout**: Desirable if the system must be easy to describe.
- **Portability and Internationalization**: Since the application and the interface often use very different computer resources, porting a system to another computer may very well require changes to the one and not the other. Internationalization means translating commands and messages to other languages, changing some icons, sorting order, time and date display, fonts, etcetera. Most if not all of these changes can in many cases be accommodated by changes in the interface.

Many of these goals are actually contradictory. It is not possible to create a single interface that is usable without training and that also pleases the user.

4.2 Goals of Mobile Phone Food Record

The set of user goals to be achieved for the Mobile Phone Food Record are:

- Record a new food(s) or drink(s) by selecting the corresponding occasion
- Capture and confirm the image before consumption
- Capture and confirm the image after consumption
- Label the food(s) or drink(s) in the image
- Edit label of the food(s) or drink(s) in the image at a later time
- Users should be able to record food(s) or drink(s) at a later time in the following scenarios:
  - The user forgets to take the image of their meal
  - The user did not have the mobile device food record with him during the meal
  - When it is not possible to take image

The overall structure of the application is relatively simple, as shown in Figure 4.1 and Figure 4.2. There are three main elements in the application which can be selected from the main form.

The screen in Figure 4.3(a). enables the user to start the Mobile Phone Food Record application. The screen in Figure 4.3(b) displays three options namely record a new meal, reviewing the meals or to use the alternate method.

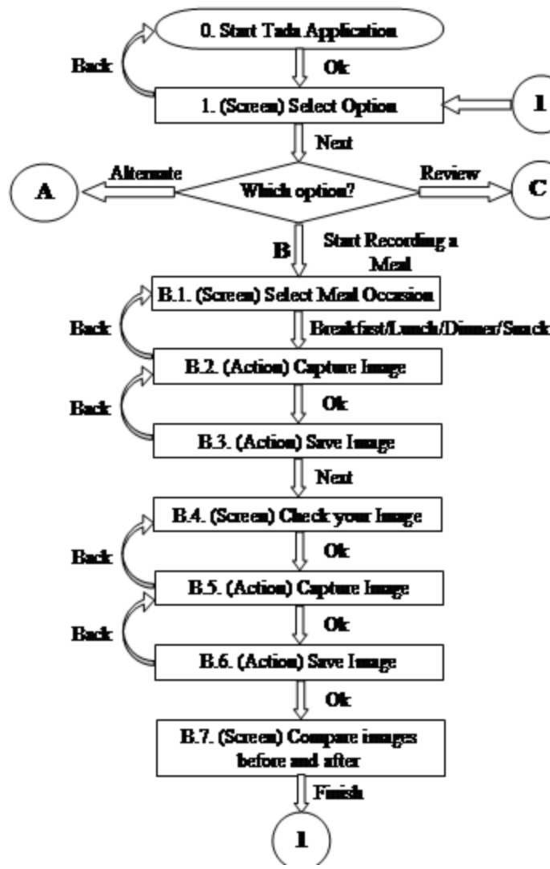
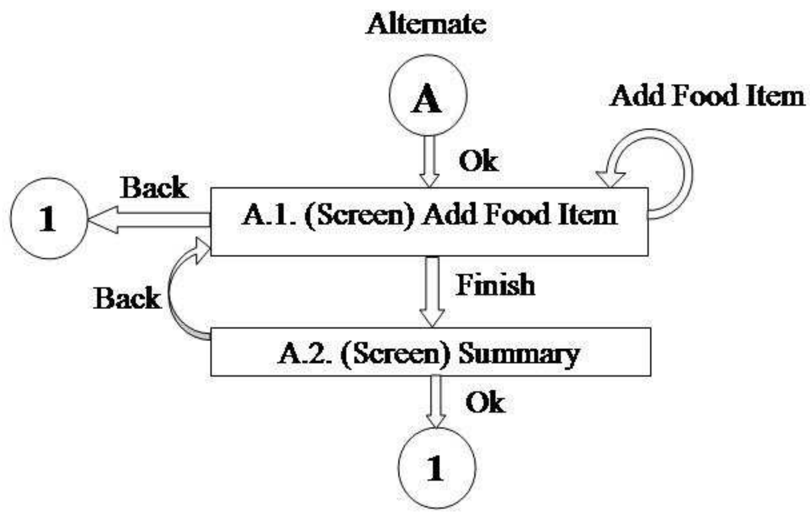
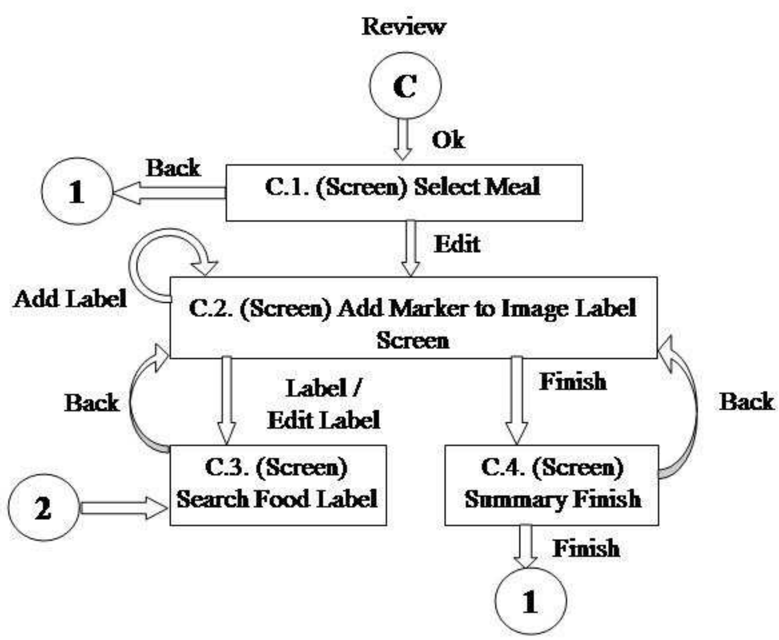


Fig. 4.1. Structure for Recording a New Meal.



(a)



(b)

Fig. 4.2. Structure of the User Interface (a) Structure for Alternate Method (b) Structure for Reviewing a Meal.

(a)

(b)

Fig. 4.3. Screen Shots (a)Start Mobile Phone Food Record. (b) Select Action.

4.3 Record A New Meal

This section of the application lets the user to select the meal occasion and capture images of their meal before and after consumption. The user can select between breakfast, lunch, dinner and snack (Figure 4.4(a)). Once the meal occasion is selected, the user is reminded to use the camera in the landscape mode (Figure 4.4(b)), before the camera is displayed (Figure 4.4(c). This ensures that both the before and after images are consistent. Once the user captures the image of the meal, then the screen in Figure 4.4(d) lets the user to review the image. The user can save the image or select the option to retake the image of the meal.

In the next screen (Figure 4.4(e)) the user can select next once the food is consumed. The screens in Figure 4.5(a), Figure 4.5(b) and Figure 4.5(c), lets the user capture the image of the meal after consumption, similar to the procedure used for capturing the before meals. Once the after image is saved a summary screen (Figure 4.5(d)) is displayed, which has both the before and after images. By selecting finish the main screen (Figure 4.3(b)) is displayed.

4.4 Review A Meal

The user can review all their meals that have been recorded. The meal that needs to be reviewed can be selected from the list of all the meals that's been recorded from the screen in Figure 4.6(a). Once the meal that is to be reviewed is selected, the before image of the meal is displayed (Figure 4.6(b)). Food items can be labeled by adding new markers and placing them on the food item to be labeled. The user can start labeling the food item by selecting label from the menu. The food label screen (Figure 4.6(c)) lets the user to search for the food items from a database, with a help of intellisense. Similarly all the food items can be labeled by adding the food markers. Once all the food items are labeled and selecting finish displays the summary screen (Figure 4.7). Reviewing the meals can also be used to edit the food labels.

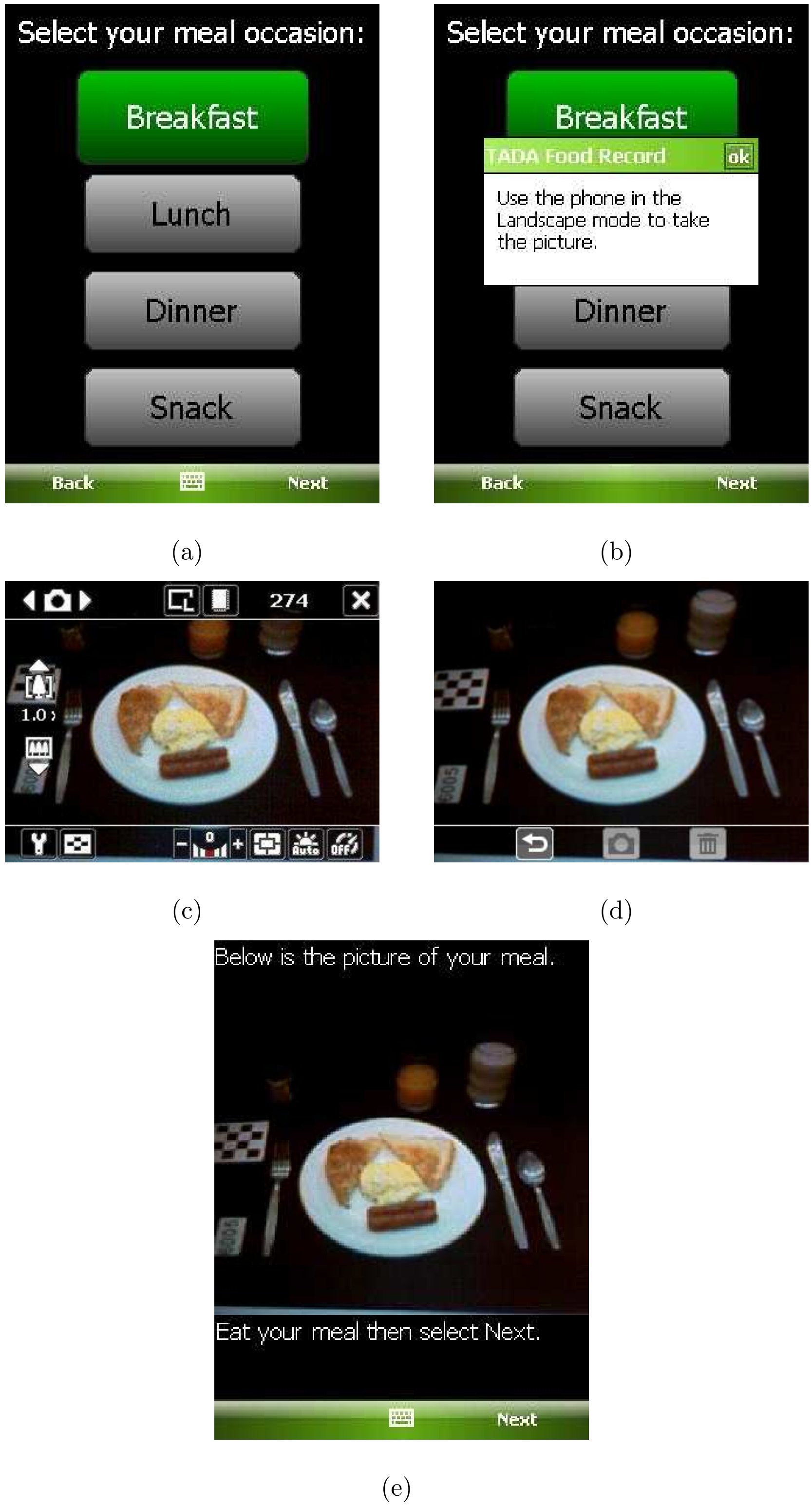
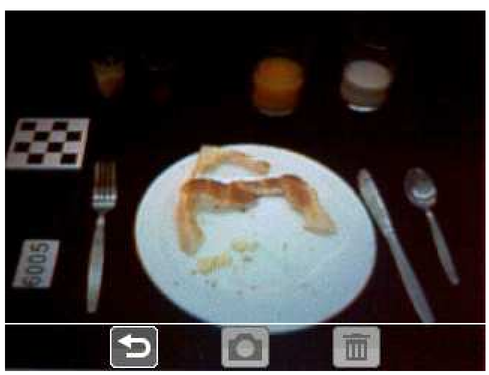


Fig. 4.4. Screen shots - (a)Select the Meal Occasion (b) Information Box to remind the user to capture the image in landscape mode (c) Show Camera and Capture Before Image (d) Review and Confirm Before Image

(a)

(b)



(c)

(d)

Fig. 4.5. Screen shots - (a)Information Box to remind the user to capture the image (b) Show Camera and Capture After Image (c) Review and Confirm After Image (d) Summary.

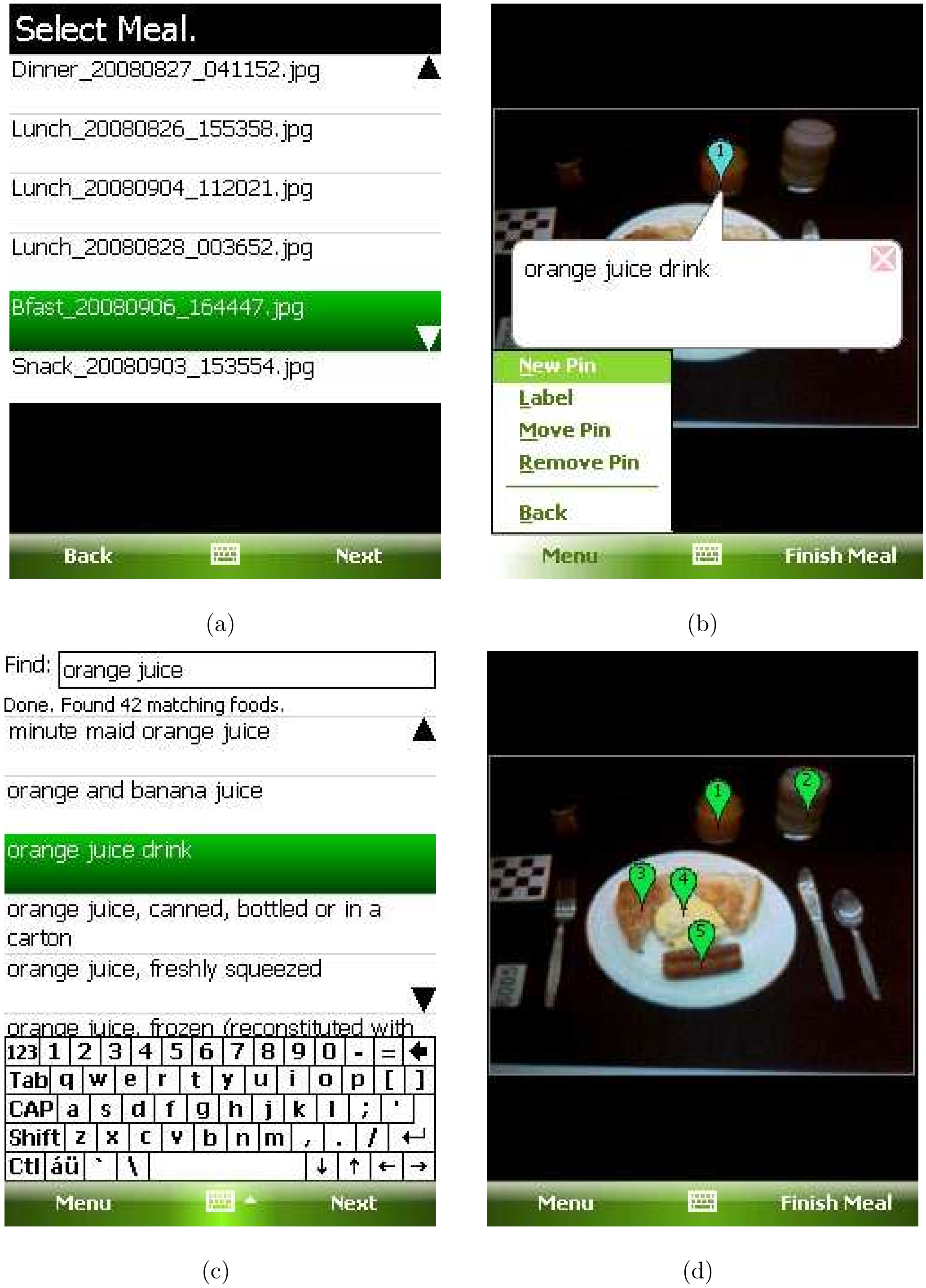
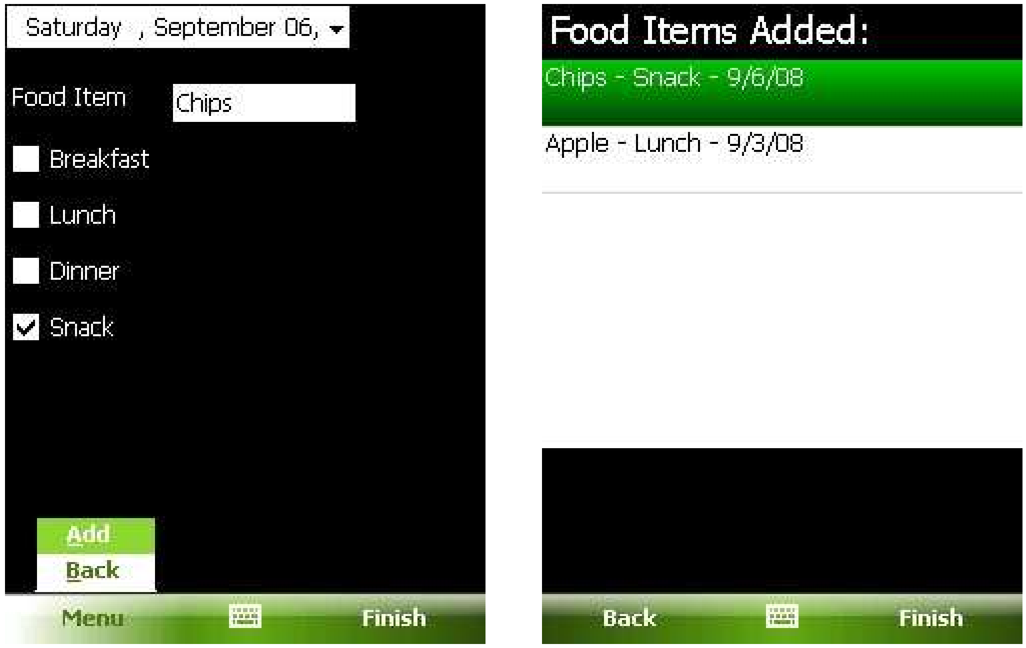


Fig. 4.6. Screen shots - (a)List of all meals recorded (b) Marker added to the Image Label Screen (c) Search Food Label (d) All food items labeled.

Fig. 4.7. Screen shots - Summary of Food Items Labeled.



(a) (b)

Fig. 4.8. Screen shots - (a)Add Food Item (b) Summary of Food Items Added.

4.5 Alternate Method

This section of the application lets the user to record food(s) or drinks(s) when capturing the image of their meals was not possible or forgotten by the user. The user can select the date when they had consumed the meal and enter the food item. The meal occasion also needs to be selected as show in Figure 4.8(a). Once all the food items are added and finish is select, the summary screen (Figure 4.8(b)) is displayed.

4.6 Usability Test of Mobile Phone Food Record

The user interface designed for the Mobile Phone Food Record was tested to assess the usability or ease of use and to quantify error. The usability test is a technique used to evaluate a product by testing it on users. The tests were performed under controlled conditions with know food amounts. Young people between 11-18 years old (Table 4.1) were recruited and served foods of know gram weights.

Table 4.1
Age Group of subjects.

Age	Number
11-14	44
15-18	36

Table 4.2
Gender of Subjects.

Males	Females
27	53

Meals and/or snacks consumed were recorded using the Mobile Phone Food Record under observation. The subjects were asked to capture the before and after images of their meal using the mpFR and a digital camera.

5. CONCLUSION AND FUTURE WORK

Assessment of dietary intake is fraught with uncertainties and has been especially understudied in the pediatric population. The goal of our work is to improve assessment of dietary intake through the further development of a novel and more precise way to measure food intake. We aim to establish a tool for recording dietary intakes that includes a mobile computing device, digital photographs, image processing, and a nutrient data base for identification and quantification of food consumption for use with adolescents. Mobile computing devices provide a unique vehicle for collecting dietary information that reduces burden on record keepers. Pictures of food can be marked with a variety of input methods that links the item for image processing and analysis techniques that estimate the amount of food. Pictures before and after foods are eaten can estimate the amount of food consumed.

Our initial effort has focused on identifying food items in an image using image analysis techniques. In our current method, we use simple 2D images for identification and quantification of food consumed. We are looking to create 3D food models to assist in pattern matching and to render our estimated sizes of the food back into the image so that we can have the user adjust the portion size to make it more accurate - larger, smaller, etc.

5.1 Contributions of This Thesis

- **Food Segmentation and Classification**: We developed an Image analysis system to automatically segment and identify each food item. We were able to achieve a classification accuracy of 94% for plastic food items and a classification accuracy of 58% for real food items.

- **User Interface Design**: We designed and implemented an user interface for a mobile phone Food Record which lets the user to record new food(s) or drink(s) by capturing the images before and after consumption. The user interface also lets the user to label each food item in the meal.

5.2 Suggestions for Future Work

- **Overlapped Food Items**: In our current system we were able to segment and identify food items under controlled settings. We need to extend the segmentation and classification for overlapped food items.
- **Texture Features**: The features, namely color and texture features, that we used was simple. Other types of features could be used for better classification.
- **Classifiers**: In our system we use the radial basis function (RBF) kernel of Support Vector Machine for classification. We need to experiment the classification results by using other types of kernel such as linear, polynomial, sigmoid for SVM. We should also try to use different types of classifiers other than SVM.
- **Software Deployment on Mobile Phones**: We need to optimize the image analysis system so it can be deployed on mobile phones. In order to avoid potential battery lifetime problems we also might want to look into client-server architectures.
- **Volume Estimation**: Based on the segmentation, we need to determine the volume of food consumed in cm^3. For many foods this will not be possible from one image of the meal. Several approaches needs to be explored, including the use of multiple images and computer visualization methods using 3D shape reconstruction techniques.
- **Estimating Food Consumed**: Once we have determined the volume in cm^3 of each food item, this information needs to be combined with the portion code and

portion weight in the USDA Food and Nutrient Database for Dietary Studies (FNDDS) to determine the gram weight of the food. Once the gram weight is determined the nutritional information in the FNDDS for each food item can be used to determine the final energy and nutritional content of the consumed food. The FNDDS does not have built in volume measures so each portion code and portion weight will need to have an additional cubic centimeter field added.

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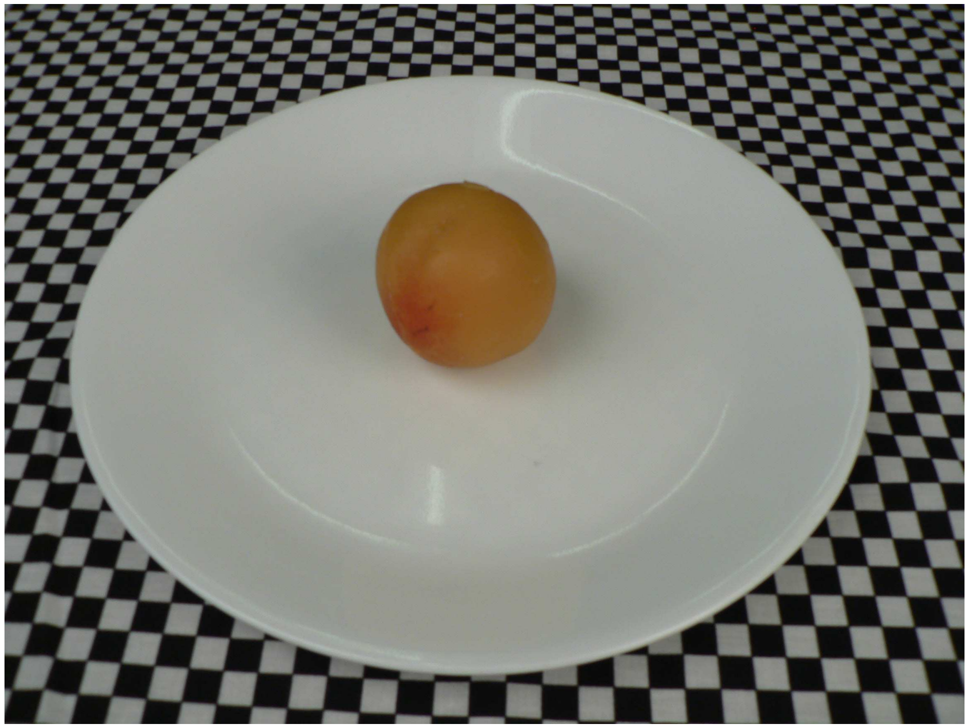
APPENDICES

A. PLASTIC FOOD

A.1 Training Data

A.2 Testing Data

A.3 Segmentation and Classification Results



(a) Peach.

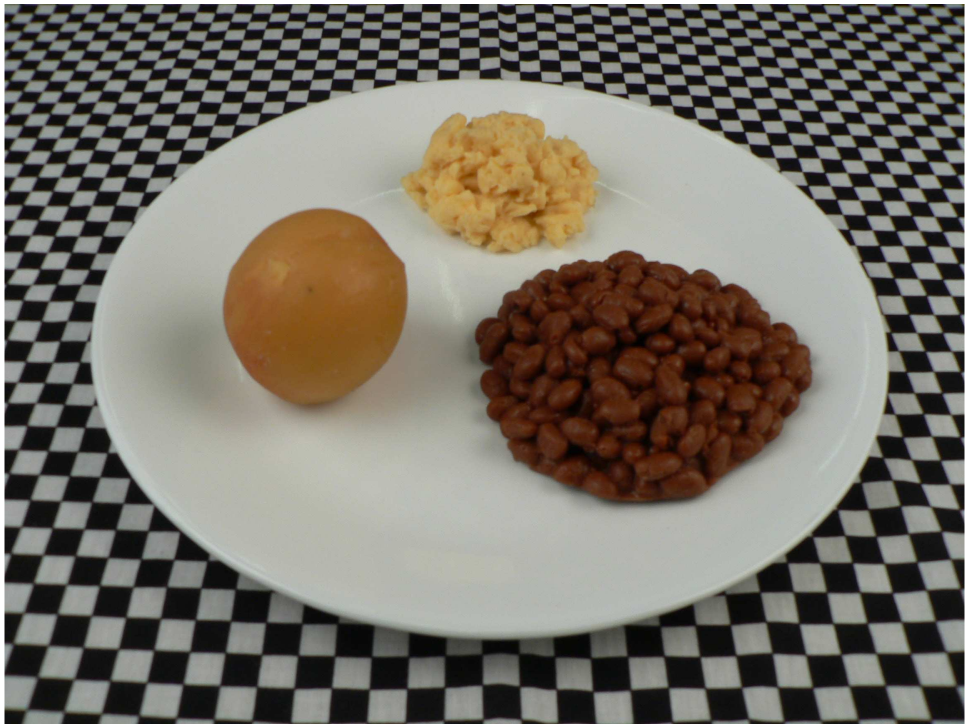
(b) Bagel.

Fig. A.1. Example of plastic food items used for training (a) Peach, (b) Bagel.

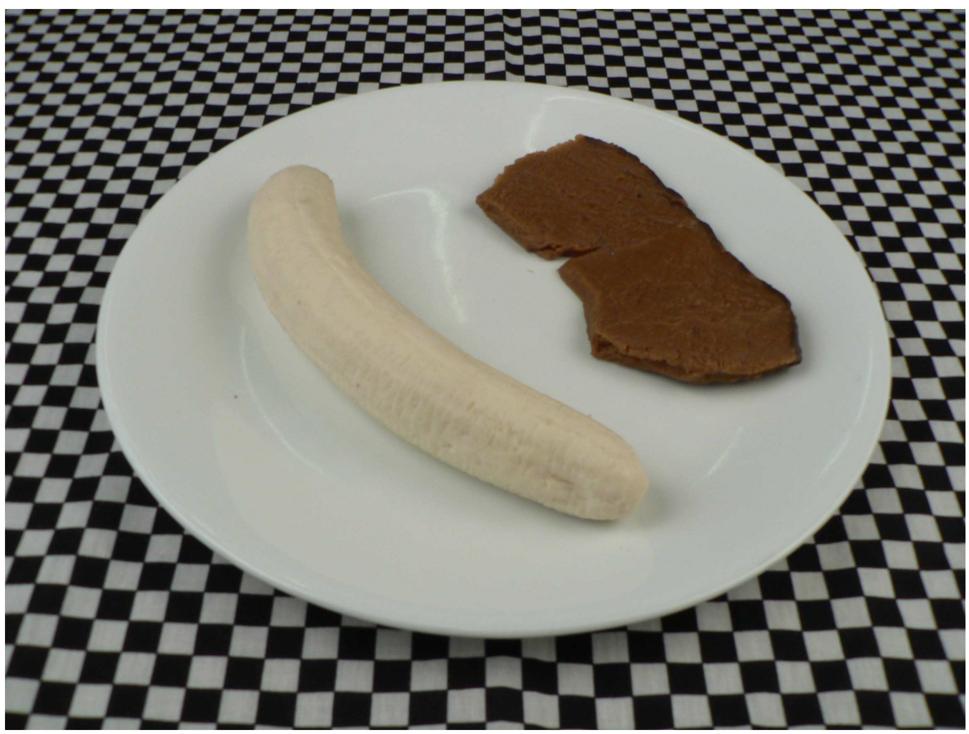
(a) Spaghetti.

(b) Beans.

Fig. A.2. Example of plastic food items used for training (a) Spaghetti, (b) Beans.

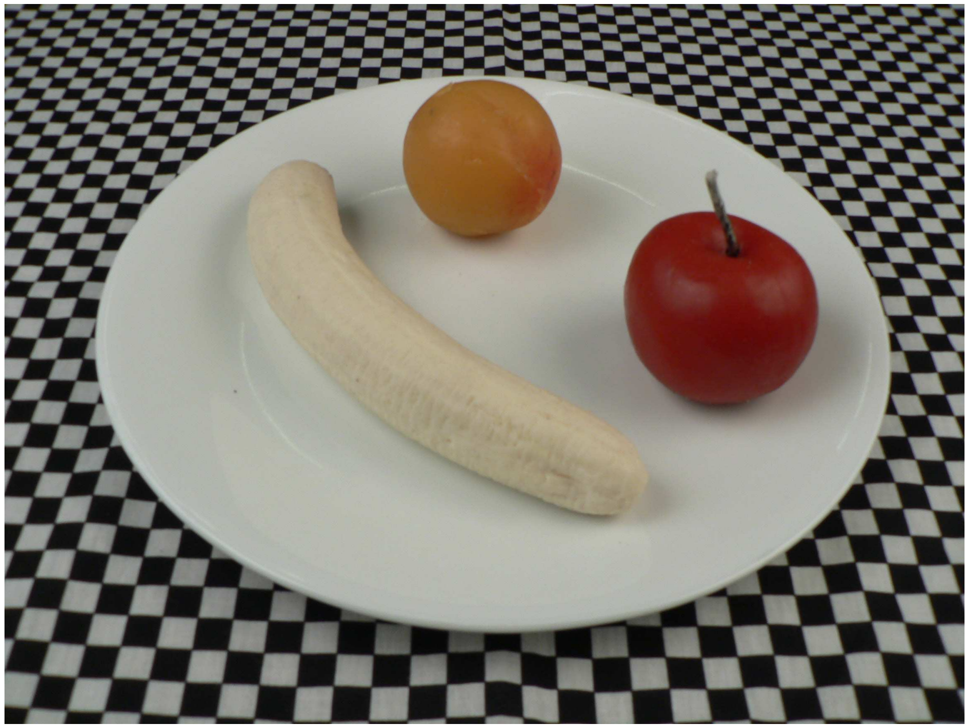


(a)

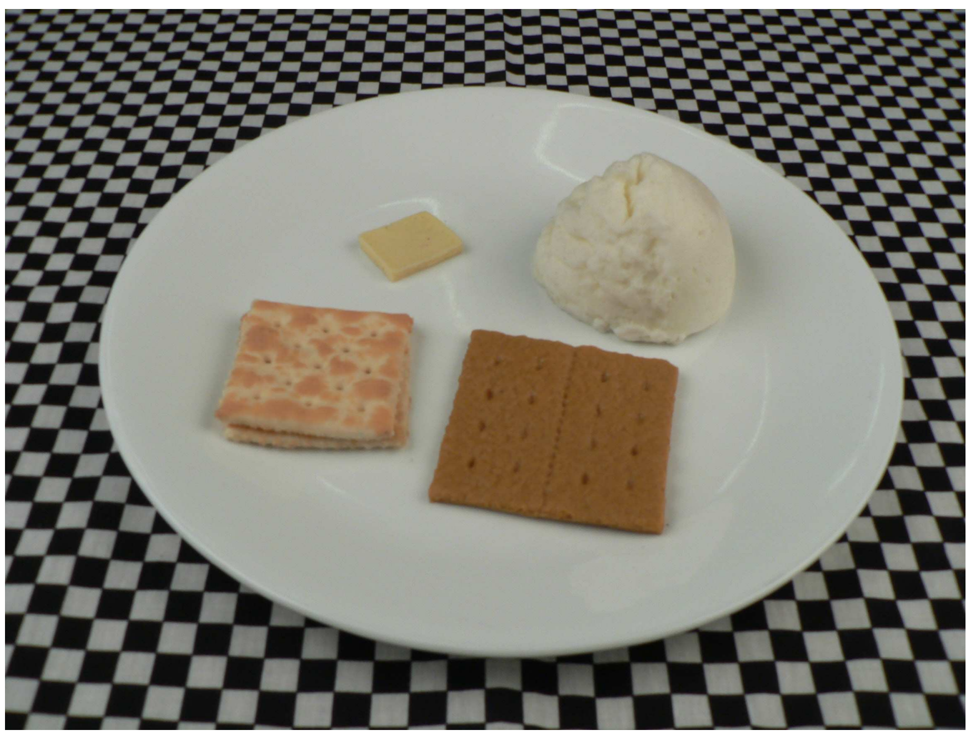


(b)

Fig. A.3. Example of plastic food items used for testing (a) Peach, Scrambled Egg and Beans, (b) Banana and Beef Roast.



(a)



(b)

Fig. A.4. Example of plastic food items used for testing (a) Banana, Apple and Peach, (b) Crackers, Butter and Ice Cream.

(a)

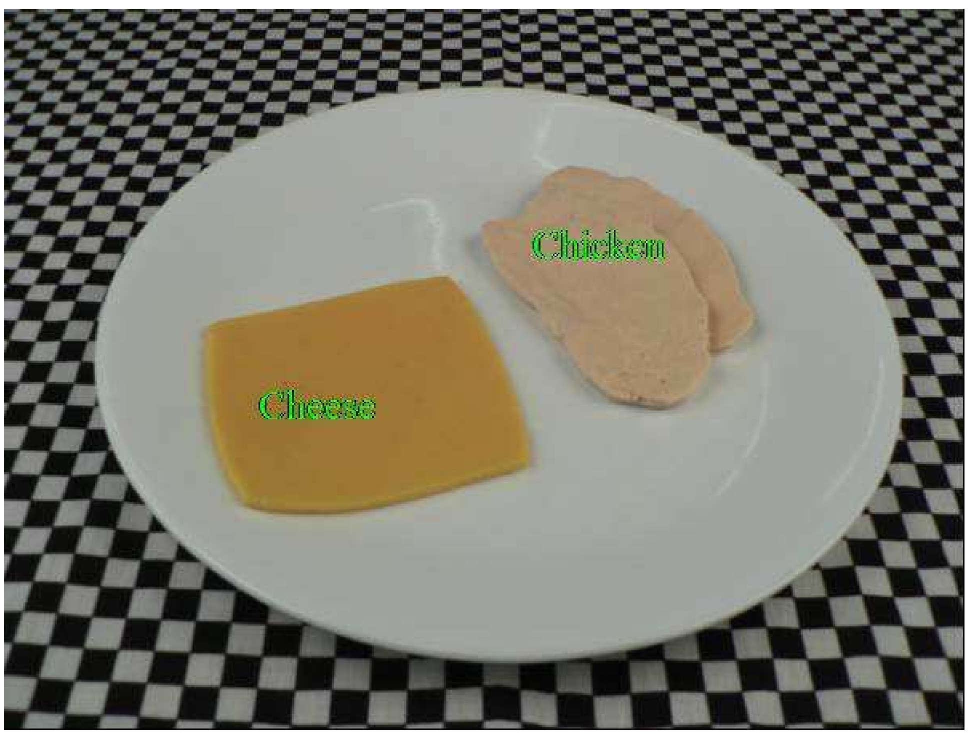
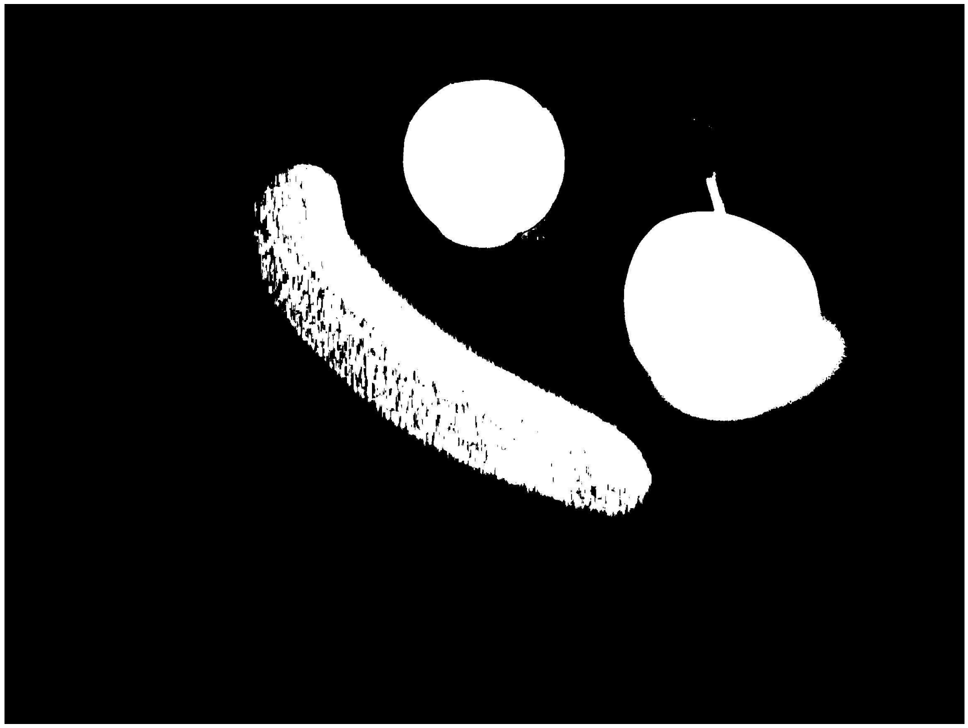


Fig. A.5. Example of classified and segmented food items (a) Segmented Food Items, (b) Successfully Classified as Cheese and Egg.



(a)

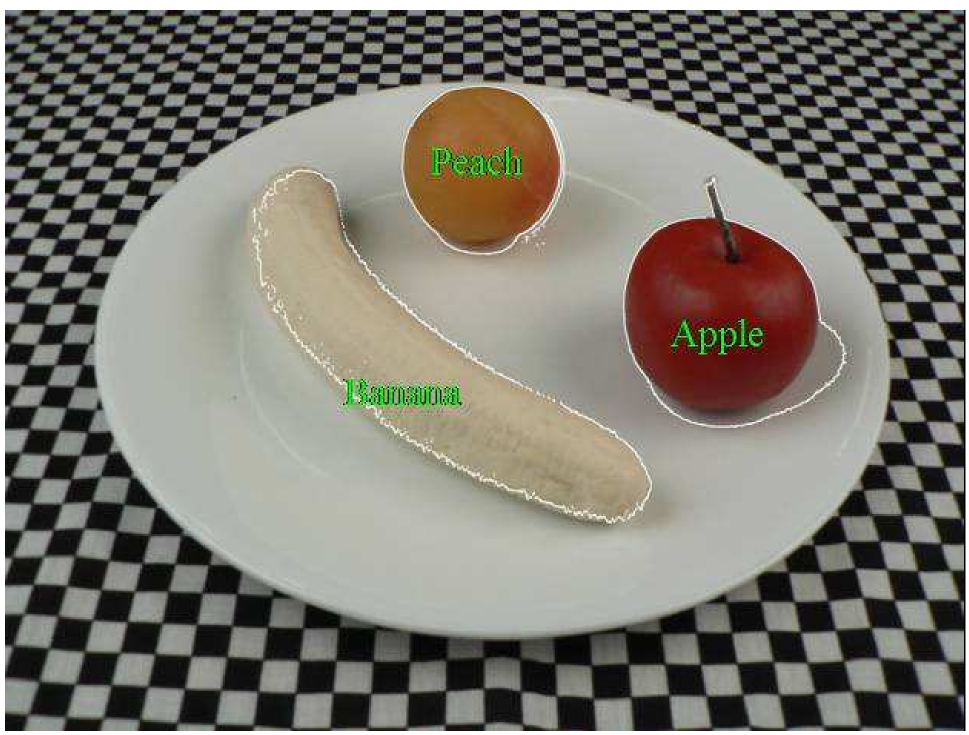
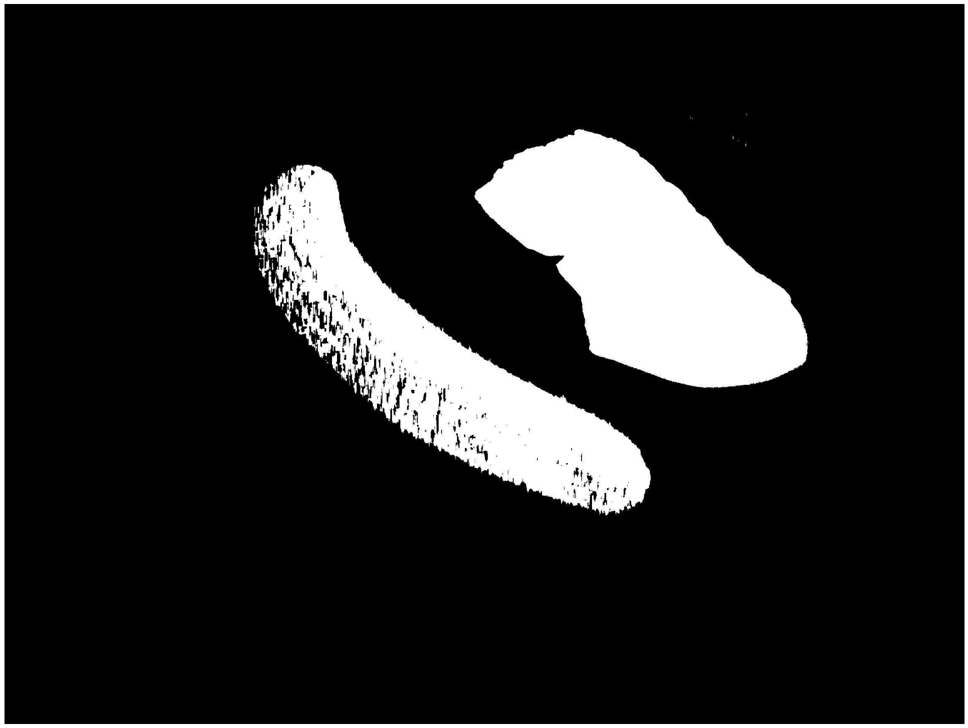


Fig. A.6. Example of classified and segmented food items (a) Segmented Food Items, (b) Successfully Classified as Banana, Apple and Peach.



(a)

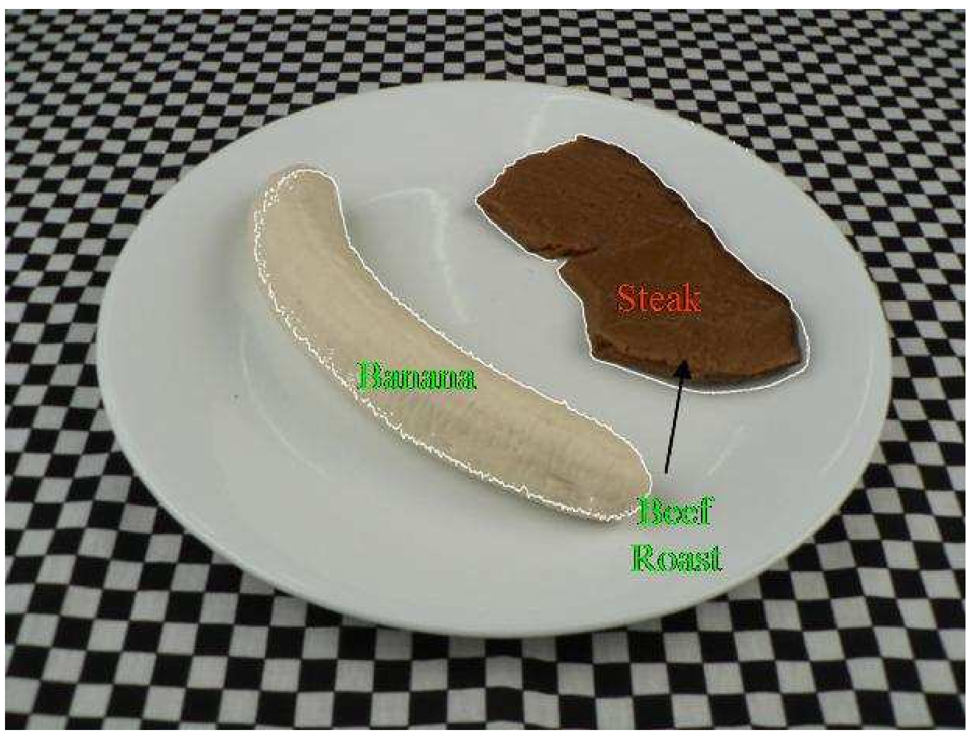


Fig. A.7. Example of classified and segmented food items (a) Segmented Food Items, (b) Successfully Classified as Banana and Wrongly Classified as Steak.

(a)

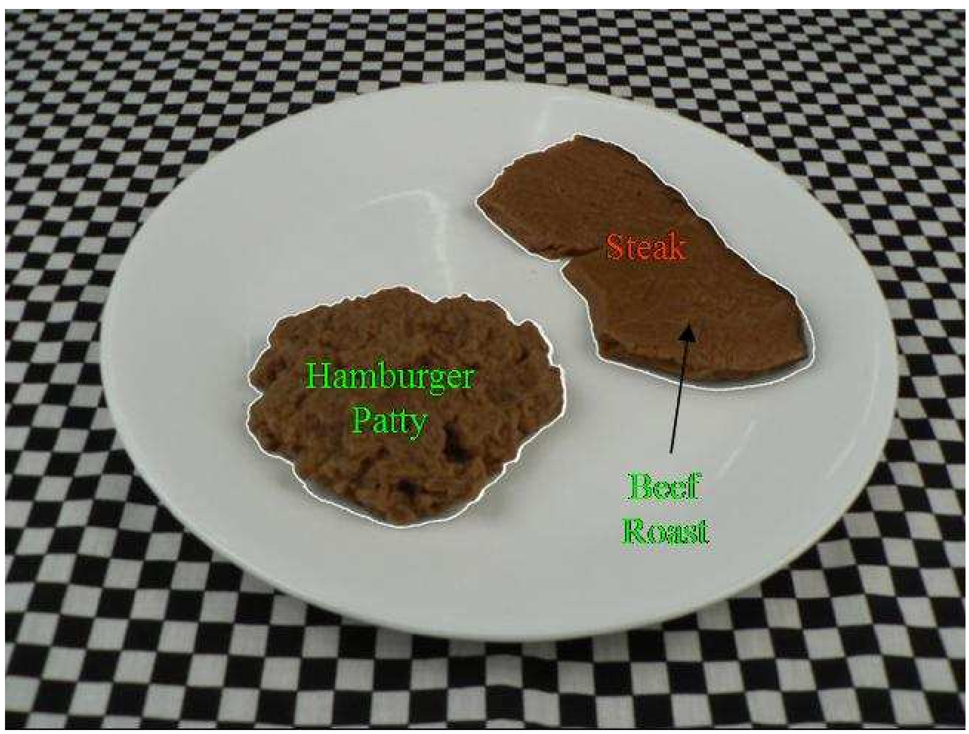
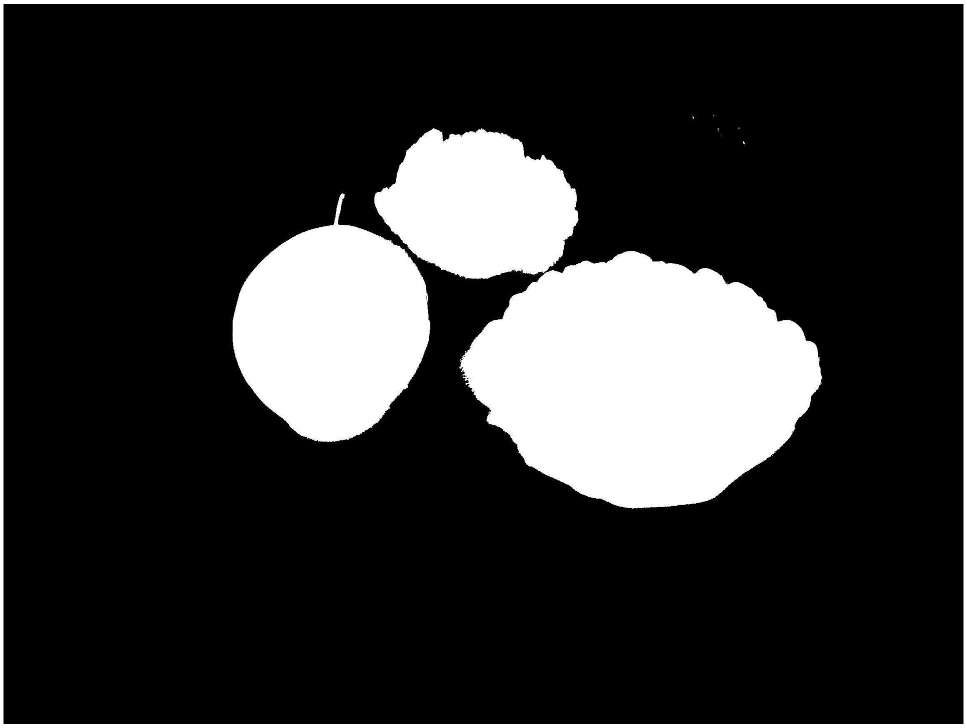


Fig. A.8. Example of classified and segmented food items (a) Segmented Food Items, (b) Successfully Classified as Beans and Wrongly Classified as Steak.



(a)

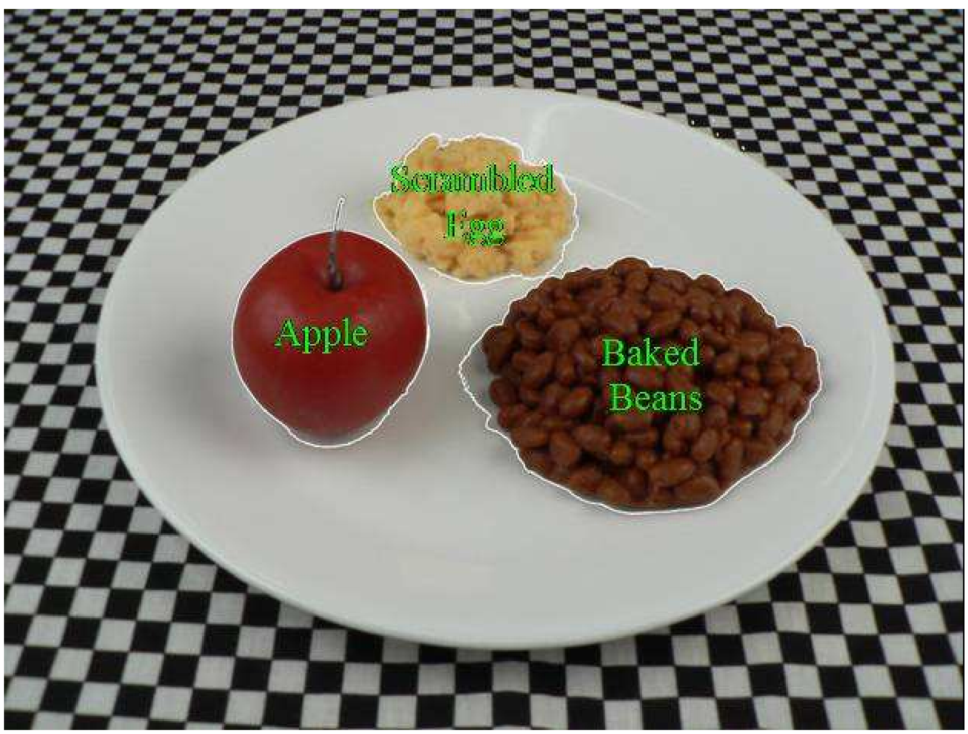


Fig. A.9. Example of classified and segmented food items (a) Segmented Food Items, (b) Successfully Classified as Beans and Wrongly Classified as Steak.

B. REAL FOOD

B.1 Training Data

B.2 Testing Data

B.3 Segmentation and Classification Results

(a) Salad

(b) Chicken.

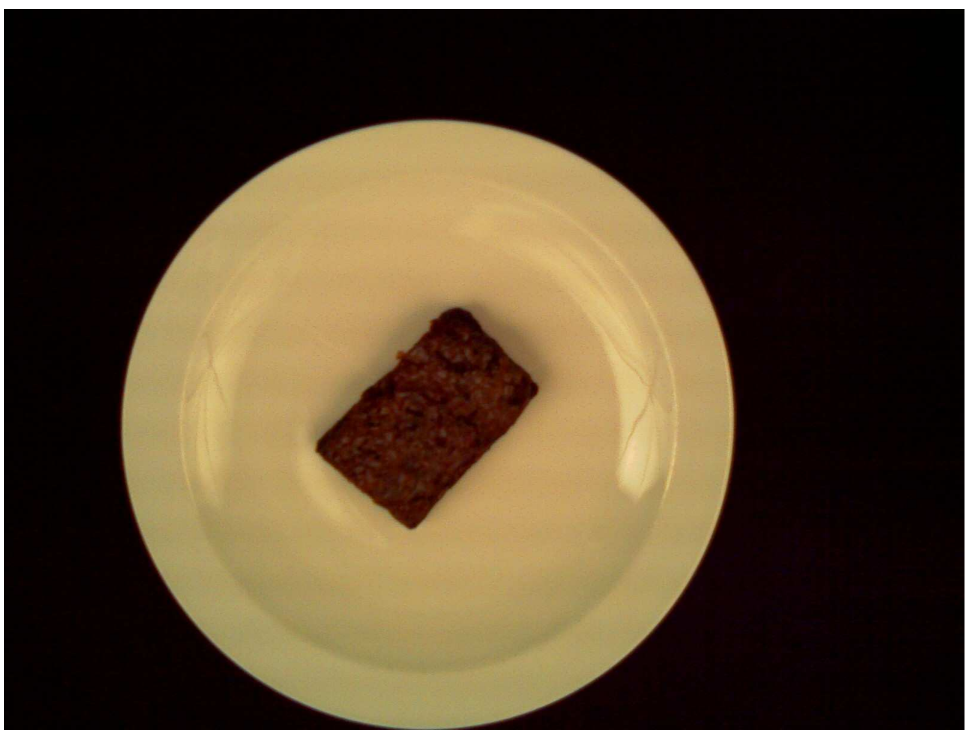
Fig. B.1. Example of real food items used for training (a) Salad, (b) Chicken.

(a) Coffee.

(b) Soup.

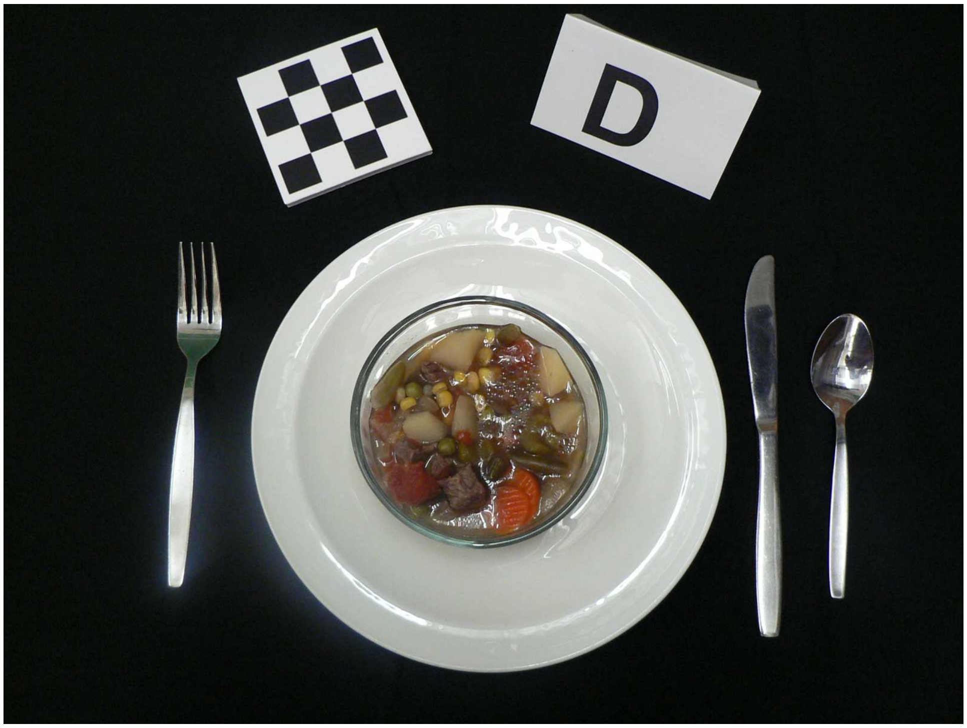
Fig. B.2. Example of real food items used for training (a) Coffee, (b) Soup.

(a)

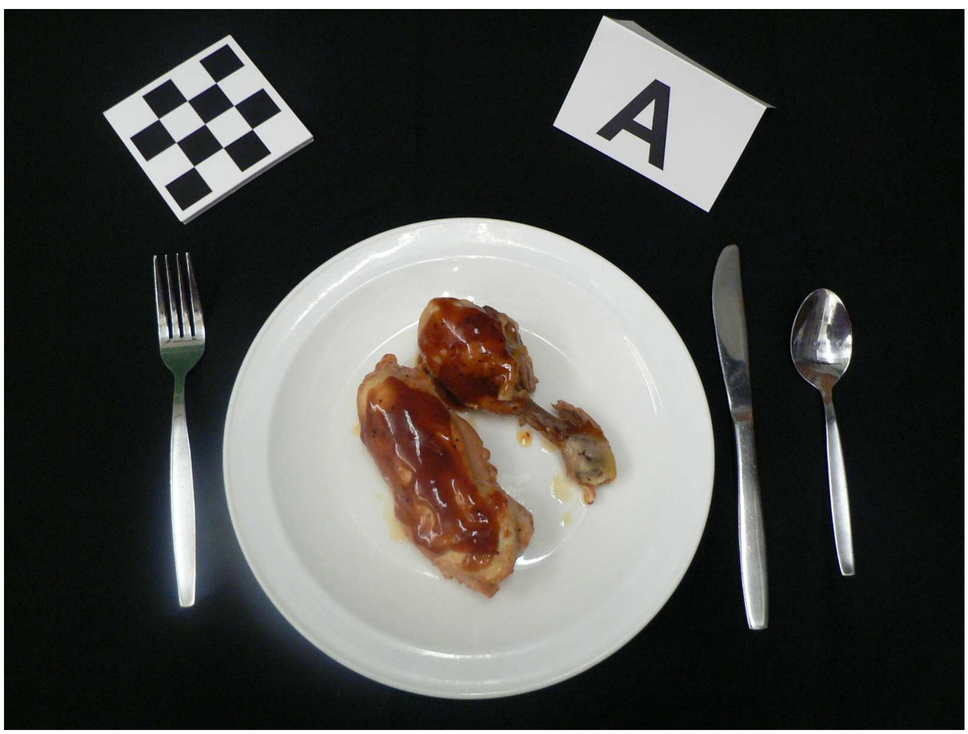


(b)

Fig. B.3. Example of real food items used for testing (a) Coffee with Creamer, (b) Brownie.

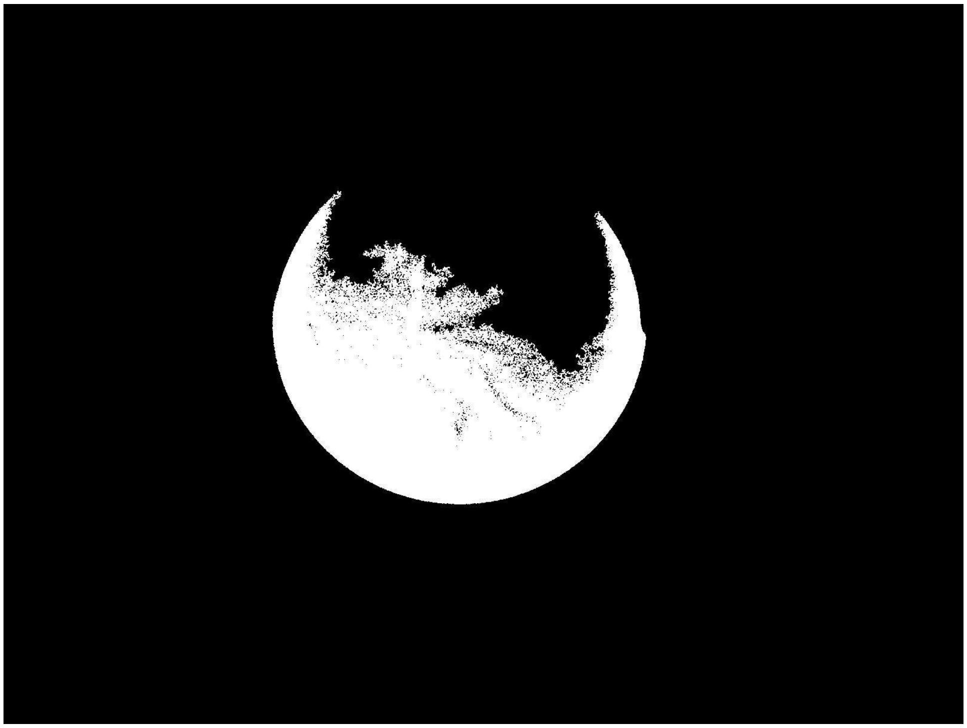


(a)



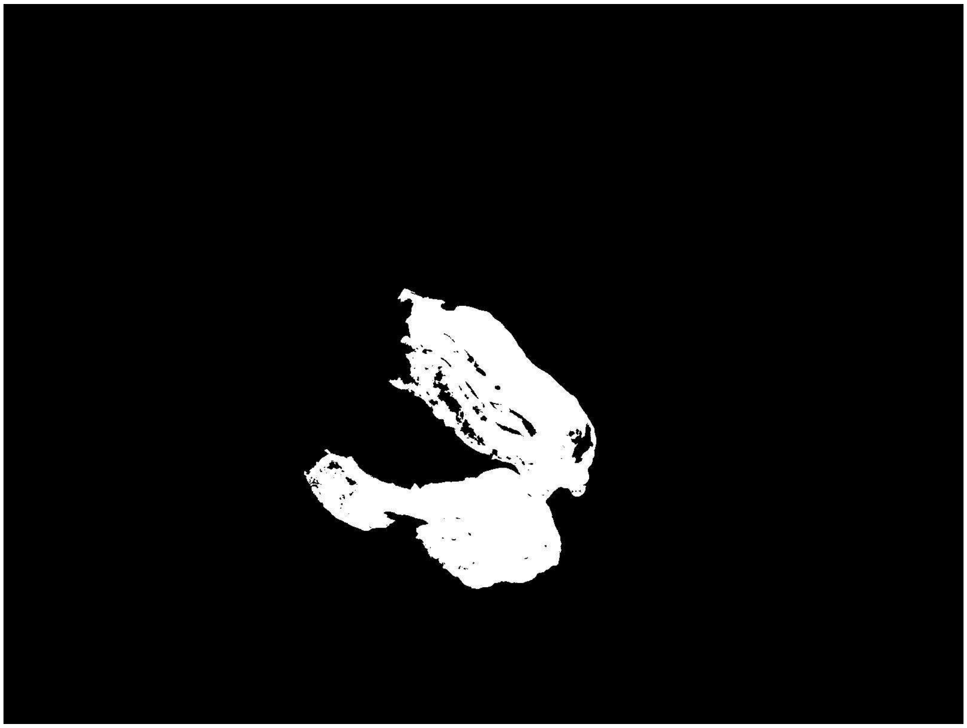
(b)

Fig. B.4. Example of real food items used for testing (a) Soup, (b) Chicken.



(a)

Fig. B.5. Example of classified and segmented food items (a) Segmented Food Items, (b) Wrongly Classified as Coffee with 2



(a)

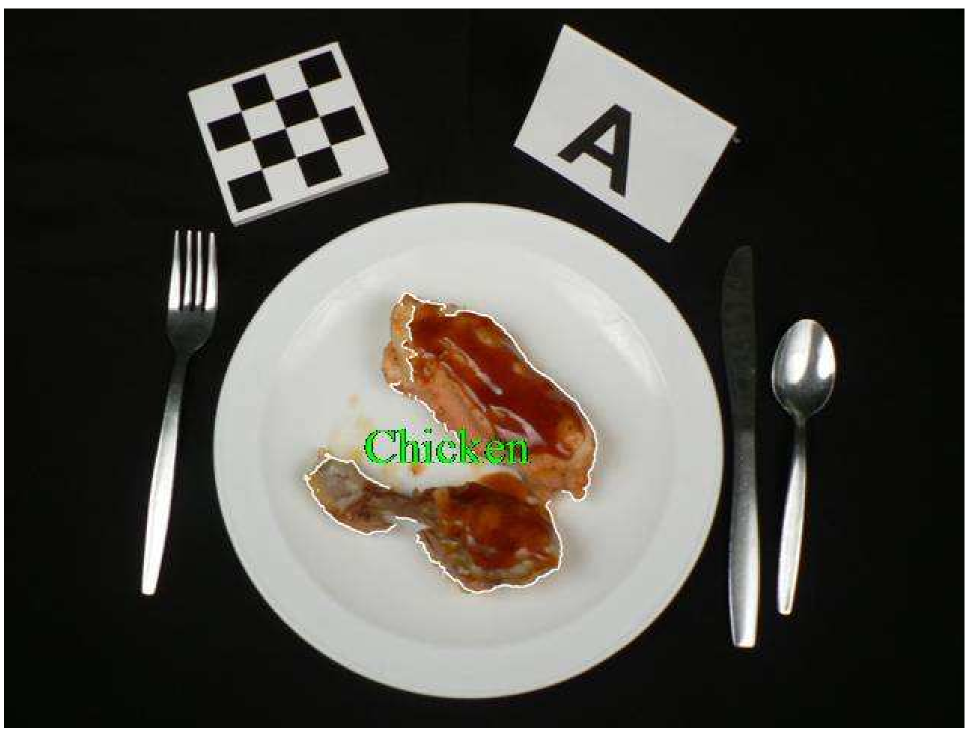


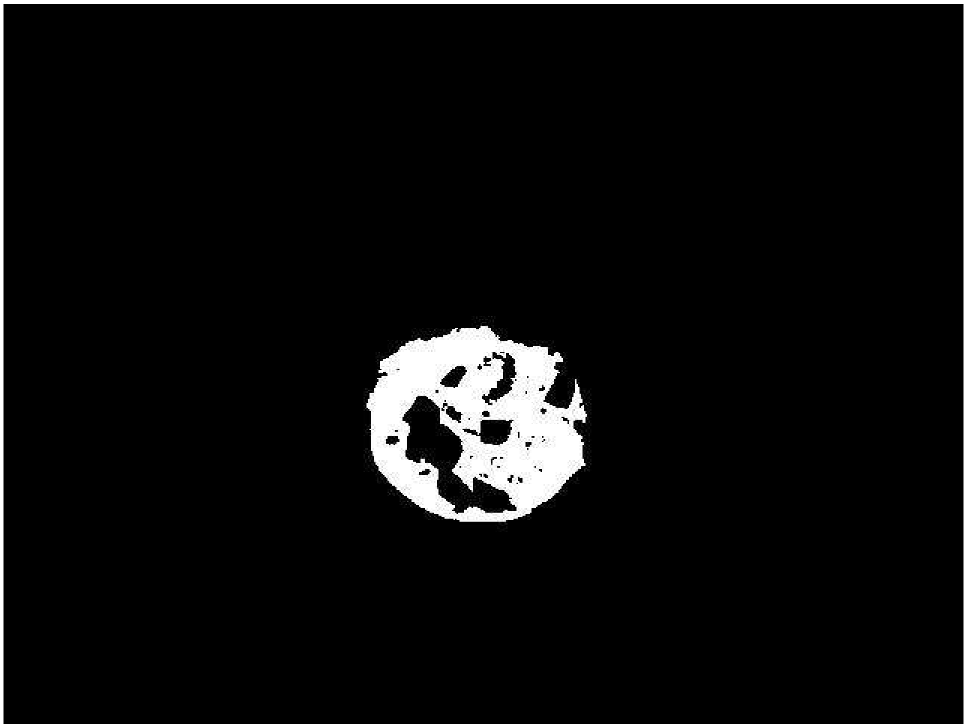
Fig. B.6. Example of classified and segmented food items (a) Segmented Food Items, (b) Successfully Classified as Chicken.

(a)

Fig. B.7. Example of classified and segmented food items (a) Segmented Food Items, (b) Successfully Classified as Soup.

(a)

Fig. B.8. Example of classified and segmented food items (a) Segmented Food Items, (b) Wrongly Classified as Soup.



(a)

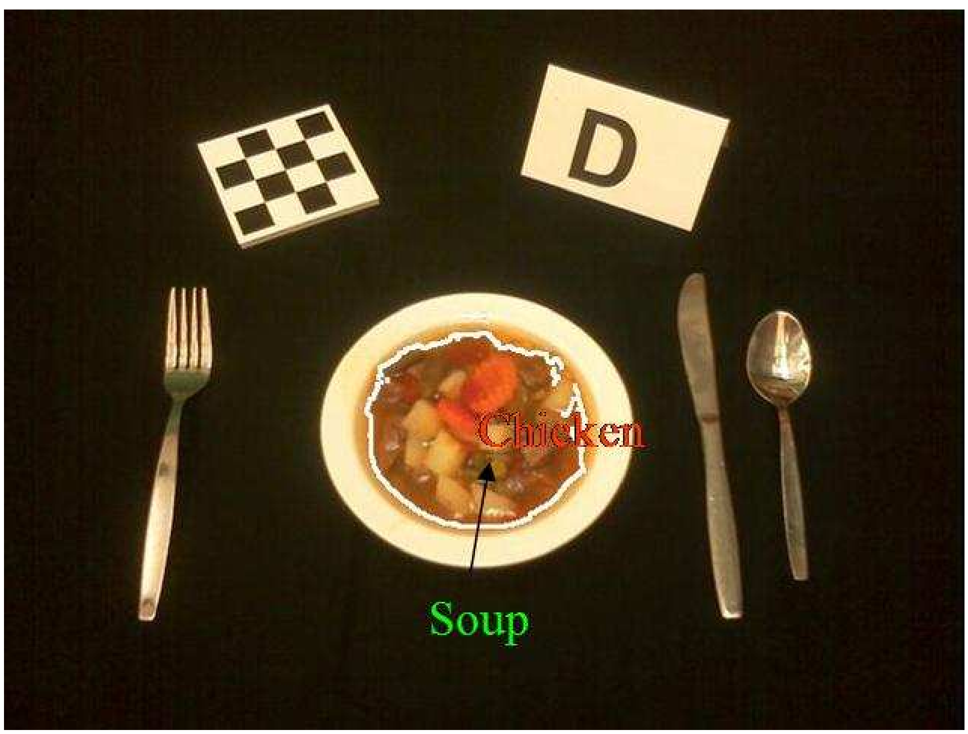


Fig. B.9. Example of classified and segmented food items (a) Segmented Food Items, (b) Wrongly Classified as Chicken.

C. IMAGE DATABASE

The Image Database web application is used to store, track and manage information related to the images captured for the project. The Image Database can be accessed at http://redpill.ecn.purdue.edu:8080. The guide provides a brief description of the background information, the table structure of the database and the usage information.

C.1 Software

The image database application was developed using web.py, a web framework for python that is simple and really powerful. The web.py framework requires the following softwares:

- **Web Server**: Apache HTTP Server
- **Database**: PostgreSQL with psycopg2 as the python client
- **CGI/FastCGI**: flup
- **Connection Pooling**: DBUtils
- **Templates**: Cheetah

C.2 Table Structure

This section outlines the table structure of the database. The tables are stored in the PostgreSQL server, an open source database. The image database uses four tables namely, pictures, picturetags, taglist and exifdata.

C.2.1 Pictures

The pictures table is used to store filename, location, resolution and timestamp about the images. The different attributes and corresponding data types in the pictures table are shown in Table C.1.

Table C.1
Pictures.

Id	Filename	Location	Created	Width	Height	Thumlocation
Integer	Text	Text	Timestamp	Integer	Integer	Text

C.2.2 Taglist

The taglist table is used to store the different food types associated with the image. The different attributes and corresponding data types in the taglist table are shown in Table C.2.

Table C.2
Taglist.

Id	Tag
Integer	Text

C.2.3 Exifdata

The exifdata table is used to store the Exchangeable Image File (exif) format data. The Exif data are extracted from the jpeg images and stored. The different attributes and corresponding data types in the exifdata table are shown in Table C.3.

Table C.3
Exifdata.

Id	Picid	ISO	Aperture	Brightness	Cammake	Cammodel	Picdate
Integer	Text	Text	Text	Text	Text	Text	Text

Endian	Exposure	Flash	Focallength	Metteringmode	Software	Lightsource
Text	Text	Text	Text	Text	Text	Text

C.2.4 Picturetags

The picturetags table is used to store the food types associated with each image. The different attributes and corresponding data types in the picturetags table are shown in Table C.2.

Table C.4
Taglist.

Id	Picid	Tagid
Integer	Integer	Integer

C.3 Navigation

Accessing the various areas of the Image database is accomplished via the navigation frame on the left hand portion (Figure C.1).

- **Image Upload**: Upload images to the database. (Login Required)
- **Image Search**: Search from the Image Database by the filename or using the tags associated with the images.
- **Image Archive**: View listing of all the images in the archive.

Fig. C.1. Screen shot of Navigation Frame.

C.4 Image Upload

To upload images the user must have a valid username and password. Enter username and password and click login to upload the images (Figure C.2(a)). Once the user logins, the upload page is displayed (Figure C.2(b)). On this page the image file to be uploaded can be selected and from the drop down box the food type can be selected. Then click Upload to upload the image to the database. A python script is used to do upload multiple files. The members of the project can access the script, upload.py, stored on the redpill server at /home/tada/public_html/image.

C.5 Image Search

To use image search, simply type the query in the image search box and click the Search button. The results page displays the thumbnail version of the image. When the thumbnail is clicked a larger version of the image along with the exif data is displayed.

The images can also be searched by the food type associated with it. Select the food type from the drop down box and click Search to display the thumbnail version of the images associated with the food type.

C.6 Image Archive

The image archive page displays the thumbnail version of all the images in the database (Figure C.4). Each page displays 8 images. By clicking the thumbnail a larger version of the image along with the exif data is displayed (Figure C.5).

(a) Login Page.

(b) Upload Page.

Fig. C.2. Screenshot of the Upload Pages (a) Login Page, (b) Upload Page.

Fig. C.3. Screen shot of Search Page.

Fig. C.4. Screenshot of the Archive Page.

Fig. C.5. Screenshot of the Detailed View Page.

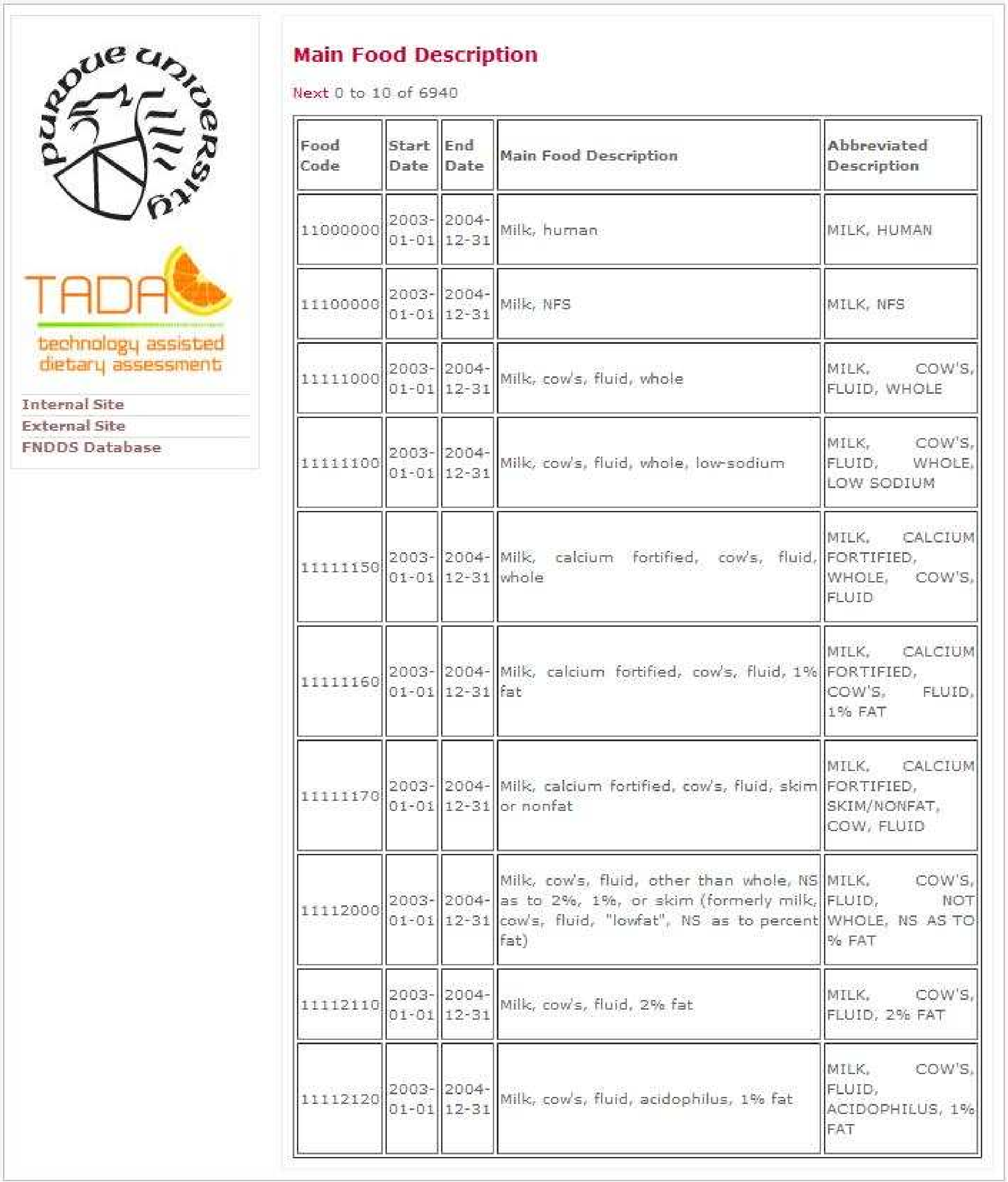
D. FOOD AND NUTRIENT DATABASE FOR DIETARY STUDIES

Food and Nutrient Database for Dietary Studies (FNDDS) is a database of foods, their nutrient values, and weights for typical food portions. The database was downloaded from the website of USDA's Food Surveys Research Group who develops and maintains the FNDDS. The database was downloaded as ASCII delimited text files. In the ASCII delimited files, al the fields are separated (delimited) by carets (˜), and text fields are also surrounded by tildes (˜). The 10 individual ASCII files were parsed using a python script and stored as tables in PostgreSQL database. The local copy of the FNDDS can be accessed at http://redpill.ecn.purdue.edu:9900.

The FNDDS has 10 different tables. A brief description and a screenshot of each table are given here:

1. **Main Food Descriptions**:
   - Primary descriptions for about 7000 food items
   - Unique 8-digit food code assigned to each main food description
2. **Additional Food Descriptions**:
   - Descriptions for about 6500 similar food items associated with specific main food items
   - Same nutrient profile and food portion weights as the main food
3. **Food Weights**:
   - Weights (in grams) for various portions of each food
   - About 30,000 weights
4. **Food Portion Descriptions**:
   - Descriptions for common portions (amounts) of foods and beverages

5. **Subcode Descriptions**:
   - Descriptions for specific snack cakes and candy
   - Unique 7-digit code assigned to each subcode description
   - Same nutrient profile as the main food
   - Unique food portion weights
6. **Food Code-Subcode Links**:
   - Records that show the association between main foods and subcodes
7. **FNDDS Nutrient Values**:
   - Complete nutrient profile (food energy and 60 nutrient/food components) for each food code
   - Source of nutrient values is the USDA Nutrient Database for Standard reference(SR), Release 16-1
8. **Nutrient Descriptions**:
   - Descriptions and measurement units for nutrients in FNDDS
9. **Moisture and Fat Adjustments**:
   - Factors used during calculation of nutrient values for some foods in the database
10. **FNDDS-SR Links**:
    - Information used to calculate nutrient values in FNDDS
    - Documents the links between FNDDS and SR



Main Food Description

Next 0 to 10 of 6940

Food Code	Start Date	End Date	Main Food Description	Abbreviated Description
11000000	2003-01-01	2004-12-31	Milk, human	MILK, HUMAN
11100000	2003-01-01	2004-12-31	Milk, NFS	MILK, NFS
11111000	2003-01-01	2004-12-31	Milk, cow's, fluid, whole	MILK, COW'S, FLUID, WHOLE
11111100	2003-01-01	2004-12-31	Milk, cow's, fluid, whole, low-sodium	MILK, COW'S, FLUID, WHOLE, LOW SODIUM
11111150	2003-01-01	2004-12-31	Milk, calcium fortified, cow's, fluid, whole	MILK, CALCIUM FORTIFIED, WHOLE, COW'S, FLUID
11111160	2003-01-01	2004-12-31	Milk, calcium fortified, cow's, fluid, 1% fat	MILK, CALCIUM FORTIFIED, COW'S, FLUID, 1% FAT
11111170	2003-01-01	2004-12-31	Milk, calcium fortified, cow's, fluid, skim or nonfat	MILK, CALCIUM FORTIFIED, SKIM/NONFAT, COW, FLUID
11112000	2003-01-01	2004-12-31	Milk, cow's, fluid, other than whole, NS as to 2%, 1%, or skim (formerly milk, cow's, fluid, "lowfat", NS as to percent fat)	MILK, COW'S, FLUID, NOT WHOLE, NS AS TO % FAT
11112110	2003-01-01	2004-12-31	Milk, cow's, fluid, 2% fat	MILK, COW'S, FLUID, 2% FAT
11112120	2003-01-01	2004-12-31	Milk, cow's, fluid, acidophilus, 1% fat	MILK, COW'S, FLUID, ACIDOPHILUS, 1% FAT

Fig. D.1. Screen shot of Main Food Descriptions.

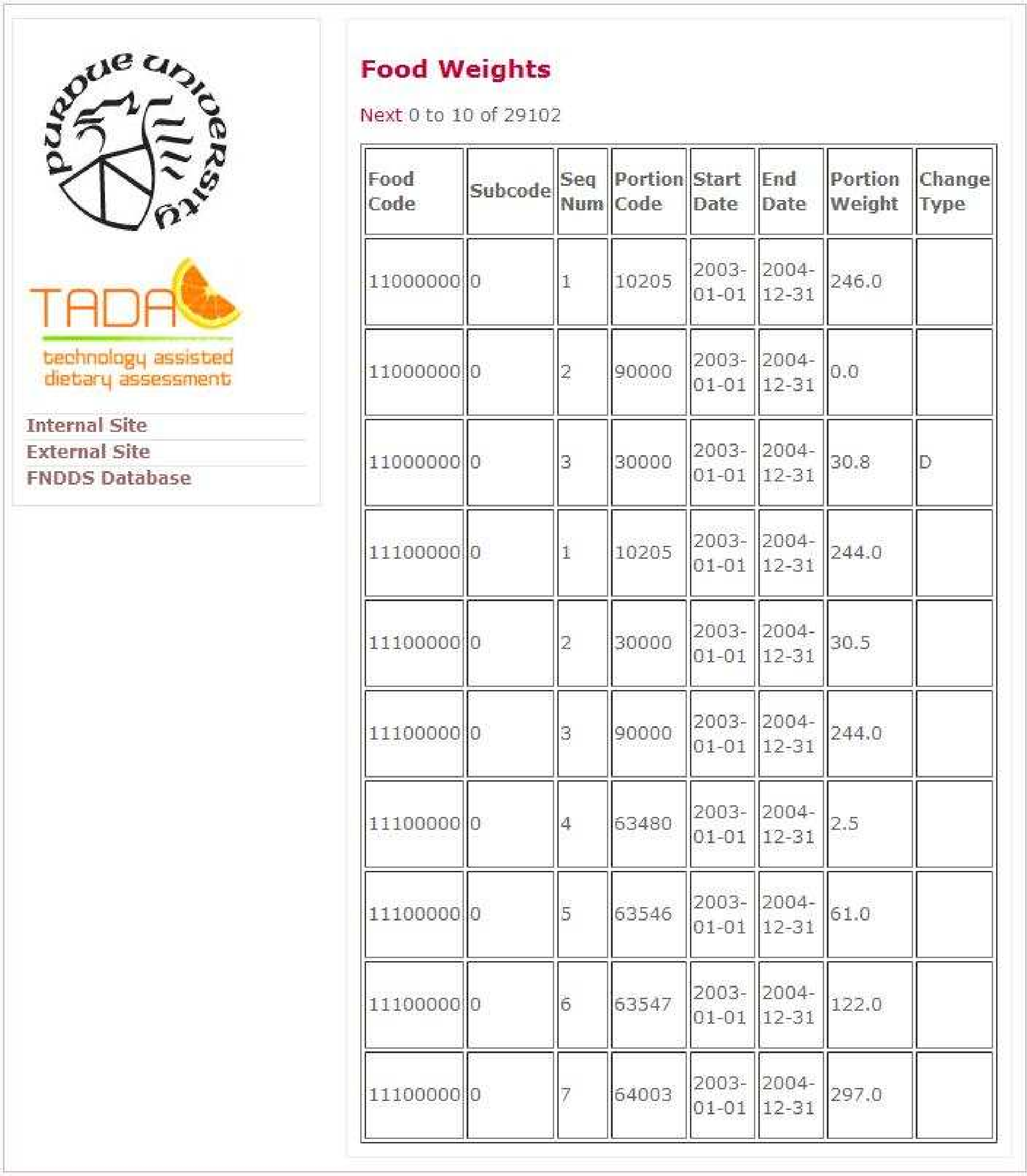
Internal Site
External Site
FNDDS Database

Addition Food Descriptions

Next 0 to 10 of 6600

Food Code	Seq Num	Start Date	End Date	Additional Food Description
11111000	1	2003-01-01	2004-12-31	3.5% or 3.8% fat milk
11111000	2	2003-01-01	2004-12-31	leche fresca
11111160	1	2003-01-01	2004-12-31	CalciMilk
11111160	2	2003-01-01	2004-12-31	lowfat milk
11111170	1	2003-01-01	2004-12-31	Lakeside TLC Calcium Plus Skim Milk
11111170	2	2003-01-01	2004-12-31	fat free milk
11112110	1	2003-01-01	2004-12-31	Hi-Protein milk
11112110	2	2003-01-01	2004-12-31	fortified milk
11112110	3	2003-01-01	2004-12-31	1.5% fat milk
11112110	4	2003-01-01	2004-12-31	reduced fat milk

Fig. D.2. Screen shot of Additional Food Descriptions.



Internal Site
External Site
FNDDS Database

Food Weights

Next 0 to 10 of 29102

Food Code	Subcode	Seq Num	Portion Code	Start Date	End Date	Portion Weight	Change Type
11000000	0	1	10205	2003-01-01	2004-12-31	246.0	
11000000	0	2	90000	2003-01-01	2004-12-31	0.0	
11000000	0	3	30000	2003-01-01	2004-12-31	30.8	D
11100000	0	1	10205	2003-01-01	2004-12-31	244.0	
11100000	0	2	30000	2003-01-01	2004-12-31	30.5	
11100000	0	3	90000	2003-01-01	2004-12-31	244.0	
11100000	0	4	63480	2003-01-01	2004-12-31	2.5	
11100000	0	5	63546	2003-01-01	2004-12-31	61.0	
11100000	0	6	63547	2003-01-01	2004-12-31	122.0	
11100000	0	7	64003	2003-01-01	2004-12-31	297.0	

Fig. D.3. Screen shot of Food Weights.

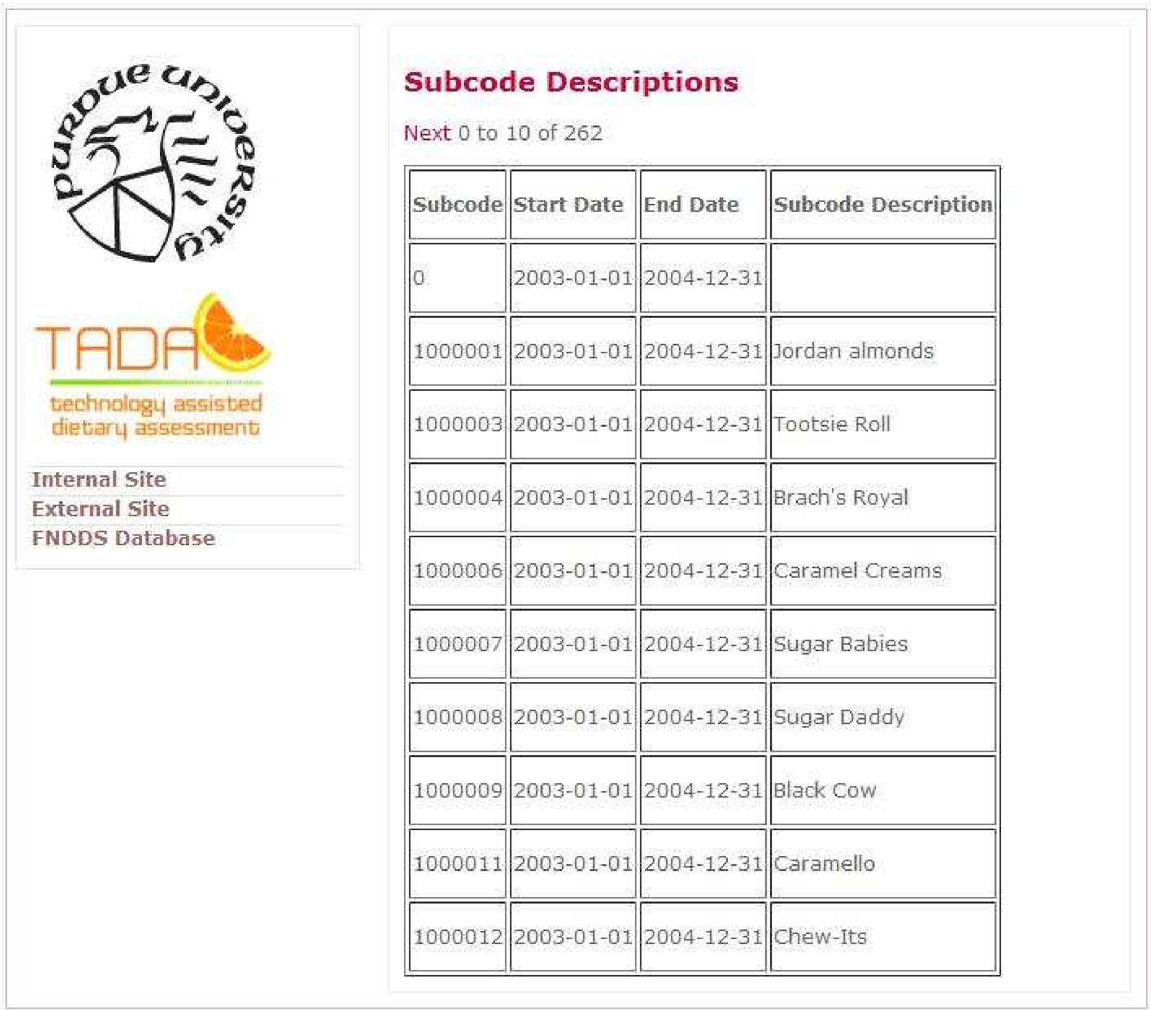
Internal Site
External Site
FNDDS Database

Food Portion Description

Next 0 to 10 of 4387

Portion Code	Start Date	End Date	Portion Description	Change Type
0	2003-01-01	2004-12-31	NONE	
10000	2003-01-01	2004-12-31	1 cup, Better Cheddars	
10001	2003-01-01	2004-12-31	1 cup, Boston Baked Beans	
10002	2003-01-01	2004-12-31	1 cup, Cheez-its	
10003	2003-01-01	2004-12-31	1 cup, Chiclets	
10004	2003-01-01	2004-12-31	1 cup, Goobers	
10005	2003-01-01	2004-12-31	1 cup, Graham Bites	
10006	2003-01-01	2004-12-31	1 cup, Jimmies	
10007	2003-01-01	2004-12-31	1 cup, Jordan	
10008	2003-01-01	2004-12-31	1 cup, Krunch Twists, crushed	

Fig. D.4. Screen shot of Food Portion Descriptions.



Subcode Descriptions

Next 0 to 10 of 262

Subcode	Start Date	End Date	Subcode Description
0	2003-01-01	2004-12-31	
1000001	2003-01-01	2004-12-31	Jordan almonds
1000003	2003-01-01	2004-12-31	Tootsie Roll
1000004	2003-01-01	2004-12-31	Brach's Royal
1000006	2003-01-01	2004-12-31	Caramel Creams
1000007	2003-01-01	2004-12-31	Sugar Babies
1000008	2003-01-01	2004-12-31	Sugar Daddy
1000009	2003-01-01	2004-12-31	Black Cow
1000011	2003-01-01	2004-12-31	Caramello
1000012	2003-01-01	2004-12-31	Chew-Its

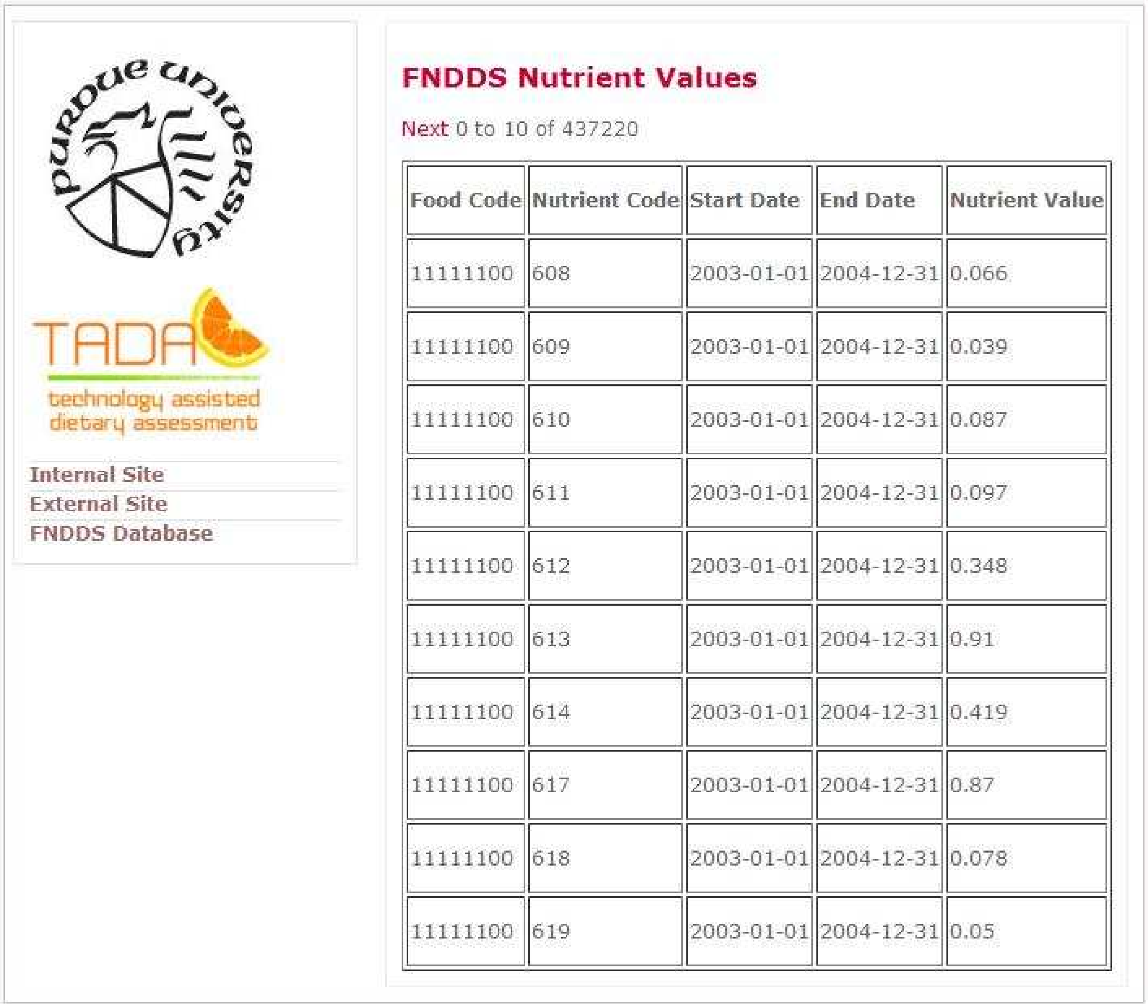
Fig. D.5. Screen shot of Subcode Descriptions.

Food Code-Subcode Links

Next 0 to 10 of 318

Food Code	Subcode	Start Date	End Date
53108200	0	2003-01-01	2004-12-31
53108200	1000230	2003-01-01	2004-12-31
53108200	1000231	2003-01-01	2004-12-31
53108200	1000232	2003-01-01	2004-12-31
53108200	1000233	2003-01-01	2004-12-31
53108200	1000234	2003-01-01	2004-12-31
53108200	1000235	2003-01-01	2004-12-31
53108200	1000236	2003-01-01	2004-12-31
53108200	1000237	2003-01-01	2004-12-31
53108200	1000238	2003-01-01	2004-12-31

Fig. D.6. Screen shot of Food Code-Subcode Links.



technology assisted dietary assessment

Internal Site
External Site
FNDDS Database

FNDDS Nutrient Values

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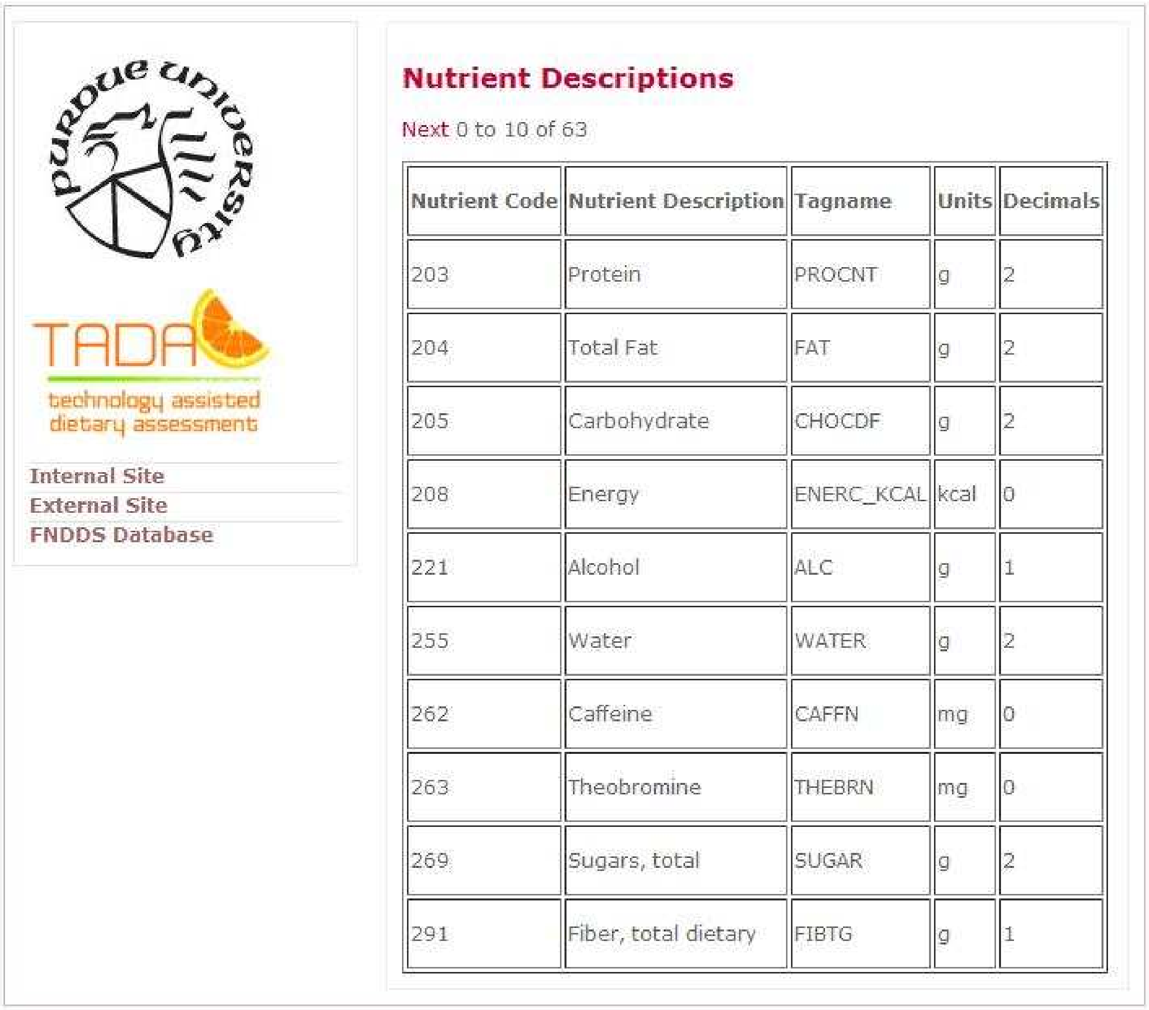
Food Code	Nutrient Code	Start Date	End Date	Nutrient Value
11111100	608	2003-01-01	2004-12-31	0.066
11111100	609	2003-01-01	2004-12-31	0.039
11111100	610	2003-01-01	2004-12-31	0.087
11111100	611	2003-01-01	2004-12-31	0.097
11111100	612	2003-01-01	2004-12-31	0.348
11111100	613	2003-01-01	2004-12-31	0.91
11111100	614	2003-01-01	2004-12-31	0.419
11111100	617	2003-01-01	2004-12-31	0.87
11111100	618	2003-01-01	2004-12-31	0.078
11111100	619	2003-01-01	2004-12-31	0.05

Fig. D.7. Screen shot of FNDDS Nutrient Values.

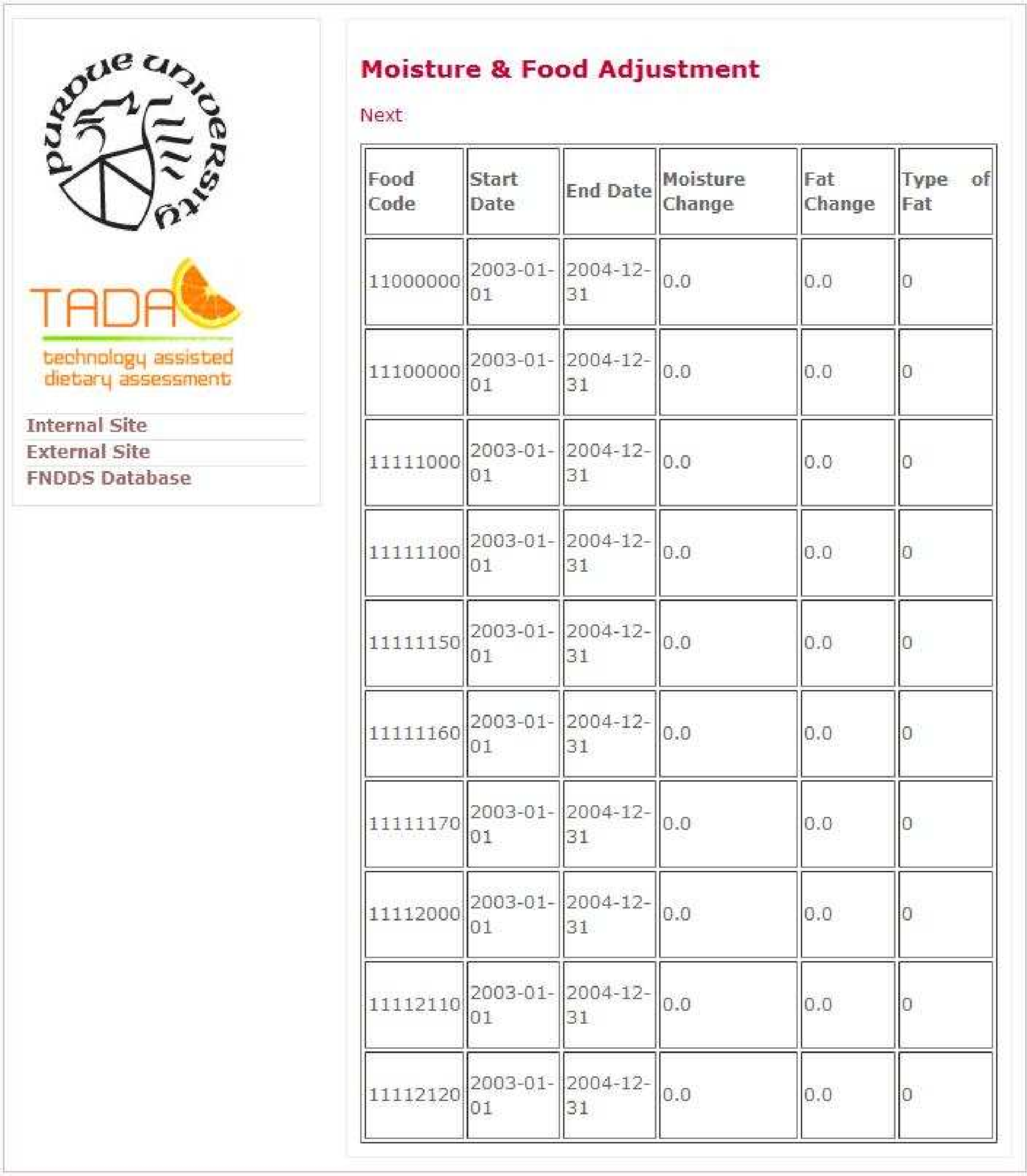


Nutrient Descriptions

Next 0 to 10 of 63

Nutrient Code	Nutrient Description	Tagname	Units	Decimals
203	Protein	PROCNT	g	2
204	Total Fat	FAT	g	2
205	Carbohydrate	CHOCDF	g	2
208	Energy	ENERC_KCAL	kcal	0
221	Alcohol	ALC	g	1
255	Water	WATER	g	2
262	Caffeine	CAFFN	mg	0
263	Theobromine	THEBRN	mg	0
269	Sugars, total	SUGAR	g	2
291	Fiber, total dietary	FIBTG	g	1

Fig. D.8. Screen shot of Nutrient Descriptions.



Moisture & Food Adjustment

Next

Food Code	Start Date	End Date	Moisture Change	Fat Change	Type of Fat
11000000	2003-01-01	2004-12-31	0.0	0.0	0
11100000	2003-01-01	2004-12-31	0.0	0.0	0
11111000	2003-01-01	2004-12-31	0.0	0.0	0
11111100	2003-01-01	2004-12-31	0.0	0.0	0
11111150	2003-01-01	2004-12-31	0.0	0.0	0
11111160	2003-01-01	2004-12-31	0.0	0.0	0
11111170	2003-01-01	2004-12-31	0.0	0.0	0
11112000	2003-01-01	2004-12-31	0.0	0.0	0
11112110	2003-01-01	2004-12-31	0.0	0.0	0
11112120	2003-01-01	2004-12-31	0.0	0.0	0

Fig. D.9. Screen shot of Moisture and Fat Adjustments.

FNDDS-SR Links

Next 0 to 8 of 27908

Food Code	Start Date	End Date	Seq Num	SR Code	SR Description	Amount	Measure	Portion Code	Retention Code	Flag	Weight	Change type to SR Code	Change type to Weight	Change type to Retn Code
11000000	2003-01-01	2004-12-31	1	1107	MILK,HUMAN,MATURE	100.0	GM	0	0	0	100.0			
11100000	2003-01-01	2004-12-31	1	1077	MILK,FLUID,3.25% MILKFAT	36.9	GM	0	0	0	36.9		F	
11100000	2003-01-01	2004-12-31	2	1079	MILK,RED FAT,FLUID,2% MILKFAT,W/ VIT A	34.1	GM	0	0	0	34.1		F	
11100000	2003-01-01	2004-12-31	3	1082	MILK,LOWFAT,FLUID,1% MILKFAT,W/ VIT A	12.4	GM	0	0	0	12.4		F	
11100000	2003-01-01	2004-12-31	4	1085	MILK,NONFAT,FLUID,W/ VIT A (FAT FREE OR SKIM)	16.6	GM	0	0	0	16.6		F	
11111000	2003-01-01	2004-12-31	1	1077	MILK,FLUID,3.25% MILKFAT	100.0	GM	0	0	0	100.0			
11111100	2003-01-01	2004-12-31	1	1089	MILK,LOW SODIUM,FLUID	100.0	GM	0	0	0	100.0			
11111150	2003-01-01	2004-12-31	1	1077	MILK,FLUID,3.25% MILKFAT	100.0	GM	0	0	0	100.0			

Fig. D.10. Screen shot of FNDDS-SR Links.