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# Pixel Bites-Estimation of Food Calorie For Diabetes Patients Using Deep Learning And Computer Vision

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***Abstract***- *One of the cutting edge fields right now are deep learning and computer vision. Using this we develop a mobile app that takes a snap shot of the food we eat daily and recognize the amount of calorie and nutritional value present in the food. It also posts a label whether the food is recommended for a diabetes patient or not. Because of this application, the patient knows whether he can consume the food or not. Thus prevents the patient from various health issues. A good dietary monitoring is also maintained by referring huge amount of data sets, since there are lots of different kinds of foods available in the world. The biggest advantage is that this application does not require the usage of internet and hence can be used anywhere at any time. Food recognition is based on the color, texture and size using various algorithms. Our system can perform automatic food detection and recognition in real-life settings. These settings include cluttered background images. Our system will also be able to identify multiple varieties of food present on a plate and simultaneously estimate their portion size.*

***Keywords***-*Watershed, KNN*

## I. INTRODUCTION

These days taking pictures of the food we eat, especially when it is bought readily made has become a habit. This habit could be put to good use if only the images we snap could be used in a beneficial way. One way to do this would be to use the images and try and process the nutritional and the calorific value of the food and give this information to the consumer of the food as a way of ensuring a healthy diet requirements are met by the food on the platter. This could be used for disease prevention and diet control. However most of these services unfortunately require manual selection of the food items from the hierarchical menus that was pre-fed to the system, which makes it time- consuming and inefficient.

We propose a system to perform food recognition using mobile. The main aim of the system is to estimate the nutrition and calorific content of the food by automatically recognizing the food without the need of any intervention from the user. The user only needs to snap a image of the food to identify the food item on the plate. The system performs the detection of the actual food in the image, crops its image, and removes the background accordingly. In order to segment the region a hierarchical segmentation is performed. The features are then extracted at different locations and scales and the salient regions are classified into different kinds of food items using a linear support vector machine classifier. Additionally the system also determines the portion size. Using this information the calorific and the nutritional content of the food present on the plate can be approximated. Based on this data, the food on the platter will be recommended accordingly. The previous approaches included capturing images in lab setting, or the user input had to be given additionally. Our system can perform automatic food detection and recognition in real-life settings. These settings include cluttered background images. Our system will also be able to identify multiple varieties of food present on a plate and simultaneously estimate their portion size.

## II. RELATED WORKS

**1.** Daniele Ravi, Benny Lo, Guang-Zhong Yang**of** Hamlyn Centre**,** Imperial College London in 2015 described an assessment that the food intake has a wider range of applications in public health and life-style related chronic disease management. The project involves real-time food recognition platform combined with daily activity and energy expenditure estimation. In the proposed method, food recognition is based on hierarchical classification using multiple visual cues, supported by efficient software implementation suitable for real-time mobile device execution. A Fischer Vector representation together with a set of linear classifiers are used to categorize the food intake. Daily energy expenditure estimation is achieved by using the built-in inertial motion sensors of the mobile device. The performance of the vision-based food recognition algorithm is compared to the current state-of-the-art, showing improved accuracy and high computational efficiency suitable for real-time feedback. Detailed user studies have also been performed to demonstrate the practical value of the software environment. Thus an Integrated framework for real-time food recognition by exploiting a hierarchy of visual features extracted from the smart phone. The proposed software environment is further integrated with daily activity recognition, allowing combined assessment of food intake and energy expenditure estimation by using a single app.

2. Hajime Hoashi, TaichiJoutou and KeijiYanai from the Department of Computer Science, The University of Electro-Communications, Tokyo**,** proposed that the recognition of food images is challenging due to their diversity and practical for health care on foods for people. In this paper, we propose an automatic food image recognition system for 85 food categories by fusing various kinds of image features including bag-of-features (BoF), color histogram, Gabor features and gradient histogram with Multiple Kernel Learning (MKL). In addition, we implemented a prototype system to recognize food images taken by cellular phone cameras. In the experiment, we have achieved the 62.52% classification rate for 85 food categories**.** Thus the food recognition system is based on the number of categories and employed image features. By integrating seventeen kinds of image features with Multiple Kernel Learning, they obtained the 62.52% classification rate for 85-food-category classification evaluated by five-fold cross-validation.

3. Giovanni Maria Farinella, Marco Moltisanti, SebastianoBattiato on 2014 made a classification of food images in an interesting and challenging problem since the high variability of the image content which makes the task difficult for current state-of the- art classification methods. The image representation to be employed in the classification engine plays an important role. This paper points out, the textures are fundamental to properly recognize different food items. For this purpose the bag of visual words model (BoW) is employed. Images are processed with a bank of rotation and scale invariant filters and then a small codebook of Textons is built for each food class. The learned class-based Textons are hence collected in a single visual dictionary. The food images are represented as visual words distributions (Bag of Textons) and a Support Vector Machine is used for the classification stage. The experiments demonstrate that the image representation based on Bag of Textons is more accurate than existing (and more complex) approaches in classifying the 61 classes of the Pittsburgh Fast-Food Image Dataset. Thus the paper evaluates the class-based Bag of Textons representation in the context of food classification. The MRS4 filter banks are used to build class-based Textons vocabularies. The class-based Bag of Textons representation obtained better results with respect to all the other methods.

4. Shulin (Lynn) Yang (University of Washington), Mei Chen (Intel Labs Pittsburgh), Dean Pomerleau (Robotics Institute), Rahul Sukthankar (Carnegie Mellon) on 2010 proposed that the food recognition is difficult because food items are deformable objects that exhibit significant variations in appearance. We believe the key to recognizing food is to exploit the spatial relationships between different ingredients (such as meat and bread in a sandwich). We propose a new representation for food items that calculates pairwise statistics between local features computed over a soft pixel level segmentation of the image into eight ingredient types. We accumulate these statistics in a multi-dimensional histogram, which is then used as a feature vector for a discriminative classifier. Our experiments show that the proposed representation is significantly more accurate at identifying food than existing methods. Exploiting the spatial characteristics of food, in combination with statistical methods for pixel-level image labeling will enable us to develop practical systems for food recognition. Uses bag-of-features models based on SIFT or color histograms, particularly when we augment pixel-level features with shape statistics computed on pairwise features.

5.Weiyu Zhang, Qian Yu, BehjatSiddiquie, Ajay Divakaran, HarpreetSawhney on 2015 proposed that the system can recognize food and estimate the calorific and nutrition content of foods automatically without any user intervention. To identify food items, the user simply snaps a photo of the food plate. The system detects the salient region, crops its image, and subtracts the background accordingly. Hierarchical segmentation is performed to segment the image into regions. We then extract features at different locations and scales and classify these regions into different kinds of foods using a linear support vector machine classifier. In addition, the system determines the portion size which is then used to estimate the calorific and nutrition content of the food present on the plate. In our experiments, we have achieved above 85% accuracy when detecting 15 different kinds of foods.As part of future work, we plan to make our system capable of personalizing the food recognition classifier based on user habits, location, and other meta-data.

## III. SYSTEM DESIGN

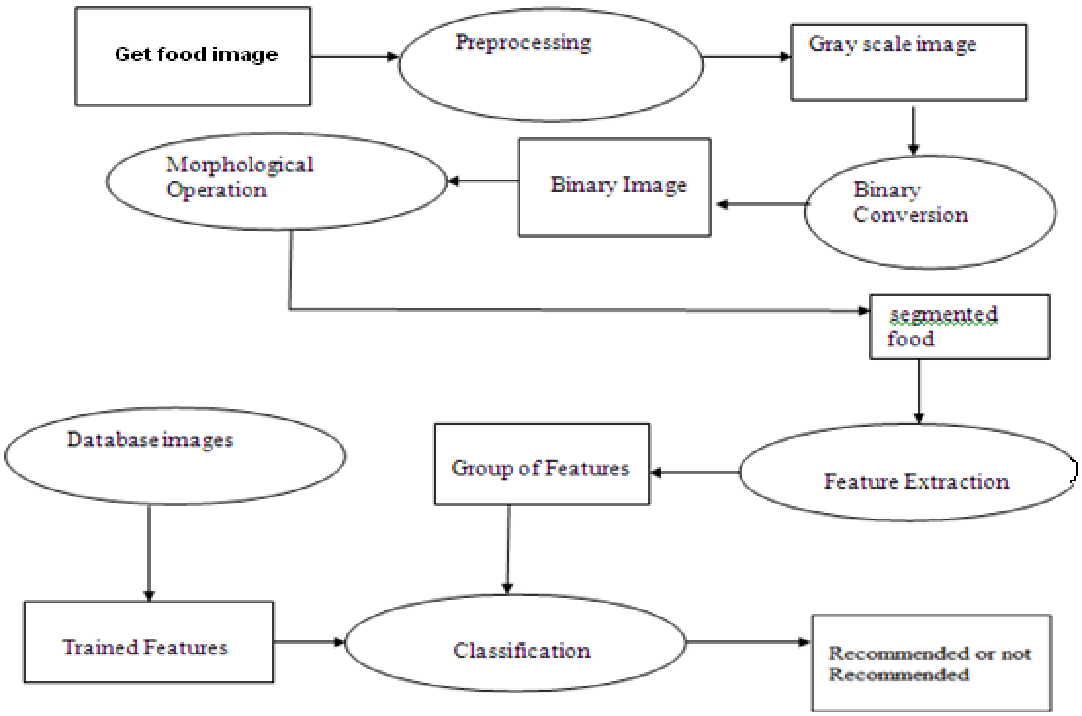


*Figure 1. System Design*

## IV. PROPOSED METHODOLOGY

### *1.Preprocessing :*

The input RGB image is resized to a height of 320 pixels. The resized image undergoes two separate processing pipeline : a saturation-based one, and a color texture one. In the first one, the image is firstly gamma corrected and then the RGB values are converted to HSV to extract the saturation channel. These values are automatically set to a threshold and morphological operations are applied to clean up the obtained binary image. A second processing based on the segmentation algorithm that works on both color and texture features.

### *2.Segmentation :*

The segmented image is then processed in order to remove non relevant regions. For instance, the regions that touch the border of the image do not belong to the food regions and thus can be eliminated. Also, regions larger or smaller than predefined thresholds can be discarded as well (e.g. the placemat, the tray, highlights). The final segmented image contains with high probability the food regions and few non relevant ones. To further ensure that only few, relevant, regions are retained for the classification phase, geometric constraints are used to clean up the output of the combining step. The bounding boxes of all the regions of interest are passed to the prediction phase.

### *3.Classification :*

The processing pipeline for the food classification used in the predictor module. Here we compare three different classification strategies: a global strategy (top path), a local one (bottom path), and a combination of them. Depending upon the K Nearest Neighbor algorithm, the food with the nearest feature is matched and provides the recommendation depending upon the threshold calorific value.

***Food Portion Volume Measurement***

In-order to calculate the surface area for a food portion, we portion the image using grid of squares onto the image segment so that each square contains an equal number of pixels and equal area. By comparing the grids with each other, the grid matches with irregular shapes, because the food portions will be irregular.Depending on the processing capabilities of the device and the expected system response time from the user's perspective, we can make the adjustment for the granularity of the grid to balance between the factors.

***Table 1. Calorie value from nutrition table***

| Food Name | Quantity | Weight | Calories |
|---|---|---|---|
| Banana | 1 | 120 | 105 |
| Guava | 1 | 138 | 72 |
| Mosambi | 1 | 140 | 47.08 |
| Chocolate | 1 | 100 | 535 |
| Sweet | 1 | 100 | 625 |

## V. ALGORITHM

The k-Nearest Neighbour classifier is by far the most simple machine learning/image classification algorithm. The algorithm is dependent on the distance between feature vectors, thus the labelling is associated with each image and so we can predict and return the actual category for which the food belongs to. In the k-NN algorithm classify the unknown data points by analysing the most common classes among the k-closest examples**.** Every data point in the k closest samples casts a priority and the category with the highest priority wins. The image to feature vector method is an extremely naive function that simply takes an input image and resizes it to a fixed width and height (size), and flattens the RGB pixel intensities into a single list of numbers. This means that our input image will be shrunk according to the output screen size, and given three channels for each Red, Green, and Blue component respectively. Furthermore, utilizing raw pixel intensities as inputs to machine learning algorithms tends to yield poor results as even small changes in rotation, translation, viewpoint, scale, etc., can dramatically influence the image itself.

The watershed algorithm identifies the watershed regions for the given input image, that can have any dimension. The watershed transformation analyses the "catchment basins" or "watershed ridge lines" in an image by treating it as a surface where light pixels representing higher elevations and darker pixels representing lower elevations. The elements labeled 0 does not belong to a unique watershed region. The elements labelled 1 belong to the first watershed region. Depending upon this the embossment of the image can be predicted. Thus the problems on distance or size of the food cannot happen, by setting the distance of the camera and food.

## VI. RESULT

We evaluate our system performance on our data set consisting of about 5 images comprising of predefined classes. We have between 5 to 10 examples of each food in our training set. The results have been derived from the confusion matrices, and thus a accuracy of 63% is obtained. The results evaluate the average classification accuracy, that is, the percentage of test images of each category of food correctly classified. The watershed features the result in the best performance and fusing all the features further improves on that performance. Furthermore, we also tested the application in a real time with plates of food that various customers got. Therefore, the test set is an on-going set which is tested on a daily basis at a restaurant among other places. We have not seen any obvious pattern in the failures when they occur. The results can be vastly improved by narrowing down the list of possibilities using information such as the prior choices indicating user habit and other such metadata, thus achieving personalization. Since the biggest advantage of this application is that, it does not require any internet, it will take a lot of time to train the food images.

The accuracy is obtained based on several food portions, and their type and volume are extracted. Using the type and volume of each food portion, its mass is extracted. Using the extracted mass, the calorie of each food portion is derived. Then the real food portion is actually weighted and its real calorie is extracted. Finally we have compared the extracted calories from the real calorific value.

 

***Table 2. Accuracy of proposed method in comparison with real values***

| Food | Weight | Calculated Calorie | Real Calorie | Accuracy (in %) |
|---|---|---|---|---|
| Banana | 120 | 94.5 | 105 | 90 |
| Guava | 138 | 65.52 | 72 | 91 |
| Mosambi | 140 | 20.24 | 47.08 | 43 |
| Chocolate | 100 | 358 | 535 | 67 |
| Sweet | 100 | 150 | 625 | 24 |
| | | | Accuracy | 63 |

## VII. CONCLUSION

Professional organizations and leading authorities from different parts of the world have concluded that proper nutrition is an important part of the foundation for the treatment of diabetes. However, appropriate nutritional treatment, implementation, and ultimate compliance with the plan remain some of the most vexing problems in diabetic management for three major reasons: First, there are some differences in the dietary structure to consider, depending on the type of diabetes. Second, a plethora of dietary information is available from many sources to the patient and healthcare provider. Nutritional science is constantly evolving, so that what may be considered true today may be outdated in the near future. There are different types of diabetes that require some specialized nutritional intervention, however, many of the basic dietary principles are similar for all patients with diabetes, pre-diabetes, metabolic syndrome or who are overweight or obese. Lastly, there is not perfect agreement among professionals as to the best nutritional therapy for individuals with diabetes, and ongoing scientific debate that spills over into the popular press may confuse patients and health care providers. Thus our proposed system focuses on these issues, creating an application to determine whether the food that is to be consumed is recommended for a diabetes patient or not. This complete system is designed taking in consideration to provide extreme dietary monitoring to help people from consuming unhealthy foods. The application calculates the result based on the calorific threshold value. The result shows that higher accuracy is achieved using this project. Thus the project is more efficient and reliable. This proposed method is verified to be highly beneficial for the society.

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