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Smart food recognition and calorie system using CNN

Madhushree GK[1], Dr Sanjay KS[2]

[1] MCA Student, PES Institute of Technology and Management, Shivamogga, Karnataka, India.
[2] HOD, Dept of MCA PES Institute of Technology and Management, Shivamogga, Karnataka, India.

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Abstract - Heaviness has been a global problem for a long time. This remains the result of dietary problems that increase obesity's susceptibility to various diseases. Maintaining a healthy diet while balancing the demands of an adult job can be hard. This document describes the creation of a clever diet journal a smartphone app that tracks diet to assist patients and obese individuals in controlling their nutrition amount consumed for a better quality of being.

The suggested system makes use of deep learning to identify food items calculate their nutritive value in relationships of calories 16,000 photos of food products from 14 distinct categories compromise the data that a multi-label classifier is trained on. We were able to calculate average calories within 10% of the definite calorie value and achieve an overall precision of roughly 80.1 per cent by using a pre-trained CNN model for classification.

Keywords: machine learning, TensorFlow framework, calorie prediction, diet monitoring, faster R-CNN, and food identification.

INTRODUCTION

Obesity accounts for 8% of all deaths worldwide each year. Among the serious illnesses and health conditions that obese people are more likely to encounter are elevated blood pressure dyslipidemia diabetes difficulty sleeping respiratory problems and a general low eminence of life. Furthermore this makes it difficult to keep maintaining correct posture during work of relaxing which increases the risk of stress damages [2 3]. While a persons genes affect their weight other issues such as confident drugs stress inactivity and unbalanced sleep patterns also contribute to obesity. Dietary consumption is some of the primary origins of obesity and fat storage. Eating more than is necessary effects in excess calorie values which are not utilized. Scientists have looked into dietary and exercise evaluations as strategies to fight obesity and raise awareness. In order to offer useful statistics to slow the progression of prolonged disorders many medical researchers have recently focused on nutritional logs and regulation. Ingestion of food is currently evaluated manually using three different methods: FFQ,24-hour recall , and diet records. Users had to keep track of food consumption over create diet histories over the course of three days. Trained personnel gave the participants thorough instructions on how to document their consumption, which was then saved for analysis in the NDSR. A systematic interview called the 24 hour recall that allows people to document comprehensive details about the participant's food during the preceding 24 hours.

SYSTEM ARCHITECTURE

Figure 1 illustrates the Dietary system structure. It comprises of a smartphone with a communication interface and a dedicated server on the back end. The Redux state management library helps the program maintain shared data across screens and React Native technology in JavaScript is used to create the user interface. Redux avoids this by storing some variables in an international store whereas the React-Native architecture requires manual information transfer to each element. Additionally diary entries user information and food item calorie data are kept in a SQLite database related to the front end. Volume estimates and image classification were performed in the back-end implementation by means of the Python CherryPy framework. Cherry Py was selected since of its easy-to-use HTTP request management interface and provision for a range of server types. Additionally its design that uses multiple threads provides great performance because it can manage numerous requests. The server receives the picture of the dish captured by a smartphone lens for additional processing. It responds by showing the name and capacity of the food after processing. This relevant content is employed to calculate how many calories a given food contains.

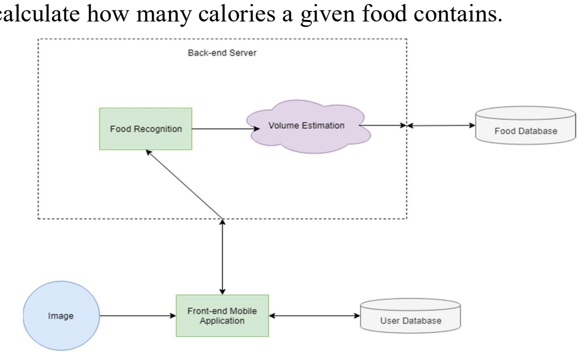

Figure 1. The Architecture Of Smart Diary.

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DATASET

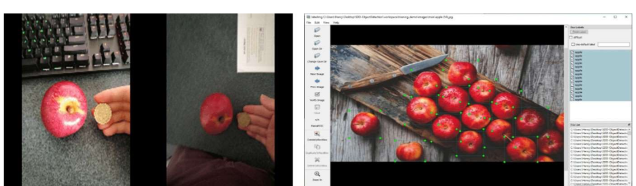
We took into consideration publically accessible datasets during the first stage of development. The box had to be identified on these datasets so as to feed region-based CNN, although they had been earlier labeled with the item name. Yet, as theFruits-360 dataset lacked diversity and the FOOD101 dataset had poor light, direction, and faintness, accuracy issues encountered by systems trained with these images. Our dataset was made by us for a training procedure in order in around to get around these problems.

Table 1. Specifies of training and test records.

Sl. No.	Group	Training	Trial	Sum
1.	Apple	671	200	871
2.	Bluebird sour milk	805	200	1005
3.	Curry of Chicken	651	200	851
4.	Coca-Cola can	1035	200	1230
5.	Coin	1546	400	1946
6.	ETA chicken	817	200	1017

IDENTIFICATION AND CLASSIFICATION OF OBJECTS

Motivated by the visual cortex of animals, Deep Learning is an effective tool for addressing the image recognition problem of food identification. When matched to other twin ordering techniques, CNNs require less pre-processing. However, if the ROI has different physical locations throughout the image, this turn out to be computationally demanding. Region R-CNN architectures are applied to solve this issue by applying selective search techniques and extracting fewer regions referred to as region proposals from the image.



(a) (b)

Figure 4. *(a) Examples of dataset images (b) and the labelling user interface.*

The quicker R-CNN consists of three neural networks. Neural networks are aimed to generate ROI that are more unlikely to comprise an enclosing item. The data is used by the detection network RPN and the feature network to create the last lesson and box. Typically, it is made up of four densely packed, fully linked layers. There are two stacked common layers. To help classify only the space within the bounding frames, the geographies were clipped according to those frames.

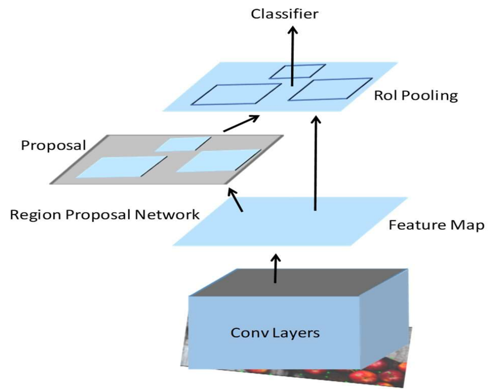


Figure 5. *In succession more quickly CNN on TensorFlow.*

VOLUME ESTIMATION

ID cards, photos, or utensils are examples of everyday objects that most people own or have access to during a diet. These items' uneven shapes or inconsistent sizes were the issue. It is very portable, and most people carry it. Although other coin potentials were in use into consideration, the NZD 2 coin was selected due to its appropriate scope for the application. We used segmentation techniques like the GrabCut method to calculate an object's volume from a two dimensional appearance. To achieve comprehensive two dimensional segmentation, this algorithm works on repeated cycles that combines GraphCut and statistics. In direction to assessment the sizes of the nutrition and currency by counting pixels, we utilized it to divide the copy by extracting the foreground. The front and backward fairly loosely separated throughout this phase.

CALORIE ESTIMATION

Finding a food's calorie count from a picture is challenging task. Without more information, it is challenging to get an accurate estimate. Previous research employs depth-sensing cameras or takes several photos of dishes taken from various perspectives. A extra precise assessment of the size can be obtained using this extra information. But our objective was to reduce the quantity of steps consumers had to take in order to document their diet. Consequently we assessed how many calories there are using a unique picture. This was consistent with our goal of giving the client with a diet indicator instead of a specific nutritional energy value. The energy value is determined by the process starts with classifying the food items in the picture and using it after that size valuation to determine the proportional size of each item. The basis to calculate the volume is that most diet items have regular shapes. They may be given an anticipated 3D shape like a sphere or cylinder to facilitate the volume estimation procedure. The regular portion scope of the occasionally formed meals was employed.

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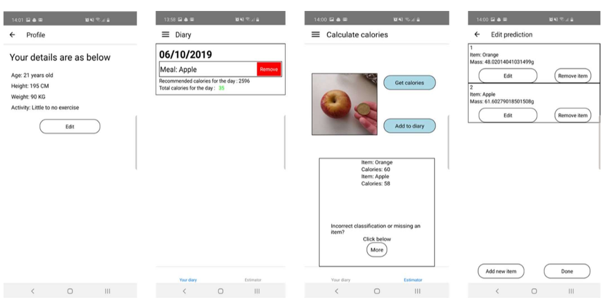
Equation (1) provides the caloric content in a given item which can help estimating the total number of calories.

$$\mathrm{Cal} = \frac{F_d \times V_F}{100} \times C \qquad (1)$$

Profile linked to the user

The food consumption is depicted in this section. In Figure 6b, the user's nutrition journal is kept in a indigenous folder and includes information such the phase of ingestion, the type of diet, and the quantity of calories. Additionally included are the total amount of calories ingested during that day as well as how many calories were eaten at each meal. The user receives a warning if the overall quantity of calories spent for the day surpasses the suggested amount. The total of suppertime entrances each day was unrestricted. User can also view their food intake history.



(a) (b) (c) (d)

Figure 6. *Various front-end components: (a) user profile; (b) database and diary component; (c) food prediction component; and (d) Nutrition modification component.*

Diary feature and food storage section

The documented food intake is displayed in this section. The users meal journal depicted in Details are stored in a local database in Figure 6b about the food type nutritional intake level and stage of intake. The total number of calories consumed during the day and the caloric value of each meal are also included. If the total amount of nutrients consumed during the period surpasses what is advised amount for the user a warning is generated. There was no cap on the daily number of meal entries at that time. Users can as well view changes in food intake over time.

Nutrition classification module

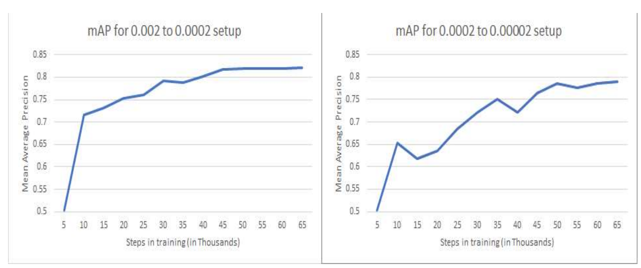
In order to utilize the meal classifier element for prediction the customer can either snap a photo or pick just one start storing on their phone and send that to the server-side system. The images should showcase the culinary items most unique qualities. A penny must also be detained equivalent to the foodstuff item at the same height, as showed in Figure 6c. To get a more precise estimate of calories, this is necessary.

Food Rectification Component

Because it depends on the viewpoint and intensity of the image, food estimate is not always accurate. To address this issue, we have included a food rectification capability. By way of seen in Figure 6d, users can use this component to add, remove, or modify things. Items can be added or changed using one of two methods. With the former, the user merely needs to deliver the heaviness measured in grams related to the meal and can choose the appropriate meal component that includes the appropriate calorie mass retrieved from the database. Under these circumstances, user can input both the calorie amount and bespoke products.

RESULTS

The model's accuracy was assessed both in real time and offline. In the real-time scenario, certain meals are identified 100 times, and the likelihood of accurate categorization is calculated. The average amount of calories across 100 photos was calculated and evaluated with respect to actual value in order to assess the calorie estimation's performance. We assessed our system's performance using mean average precision(mAP).



The misclassification might reduce the applications usability but manual selections remains available to the user the correct item using the meal correction screen. The program was tested in real time at those locations. This application may be easier to use if the device has object detection capabilities. For example the model simultaneously takes a picture and instantly identifies food. In this way the program displays the object on the screen when it is detected and the user can record their time to determine the optimal location for an accurate classification. We used image augmentation at the current employment based on identifying the dataset that is restricted and perhaps will not have a picture under specific conditions.

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Table 2. Outcomes obtained by testing the real-world setting

Item	Accuracy	Mean Calorie Intake	True Calorie Count
Soft drink Can	60%	153	142
Apple	92%	77	78
Tangerine	91%	52	59

The GrabCut algorithm's poor segmentation of the image, which resulted in extra background pixels remaining in the image, was probably the cause of the overestimation. Furthermore, the placement of the currency affected the volume. As explained in Figure 8, it is necessary on behalf of the user to keep the coin aligned with the food item's height measurement. If the penny is positioned placed above the food item the estimated total calorie count is lower and when it is positioned lower it is higher. It is simple to obtain an accurate if the user is aware of how high the coin should be held. Additionally the drupe was not consistently precisely spherical with respect to the tangerine and apple estimates. Based on which side apple is facing the camera different calculations of calories are made. The level of calories which may be estimated is limited because the items scope is based on an image. This degree of error does not pose a major concern since it is reasonable predictor of users nutritional intake.

Figure 8. Estimation of Volume.

Figure displays a series of screenshots captured while utilizing the suggested smartphone application, alongside with a thorough explanation of the foodstuff recognition procedure and the outcomes produced in the real-life scenario. Food products are identified by the system, which also calculates their nutritional worth. The system generates a variation of warnings, for instance calorie count identification of nutrient-rich foods, successful food item saving, and surpassing the suggested calorie count.

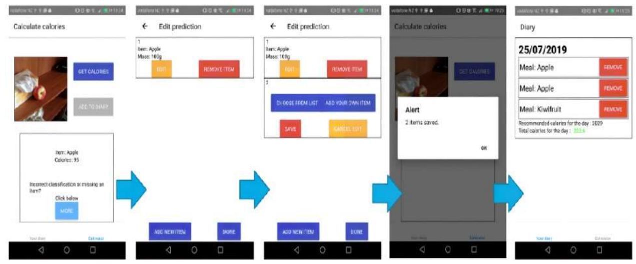

Figure 9.Results of mobile application.

We contrasted the outcomes with those published in cutting-edge research that was comparable to ours. . Although none of the preceding systems were mobile-based, the mainstream them provided great accuracy. These are resource-rich desktop programs that are unable to give users real-time information. The only mobile-based systems with accuracy comparable to ours are [41,45]; in fact, Ref.[28] has a worse accuracy rate rather than the suggested system despite being able to handle more food categories.

CONCLUSION

In this study, we describe the scheme and expansion of a phone appearance for nutritive awareness that monitors diet intake and nutritional content to assist overweight individuals in losing weight. By creating an application that customs the Grab Cut method and the Tensor Flow Object recognition API for food acknowledgment and identification, we take advantage employing deep CNN architectures(such as faster R-CNN). Exceeding 16,000 photos as a part of training the algorithm involved fourteen separate categories, incorporating the standard objects. The trial conclusions specified which the suggested scheme has a complete precision approximately of the overall caloric content count fell within a 10% range from the real value of. In the existing application we accepted fourteen groups regarding the food which comprise junk food item as well as the beverages, that are harmful potentially harmful to health. Moving forward we strive to incorporate additional classification types and use applying image augmentation in order to enrich the current dataset, thereby increasing the system's precision.

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