A LITERATURE SURVEY ON NUTRITION ASSISTANT APPLICATION

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Abstract:

Nutrition assistant application plays an important role in evaluating accurate BMI calculation and displaying nutrients of scanned foods. Due to the ignorance of healthy food habits, obesity rates are increasing at an alarming speed, and this is reflective of the risks to people's health. People need to control their daily calorie intake by eating healthier foods, which is the most basic method to avoid obesity. However, although food packaging comes with nutrition (and calorie) labels, it's still not very convenient for people to refer to App-based nutrient dashboard systems which can analyze real-time images of a meal and analyze it for nutritional content which can be very handy and improves the dietary habits, and therefore, helps in maintaining a healthy lifestyle. Biomarkers are medical signs that in a broad sense "provide objective indications of the medical state observed from outside the patient and can be measured accurately and reproducibly". In other words, biomarkers can act as a metric for today or as a prognosticator for tomorrow. Biomarkers can be produced by a sole metric from an examination or observation or by a combination of metrics. For example, the well-known body mass index(BMI) is a combined biomarker that is derived from the mass and height of an individual.

Introduction:

This project aims at building a web App that automatically estimates food attributes such as ingredients and nutritional value by classifying the input image of food. Our method employs **Clarifai's AI-Driven Food Detection Model** for accurate food identification and Food API's to give the nutritional value of the identified food. As weight is an important indicator of health, BMI (height / mass index) will be considered as a target for our deployed deep neural network. The standard biochemistry profile results will be used as features/inputs for the training of the neural network.The BMI data will be transposed in a x*3 table and separated into three groups, depending on the commonly used ranges to classify weight categories based on the following.

Conception:

BMI CLASSIFICATION

Statement Comparison Category Binary result

if less than 18.5 underweight [0,0,1]

else if between 18.5

and 25

normal [0,1,0]

else if over 25 overweight [1,0,0]

Due to limitations of our sample data, the categories of obese and overweight have been consolidated. If any resulting data points from the initial data processing are more prominent in defining and predicting the BMI, then those data points will be used in a similar process as targets.

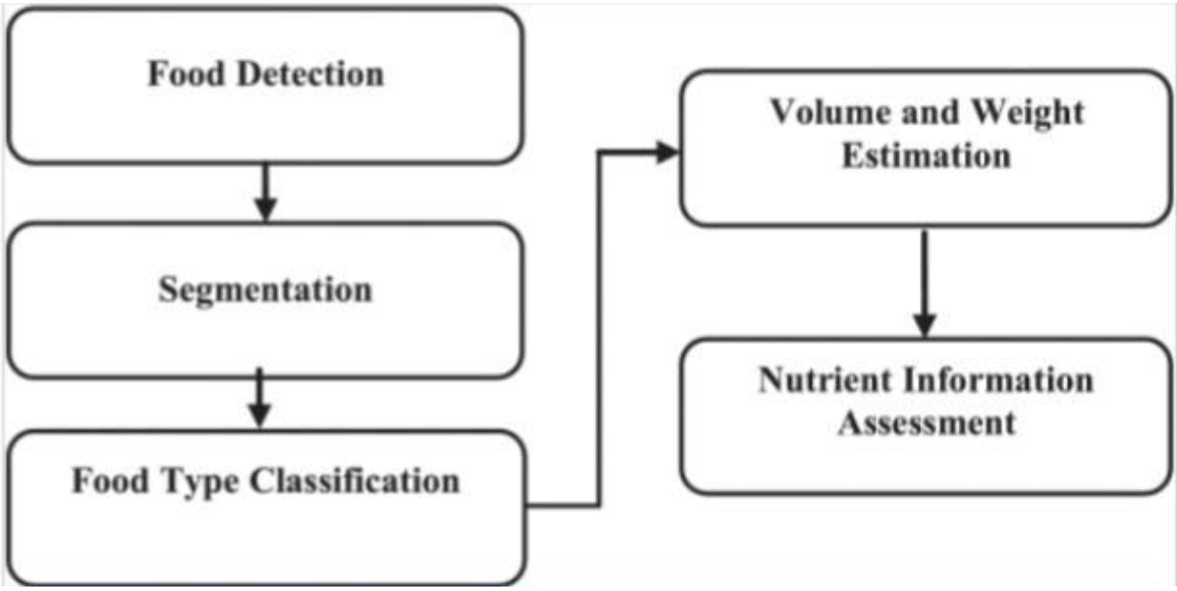
Obesity and overweight are defined as the result of energy imbalance between calories intake and expenditure. This has been related to the risks of developing chronic heart diseases, diabetes, and other vascular syndromes. Obesity was the leading cause of death in 2012, with more than 1.9 billion overweight adults, and 650 million of those were obese. Nutritionists attempt to address these issues traditionally by analyzing and monitoring the daily eating habits of their patients or alternatively by examining the images of consumed food. However, the results are affected by the lack of correct logging of food intake by the patients or by the imprecision in estimating the portion size by simple examination of the food images.

Conventional dietary assessment programs require maintaining a daily record of consumed food, manual identification of its contents, and an estimation of its volume [4], [5]. However, these methods pose a challenge for elders especially when it involves an accurate estimation of the amount and time of the food intake. For these reasons, the need for a sophisticated system to automatically carry out all the tasks of food intake, such as detection, food type classification, and volume estimation, has been the main focus in many recent research efforts.

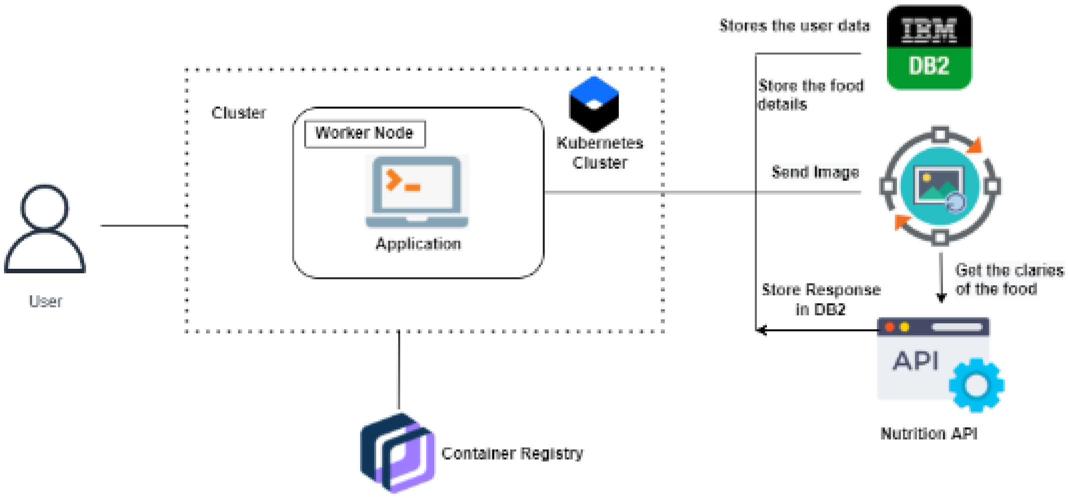
Recent developments in smartphone applications have made it possible to develop an efficient and more convenient solution for automatic nutrition assessment .That smartphone-based nutrition applications show higher user retention than traditional assessment methods . However, most of these applications require user intervention and manual input of food items affecting its performance on food content assessments.

The advancements in machine learning and computer vision based applications have paved the way for more robust dietary assessment tools. The general purpose of vision-based methods is to recognize the food, estimate its volume, and assess the related nutrient information. With the development of deep learning algorithms, food detection and recognition accuracy have been drastically improved. However, the performance and effectiveness of such solutions depend on several factors. First, optimal classification accuracy can be attained by training the image classifier with a large number of food images for each class. Additionally, a proper segmentation approach must be chosen and implemented to identify all food segments within a single image, in addition to the extraction of these segments from the image background. Finally, after identifying the food, volume estimation of each food item must take place to assess the corresponding weight and nutrient information.

CONCEPTUAL ARCHITECTURE:



TECHNICAL ARCHITECTURE:



WORK FLOW OF THE PROJECT:

This section summaries the findings according to research questions, also presents the studies that grouped by after applying the data mining process. These results populate the classification scheme, which evolves while doing the data extraction.

User-Interaction:

The user interacts with the webpage to scan and load an image and the user inputs details.

Methodology:

FOOD DETECTION:

Food Recognition deals with recognition of food item when given an image. Owing to the great success of CNNs, we experimented with top performing pre-trained models to train our dataset using transfer learning. Based on their performance in other domains, we selected several pre-trained CNN models such as VGG-16, VGG-19 [18], Inception-v3 [39], Inception-v4 [40] and ResNet [41]. These models are pre-trained on the Imagenet dataset. Transfer learning is used to train these models on our dataset. The last fully connected layer is removed and appended with dropout, ReLU activations and softmax layers. Fine tuning the model on our dataset took about 15 hours on a single Titan X GPU with 12GB of memory. Models based on Inception-v3 and Inception-v4 gave better performances and were used as the recognition engine in the rest of the paper.

ATTRIBUTE ESTIMATION:

The next task after food recognition is to compute the food attributes including the ingredients and their nutritional value. As mentioned in Section II, there are generally two approaches used. In the first approach, the food portion size is estimated and then standard nutritional tables are used to compute the attributes. In the second approach, the food attributes are learned directly from the image.We take a completely different approach and use vector space representation of words from a large dataset. To get accurate and relevant results from vector space embeddings of words, we proceeded to collect a large amount of text data from the internet, mostly from food and nutrition sites. The collected data is then trained using Word2Vec , which produces word embeddings. Syntactically and semantically similar words are adjacent or have smaller distance in the vector space as compared to words that are not similar. The motive is to find food attributes by measuring the distance between the food item and the ingredients in the learned vector space. Small distance between the food item and an attribute means they occur closely in the original text and the probability of that attribute appearing in the food item is high.

Dataset:

Our goal is to make a dataset that contains common food items, augmented with subcontinental dishes. We started by experimenting on the publicly available dataset of food images, i.e. Food-101 [7]. It contains 101 classes of food items with 1000 images for each class. Food-101 is designed specifically for multi-class classification. There are other datasets as well that have been used for food recognition previously; one such dataset is Food-5k. Food-5k contains 5000 images, out of which 2500 are of food and 2500 of non-food. However, this dataset can be used only for binary classification to discriminate food items from non-food items and therefore, is not suitable for our task. Moreover, Food-101 does not include food items or classes from the subcontinental cuisine which makes a large portion of the food that people intake in the subcontinental region. Some subcontinental dishes exhibit low inter-class variation and are very similar to each other, so collecting high quality data for accurate classification of different categories is a big challenge. The results returned by Google search engine against textual search queries for food images are quite relevant with very low noise content. Based on such results from Google search engine, our new dataset is created by querying Google against each label of our dataset. The newly formed dataset has classes from Food-101, that are common and eaten everywhere. Thus, the final dataset contains all the food items from Food-101 dataset and 100 additional subcontinental food classes. The dataset is split into training and validation images. Each class contains around 800 training images and 200 validation images.

1. **Software Required:**

Python, Flask , Docker.

2. **System Required:**

8GB RAM,Intel Core i3,OS-Windows/Linux/MAC ,Laptop or Desktop.

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