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Food and Nutrition Evaluation for the Visually Impaired

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Abstract: In this paper, we apply a convolutional neural network (CNN) to the tasks of detecting and recognizing food images. Because of the wide diversity of types of food, image recognition of food items is generally very difficult. However, deep learning has been shown recently to be a very powerful image recognition technique, and CNN is a state-of-the-art approach to deep learning. We applied CNN to the tasks of food detection and recognition through parameter optimization. We constructed a dataset of the most frequent food items in a publicly available food-logging system, and used it to evaluate recognition performance. We also implemented a set a labels for each food item which describes the nutrition content such as carbs, calories etc. CNN showed significantly higher accuracy than did traditional support vector machine based methods with handcrafted features. In addition, we found that the convolution kernels show that colour dominates the feature extraction process. For food image detection, CNN also showed significantly higher accuracy than a conventional method did.
Keywords: Android, food view, nutrition, camera, health

I. INTRODUCTION

Millions of people live in this world with incapacities of understanding the environment due to visual impairment. Although they can develop alternative approaches to deal with daily routines, they also suffers from certain navigation difficulties as well as social awkwardness. For example, it is very difficult for them to identify the food item in front of them.Food is the most essential requirement for sustenance of human life. Even if a human being does not have shelter over their head or clothes over their body, they would still survive if they get wholesome nutrition. That is why all over human history, we have been motivated to search and seek food. Throughout history food has acted as a catalyst for societal transformation, societal organization, competition, development, conflict and expansion. Food is also an important part of country's culture. Good nutrition is an important part of leading a healthy lifestyle. Combined with physical activity, our diet can help us to reach and maintain a healthy weight, reduce our risk of chronic diseases (like heart disease and cancer), and promote your overall health.

Unhealthy eating habits have contributed to the obesity epidemic in the United States: about one-third of U.S. adults (33.8%) are obese and approximately 17% (or 12.5 million) of children and adolescents aged 2—19 years are obese. Even for people at a healthy weight, a poor diet is associated with major health risks that can cause illness and even death. These include heart disease, hypertension (high blood pressure), type 2 diabetes, osteoporosis, and certain types of cancer. By making smart food choices, we can help protect ourselves from these health problems.

In our project, we build a real-time food identification application with a goal to provide the name of the food item and also its nutrition content values such as carbs, calories, fats, proteins[1][11]. This information will help a visually impaired person to identify what food item is front of him. This application can also be used by foreigners toexplore more on the local food cuisine.

II. RELATED WORK

The task to recognize what the food is in one image could be categorized into several problems. Most existing research work in food recognition assumes that only one food item is present in each image. Here, we review some of these works. In Bossard et al. [2014], researchers created a food database named Food 101 containing 101 different food categories. For each category, there were 1,000 images. First, they extracted the color features for super-pixels on each image. Then, all the super-pixels were clustered into groups using Random Forest based on their respective Fisher vector encoded feature vectors to obtain discriminative components across all the images, and they achieved a test accuracy rate of 50.8%. Kagaya et al. [2014] used a trained Convolutional Neural Network (CNN) for both food and non-food detection. They built a food database of 170,000 images containing 10 popular food items. Using six foldcross validation, the optimal CNN hyper parameters related to the number of layers, the pre-processing, and the training were decided. Experiments showed that CNN outperformed all the other baseline classical approaches by achieving an average accuracy rate of 73.7%.

In Zhu et al. [2015], researchers proposed a method for dietary assessment to automatically identify and locate food in a variety of images. Two concepts were combined in their algorithm. First, a set of segmented objects were partitioned into similar object classes based on their features, and for solving the problem, they applied different segmentation methods. Second, automatic segmented regions were classified using a multichannel feature classification system, and SVM was used as their classifier. The final decision was obtained by combining class decisions from individual feature [12].

The authors of Zhang et al. [2015] developed a mobile application for multiple-food recognition of 15 food categories on the phone without any user intervention. First, the user took a photo of a food plate, and a cropped 400×400 food image was uploaded to the server for food recognition. On the server side, the food image was first segmented into possible salient regions, and these regions were further grouped based on the similarity of their color and their HOG and SIFT feature vectors. Normally, a typical food image yielded about 100 salient segment regions. They collected 2,000 training images for 15 classes with a mobile phone camera, since they had discovered that the model trained with images downloaded from the Internet could not generalize well for images taken on mobile phones. They trained a linear multiple-class SVM classifier for each class using the Fisher vector encoded feature vectors (including SIFT and color features) of salient regions. They reported a top-1 accuracy rate of 85% when detecting 15 different kinds of foods in their experiments.

More recently, Zhang et al. [2016] proposed a multi-task system that can identify dish types, food ingredients, and cooking methods from food images with deep convolutional neural networks. They built up a dataset of 360 classes of different foods. To reduce the noises of the data, which was collected from the Internet, outlier images were detected and eliminated through a one-class SVM trained with deep convolutional features. They simultaneously trained a dish identifier, a cooking method recognizer, and a multi-label ingredient detector. They share a few low-level layers in the deep network architecture. The proposed framework shows higher accuracy than traditional method with handcrafted features. In Akbari Fard et al. [2016], authors introduce an automatic way for detecting and recognizing the fruits in an image to enable keeping track of daily intake automatically using images taken by the user. The proposed method uses state-of-the-art deeplearning techniques for feature extraction and classification. Deep learning methods, especially convolutional neural networks, have been widely used for a variety of classification problems and have achieved promising results. The model has achieved an accuracy of 75% in the task of classification of 43 different types of fruit. In Singla et al. [2016], authors report experiments on food/non-food classification and food recognition using a GoogLeNet model based on deep convolutional neural network. The experiments were conducted on two image datasets, where the images were collected from existing image datasets, social media, and imaging devices such as smart phone and wearable cameras. Experimental results show 83.6% accuracy for the food category recognition. They mention the main reason for not achieving a higher recognition accuracy on certain types of food images is the complex mixture of food items in the image and the high visual similarities between some images across categories. Shimoda and Yanai [2016] propose an intermediate approach between the traditional proposal approach and the fully convolutional approach. They especially propose a method that generates high food-ness regions by fully convolutional networks and back-propagation-based approach with training food images gathered from the Web. In their work, they achieved reduced computational cost while keeping high quality for food detection. In Su et al. [2016], they propose a game theoretic resource allocation scheme for media cloud to allocate resource to mobile social users through brokers. In their work, a good framework of resource allocation among media cloud, brokers, and mobile social users is presented. Media cloud can dynamically determine the price of the resource and allocate its resource to brokers. Finally, in Dehais et al. [2016], authors propose a method to detect and segment the food dishes in an image. The method combines region growing and merging techniques with deep CNN-based food border detection. A semi-automatic version of the method is also presented that improves the result with minimal user input. The proposed methods are trained and tested on non-overlapping subsets of a food image database, including 821 images, taken under challenging conditions and annotated manually. The automatic and semi-automatic dish segmentation methods reached average accuracies of 88% and 92%, respectively[9].

III. PROPOSED SYSTEM

A. Constructing Food Image Dataset

In the back-old days, the main purpose was to implement a robust dataset of many meal images. Main importance was given to meal objects commonly consumed in India. We first created 141 "top domains" representing generic types of foods and liquids. Some of the main domain are: egg Rice, Grilled mutton, Ice Cream, etc. For each of these main domain, we detected many food-items that belong to the domain. For example, the drinks super category would have pepsi, lemon juice, and lychee as the food items. In this issue, we detected a total of 800 different meal items. Generally, this is the total number of classes. The model would be trained to make choices on these visual mean categories (or classes).

In the case where finer grained detections were needed at the domain level, the end-user would have the option to manually select item from the prediction made. For example, given an image Dosa, the model would predict edible item and dosa under it, and if the model was not able to predict the food, then the user can manually send the data sets so that the app can be further improved. As our target domain was primarily India, we laid main focus on meals commonly consumed in India. Out of the 140 categories and 800 visual food categories, 9 categories (Desserts, liquids, etc.) And 110 visual meals are used to this purpose. During the dataset gathering, we ensured that we had at least 400 images for each of these 110 visual meals. The images were collected by python web scrapper written in python scripting from google, Bing, , Flickr, Facebook and other media's, for each of the food categories.

The older image gathering process was labor-intensive and inefficient, requiring users to physically search item and select appropriate images to download a given meal domain. To reduce the human efforts and make things seamless,, we developed Food image System (FIS), a python based script for automatic crawling and annotating food images. In the above script, the input will the keywords or the related words to the food, and then using the google_images_download(i.e, a module in python**),** when the script is processed in the bash terminal, the script download all the data sets/ images for each of the meal, by making directories of each sub-food category and downloading the related images into those sub directories, once the script is complete, we then have our data set, which is ready for training

B. Training

Our initial step was to come up with a pre-trained model by using CNN (convolution neural networks).For this we segregated images of one of the class and labelled them using a naming set. This set of images will we used to train the model which act as a positive data set. In the second part of training we consider only negative image sets to train the model as to what has to be ignored. Once we have the model generated from the training process, we can load it into the application and test it upon the images that were uploaded by the regular users. The image is run against the model which generates a list of possible names. The name with the highest probability is prompted to the end user [2]

From a technical perspective, the neural network that we have used, will computes a differentiable function on its inputs. Now for example, our app will compute the image against a trained model and label set to determine the output, [3]

P(predefined_label / the input image)

we have used the term (ReLU) rectified linear unit to refer to a unit in the neural net that would use the activation function max(0; x).Now the next sept is to determine set of biases and weights which will guarantee us the lowest cost possible. In order to achieve this, we have used an algorithm called as stochastic_gradient_descent. By using a relatively smooth cost function like the quadratic_cost it came out as to small changes in weights and biases will give as lower costs in a effective manner. By using this process we will be able to come close to our expected results. Our goal is to train the neural network in such a way to achieve optimum weights and biases which will help us minimize the quadratic_cost function.For example our algorithm can we used to classify apple or cider in the learning phase without affecting any of the other classes. The changes in detla value will the affect the classification of food drastically.

System flow diagram

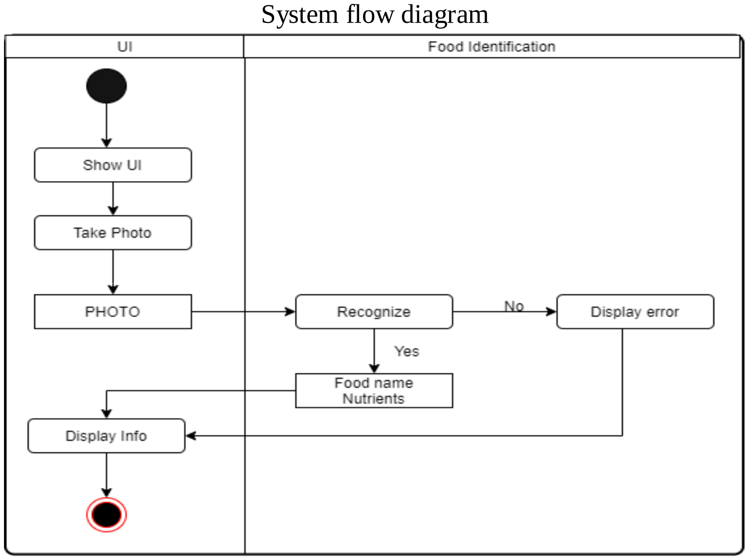

Fig 2: Overall flow

We have developed an android application. Our classifier is running on the phone so internet is not required and it makes the application lot faster. We have used TensorFlowlite to optimize out model to fir our android phone.When the user clicks to start our system, it will redirect him/her to the camera. The user then captures the images of the food. The image captured is evaluated against the previously trained model. If the food item is recognised, a new screen is displayed with information such as name of the food item its nutrient content such as proteins, carbs, fats. If the food is not identified an error message is displayed ("eg: sorry, the item could not be recognized") users can also send us the unrecognised image within the application so we can tweak our model accordingly [5-8][13].

IV. CONCLUSION

In this paper, we have addressed the effectiveness of CNNs for food image recognition and detection. We found that CNN performed much better than did traditional methods using handcrafted features.This project would help the visually impaired people in identifying the food item in front of them with ease. It also helps them take note on the nutrition value of the food they are consuming. Foreigners can explore more about our local cuisine

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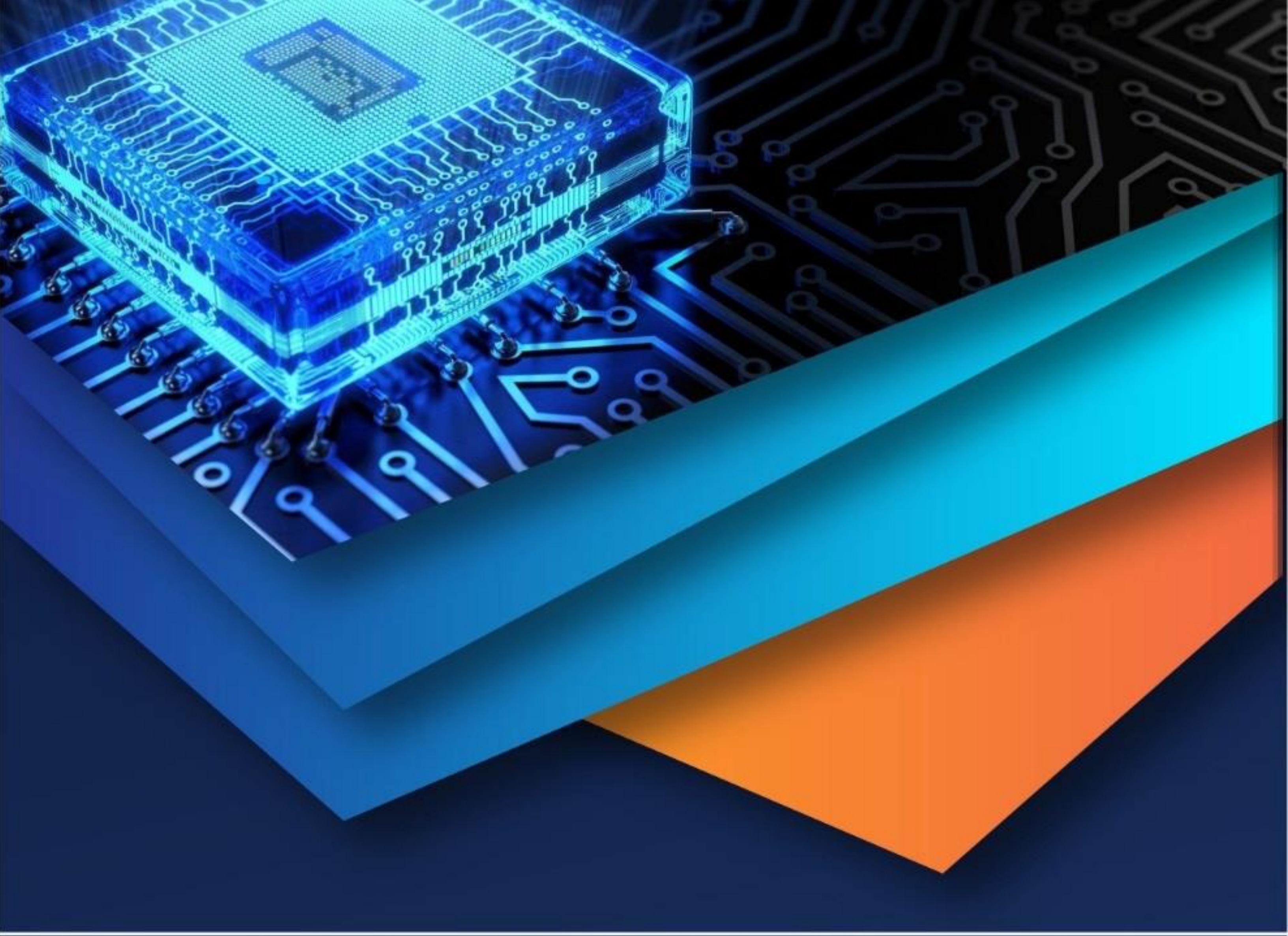

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