Smart Restaurant Billing System With Globalized Menu Using Android Iot

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ABSTRACT

Focusing on self-service restaurants, food recognition algorithms could enable both monitoring of food consumption and the automatic billing of the meal grabbed by the customer. The latter is quite relevant because remove the need for a manual selection of the chosen dishes, allowing to speed-up the service offered by these restaurants. Internet users are become huge nowadays; in concern with time saving and manual billing feature to be avoided we propose an automatic billing alert system with globalization of restaurant menu. The proposed design uses Android application to enable the user to select the menu which is globalized in the IOT screen or android database. The selected image of the food recipe is processed using image processing. The image processing is done using MATLAB. Whereas the food recognition is done using Deep Neural Network and bill estimation is transferred to android application based display screen in which a pop up message can bring out the payable amount.

I. INTRODUCTION

The image processing is the method used for detecting the food in the plate using Deep Neural Network.The image processingis the physical process used to convert image signal into a physical image. The image signal can be either digital nor analog. The actual output itself can be an actual physical image or the characteristics of an image. Thus the image of the food in the plate is capture through mobile phone or camera. The image is preprocessed so that it can be identified what kind of food it is. The preprocessing of image is the process of converting form RGB value to the HSV image. The HSV image undergoes a process know as bounding box. It is used to locate the food in the plate by eliminating the rest of the place in the plate. It helps to identify the food and its calories. After identifying each food in the plate bill estimation is done. Each restaurant has its own price and texture for their food. Hence database is maintained for each restaurant. The database contains their own food images and their price. So that it helps to know the price of the each dishes. It helps to calculate the amount of the food ordered by the customer. The calculated amount is send to the customers mobile as a pop up message. Then the payment can be done using mobile app like payzapp. The image processing is done using the software MATLAB. The MATLAB high-performance language for technical computing integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. It allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non interactive language such as C or Fortran.

II. EXISTING SYSTEM

In the existing system, Semantic Food Detection, this integrates in the same framework food localization, recognition and segmentation.It is applied to thhe problem of food tray analysis in self-service restaurants.they integrate both techniques, food and non-food semantic segmentation with food detection, through the application of two procedures: a probabilistic procedure that allow us remove the background detections, and a custom non-maximum suppression procedure to avoid the occurence of duplicate detections. Regarding the architecture, the two pathways are used in parallel for food detection and semantic segmentation. The purpose of applying this separate computation is to take advantage of the benefits of each method separately to later combine them. In this manner, they do not condition each other, but reinforce themselves. In particular they propose an end to end architecture which directly feeds the segmentation output into the detection, the segmentation errors could not be recovered and, therefore, they could negatively influence the detection performance. It significantly outperforms the state-of-art in terms of recall and mean average accuracy. Furthermore the model is less sensitive to class imbalance and the mean of errors per foods placed on a tray. CNN-based models have been able to progressively improve the result of food recognition.

III. LITERATURE SURVEY

This paper considers the problem of recipe-oriented image-ingredient correlation learning with multi-attributes for recipe retrieval and exploration. Existing methods mainly focus on food visual information for recognition while we model visual information, textual content (e.g., ingredients), and attributes (e.g., cuisine and course) together to solve extended recipe-oriented problems, such as multimodal cuisine classification and attribute enhanced food image retrieval. As a solution, we propose a multimodal multitask deep belief network (M3TDBN) to learn joint image-ingredient representation regularized by different attributes. By grouping ingredients into visible ingredients (which are visible in the food image, e.g., “chicken” and “mushroom”) and non visible ingredients (e.g., “salt” and “oil”),M3TDBN is capable of learning both midlevel visual representation between images and visible ingredients and non visual representation. Furthermore, in order to utilize different attributes to improve the inter modality correlation, M3TDBN incorporates multitask learning to make different attributes collaborate each other. Based on the proposed M3TDBN, we exploit the derived deep features and the discovered correlations for three extended novel applications: 1) multimodal cuisine classification; 2) attribute-augmented cross-modal recipe image retrieval; and 3) ingredient and attribute inference from food images. The proposed approach is evaluated on the constructed Yummly dataset and the evaluation results have validated the effectiveness of the proposed approach.[1]

In this work we address the task of semantic image segmentation with Deep Learning and make three main contributions that are experimentally shown to have substantial practical merit. First, we highlight convolution with up sampled filters, or atrous convolution as a powerful tool in dense prediction tasks. Atrous convolution allows us to explicitly control the resolution at which feature responses are computed within Deep Convolution Neural Networks. It also allows us to effectively enlarge the field of view of filters to incorporate larger context without increasing the number of parameters or the amount of computation. Second, we propose atrous spatial pyramid pooling (ASPP) to robustly segment objects at multiple scales. ASPP probes an incoming convolution feature layer with filters at multiple sampling rates and effective fields-of-views, thus capturing objects as well as image context at multiple scales. Third, we improve the localization of object boundaries by combining methods from DCNNs and probabilistic graphical models. The commonly deployed combination of max-pooling and down sampling in DCNNs achieves invariance but has a toll on localization accuracy. We overcome this by combining the responses at the final DCNN layer with a fully connected Conditional Random Field (CRF), which is shown both qualitatively and quantitatively to improve localization performance. Our proposed “Deep Lab” system sets the new state-of-art at the PASCAL VOC-2012 semantic image segmentation task, reaching 79.7% mIOU in the test set, and advances the results on three other datasets: PASCAL-Context, PASCAL- Person- Part, and Cityscapes. All of our code is made publicly available online.[2]

Food image recognition is one of the promising applications of visual object recognition in computer vision. In this study, a small-scale dataset consisting of 5822 images of ten categories and a five-layer CNN was constructed to recognize these images. The bag-of-features (BoF) model coupled with support vector machine was first tested as comparison, resulting in an overall accuracy of 56%; while the CNN performed much better with an overall accuracy of 74%. Data expansion techniques were applied to increase the size of training images, which achieved a significantly improved accuracy of more than 90% and prevent the over fitting issue that occurred to the CNN without using data expansion. Further improvement is within reach by collecting more images and optimizing the network architecture and relevant hyper-parameters.[3]

We propose a new dataset for the evaluation of food recognition algorithms that can be used in dietary monitoring applications. Each image depicts a real canteen tray with dishes and foods arranged in different ways. Each tray contains multiple instances of food classes. The dataset contains 1027 canteen trays for a total of 3616 food instances belonging to 73 food classes. The food on the tray images has been manually segmented using carefully drawn polygonal boundaries. We have bench marked the dataset by designing an automatic tray analysis pipeline that takes a tray image as input, finds the regions of interest, and predicts for each region the corresponding food class. We have experimented with three different classification strategies using also several visual descriptors. We achieve about 79% of food and tray recognition accuracy using convolution- neural- networks-based features. The dataset, as well as the benchmark framework, are available to the research community.[4]

Convolution networks are powerful visual models that yield hierarchies of features. We show that convolution networks by themselves, trained end-to-end, pixels-to-pixels, improve on the previous best result in semantic segmentation. Our key insight is to build “fully convolution” networks that take input of arbitrary size and produce correspondingly-sized output with efficient inference and learning. We define and detail the space of fully convolution networks, explain their application to spatially dense prediction tasks, and draw connections to prior

models. We adapt contemporary classification networks (Alex Net, the VGG net, and Google Net) into fully convolution networks and transfer their learned representations by fine-tuning to the segmentation task. We then define a skip architecture that combines semantic information from a deep, coarse layer with appearance information from a shallow, fine layer to produce accurate and detailed segmentations. Our fully convolution network achieves improved segmentation of PASCAL VOC (30% relative improvement to 67.2% mean IU on 2012), NYUDv2, SIFT Flow, and PASCAL-Context, while inference takes one tenth of a second for a typical image.[5]

IV. PROPOSED SYSTEM

In the proposed system an automatic billing alert system with globalization of restaurant menu etc. The proposed design uses Android application to enable the user to select the menu which is globalized in the IOT screen or android database. The selected image of the food recipe is processed using image processing MATLAB and bill estimation is transferred to android application based display screen in which a pop up message can bring out the payable amount. The proposed system uses Adaptive Deep network for adjustable as well as accurate results. ADN is used here, which attempts to exploit the sparsity (complexity) of neuron connections. Memory computations are adjustable here. It saves time by paying the bill through phone. There is no need to wait for the bill after taking the food. We can know the amount as soon as all the ordered food reaches the table. It is implemented as an android app. While identifing the dishes it also calculate the calories value which is useful for the customers who is on diet, sugar patient and also for those who cares for their health condition.

V. ARCHITECTURAL DIAGRAM AND EXPLANATION

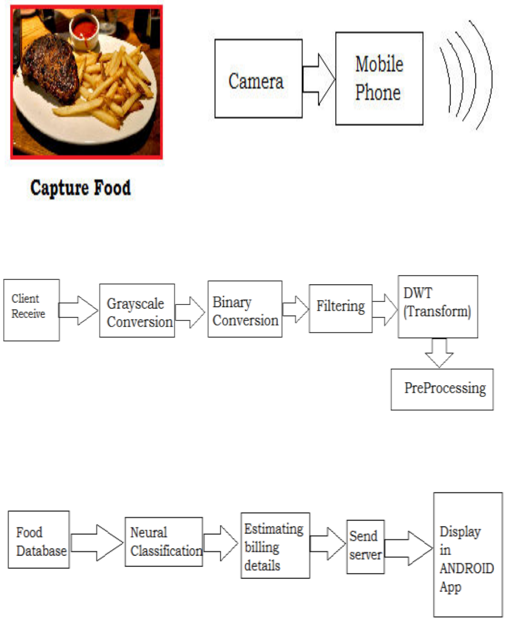


Fig 1 Proposed Architecture

The dish ordered by the client reaches the table which is captured as a photo by the camera attached above facing the table.The captured image is then send to the back end processing. In the Database the images of whole menu of the restaurant is stored which is then compared to the captured image.so that the machine learning technique is used to train the system to kow what food is that.Then the amount of the food ordered by the client is calculated and then send to the mobile phone of the client which is payed by the customer using the mobile banking or mobile app.In the preprocessing the process involve is image processing where the image is convered to grey scale using the conversion and the binary thresholding is done to eliminate the unwanted area in the tray and plate to plot the food alone.ROI approximation is the process of finding what food from the image.Contrast adjustment is the process of adjusting the color of the image so that it suits the image in the database.Using those preprocessing technique the feature is extracted.Food is given as input so the preprocessing techniques are grey conversion, binary thresholding, ROI approximation, Contrast adjustment is done. In the the database the preprocessing techniques is same as food input preprocessing.From both the input that is food input and database input the feature is extracted and enters into the post processing. The post processing includes the machine learning technique, the algorithm used is deep neural network and prediction of the image which is compared with the IOT cloud images.

VI. MODULES

- Converting RGB to HSV image
- Bounding Box detection
- Identification of food
- Billing process
- Payment process

VII. MODULE DESCRIPTION

7.1. Converting Rgb To HSV Image

The input RGB image is resized to an height of 320 pixels. The resized image undergoes two separate processing pipelines: 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 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.

7.2. Bounding Box Detection

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.

7.3. Identification of Food:

This module consists of neural network block with adaptive learning scheme for analyzing the food images. Then the images are compared with the database images and identify the food item and know the cost of the particular food. Such a way that all the food item in a plate is identified. Each image is displayed with its name and calories of that particular food is also displayed. The calories are known by tabulating it in the database. It helps the customer who is on diet whether the particular food can be taken or not.

7.4. Billing process

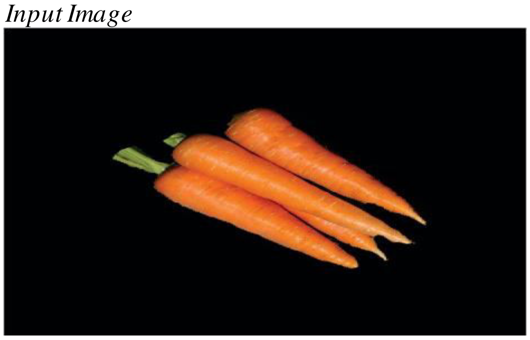
This module consist of calculating the amount of the ordered food by the client. Each food price is known, then the full amount of the food placed in the tray is calculated.

7.5. Payment Process:

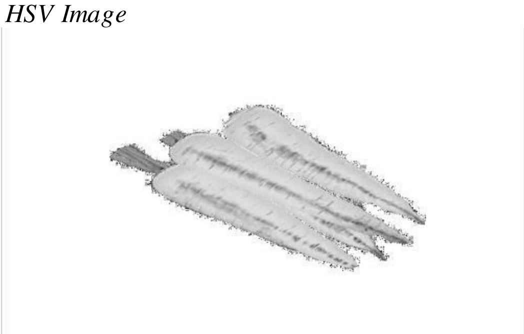
This Module consist of sending the calculated amount to the client mobile as a pop up message.Then the payment is done through the mobile app such as Google Pay, PazApp etc., or through the mobile banking.It helps in decreasing the manual process and also the time.

VIII. SCREENSHOTS

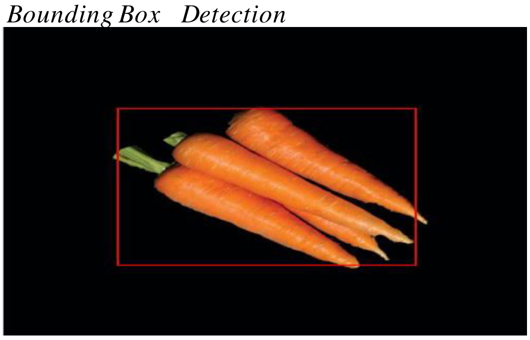
8.1. Input Image



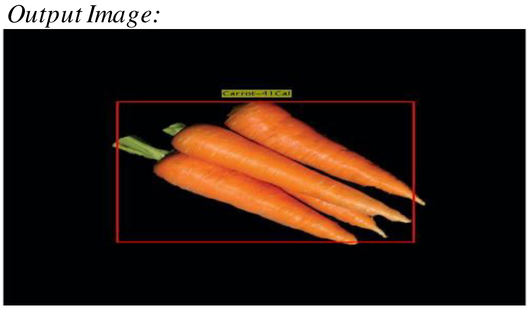
8.2. HSV Image



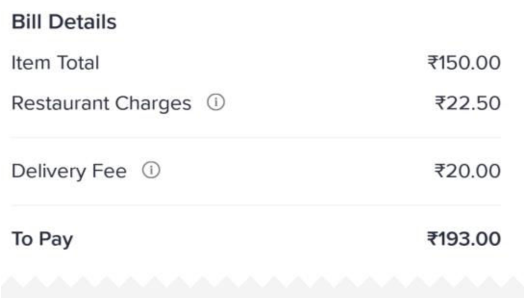
8.3. Bounding Box Detection



8.4. Output Image:



8.5. Bill Popup Message:



8.6. Bill Payment

IX. CONCLUSION

We present a novel system that performs Semantic Food Detection applied to the problem of food tray analysis in self-service restaurants. More precisely, we integrate both techniques, food/non-food semantic segmentation with food detection, through the application of two procedures: probabilistic procedures that allow us remove the background detections and a custom non-maximum suppression procedure to avoid the occurrence of duplicate detections. 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. 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.

X. FUTURE ENHANCEMENT

In this paper the process of recognition and calculating the bill amount has been done which can be further processed by calculating the discount value based on estimating the time between the ordering and delivering the food.and also finding the combo food and its discounted amount.

XI. REFERENCE

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[5] M.Bolanos, A.Ferra, and P.Radeva, “Food ingredients recognition through multi-label learning,” in International Conference on Image Analysis and Processing. Springer, 2017, pp. 394–402.