DEEPFOOD: FOOD IMAGE ANALYSIS AND DIETARY ASSESSMENT VIA DEEP MODEL

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ABSTRACT: Food is an important for human life and its mandatory to know dietary details before consuming them to lead a healthy life and to automatically identify dietary details in this has introduced. Region base convolution neural network algorithms which get trained by using regions from the image and this region will be in the form of food and this algorithm not only detect region of food but also classify food and based on that food classification dietary details will be displayed. To implement it used VGG16 based Faster RCNN (Region Convolution Neural Network) algorithm and to trained this algorithm used UECFOOD 100 dataset. This dataset contains bounding boxes only for one food in the plat so this algorithm can efficiently be identified on food from plate and trained this FRCNN algorithm using UECFOOD 100 dataset. That have used an algorithm which can detect one food from plate and this same algorithm can be trained to detect multiple foods in a plate if we found such dataset. Same application can be applied for videos as video is nothing but sequence of frames.

INTRODUCTION

According to the statement from World Health Organization (WHO), obesity and overweight are defined as abnormal or excessive fat accumulation that presents a risk to health. It claims that fundamental cause of such issues is an energy imbalance between calories consumed and expended. Since 2016, there were already over 1.9 billion adults overweight in the world, and the obesity epidemic has been growing steadily but not a single country has been able to reverse it so far. In the United States, in 2019, adult obesity rates now exceed 35% in nine states and 30% in 31 states, the annual medical cost of obesity-related illness healthcare including heart disease, stroke, type 2 diabetes and certain types of cancer are a staggering 190.2 billion US dollars, and the medical cost for people who have obesity was $1,429 higher than those of normal weight. Though there are various factors may cause obesity such as certain medications, emotional issues like stress, less exercise and poor sleep quality, eating behavior - what and how people eat is always the major problem that results in weight gain. Calories as well as other nutrition ingredients like fat, carbohydrate and protein are measures of energy. There are more and more people would like to keep track of what they eat and the amount of nutrition contents they get every day to see whether they are having a healthy diet. Therefore, an accurate estimation of dietary caloric intake will be very important for wellbeing. Besides, the rapid development of Internet of Things (IoT) and the explosion of data enhances the social media user experience. People become willing to record, upload and share food images on the websites like help, Dianping1 and Yummly,2 thus it is now more convenient than ever to find a huge amount of data (images and videos) related to food. It is even more necessary than ever to develop tools for detecting and recognizing food from images in order to promote the analysis of the nutritional ingredients from receipts and track the personal habit of eating and drinking. Currently, there are three types of most commonly used methods to manually assess dietary intake including diet records, 24-hour recall and food frequency questionnaire (FFQ). For diet records, subjects need to record the food and beverage consumed over three consecutive days (two weekdays and one weekend day). Detailed instructions on how to record intake must be provided by trained staff and the completed records need to be entered into a application such as Nutrition Data System for Research (NDSR) for analysis. By applying 24-hour recall, subjects are asked to report all food/meals consumed in the past 24 hours, which can be done via telephone call or face-to-face interview. The data from subjects are required to be collected and analyzed, an interview for details will be conducted by trained staff. Subjects using FFQ method are asked to report how frequently certain food and beverage items were consumed over a specific period of time (e.g., 1 year). Most FFQs are available in paper or electronic format listing general questions about everyday diet and cooking practice. Software programs are deployed to calculate nutrient intake by multiplying the reported frequency of each food by the amount of nutrient in each food item. Although we already have these gold-standard methods for reporting diet information, at least one drawback exists that we cannot ignore - such methods still suffer from bias since the subject is required to estimate their dietary intake by themselves. Dietary assessment finished by participants can result in underreporting and underestimating of food intake. In order to get rid of the bias and improve the accuracy of self-report, many automatic or semi-automatic eating monitoring systems have been proposed. Additionally, recently there are an increasing number of applications built on mobile platforms (i.e., smartphones) for food analysis. For example, Zhu et al. proposed a segmentation base food classification method for dietary assessment. They aim to determine the regions where a particular food is located in an image where a particular food is located and correctly identify them by using computer vision techniques. Another cloud-based food calorie measurement system is developed by Pouladzadeh et al. using Support Vector Machine (SVM) to recognize food and calculate the calories of each item.

CNNs can be retrained for new recognition tasks and built on pre-existing networks. These advantages open up new opportunities to use CNNs for real-world applications without increasing computational complexities or costs. As seen earlier, CNNs are more computationally efficient than regular NNs since they use parameter sharing. The models are easy to deploy and can run on any device, including smartphones. Convolutional neural networks are already used in a variety of CV and image recognition applications. Unlike simple image recognition applications, CV enables computing systems to also extract meaningful information from visual inputs (e.g., digital images) and then take appropriate action based on this information.

LITERATURE SURVEY

[1] Food Balance Estimation by Using Personal Dietary Tendencies in a Multimedia Food Log We have investigated the "FoodLog" multimedia food-recording tool, whereby users upload photographs of their meals and a food diary is constructed using image-processing functions such as food-image detection and food-balance estimation. In this paper, following a brief introduction to FoodLog, we propose a Bayesian framework that makes use of personal dietary tendencies to improve both food-image detection and food-balance estimation. The Bayesian framework facilitates incremental learning. It incorporates three personal dietary tendencies that influence food analysis: likelihood, prior distribution, and mealtime category. In the evaluation of the proposed method using images uploaded to FoodLog, both food-image detection and food-balance estimation are improved. In particular, in the food-balance estimation, the mean absolute error is significantly reduced from 0.69 servings to 0.28 servings on average for two persons using more than 200 personal images, and 0.59 servings to 0.48 servings on average for four persons using 100 personal images. Among the works analyzing food images, this is the first to make use of statistical personal bias to improve the performance of the analysis.

[2] An Overview of the Technology Assisted Dietary Assessment Project at Purdue University In this paper, we describe the Technology Assisted Dietary Assessment (TADA) project at Purdue University. Dietary intake, what someone eats during the course of a day, provides valuable insights for mounting intervention programs for prevention of many chronic diseases such as obesity and cancer. Accurate methods and tools to assess food and nutrient intake are essential for research on the association between diet and health. An overview of our methods used in the TADA project is presented. Our approach includes the use of image analysis tools for identification and quantification of food that is

consumed at a meal. Images obtained before and after foods are eaten are used to estimate the amount and type of food consumed.

[3] Personal dietary assessment using mobile devices Dietary intake provides valuable insights for mounting intervention programs for prevention of disease. With growing concern for adolescent obesity, the need to accurately 8 measure diet becomes imperative. Assessment among adolescents is problematic as this group has irregular eating patterns and have less enthusiasm for recording food intake. Preliminary studies among adolescents suggest that innovative use of technology may improve the accuracy of diet information from young people. In this paper we describe further development of a novel dietary assessment system using mobile devices. This system will generate an accurate account of daily food and nutrient intake among adolescents. The mobile computing device provides a unique vehicle for collecting dietary information that reduces burden on records that are obtained using more classical approaches. Images before and after foods are eaten can be used to estimate the amount of food consumed.

[4] Evaluation of dietary assessment instruments against doubly labeled water, a biomarker of habitual energy intake Epidemiological studies of diet and disease rely on the accurate determination of dietary intake and subsequent estimates of nutrient exposure. Although methodically developed and tested, the instruments most often used to collect self-reported intake data are subject to error. It had been assumed that this error was only random in nature; however, an increasing body of literature suggests that systematic error in the reporting of true dietary intake exists as well. Here, we review studies in which dietary intake by self report was determined while energy expenditure was simultaneously measured using the doubly labeled water (DLW) method. In seeking to establish the relative accuracy of each instrument to capture true habitual energy intake, we conclude that none of the self-reported intake instruments demonstrates greater accuracy against DLW. Instead, it is evident that the physical and psychological characteristics of study participants play a significant role in the underreporting bias observed in these studies. Further research is needed to identify under reporters and to determine how to account for this bias in studies of diet and health.

EXISTING SYSTEM

Although we already have these gold-standard methods for reporting diet information, at least one drawback exists that cannot be ignore - such methods still suffer from bias since the subject is required to estimate their dietary intake by themselves. Dietary assessment finished by participants can result in underreporting and underestimating of food intake [48]. In order to get rid of the bias and improve the accuracy of self-report, many automatic or semi-automatic eating monitoring systems have been

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proposed. Additionally, recently there are an increasing number of applications built on mobile platforms (i.e., smartphones) for food analysis. For example, Zhu et al. proposed a segmentation-based food classification method for dietary assessment. They aim to determine the regions where a particular food is located in an image where a particular food is located and correctly identify them by using computer vision techniques. Another cloud-based food calorie measurement system is developed by Pouladzadeh et al. using Support Vector Machine (SVM) to recognize food and calculate the calories of each item.

DISADVANTAGE: More time complexity for machine learning classification techniques. Machine learning techniques has less accuracy compared to Deep Learning.

PROPOSED SYSTEM

To implement this project, we have designed following modules Upload UECFood 100 Dataset: using this module we will upload food dataset to application Data Preprocessing: using this module it will read all food images and bounding boxes from dataset and this bounding box helps in extracting REGIONS from images. In this module training data will be generated using images and bounding boxes regions Train VGG16 Faster RCNN Algorithm: using this module it will trained VGG16 FRCNN algorithm by using pre-processed images and bounding boxes region and then calculate accuracy and loss of the training model and our able to achieve 92% food classification accuracy. Faster RCNN Accuracy Graph: using this module we will plot FRCNN training accuracy and loss graph Classify Food & Dietary from Image: using this module it will upload test image and then application will apply FRCNN model on test image to classify food from the plate and display dietary details.

There is total 5 important steps used in this project as mentioned in the above fig 4.1 and they are as follows: Upload UECFood 100 Dataset Data Pre-processing Train VGG16 Faster RCNN Algorithm Faster RCNN Accuracy Graph Classify Food & Dietary from Image.

ADVANTAGE: Less time complexity higher accuracy

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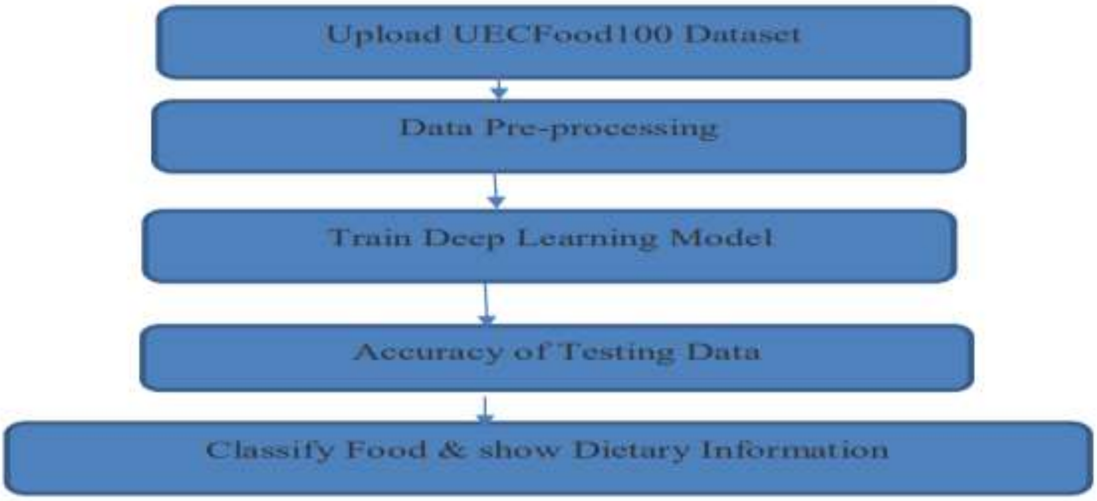

Fig: Flowchart for proposed method

Food category recognition and analysis has been a popular research area in the field of nutrition study. However, it is relative difficult because food items are deformable objects with significant variations in appearance. The food items may either have a high intra-class variance (similar foods such as beef and steak look very different based on how to cook them), or low inter-class variance (different foods like fish and pork look very similar). Different approaches have been proposed to recognize food items in image using geometry features such as SIFT descriptor, color histograms or GIST and shape context . Moreover, Felzenszwalb use triangulated polygons to represent a deformable shape for detection and Jiang et al.proposes learning a mean shape of the target class based on the thin plate spline parametrization. Besides, Belongie choose n pixels from the contours of a shape and then form n−1 vectors as a description of the shape at the pixel level. Though geometry feature-based approaches work well in object detection for the certain types of items, there are two main problems for food related tasks. The first problem is that geometry feature-based methods need to detect features like edges, counters and key points or landmarks, which may not be available in food images. The other problem is that it is hard to describe the shape of a food item in real world thus calculating shape similarity is very hard.

To overcome the problems described above, approaches using statistical features are proposed. Instead of edge or key point, the methods focus on local, statistical features like pairs of pixels. Since the statistical distribution of pairwise local features could extract important shape characteristics and spatial relationships between food ingredients, thus facilitating more accurate results in object recognition. For example, Yang et al. explore the spatial relationships between different ingredients (e.g., vegetables and meat in one meal) by employing a multi-steps discriminative classifier. Each pixel in the image is assigned a vector indicating the probability of the pixel belongs to nine food ingredients [54]. A multi-dimensional histogram generated by using pairwise statistic local features, then the histogram is passed into a multi-class SVM for image classification.

Machine Learning Methods for Food Recognition;

Recently, there has been an increasing number of research conducting experiments and researches toward the fields of food classification, leveraging machine learning/deep learning algorithms. Aizawa et al. Proposed a Bayesian framework base approach to facilitate incremental learning for both food detection and food-balance estimation. Bossard et al. Used Random Forest on the Food-101 test set achieving a classification accuracy with 50.67% by mining discriminative components. The random forest model is used for clustering the superpixels of the training dataset. Other advanced classification techniques were also applied in the work including Improved Fisher Vectors (IFV), Bag-of-Words Histogram (BOW), Randomized Clustering Forests (RCF) and Mid-Level Discriminative Superpixels (MLDS) . As the computational power is getting stronger, convolutional neural network (CNN) and deeper models are also widely used in food recognition and provide better performance. Kagaya et al. Applied the CNN model in food image classification. They achieved a very high accuracy of 93.8% on food and non-food item detection. The experimental results on food recognition showed that the proposed CNN solution outperformed all other baseline methods - achieved an average accuracy of 73.7% for 10 classes. What is more, a fine-tuned the AlexNet model is used in the work. The method achieved the promising results on public food image datasets so far, with top-1 accuracy of 67.7% for UEC-FOOD-256. Hassannejad et al. Apply a 54 layers CNN model to evaluate the effectiveness of deep model in food image classification. The model is based on the specifications of Google's image recognition architecture - Inception. In 13 addition, Google Net was used in for food recognition to build a Im2Calories system on Food101 dataset. Additionally, researchers start to investigate which features and models are more suitable for the food recognition, and comply them into food analysis system to calculate the calories. In order to automatically estimates the food calories from a food image, multi-task convolutional neural networks is used for simultaneous learning of food calories, categories, ingredients [18]. What's more, a generative adversarial network approach is also proposed for food image analysis. Though food recognition and nutrition contents analysis have been well discussed by above work, two basic challenges remain. Firstly, most of the approaches are dealing with image with single food item. Secondly, it is still time consuming (2 seconds in general) to detect and classify the food in images. In this paper, we aim to address these issues and propose an automatic food recognition system to identify the food from images and generate dietary assessment reports for long-term healthcare plan.

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PERFORMANCE ANALYSIS

We begin with a diagram of our suggested substantial modification based totally gadget for food prevalence and sustenance inquiry in this section. Following that, we check the execution data of each device piece. We refer readers to the proposal in this assignment for further documented previous statistics and specialized info regarding our food testing machine. We offer a sophisticated reading-up-based device for food item detection in this research, and we break down the nutritional components of each supper image. Our model has three important steps, as shown in Figure 3. • We start by using the Region Proposal Network from the Faster R-CNN model to focus the areas of interest (ROIs). The ROIs might aid in separating the diner's gadgets from the heritage and improving the execution of the identification model. • The second step is to use a well-designed Convolutional Neural Network (CNN) to classify fixed ROIs into multiple food item groups. In the meanwhile, a relapse module is used to locate the food groups inside the image. • The last step is to use cutting-edge age-based healthful evaluation hardware to appraise suppers nutrients and generate a wellbeing record for customers based only on their dinner previews.

As discussed in section III-B, region based object detection approaches possess leading accuracy on object recognition. As how it is defined, it proposes different regions from the input image, and classify them into different categories. The traditional region-based object objection methods use a sliding window go through the image. It will make the whole process extremely slow especially when the deep CNN models are employed. Early region-based detection CNN (e.g., R-CNN [25] and Fast R-CNN rely on the input generic region proposals such as selective search [61] and Edge Box , etc. Such hand-crafted process is time consuming due to computational burden of proposal generation. To address this issue, Ren et al. [51] found a way to make the region proposal more efficient, called Faster RCNN. Faster R-CNN has 4 main parts including the feature extraction (a basic convolutional module with convolution layer, activation function and pooling layer), region proposal (anchors classified as foreground region or background region), bounding box regression (fix the anchors location) and classification.

In this paper, we apply Faster R-CNN model to detect the food items from the images. This section only briefly introduces the key aspects of the Faster R-CNN, for more technical details we refer readers to the original paper.

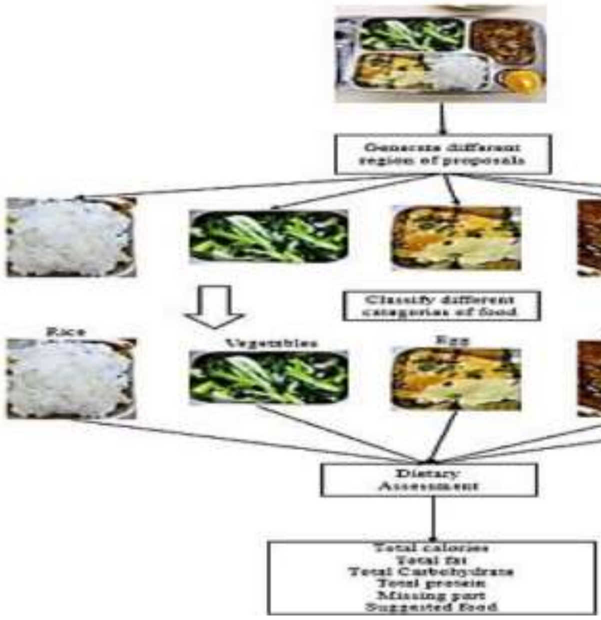

Fig: The automatic three steps system of food recognition and nutrition analysis system

RESULT AND DISCUSSIONS

Food is essential for human survival, and it is necessary for individuals to recognise dietary data before swallowing it in order to live a healthy lifestyle and to be aware of dietary data on a daily basis. The author of this paper has presented REGION base convolution neural local area calculations, which are accomplished by utilising regions from the image, and this district could be within the type of food, and this arrangement of rules staggers on the area of food as well as group suppers, and thus dinners order dietary information can be displayed.

It will check all supper photographs and leaping canisters from the dataset with this module, and these bouncing boxes allow us to remove REGIONS from pictures. The use of photographs and bouncing receptacles areas will be used to create instruction records in this module.

Using this module, we will prepare the VGG16 FRCNN calculation using pre handled images and jumping boxes, then check accuracy and absence of the preparation 23 form, and utilize our equipment to achieve 92 percent supper's class exactness.

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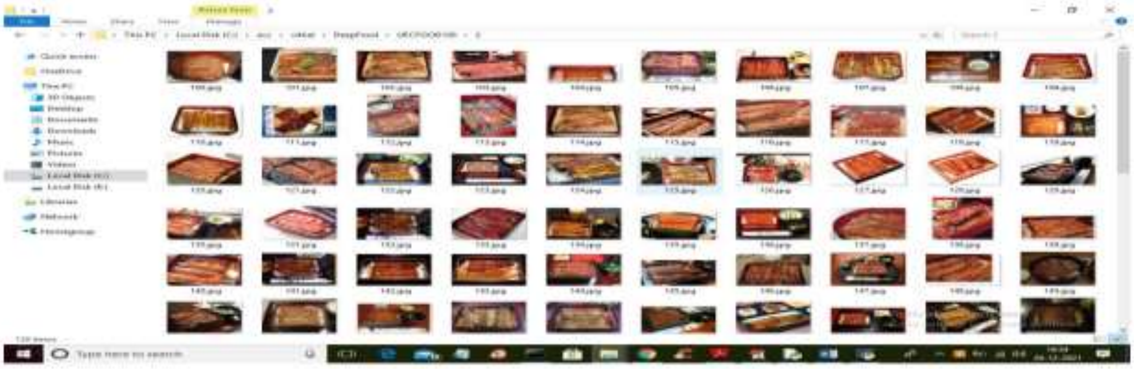

Fig: Upload the meals dataset to the program.

Fig: User interface of the code

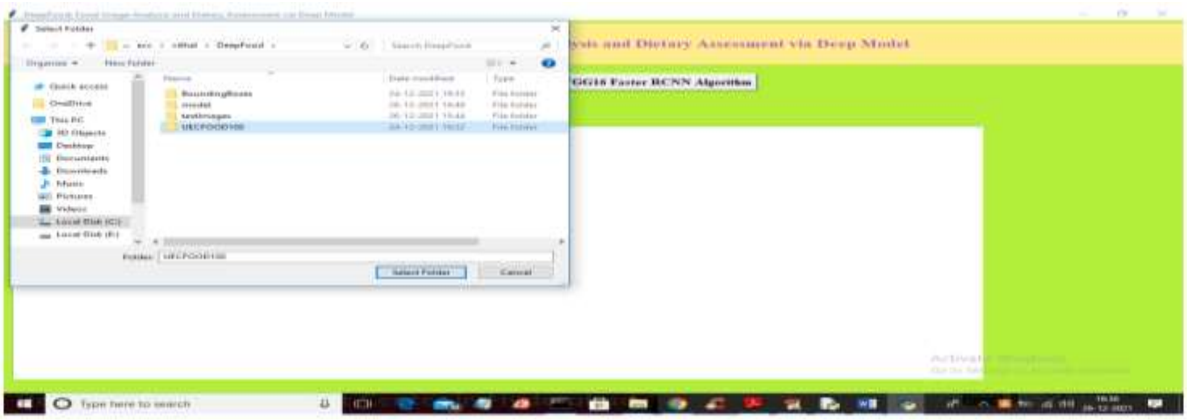

Fig: Uploading the input Image

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Fig: Pre-processing the data

Fig: FRCNN training is completed with 92% accuracy

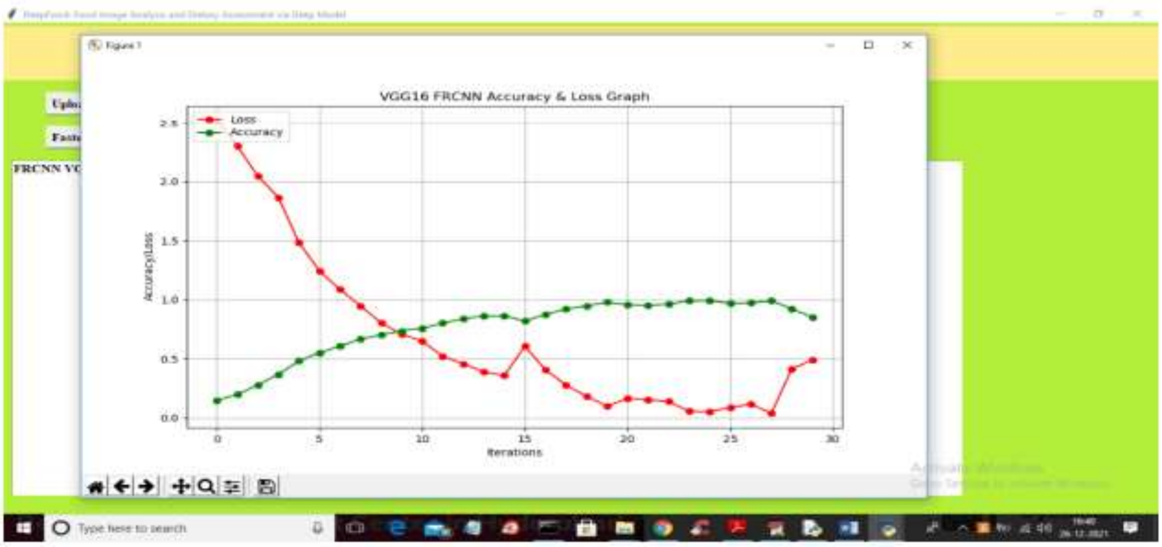

Fig: Plotting graph between accuracy and loss

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CONCLUSION AND FUTURE SCOPE

CONCLUSION: In this paper, we find the food prominence and wholesome appraisal issue via utilizing profound learning strategies. In exact, to have higher information on object discovery and supplements assessment, we practice the contemporary Faster RCNN variant to produce ROIs and utilize a profound neural organization to extricate the trademark map for dinner object ubiquity. We dissect the supplements of identified food and sum up the record of the supper essentially founded on current age-based absolutely dietary appraisal gear.

FUTURE SCOPE: 1) to recommend food to maintain healthy lifestyle. 2) To give proper and balanced food suggestion to patients according to health issue. 3) To provide information about processing, quality of food.

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