iLog 2.0: A Novel Method for Food Nutritional Value Automatic Quantification in Smart Healthcare

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***Abstract*—In order to be healthy and well-nourished, one must consume a nutritious diet. Many chronic noncommunicable diseases, such as heart disease, diabetes, and cancer, can be prevented by taking healthy and balanced diet. Dietary diversity and moderation in salt, sugar, saturated fat, and trans fat consumption are needed for a balanced diet. The proposed system iLog 2.0 aims for estimating nutritional values of food. It uses state-of-the-art object detector to detect the food object. Food quantification has been performed. It makes the estimation of nutritional values more accurate. A high success rate has been achieved. This preliminary research shows promise in estimating nutritional value of the food.**

***Index Terms*—Smart Healthcare; Healthcare CPS; Diet Management; Food Nutrition.**

I. Introduction

"Let food be thy medicine" as the adage goes, has never been more appropriate. Food provides the nutrients our bodies need to function. If we don't get enough nutrition or the wrong ingredients, our health suffers. Overeating or not eating enough can lead to weight gain, malnutrition, and chronic disorders like obesity, diabetes, heart disease, renal disease, hypertension, or deadly diseases like cancer as in Fig. 1 [1]–[3]. Obesity and inflammation cause most diseases. Processed foods, refined sugar, salt, trans fat, chemicals and preservatives, and food color cause obesity, inflammation, cardiovascular diseases, and diabetes. People are changing their diets to address these challenges. Diet control is a concern for everyone. Diet management involves balancing what you consume and how you track it.

The majority of the food intake monitoring systems available are heavily dependent on user inputs [1], [2], [4]. Manual input is needed to quantify the food intake. This can be quite laborious and time-consuming, causing consumers to avoid using these systems for extended periods of time. Furthermore, as these systems are dependent on user-provided inputs, oftentimes users provide inaccurate data, which generates a wrong result. These systems mostly provide information on the calorific value of the food, how much calories are consumed, how much is remaining for the whole day. It is because the goals of these solutions are a balanced weight and a related diet. However, low calorie consumption does not always mean a healthy diet. People with high blood pressure need a low salt diet, diabetic patients must maintain a no sugar diet, people with inflammatory diseases should follow an anti-inflammatory diet and so on. Hence, tracking of sugar, sodium, saturated fat, carbohydrates, and protein is also essential.

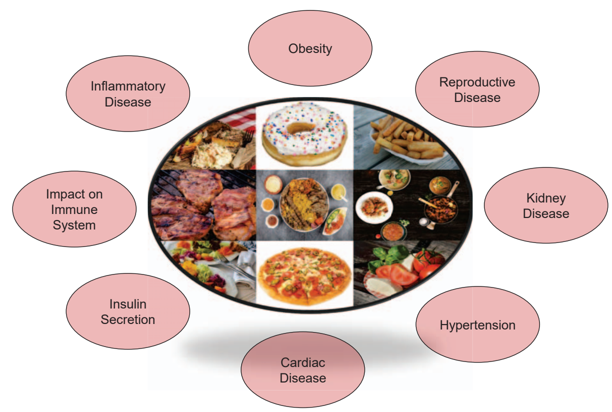


Fig. 1. Impact of Unbalanced Diet on Our Body [1], [2], [4].

In this paper, we propose *iLog 2.0*, a novel system to automatically estimate the nutritional value of food. It is an advancement of iLog [2] where the food calorific value was measured. In this article, a full assessment of the saturated fat, cholesterol, sugar, sodium, protein, and carbohydrates of the meal has been performed with the state-of-the-art object detector which runs on the edge device. A holistic approach to food has been provided. It can be tailored to the needs of the user, for example, the American Heart Association [5] recommends that a normal healthy person consume no more than 2.3 grams of salt per day, but if a person has high blood pressure, the salt intake should be much lower. Our system has the provision for such a type of customization. People suffering from health issues such as diabetes, high blood pressure, and inflammatory diseases can assess their food before eating it. It essentially helps them control their diseases.

The rest of the paper has been organized as follows. The novelty of the proposed solution has been presented in Section II. Section III discusses several existing works and prepares the background for our work. The proposed solution has been described in Section IV in detail along with the experimental validation. Results and a comparative analysis have been provided in Section V. Finally, the paper has been winded up in Section VI with a discussion of future work.

II. Novelty of the Proposed Solution

The novelties of the proposed work *iLog 2.0* are:

1) It is a food nutrient tracking system that is completely automated. The user only needs to take an image of the platter.
2) No manual input of food type or quantity is required. The image taken will suffice for the food's nutrient estimation.
3) It is completely personalized. The user can set a predetermined goal as prescribed by the doctor in addition to the standard target.
4) It is a system that works well on the edge. It will be accessible through a mobile app.
5) It is a real-time estimation that gives the user an idea of the food's nutrients before eating.

III. Related Works

With the recent hardware development trend, such as high-performance computing processors and hardware accelerators, the advancement of Information and Communication Technologies (ICT), the introduction of various computing paradigms, particularly IoT, edge computing platforms, and edge-appropriate AI models novel frameworks like smart healthcare [6] and smart agriculture [7] are a reality. As specific application is automatic dietary intake estimations, which are primarily mobile app-based. However, several varying factors limit the success rate of these systems, either in terms of accuracy, accessibility, or ease of use. In this section, we discuss some of the work in this field.

In [8], an edge-cloud approach has been taken for dietary assessment. Image textural features have been used to process the food images at the edge devices, and a convolutional neural network (CNN) is used for classification of the food in the cloud. Food has been recognized in the Food-101 dataset, but no nutritional value has been estimated in this work. In [9], food attributes have been estimated in real time. Deep learning methods have been used to recognize food, and food attributes have been recognized using a textural corpus. Our work is in the same context, but in our case, the nutrients are estimated from the image.

Mask-RCNN and union post processing were used to estimate food calories and analyze food nutrients [10]. Food weight is estimated from the number of pixels in the mask and a linear regression model. Nutritional and calorific values per serving of food is predicted in [11]. Here, no quantification has been done.

The color of the pureed food has been used to measure the vitamin A content using a deep autoencoder network [12]. In this work, only a specific nutrient has been detected. Bag-of-features model has been used to recognize food for diabetic patients in [13]. It uses scale-invariant feature transforms to compute dense local features on the HSV color space to generate a visual dictionary of 10,000 words, and then uses linear support vector machine classifiers to classify the food photos. No nutrient value is calculated here. In another work, Attention Fusion Network has been used for fine-grained food recognition and the Food-Ingredient Joint Learning module for ingredient recognition [14]. Though the accuracy for food recognition is high but ingredients recognition is moderate to low.

A deep CNN has been used [15] for food classification and ingredient recognition. But no nutritional value is detected in this work. [16] is distributed in several computing platforms. A mobile cloud-based food calorie estimation system has been proposed. Here, a cloud Support Vector Machine with Map Reduce technique is utilized to recognize the food. Before eating and also with the leftover food, calories are measured. Image graph cut segmentation has been used for that. As a reference point of measurement, a thumb should be present in the same frame with the food photo. Here also, calorific value has been measured. Another issue is thumb size variation. Thumb size varies with the height of the person generating an erroneous result.

The work [17] presents a CNN-based model for food recognition and text2vec for attribute estimation. It is a client-server-based model. However, mixed foods, cooked foods, and liquid foods are not included in the system. Here also, it focuses on the calorific value of the food. In [18], a piezoelectricity-based wearable system was used to recognize the food and measure calorie intake. The piezoelectric sensors detect skin movement from the lower trachea while eating. After detecting the weight of the food, a final calorie measurement was performed. No other nutritional value has been counted here.

To measure the calorific values from food volume, different methods are presented in different publications, e.g., a multilayer perceptron model has been used in [19], an image analysis-based approach in [20], and a CNN-based method in [21]. Some of the work also includes ingredients and cooking instructions in addition to calorific values [22]. Multi-task CNN is used for this job. Thw The work [23] recognizes different types of food. Hence, it is clear that there are several papers for calorific value calculation, but very few papers are there for nutritional value of the food.

IV. The Proposed Solution: iLog 2.0

A. Overview

The system-level overview of the proposed system has been shown in Fig. 2. The system is distributed across different computing platforms, focusing on edge platform. Here, both end and edge platforms are on the same level, as a smart phone camera is on the end platform, whereas the smart phone itself is the edge platform. The end device or smart phone camera is used to take images of the food, so image acquisition is performed at the end level. The majority of the work is performed at the edge or on the phone. The jobs done at the edge are image preprocessing, object detection, food quantification, and decision. The cloud platform is used for storing images with labels and food nutritional values. Any future fine-tuning of the model can also be done on the cloud.

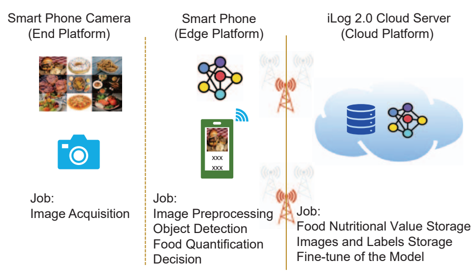


Fig. 2. System Overview of iLog 2.0.

B. Methodology

This section describes the process of food nutritional value estimation in detail as in Fig. 3. When the user wants to check the food nutrient value of food, she takes a picture of the food along with the reference object using her smart phone. The details of the reference object have been discussed in detail in Section IV-B2.

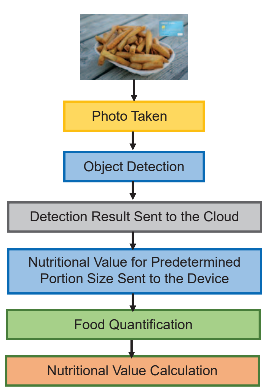


Fig. 3. Process Workflow of iLog 2.0.

Once the photo is taken, the features are extracted from the food image and used for food object detection. After the food object is detected, the result is sent to the cloud to receive the stored nutritional value. These values are for a typical portion size. So when these values are sent to the edge, they are used for calculating the nutritional value of the food on that plate. The portion size may not be the same as our stored value. So food quantification is required. For that purpose, the reference is needed. Once food quantification is done using the process in Section IV-B5, the nutritional values are displayed. The process can be accessed through the mobile app *iLog 2.0*. Fig. 4 shows the development workflow of *iLog 2.0* from data acquisition to inference.

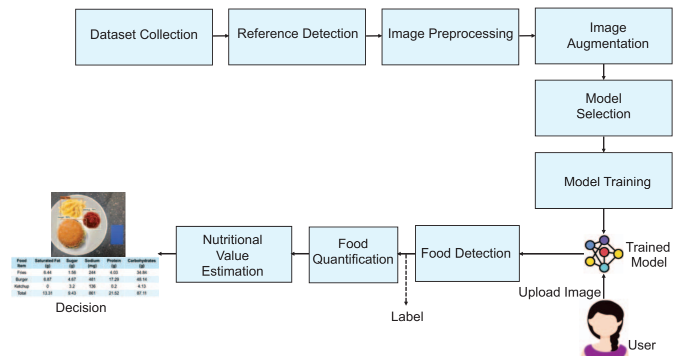


Fig. 4. Development Workflow of iLog 2.0.

1) Dataset Acquisition: Food classification uses a modified customized dataset [24]. Some images are from Food-101 [25], and some are downloaded from Google Images. Instead of Food-101's 101 classes, the customized dataset uses a total of 19 classes, of which 15 are from [25]. LabelImg [26] annotates the images with bounding boxes. 1500 training photos and 374 test photographs from 19 classes were used. Apple pie, beer, bolognese pasta, bread, burgers, carbonara pasta, chantilly cake, coffee, cream, fries, hot dogs, ice cream, ketchup, omelette, pie, potatoes, rice, salad, and sandwiches are in our dataset. For food nutrition, a public dataset [27] was used.

2) Reference Detection: Reference selection is one of the key factors in food quantization. When the food photo is taken by the smart phone camera, depending on the distance from the table, the size of the food plate in the image will vary. There are different ways of food quantification - use of a reference object [16], image segmentation [28], and measuring the distance between plate and phone [29]. Here we follow the first approach of using a reference object due to its simplicity.

Every credit card is the same size, irrespective of the issuing financial institution or country. It has a standardized size of $8.56cm \times 5.39cm$. Hence, a credit card can be used as an object of reference. It is placed just beside the plate on the same table. So when the photo is taken, the photo of the credit card is in the same frame as the food. To use the card as a reference, it is detected using Algorithm. 1. The detected card is used to calculate the portion size of the detected food as stated in Section IV-B5.

3) Image Preprocessing and Augmentation: Images have been preprocessed. They have been resized and normalized before data augmentation. The data was augmented to create a more varied set of images in the training dataset. The aug-

Fig. 5. Reference Selection of iLog 2.0.

Algorithm 1: Process of Detecting the Reference Card.

1: Set the color of the card.
2: Transform the image from RGB to HSV color space.
3: Calculate the card's rectangular area.
4: Find the ratio between card's true size to the image size.
5: Find all the contours.
6: Select the card's contour.
7: Determine Minimum Bounding Box.
8: Length and Width of the Bounding Box are Noted.

mentations included flipping images horizontally and cropping them with a minimum scale size of 0.1 and a maximum scale size of 2.0. Padding to the maximum dimension has been kept to True.

4) Model Selection: As the feature extractor of the object detector, a pre-trained EfficientDet D0 model [30] has been used. Transfer learning reduces the training time along with improved accuracy. EfficientDet D0 is a state-of-the-art network with higher efficiency. It is a combination of EfficientNet B0 [31] and a bidirectional feature pyramid network (FPN) [32] [33]. Single Shot MultiBox Detector (SSD) [34] has been used for localization of the object.

Two different loss functions were used for classification and localization. For classification, the *weighted sigmoid focal* loss function has been used, while for localization, the *weighted smooth L1* loss function has been used.

5) Food Quantification: Once the reference card and food are detected from the image, the detected food label is sent to the cloud. The stored nutritional values from the public dataset [27] are sent to the device. This is for predetermined values for a particular portion size. However, proper quantification of the detected food is done using Algorithm. 2. Here, actual dimension of the food is calculated by comparing it with the reference object. A factor of 0.8 is multiplied with the calculated volume to address the extra area in the rectangular bounding box. As majority of the served food are mostly circular and plated in circular or oval plates, there are empty spaces in the rectangular bounding box where there is no food. After calculating the number of pixels in the empty space of the bounding box with respect to the whole bounding box, the value 0.8 has been carefully chosen and validated with several images. However, this could be avoided with polygon bounding box rather than rectangular bounding box. Finally, converting the volume to weight (with the help of the extrapolated data from the Food-A-Pedia [27] database), the nutritional values of the food on the plate are calculated.

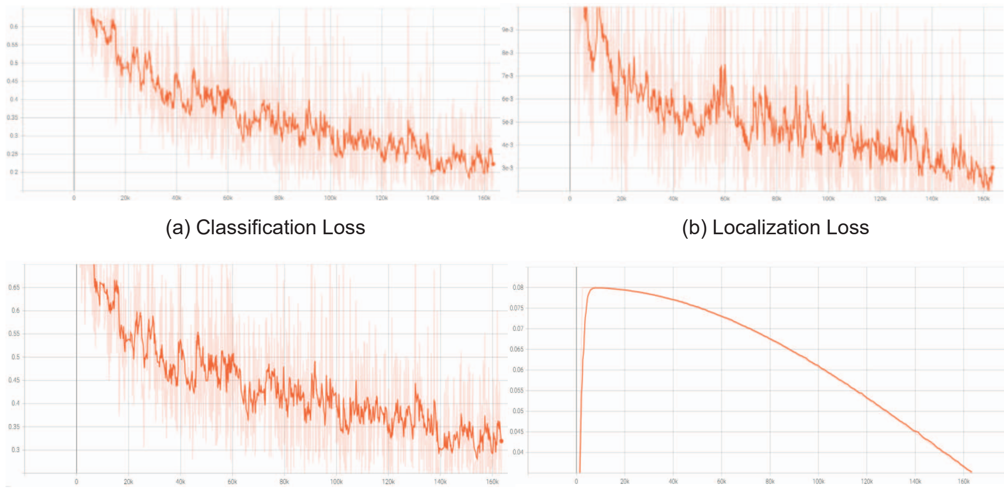
Algorithm 2: Process of Quantifying the Detected Food.

1: **Input:** Testing Image
2: **Output:** Food Nutritional Value
3: Take a photo of a plate of food along with the reference card beside from the top angle.
4: Pass the image through the food detection model to obtain bounding boxes of detected food on the plate.
5: Card area with respect to the image is measured using Algorithm. 1.
6: Calculate ratios of the actual length (8.56 cm) and width (5.39 cm) of the reference card to the pixel length and width of the detected card in the photo.
7: Multiply the length and width of the bounding box of the detected food with the ratio to find the actual dimensions of the detected food.
8: Based on the detected food class, use the preset generalized height of the food.
9: Calculate the total volume $length \times width \times height$ cm^3 of the detected food.
10: Multiply this volume by a constant of 0.8 to achieve a more accurate representation of the volume of food (accounting for extra area resulting from the rectangular bounding boxes).
11: Then, using the gram to cubic centimeter conversion for the specific food (ex: Rice - 0.87 grams per cubic centimeter, Ice Cream – 0.96 grams per cubic centimeter), determine the amount of grams of food that are present on the plate.
12: Finally, extract the corresponding nutritional value using the Food-A-Pedia [27] database.

V. Validation of iLog 2.0

iLog 2.0 has been implemented and evaluated on a laptop with an AMD Ryzen 7 4800H with Radeon Graphics 2.90 GHz processor, 32.0 GB RAM, and a NVIDIA GeForce RTX 2060 6GB GPU. Raspberry Pi 4 has been used as an alternative to cloud storage for this preliminary work. TensorFlow 2.0 Object Detection API has been used for food detection. Stochastic Gradient Descent (SGD) with Momentum has been used as the optimizer with an initial learning rate of 0.08 and a learning schedule with cosine decay. Fig. 7 shows the plots for classification loss, localization loss, total losses, and learning rate with the number of iterations. These plots were visualized during the training of the object detector.

To evaluate the model, 374 images have been used. Fig. 7 shows the classification results. In almost all scenarios, food classification with localization was correct. However, the confidence scores in several images are moderate due to no space or very little space between two different foods on the plate. More versatile food plating is required to have higher a confidence score.



(a) Classification Loss

(b) Localization Loss

(c) Total Loss

(d) Learning Rate

Fig. 6. Different Losses and Learning Rate w.r.t. Number of Iterations.

Fig. 7. Classification by iLog 2.0.

Fig. 8 shows the nutritional values of two sample food plates. The nutritional values have been estimated by performing food quantification using Algorithm 2 for a dataset [27].

Food Item	Saturated Fat (g)	Sugar (g)	Sodium (mg)	Protein (g)	Carbohydrates (g)
Fries	6.44	1.56	244	4.03	34.84
Burger	6.87	4.67	481	17.29	48.14
Ketchup	0	3.2	136	0.2	4.13
Total	13.31	9.43	861	21.52	87.11

Food Item	Saturated Fat (g)	Sugar (g)	Sodium (mg)	Protein (g)	Carbohydrates (g)
Rice	0.3	0.3	6	12.9	135
Salad	0.8	3.9	264	1.1	7
Total	1.1	4.2	270	14	142

Fig. 8. Nutritional Value Estimation by iLog 2.0.

Several performance metrics have been calculated for the *iLog 2.0* system [35]. Precision, recall, and intersect-over-union (IoU) have been calculated for classification. The dice coefficient and IoU have been calculated for the localization. Table. I describes the performance metrics. As it is more important for the model to correctly identify that a certain food is present (lowering false negatives), even if this means identifying more food than there is (increasing false positives), the user should not be given a nutritional estimate that is possibly lower than what they are eating because this can jeopardize their health. That justifies the higher *recall* value.

TABLE I
PERFORMANCE METRICS OF ILOG 2.0

Types	Metrics	Values
Classification	Recall	90.0%
	Precision	80.3%
	IoU	73.7%
Localization	Dice Coefficient	80.3%
	IoU	68%

VI. CONCLUSION AND FUTURE WORK

What we eat matters most to staying healthy. Researches [36], [37] show that a healthy diet plays a key role in keeping away diseases. Hence, we should be watchful while eating. Not only calorific values, but other nutrient values need to be monitored too.

In this paper, a food nutritional value estimation system *iLog 2.0* has been proposed. It has addressed several things -

- It is an automatic system. It can measure the food's nutritional values from the image of the food.
- Because food quantification is done by measuring the volume of the food and then converting the volume to weight, the nutritional values are more precisely estimated. However, no provision is made for unfinished meals. If the user does not finish the meal, the accurate measurement will not be reflected in the system.

- Our system can be customized according to the user's requirements. But, if the user orders any customized food, e.g., no salt diet or extra butter, these inputs need to be manual as they are not understood from the image. Hence, even if the system is customized as per the needs of a specific user, it is not automatic for customized food.

In future work, a no-reference food quantification system will be proposed. The precision and IoU need to be improved. More food items will be included in the system. The system will be updated cuisine by cuisine. Finally, the mobile app will be built.

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