

ANALYSIS OF DEEP LEARNING BASED DETECTION AND ESTIMATION OF CALORIES IN FOOD IMAGES

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Abstract

Everyone aspires to live a healthy life as health awareness increases throughout the world. The fast-paced environment leads to, obesity and its related issues as a major public health concern.. Obesity is defined as having a BMI greater than 30 kg/m². Numerous ailments, including high cholesterol, liver failure, problems in breathing, heart problems, diabetes, and cancer, are made worse by obesity. By eating nutritious meals that are low in calories and high in nutrition, obesity can be managed. The choice of the best solution to control our weight is a difficult daily food intake that needs to be monitored to lose weight safely. The use of deep learning-based food recognition methods offers a potential remedy for this problem. The suggested effort seeks to examine various deep learning algorithms and offer the best solution for food recognition. This effort will undoubtedly help those who are new to the area comprehend the fundamentals of automated food recognition.

Keywords: Calorie Estimation, Food Identification, Review, Survey

Introduction

Food is both the body's fuel and one of the fundamental needs of humans. Humans' eating habits have evolved as a result of the modern lifestyle, and now they tend to consume ready-made, packaged, and fast meals while doing less physical work or exercise. This type of unbalanced diet raises the likelihood of developing disorders like obesity, heart issues, and a wide range of other illnesses. Obesity occurs when excess body fat builds up to the point that it could be harmful to one's health. The difference in the amount of food intake and the energy expended by humans is the primary contributor to obesity. Therefore, it is necessary to measure daily food intake in order to maintain a healthy weight. Recognizing and analyzing food items from photos has become an emerging

research topic because of the availability of a large number of images on the web. The current methods for nutritional assessment must depend on memory to recall meals consumed in the last few years, which causes difficulties with accurately documenting dietary calorie intake. This study examines current articles that have discussed deep learning-based food recognition.

Dietary disorders have rapidly increased over the past few decades due to improper eating habits. System-based dietary evaluation systems can be very useful and help people change their eating habits, which leads to a healthier life [1]. These systems can capture real-time photographs of meals and evaluate them for nutritional value. The way people track their health has undergone a radical change as a result of recent advances in computer vision and artificial intelligence, and a plethora of new applications have been made possible [2].

Shroff et al. [3] created a food identification application for the division of fast-food images into four categories. Each food item is segmented as, a vector of colour with RGB values, dimension, and texture features are computed and input to a feed-forward artificial neural network (ANN). As a result, for hamburgers, fries and chicken nuggets, 95%, 80% and 90% accuracies are achieved respectively. Implementation specifics, such as data structures and quantization techniques, can also have an impact on accuracy. To maximize quantization, for instance, [4] recommends using Fisher Vectors rather than the more traditional BoF (Bag-of-features). The difficulty lies in selecting the appropriate features and figuring out how to best depict them. Support vector machine (SVM) has often been trained using the extracted features [5], with a combination of these features being utilized to increase accuracy.

Various methods and strategies for food recognition as well as volume estimation from recognized food have been covered in this study paper. The work is divided into three sections: introduction, table of reviewed methodologies, and conclusion and future directions. The first section includes numerous reviews.

Literature Review

A method is suggested in [6] to help people track their daily caloric intake and keep a balanced diet. Utilizing a convolution neural network, it will accurately classify and identify the food qualities as well as detect the food's contents (CNN).

The proposed methodology has three processes the first deals with the transfer learning-based CNN model, the second deals with text recovery, and the third deals with text data training. The CNN model performs better than SVM models. This System has 85% accuracy in classifying food attributes. The limitation of this system is it could not classify mixed food images accurately.

[7] Applied Convolution Neural Network (CNN) to perform detection of food images and recognize them. Three methods Spatial Pyramid Matching (SPM), GIST features SVM and The ScSPM (Sparse Codeing Spatial Pyramid Matching) package have been prepared for food recognition. In recognition, 70 % accuracy has been achieved compared to the existing methodology. It uses the dataset of approximately 1,70,000 images collected from the Food logging app that was available publicly. Food detection divides the dataset into 10 groups training-8 groups, validation-1 group, and testing-1 group. It uses a dataset of 1234 general food images and 1980 Non-food Images from social media. Food detection provides an accuracy of 93.8% compared to the traditional support vector method. But this approach did not detect correctly some food items sometimes.

In paper [8] a CNN-based identification of food image algorithm was developed to improve the efficiency of dietary assessment by analyzing the food. The new CNN algorithm uses the Inception model to represent a convolution that is optimized to conduct size reduction and depth increase. It uses the real-world food datasets UEC and Food-101. The accuracy of the proposed approach for UEC-100 is 94.6 % and Food-101 is 93.7% compared to existing approaches. This approach has a limitation as time consumption for preparing pre-trained data.

[9] Provides a solution for measuring volume and calories using a deep learning algorithm. It uses CNN for calculating food calories, Tensor Flow's API for food item recognition from images, Random Forest, and SVM for better accuracy. It works on the Dataset ECUSTFD which contains 2870 pictures of 19 unique food varieties. It provides an accuracy of 92% compared to the existing method. This method is limited in the volume estimation of ellipsoid shapes.

[10] Detects varieties of food and calculates calories per serving of detected food from an input image. It has four stages Image acquisition, Neural Network training, Image Segmentation, and Calorie estimation - 1. Image acquisition uses the dataset Fruits 360 which contains 90483 images of 131kinds of fruits and

vegetables for this method 15 types of fruits and vegetables are considered. 2. Neural Network Training-Convolution Neural Network (CNN) is used for training. 3. Image segmentation- Morphological functions and OpenCV is used for segmentation. 4. Calorie estimation uses mathematical formulas. Though it has high performance it could not calculate calories for fast food and cooked food since it could not identify ingredients present in the food.

In [11] a Faster Region-based Convolutional Neural Network(R-CNN) framework was presented to detect food images. It includes Region Proposal Network (RPN) and Object Detection Network which are used to detect and segment an image. The GrabCut algorithm was implemented to identify food contour in the images and formulas for volume estimation from segmented images. This method works well on a novel dataset [EDUSTFD]of 2978 food images with annotation, volume, and mass records. This method provides an effective result compared to the existing method. The aim of this approach is to produce effective results only for whole, stable, and less prone to deformation food.

[12] Proposed a multitask CNN for estimating the food calorie from an image of food by simultaneously identifying food calories, ingredients, and the making of the recipes. It constructs two datasets annotated with calorie values from Japanese and American recipe websites. The multitask CNN produces effective results compared to Single-task CNN. Since the dataset was collected from a website the calorie value annotated cannot be guaranteed. Therefore, it is considered that it is hard to estimate the food calorie with high accuracy based on this dataset.

In paper [13] proposed a calorie content estimation for dietary assessment. The calorie estimation was done by extracting the features of color, circle, a bag and block. The dictionary is used to match the attributes and determine the top n related photos. The top n average calorie content is then calculated. It builds a dataset of 6512 images contained in food logging. The accuracy of estimation is 79% compared to other methods like SVM, and single-task CNN.

[14] Examined the efficiency of the Deep Convolution Neural Network (DCNN) for the food image recognition process. The object recognition stages like local feature extraction, feature coding, and learning are included in DCNN. The proposed system used pre-trained DNN for the ILSVRC1000-class dataset.

Additionally, the system included 1000 categories of images from ImageNet 21000 for pre-trained DNN. Then both the DCNN pre-trained with 1000 categories and pre-trained the DCNN with 2000 categories. The two Japanese datasets UEC-FOOD100 and UEC-FOOD256 have been used. The UEC-FOOD100/256 dataset's classification accuracy was 78% and 67.57%, respectively, demonstrating that the performance had been improved by fine-tuning the DCNN that had been pre-trained with so many food-related categories (DCNN-FOOD).

[15] Explains an Automated Food Intake Evaluation System (AFIES) to estimate the food portions accurately and stored them for a dietician review. The first stage consists of a reference card detection module that specifies a reference card with a pattern of Bull's eye to be used before taking a picture and a Harris corner detector to identify the corner of the card. The next module food region segmentation and classification extract the features of the image using Color RGB classifier. The food amount estimation module estimates the amount of food using an association between food region area and gram amount of food in the image. In manual review, the stored food type and gram equivalent were reviewed by the dietician if needed estimated gram amount can be changed manually. The constraint in this system is that it uses a color feature for segmentation but it does not work well for different food with similar color feature.

[16] Proposed a technique for food recognition based on bag-of-features automatically. The methodology has two steps Food Image Description and Image classification. The Food Image Description adopted the BoE model which involves Key point extraction, Local feature descriptor and Descriptor quantization. In the food Image classification module, Random Forest (RF) is used. The dataset was constructed with 4868 images with 11 classes collected from the Web. The limitation of this methodology is that it fails to recognize images with less pre-trained images in the dataset. This methodology works with 78% accuracy.

In [17] classification food using image processing and Artificial Intelligence has been proposed. Image processing involves in segmentation of food and extracting the parameters of food such as Area, Major Axis, Euler Number, Solidity, Equivalent Diameter, Extent, Perimeter, etc. The detection process involves surface features and bag-of-feature. The accuracy of detection is 79%.

[18] Proposed an algorithm using improved MLP for identifying food items with high efficiency and accuracy. It has four processes Resizing the input image, Feature Extraction, Segmentation, and classification. Based on the feature's size, shape, and texture segmentation is performed. The classification includes Multilayer Perceptron and SVM methods. The dataset for this algorithm includes images of apple, banana, bread, guava, pizza and pomegranate. This method provides high accuracy compared to other methods.

[19] Developed a method for food recognition and calorie estimation for an input image. The method takes two images views as input, one - the top view and two- the side view. A Faster R-CNN framework was used to detect each food and calibrate the object-CNN framework including Region Proposal Network (RPN) and Object Detection Network. The food contour has been extracted by the GrabCut algorithm. The volume estimation was done followed by calorie estimation. ECUSTFD dataset has been used in this method. The accuracy of object detection was 93% and effective compared to Exemplar SVM.

In [20] an application has been developed for calorie measurement using Deep Learning and Neural networks which classify 100000 food images for system training. It integrates a calorie measurement application on mobile to Deep Neural Network. It uses Graph Cut segmentation method for food detection. A series of photos belonging to a specific class are initially taken by the Deep Learning Neural Network, which then labels them with an object name-set and trains the system. Retrain the with the set of negative images. The dataset for this application includes 30 distinct food category subcategories. The accuracy of calorie estimation of a single food portion was 99%. The application was bounded to single food recognition.

Table 1 Comparison of different Methodologies

Sl.no	Year	Authors	Objective	Methodology	Techniques Used	Samples	Accuracy
[6]	2020	Zhidong Shen, Adnan Shehzad, Si Chen, Hui Sun, Jin Liu.,	Improve the accuracy of the pre-training mode	Deep learning	Convolution Neural Network (CNN) Transfer learning- based CNN model. Text recovery Text data training	100s and 1000s of food images	85%
[7]	2014	HokutoKagaya, Kiyoharu Aizawa, Makoto Ogawa	Food detection and recognition through parameter optimization	Deep Learning	CNN Spatial Pyramid Matching (SPM) GIST features + SVM ScSPM package	1,70,000 images from the food Logging APP.	93.8%
[8]	2016	Chang Liu, Yu Cao, Yan Luo, Guanling Chen, Vinod Vokkarane, and Yunsheng Ma	Create CAD solutions to bolster and increase the precision of the current dietary measurements.	Deep Learning	New CNN Inception model optimized convolution	UEC-256 and Food-101	UEC-100 - 94.6 % UEC-100 - 94.6 %
[9]	2021	V Balaji Kasyap, N. Jayapandian	Unique solution for measuring calorie	Deep Learning	CNN Tensorflow's object detection API Random Forest	ECUSTFD- 2870 images	92%
[10]	2020	Dhanalakshmi S, Harshitha S, Mukeshwar Varma D, and Mayuri P	Estimates per serving calories of each food detected in a single image	Deep learning and image processing	Image acquisition Neural Network training Image segmentation Calorie estimation	90483 images of 131 fruits and vegetables	Not mentioned
[11]	2017	Yanchao Liang, Jianhua Li	Food recognition and Estimation of calorie of food	Deep learning	Faster R-CNN Network(R- CNN) Grab-cut Algorithm	ECUSTFD- 2870 images	Not mentioned

[12]	2017	Takumi Ege, Keiji Yanai	Food recognition and Estimating the food calorie	Deep learning	Multitask CNN	Images from Japanese and American Receipe sites	Not mentioned
[13]	2011	Tatsuya Miyazaki, Gamhewage C. de Silva, Kiyoharu Aizawa	Image-analysis based approach to calorie content estimation for dietary assessment	Image processing and machine learning	Extracting features Triaining based on mechine learning Identifying visual similarities	Food Log (6512 images)	79%
[14]	2015	KeijiYanai, Yoshiyuki Kawano	To Examine the efficiency of deep con- volutional neural network (DCNN) for food image recognition task	Deep learning	Deep Convolution Neural Network (DCNN)	UEC, FOOD100/ 256	78.77% - UEC 67.57%- FOOD100/ 256
[15]	2009	Corby K. Martin, Sertan Kaya, Bahadir K. Gunturk	To create an Automated Food Intake Evaluation System (AFIES)	Image processing and Deep learning	Reference card detection- Bull's eye pattern. food region segmentation Classification food amount estimation modules.	Images from website	99% for single food
[16]	2014	Marios M. Anthimopoulo, LauroGianola, Luca Scarnato, Peter Diem, and Stavroula G. Mougiakakou	Automatic food recognition based on bag-of-features	Image processing and Deep learning	Food Image Description Image classification	Images with 11 Classes collected from Web	78
[17]	2018	Priya Gupta, Shikha Gupta	To determine and classify the food	Image processing and AI	Segmentation Extraction Detection- surface and bag-of feature	IILSVRC 1000	79%
[18]	2021	R. Dinesh Kumar, E. Golden Julie,Y. Harold Robinson, S. Vimal, Sanghyun Seo	Identifying the food type and its calorific value estimation	Machine learning	Improved MLP Scale Invariant Feature Transform Gabor Filter	Apple,banana ,bread,guava, pizza and pomegranate	Not mentioned

					Method Multilayer Perceptron SVM method		
[19]	2018	YanchaoLianga, Jianhua Lia	To estimate calorie of food	Deep learning	Faster R-CNN framework Region Proposal Network(RPN) Object Detecion Network Grab-cut algorithm	ECUSTFD	93%
[20]	2016	Parisa Pouladzadeh, Pallavi Kuhad, Sri Vijay Bharat Peddi, Abdulsalam Yassine, Shervin Shirmohammadi.,	An assistive calorie measurement system	Deep learning	Deep Neural Network	30 different categories of food	99% for single food recognition

Conclusion

It has been discovered that a number of strategies have been suggested for estimating calories and eating regulation using input photographs of food. Different segmentation methods are used to extract the various dietary features. Various applications of the Convolution Neural Network (CNN), a deep learning technology, have been developed, primarily for the detection of food. For accurate food detection, a system has to have a large training set of images. Comparing single food detection to mixed food image detection, the examined techniques produce more or less positive results. By expanding the dataset used for the model's pre-training, mixed food can be identified with greater accuracy. This research can be expanded in order to determine the caloric content of blended foods. Furthermore, it can be altered dependent on the illness or age factor.

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