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Food Calorie Estimation Using Deep Learning

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Abstract- Precise methodologies for gauging food and energy consumption are imperative in combating the epidemic of obesity. Furnishing individuals or patients with streamlined and sophisticated solutions aimed at quantifying their dietary intake and amassing relevant dietary data represent paramount insights for protracted prevention endeavors and efficacious treatment regimens. Within this discourse, we posit the inception of an auxiliary calorie quantification mechanism, envisaged to fortify patients and medical practitioners in their campaign against diet-induced maladies. Our envisaged framework operates seamlessly on smartphones, affording users the facility to capture images of meals and discern calorie intake levels automatically. To achieve precise food identification within the framework, we leverage deep convolutional neural networks, meticulously trained on a repository of 10,000 high-fidelity food depictions. Our findings evince an unparalleled accuracy rate of 99% in recognizing individual food portions. Furthermore, the elucidation and execution of the proposed system are meticulously expounded within this exposition. The contemporary state of physical well-being in our society hinges significantly upon the quantification of caloric intake; thus, the vigilant monitoring of caloric consumption stands as an indispensable facet of preserving optimal health. When one's Body Mass Index falls within the range of 25 to 29, it signifies an excess weight burden; surpassing a BMI of 30 denotes the onset of obesity. To achieve or sustain a healthy weight, individuals must meticulously track their caloric intake. Presently, the process of caloric estimation relies on manual methods. However, our proposed model offers a distinctive solution, employing advanced deep learning algorithms. The meticulous calculation of food calories assumes paramount importance in the medical domain, as it directly impacts one's state of health. This calculation is derived from images of various food items, encompassing fruits and vegetables, and is facilitated by neural network technology. Among the array of methodologies, Tensor Flow emerges as a premier choice for classifying machine learning models. Leveraging Convolutional Neural Networks, our method is adept at computing food calories based on inputted food images. The efficacy of our proposed CNN model is assessed through primary metrics such as volume error estimation and secondary metrics such as calorie error estimation. Remarkably, our model demonstrates a 20% reduction in volume error estimation, underscoring its superior accuracy compared to existing models.

Index Terms- calorie quantification, food identification, segmentation, graph segmentation, deep learning.

I. INTRODUCTION

In this contemporary epoch characterized by advancements in science and technology, the food industry confronts a significant challenge: the pervasive issue of food spoilage. Within this context, perishable items such as fruits, vegetables, and meats succumb to decay, posing a formidable dilemma. Compounding this issue is the insidious nature of undetected spoilage, whereby compromised goods find their way into the hands of consumers. Consequently, there arises an imperative for an automated mechanism not only to enhance the precision of spoiled food detection but also to estimate the caloric content therein. This endeavor primarily centers on aiding non-governmental organizations (NGOs) and establishments in maintaining the integrity of their food supply, ensuring the provision of untainted edibles. Moreover, it aspires to facilitate the monitoring of caloric intake, thereby fostering the dissemination of well-balanced dietary offerings. Central to our initiative is the development of a mobile application designed to furnish users with comprehensive data pertaining to the caloric content of various vegetables and fruits. Utilizing image recognition technology, users can simply upload images of produce, enabling them to monitor their caloric intake and uphold a wholesome dietary regimen.

To realize this automation, we envisage deploying an array of intelligent sensors, including temperature sensors and MQ3 sensors, integrated with microcontrollers such as the Node

MCU. Upon the detection of spoiled or stale food items, an audible alarm will be triggered alongside the illumination of an LED indicator, thereby alerting stakeholders. This endeavor is complemented by the creation of a dedicated IoT application, empowering consumers to access detailed information regarding the identified fruit or vegetable, including its caloric value. Furthermore, the application employs image classification algorithms to ascertain the identity of the uploaded produce and provide corresponding caloric estimations.

The seamless interaction between the application's frontend and backend is facilitated by the Stream lit framework, affording users effortless access via a designated URL. Through a user-friendly interface, individuals can readily upload images for analysis and receive real-time feedback regarding the caloric content of their chosen produce.

Obesity, afflicting both adults and children, stands as a pervasive global scourge. Its genesis lies in the confluence of overindulgent food consumption and a dearth of physical exertion. Hence, the imperative to precisely gauge dietary intake emerges as paramount. Initial inquiries into adolescent populations intimate that leveraging technological innovations may enhance the fidelity of dietary data acquisition among the youth. Moreover, the sedentary lifestyle increasingly embraced by individuals inadvertently severs their connection with vigilant scrutiny of energy intake through food. Conclusive evidence underscores the metabolic derangements precipitated by obesity, heightening susceptibility to deleterious health sequelae such as diabetes, hypertension, and dyslipidemia.

Despite a general awareness of the symbiotic relationship between diet and health, disseminated nutritional guidance has not stemmed the tide of diet-related maladies or fostered wholesome eating habits among individuals. Often inundated with copious nutritional information and guidelines, individuals find themselves overwhelmed, struggling to distill actionable insights regarding dietary choices. Furthermore, a lack of nutritional acumen, erratic eating patterns, or lapses in self-discipline render many oblivious to monitoring or regulating their daily caloric intake. Empowering patients with enduring solutions necessitates the deployment of innovative mechanisms capable of effecting lasting transformations in dietary habits and calorie management.

This paper delves into the exploration of deep learning methodologies for the classification and discernment of food items. Deep learning, an evolving paradigm within the realm of machine learning, has garnered attention in recent years for its capacity to propel machine learning systems towards the revelation of multifaceted layers of representation. We elucidate how deep learning stands as a potent tool in significantly augmenting the precision of food classification and recognition tasks. Our proposed framework introduces two pivotal advancements to the current state of the art:

We advocate for the integration of deep learning neural networks to enhance the accuracy of food classification and calorie measurement systems. Empirical findings from our experimentation, amalgamating various segmentation techniques such as color, texture, graph-cut segmentation, alongside deep learning neural networks, showcase an impressive 99% accuracy in recognizing individual food portions.

II. LITERATURE SURVEY

Previous research has explored various aspects of food spoilage and calorie estimation across diverse academic disciplines [1] An implementation involving an Arduino sensor-based method for detecting food spoilage and a project dedicated to monitoring temperature in a confined server environment has been previously documented. In this setup, data transmission occurs online, and if predefined thresholds are surpassed, the system activates conditioning mechanisms to regulate temperature within specified parameters.

This paper introduces an Internet of Things (IoT)-based framework comprising a microcontroller Arduino Uno, a Bluetooth module, and an array of electrical and biosensors, including pH, dampness, and gas sensors. The DHT-11 sensor is employed to measure temperature and humidity, while the MQ2 sensor facilitates the detection of volatile compounds, all integrated with the Arduino board. This IoT system transmits essential data to users via the ESP8266 Wi-Fi module, with a specific focus on maintaining optimal storage conditions for perishable food items [2].

Additionally, other notable contributions in the realm of IoT include a smart weighing system tailored for agricultural crates [3], as well as the development of a novel deep learning-based food recognition system optimized for dietary assessment, operating within an edge computing service infrastructure.

Chang Liu, Yu Cao, Yan Luo, Guanling Chen, Vinod Vokkarane, Ma Yunsheng, and Song Qing Chen, esteemed members of the Institute of Electrical and Electronics Engineers (IEEE), have undertaken a comprehensive study focusing on the nutritional estimation of food. Their research employs visual-based food recognition algorithms leveraging edge computing methodologies. Central to their project is the utilization of a visual sensor to capture food images, mobile phone technology for image pre-processing and segmentation, and a server operating within the cloud layer, housing a pre-trained Convolutional Neural Network (CNN) model for image classification. The intricate food recognition system features multiple stages, commencing with image pre-processing at the front-end component and culminating in image segmentation, facilitated by CNN-based food image analysis. Recognizing the paramount significance of nutrition for sustaining life, the authors underscore the critical role of environmental factors, such as humidity and temperature, in fostering bacterial proliferation within food items, leading to detrimental spoilage and potential health hazards.

In India, statistical analyses have highlighted regions such as West Bengal, Karnataka, and Gujarat as reporting the highest average outbreaks of foodborne illnesses and deaths. Detecting food spoilage from production to consumption stages emerges as a vital imperative, given the dire consequences of conventional, time-consuming detection techniques. Consequently, the authors advocate for the adoption of advanced vision-based approaches, incorporating cutting-edge technologies like nanotechnology and state-of-the-art machine learning algorithms.

Nanotechnology-based sensing methodologies, exemplified by the employment of the MQ3 sensor, offer selective and specific detection capabilities for toxins and pathogens such as acetone and ethanol in spoiled food. Moreover, the inclusion of an oxygen sensor enables the identification of microbial contamination, as lower oxygen levels in the immediate environment indicate the presence of germs. The integration of these sensors into food detection systems signifies a transformative leap towards intelligent food surveillance, with plans underway to incorporate them into an Arduino Uno board—a widely acclaimed prototyping platform—capable of measuring and transmitting data to IoT platforms.

Within this segment, we expound upon several prevalent methodologies for quantifying food intake that have emerged in recent years. Our primary aim herein is to delineate both the salient advantages and limitations of these techniques, thereby underscoring the innovative contributions of our proposed system.

Among the foundational works in this domain is the 24-Hour Dietary Recall (24HR), a seminal approach dating back to [13]-[14]. This method entails the meticulous recording of daily food consumption over a 24-hour period, with individuals required to recall all foods and beverages consumed within the preceding day leading up to the interview. Notably, food portion estimates are standardized through the use of calibrated cups and spoons, with recorded quantities subsequently converted into nutrient intake values via food composition tables. Another notable method is the Food Frequency Questionnaire (FFQ), which, as described in [15], primarily focuses on delineating dietary patterns and culinary habits rather than directly quantifying caloric intake.

However, both the 24HR and FFQ methodologies suffer from significant drawbacks, including delayed reporting of consumed foods, underestimation of food portion sizes, reliance on memory recall, and the need for skilled interviewers proficient in estimating caloric and nutrient intake. Furthermore, these methods fail to capture the usual dietary intake and necessitate complex calculations to estimate consumption frequencies.

In contrast, alternative approaches, as described in [16][17], involve the use of pre- and post-eating food weighing alongside specialized kitchen appliances equipped with internal scales. While promising, these methods are fraught with user inconvenience and heightened potential for underreporting due to user forgetfulness or reluctance to adhere to such protocols. To address these challenges, researchers have endeavored to develop simplified and automated methods for food content analysis, as evidenced in [19] [18]-[25]. Notably, in [18], a web-based application is proposed to detect obesity risk factors by acquiring and registering data on diet, exercise, sleep, and body fat mass. Despite its potential, such systems are marred by user inconvenience and the steep learning curve associated with their utilization.

In [19], authors propose a novel system leveraging food images captured and stored by multiple users on a public web service called Food Log. However, the accuracy of this approach is constrained by the limited dataset size comprising 6,512 images. Additionally, [20] introduces a sophisticated 3D/2D model-to-image registration framework tailored for estimating food volume from single-view 2D images, employing morphological operations for food segmentation and user-selected 3D shape models for size estimation. Finally, [23] adopts a method involving pre- and post-food consumption image capture to recognize and classify food items, with the aid of pre-measured and predefined patterns within the images to facilitate size translation

III. METHODOLOGY

The principal aim of this endeavor is to pioneer an innovative methodology in image classification, proficient in precisely distinguishing diverse food categories in accordance with specified criteria. This endeavor commences by employing an array of pre-processing methodologies on food images to optimize their clarity and fidelity. Subsequently, the model undergoes rigorous training and evaluation to ascertain its efficacy, thereafter being deployed for food classification adhering to predefined criteria.

Food detection module

Step 1: T Firstly, input images or videos are acquired.
Step 2: the videos are converted to frames for processing
Step 3: a database is created by storing images of each animal, which will serve as a training set for the program
Step 4: the input image frames are compared with the images in the database.

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Step 5: To achieve this, a misread function is utilized for image reading and pre-processing is performed on the image. Blob detection is then carried out on the frame, and the blobs are matched with images from the training database.
Step 6: check is performed to determine if there is a match between the input frame and the database images.
Step 7: an array is created, and the program is written to identify food and determine if calorie information is desired.
Step 8: if statements are used to increment the count whenever food is identified. To obtain the count we use if statements to increment count when identified.

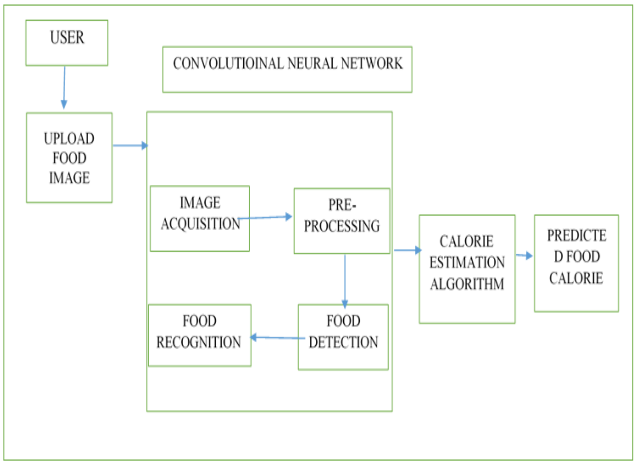

Figure 1: System Design and Architecture

System design encompasses the meticulous process of formulating a comprehensive plan or blueprint tailored to fulfill the specified requisites of a system. This undertaking entails delineating the architecture, constituent elements, interfaces, and requisite data indispensable for realizing the envisaged outcome. Fundamentally, system design epitomizes the application of systemic principles within the ambit of product development. Its pivotal role in software engineering is underscored by the profound impact that the quality of design exerts on the ultimate deliverable.

Throughout the design phase, the primary objective is to discern the requisite modules essential for constructing the system and delineate their optimal arrangement to ensure efficient fulfillment of requirements. This pivotal phase represents a linchpin in the problem-solving continuum, laying the groundwork for the entire project's trajectory. The overarching aim is to sculpt a holistic software design that comprehensively incorporates all essential components and interfaces.

The paramount aim of system design is to craft a blueprint facilitating the development team's endeavor to erect a system that meticulously aligns with the specified requirements in the most efficacious manner conceivable. This endeavor entails meticulous consideration of factors such as scalability, maintainability, and performance. By crafting a robust design, the team can ensconce the delivery of a product of unparalleled quality, impeccably attuned to the needs and expectations of end-users.

1. Indian Food Dataset

Dataset: The compilation of the Indian Food dataset encompasses an array of food categories, each accompanied by a collection of sample images. Nevertheless, the dataset is marred by certain limitations, notably the presence of noise attributed to images featuring multiple food items and instances of mislabeling. Moreover, a significant portion of the images exhibits vibrant color saturation. The accompanying figure serves to exemplify the assortment of food images encapsulated within the Indian Food dataset.

2. Image Preprocessing

The Indian Food dataset is segregated into distinct subsets, namely the training and testing sets, comprising diverse categories of food images. The training set comprises representative images from each category, while the testing set encompasses the remaining images. Cumulatively, the dataset comprises a predetermined quantity of images allocated for training purposes, with a corresponding number earmarked for testing. Subsequently, the Convolutional Neural Network (CNN) model is trained utilizing the images from the training set, followed by an evaluation of its performance against the testing set.

3. Training the CNN Classifier using Pretrained Models

In the pursuit of training the model, the Transfer Learning technique is employed. Primarily utilized for image recognition endeavors, the Convolutional Neural Network (CNN) stands as a quintessential variant of Deep Neural Networks. Comprising pivotal layers including hidden and fully connected layers, the CNN assumes responsibility for feature extraction and learning from training images via its hidden layers, while the fully connected layers facilitate image classification. Inspired by the intricate architecture of the human nervous system, characterized by interconnected neurons, the CNN mirrors this mechanism, with neurons transmitting messages akin to layers communicating to extract features from input data.

Functioning through a succession of layers, the CNN employs convolutional layers to execute convolution on the input data using filters, thereby extracting pertinent features. The proposed system incorporates four layers, encompassing the convolution, ReLU, pooling, and fully connected layers, synergistically harmonizing to extract features from input data. Boasting a CNN architecture comprising seven convolutional layers, each equipped with a kernel size of xyz, the system further integrates max-pooling layers to diminish image dimensions while preserving spatial invariance, thereby mitigating computational overheads. The ReLU activation function fosters expedited training through its propensity for

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sparser outputs and nullification of negative elements, thereby forestalling over fitting. Furthermore, a dropout rate of 0.8 is implemented as a precautionary measure against over fitting, while the fully connected layer serves to map and classify features for image categorization.

The utilization of the soft max function as a final layer in classification tasks serves to transform the output scores of the penultimate layer into a probability distribution across classes, with the cross-entropy loss function employed to train its parameters. This integral function culminates in the conversion of predicted probabilities into a comprehensive probability distribution, thereby facilitating the classification process.

4. Validation and Testing Custom Dataset

Following the model's training on the designated training dataset, constituting a subset of data aimed at instructing the model, the model undergoes validation utilizing a separate validation dataset. This distinct dataset serves as a means to impartially assess the model's efficacy while iteratively refining its hyper parameters. Subsequently, the model's veracity is put to the test utilizing a dedicated test dataset, serving as a representative sample of data essential for evaluating the model's capacity for generalization and its adeptness in rendering precise predictions on novel, unseen data instances

5. Caloric Extraction from Classified Images

Subsequent to scrutinizing the food image and ascertaining its categorization, our classifier is poised to extrapolate the calorie content inherent within the food item based on the pre-existing dataset. Additionally, the classifier furnishes an accuracy metric delineating the precision of the calorie estimation procedure.

IV. EXPERIMENTAL AND RESULT

This section delineates the empirical outcomes derived from our system. In this endeavor, we amalgamated Graph Cut segmentation with deep neural network techniques. The fusion of these methodologies facilitated a substantial enhancement in the precision of our food classification and recognition endeavors, surpassing the achievements detailed in our prior study [12]. By leveraging the dual models to identify food portions and employing the size and shape attributes gleaned from the graph cut algorithm, we can ascertain the aggregate calorie content of the food portions.

Preceding the implementation of the image recognition algorithm within the Android application, our approach initiates with the generation of a pre-trained model file utilizing the CNN network. This process entails the initial acquisition and labeling of a corpus of images belonging to a specific class (e.g., 50 images of the apple class), constituting the set of relevant (positive) images. Subsequently, the system undergoes training using these images, followed by retraining with a set of negative images (i.e., images devoid of the relevant objects). In our scenario, the system is trained with background images to preclude their misclassification as part of the image class. Upon the generation of the model file from the training phase, it is seamlessly integrated into the Android application and subjected to testing using images captured and submitted by the user. The label with the highest probability is presented to the user via a dialog box for confirmation of the object name. Upon user affirmation, if the suggested food type is deemed accurate, the user selects "Yes," prompting the application to display the estimated calorie value of the food type. Conversely, if the user deems the suggested food type inaccurate, they opt for the "No" button, eliciting a prompt for the user to input the correct food type. Subsequently, the application displays the estimated calorie value based on the user's input.

Our dataset encompasses 30 distinct categories of food and fruits, partitioned into training and testing sets, with approximately 50% of the fruit images allocated to train the system, while the remaining images constitute the testing set. As illustrated in Figure 5 and detailed in Table 3, the incorporation of graph cut segmentation and the Deep Neural Network algorithm has yielded enhanced recognition capabilities. Our system adeptly identifies food portions with a high degree of accuracy, achieving a recognition speed of 3 seconds.

Table 1 repeated uncertainty of measurement

food items	Real calories	Average calories	Standard error
Red apple	80	80	0
Orange	71	70	0
Tomato	30	30	0.01
carrot	30	28	0.1
bread	68	68	0.6
Pasta	280	276	0.4
Egg	17	17	0
Banana	10	10	0
Cucumber	30	30	0.26
Green pepper16	16	16	0.04
Strawberry 53	53	52	0.5

The results presented in Table I evince a remarkable 99% accuracy in our single food portions. Furthermore, our measurement methodology encompasses the repetition of the same measurement multiple times to bolster confidence in the experimental data. This iterative approach enables a more precise estimation of uncertainties by evaluating the

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reproducibility of the measurements. Key statistical quantities such as average (or mean), standard deviation (a measure of data dispersion), and standard error (an estimate of uncertainty in the average of measurements) are paramount when dealing with repeated measurements. Each category within our dataset comprises more than 100 images, and the corresponding statistical summaries are delineated in Table 1.

Table 2 food recognition accuracy for single food

S. NO	Food items	Using color-texture segmentation	Using graph-cut-c0lor-texture segmentation	Using deep neural network method
1	Red apple	97.64	100	100
2	Orange	95.59	97.5	100
39	Corn	94.85	96	99.5
4	Tomato	89.56	95	100
5	Carrot	99.79	100	100
6	Bread	98.39	99	99
7	Pasta	94.75	98	100
8	Sauce	88.78	92	98
9	Chicken	86.55	89	100
10	Egg	77.53	83	100
11	Cheese	97.47	97	100
12	Meat	95.73	96	100
13	Onion	89.99	93	99.5
14	Beans	98.67	98	100
15	Fish	77.7	85	100
16	Banana	97.65	97	100
17	Green apple	97.99	97	99
18	Cucumber	97.66	98	100
19	Lettuce	77.55	85	100
20	Grapes	95.7	95	99

The findings indicate that the mean calorie estimates closely approximate the actual values, underscoring the system's precision. Furthermore, the narrow range of standard error underscores the accuracy of the system. The comprehensive accuracy of the system employing both methodologies is detailed in Table 2.

V. FUTURE WORK

Expanding the array and diversity of sensors employed in the project would enable us to detect food spoilage across a broader spectrum of food items. Enhancements to the software model could refine its precision in identifying spoiled or stale food when presented with real-time images of such items. Our prospective agenda entails augmenting our image database and implementing the methodology delineated in this paper to evaluate composite food compositions. Subsequent investigations in this domain might entail crafting more intricate models aimed at tackling these hurdles and enhancing the precision and applicability of such models. Ultimately, the progression of food identification and calorie estimation methodologies could wield substantial influence in fostering nutritious dietary practices and enhancing healthcare results.

VI. CONCLUSION

Food recognition and calorie estimation represent pivotal endeavors within the realms of computer vision and healthcare, holding substantial ramifications for dietary surveillance, weight regulation, and medical care. Recent strides in deep learning, notably leveraging convolutional neural networks, have yielded encouraging outcomes in precisely discerning food categories and gauging their caloric value based on images. Nevertheless, persistent challenges persist in this domain, including fluctuations in serving sizes, ambient illumination disparities, and food arrangement intricacies, alongside the integration of supplementary data like ingredient compositions and nutritional profiles. With the aid of the devised hardware model, we successfully identified spoiled food and employed the software model to forecast and compute the caloric content of various fruits and vegetables. Expanding the array of sensors employed in the project will enable us to extend the detection of food spoilage to a broader spectrum of food items. Additionally, enhancements to the software model can refine its accuracy in identifying spoiled or stale food through real-time analysis of uploaded images. The objective of our study is to equip users with a sophisticated, intuitive, and precise system aimed at fostering awareness of their calorie consumption. Employing a distinctive blend of graph cut segmentation and deep learning neural networks, we aimed to accurately categorize and identify food items. Our findings demonstrate that this fusion yields a robust tool capable of achieving a 100% accuracy rate in food recognition within our system. We also outlined the implementation of a virtualization strategy for the application, enabling us to leverage cloud-based resources. Moving forward, our plan entails expanding our image database and applying the methodology outlined in this paper to assess mixed food portions.

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