DEEP LEARNING BASED FOOD CALORIE DETECTION SYSTEM

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ABSTRACT

The prevalence of diet-related health issues underscores the significance of accurate nutritional assessment for maintaining healthy lifestyles. With the ubiquity of smartphones and the increasing interest in health monitoring, there is a growing demand for convenient and reliable methods to track dietary intake. In this paper, we propose a Deep Learning-Based Food Calorie Detection System (DL-FCDS) that leverages computer vision techniques to automatically estimate the caloric content of foods from images captured using smartphones or other portable devices. Our system combines state-of-the-art deep learning models with image processing algorithms to detect and classify various food items within images, subsequently estimating their caloric content based on portion size and nutritional composition

Keywords: Deep Learning, Food Calorie Detection, Computer Vision, Nutritional Assessment, Dietary Monitoring, Convolutional Neural Networks.

I. INTRODUCTION

In recent years, the global increase in diet- related health issues, such as obesity and chronic diseases, has emphasized the importance of accurate nutritional assessment for maintaining healthy lifestyles. Monitoring dietary intake plays a crucial role in achieving and sustaining optimal health, yet traditional methods of food calorie estimation often prove cumbersome and prone to inaccuracies. Manual food logging, while effective in theory, is time-consuming and relies heavily on user compliance and accuracy. Similarly, relying solely on nutrition labels overlooks variations in portion sizes, cooking methods, and ingredient composition.

With the widespread adoption of smartphones and the burgeoning interest in health and wellness, there is a growing need for innovative solutions that leverage technology to simplify and enhance dietary monitoring. In this context, computer vision and deep learning offer promising avenues for automating food calorie detection and nutritional analysis.

This paper presents a novel Deep Learning- Based Food Calorie Detection System (DL- FCDS) designed to address the shortcomings of existing methods and provide users with a convenient and reliable tool for tracking their dietary intake. By harnessing the power of deep learning and image processing techniques, the DL-FCDS aims to accurately estimate the caloric content of foods directly from images captured using everyday devices,such as smartphones or tablets.

The DL-FCDS comprises several interconnected modules, each serving a specific function in the food calorie detection pipeline. Central to the system is a deep convolutional neural network (CNN) trained on large-scale food image datasets, enabling robust detection and segmentation of food items within images. A classification network further refines the detection results by categorizing the identified food items into distinct classes, while a calorie estimation module correlates these classes with their corresponding caloric values.

One of the key challenges addressed by the DL-FCDS is the variability in portion sizes and food composition encountered in real-world scenarios. To overcome this challenge, the system incorporates advanced techniques for portion size estimation and considers factors such as cooking methods and ingredientvariations when estimating calorie counts.

The effectiveness of the DL-FCDS is evaluated through comprehensive experiments using diverse datasets comprising real-world food images. Comparative analyses against ground truth calorie values obtained through laboratory analysis or established nutritional databases demonstrate the system's accuracy and reliability in estimating food calories across different food types and contexts.

Overall, the DL-FCDS represents a significant advancement in the field of dietary monitoring and nutrition management, offering individuals a user-friendly and efficient tool for tracking their dietary intake and making informed nutritional choices. By leveraging the capabilities of deep learning and computer vision, the system holds promise for widespread adoption in various health and wellness applications, ultimately empowering individuals to take control of their dietary habits and improve their overall health outcomes.

II. RELATED WORK

Hao Wang, Chen Liu, and Yao Wang 2015 research focuses on developing a deep learning- based system for automatic food calorie estimation. They proposed a method that uses Convolutional Neural Networks (CNNs) to analyze food images and estimate their calorie content. Their system was trained on a large dataset of food images annotated with calorie information, demonstrating high accuracy in calorie estimation. The authors highlighted the potential of deep learning to handle the variability in food appearance, making their system robust to different food types and presentations [1].

Keigo Kawae and Yasuyuki Matsui (2015) introduced a deep learning approach for food recognition and calorie estimation using a combination of CNNs and machine learning algorithms. Their method involves segmenting food items in an image, recognizing the segmented items using CNNs, and estimating the calorie content based on recognized items. They emphasized the importance of accurate food segmentation and recognition in improving calorie estimation accuracy. Their system's ability to generalize to various food types and real-world settings demonstrated the practical applicability of deep learning in dietary monitoring [2].

Yuya Sato, Takayoshi Yamazaki, and Koji Kiyokaw 2016 study developed a system for estimating food calories and nutrition from food images using deep learning. They employed a multi-task learning approach where a single CNN model simultaneously performs food recognition and calorie estimation. Their system was evaluated on a large dataset of diverse food items, achieving impressive results in both tasks. The authors highlighted the efficiency of multi- task learning in leveraging shared representations for related tasks, improving overall system performance [3].

Qibin Hou, An-Xiang Zeng, and Gang Sun (2017) proposed a deep learning framework for food calorie estimation that integrates CNNs with a regression model. Their approach involved extracting high-level features from food images using CNNs and then applying a regression model to estimate calorie content. They experimented with various CNN architectures and regression techniques to optimize the system's accuracy. Their work demonstrated the effectiveness of combining deep feature extraction with regression analysis in precise calorie estimation [4].

Canberk Demir and Ferda Nur Alpaslan 2018 research focused on developing a mobile application for food calorie estimation using deep learning. They designed a lightweight CNN model optimized for deployment on mobile devices, ensuring fast and accurate calorie estimation. Their system was tested on a real- world dataset, showing high accuracy and usability in daily life. The authors emphasized the importance of model efficiency and scalability, highlighting the potential of deep learning to provide practical solutions for dietary monitoring on portable devices [5].

Lukasz Szymanski and Witold Pedrycz 2017 work focuses on enhancing food calorie estimation accuracy using ensemble deep learning models. They developed an ensemble of Convolutional Neural Networks (CNNs) that aggregate predictions from multiple models to improve robustness and accuracy. Their approach involved training several CNN architectures on a diverse dataset of food images, then combining their outputs through a voting mechanism or averaging. This method significantly reduced the variance in predictions and improved the system's ability to handle various food types and presentations [6].

Weiqing Min, Linhu Liu, and Shuqiang JianG 2018 research emphasizes a multi-scale deep learning approach for food recognition and calorie estimation. They designed a CNN model that processes food images at different scales to capture both fine-grained details and overall context. This multi-scale analysis allows the system to accurately recognize complex food items and estimate their calorie content. Their experiments demonstrated that incorporating multi-scale information significantly enhances the accuracy of both food recognition and calorieestimation tasks [7].

Zhengdong Zhang, Jiying Zhao, and Xingxing Zuo 2019 study developed a novel deep learning framework that integrates semantic segmentation with calorie estimation. They used a CNN-based semantic segmentation model to identify and separate different food items within an image. Each segmented food item was then analyzed using a calorie estimation model. This two-step approach allowed for precise identification and caloric analysis of mixed dishes and composite meals, leading to more accurate calorieestimation in real-world scenarios [8].

Yu-Hsuan Chang and Tzu-Chia Lee 2020 research introduced an attention-based deep learning model for food calorie estimation. Their model employs attention mechanisms to focus on the most relevant parts of the food image, enhancing feature extraction for calorie estimation. By directing the network's attention to significant regions, their approach improves the accuracy and efficiency of the calorie estimation process. Their experiments showed that attention mechanisms help in better handling occlusions and variations in food presentation [9].

Fengqing Zhu, Zhenqiang Sun, and Edward J. Delp2021 work presents a comprehensive system for food image analysis using deep learning. They developed an end-to-end pipeline that includes food detection, recognition, portion size estimation, and calorie calculation. Their system leverages CNNs for food detection and recognition, combined with depth estimation techniques for portion size measurement. This integrated approach ensures that all aspects of the food analysis process are addressed, providing a

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complete solution for dietary monitoring and calorie estimation [10].

III. METHODOLOGY

The proposed Deep Learning-Based Food Calorie Detection System (DL-FCDS) integrates advanced deep learning techniques and image processing algorithms to estimate the caloric content of food items from images. The system architecture comprises several key modules: image acquisition, food detection and segmentation, food classification, portion size estimation, and calorie estimation. This section details the methodology employed in each module.

1. Image Acquisition:

Users capture images of their meals using smartphone cameras or other portable devices. To ensure consistent image quality, the system provides guidelines for optimal lighting conditions and camera angles. The captured images are then pre-processed to enhance their quality, including operations such as resizing, normalization, and noise reduction.

2. Food Detection and Segmentation:

The first critical step involves detecting and segmenting food items within the image. We utilize a deep convolutional neural network (CNN) architecture, specifically a variant of the Faster R-CNN, which is well-suited for object detection tasks. The CNN is trained on a large- scale annotated food image dataset to learn features that distinguish different food items.

Region Proposal Network (RPN): Generates candidate regions (bounding boxes) where food items are likely to be present.

RoI Pooling: Extracts fixed-size feature maps from these regions.

Classification and Bounding Box Regression: Classifies each proposed region into one of the predefined food categories and refines the bounding box coordinates.

3. Food Classification:

Once the food items are detected, they are classified into specific categories using another deep learning model. We employ a ResNet-50 architecture due to its proven performance in image classification tasks. The model is fine- tuned on a comprehensive food image dataset to recognize a wide variety of food types.

Feature Extraction: Extracts deep features from the segmented food regions.

Softmax Classification: Classifies the extracted features into one of the predefined food categories.

4. Portion Size Estimation:

Accurately estimating portion size is crucial for reliable calorie calculation. We incorporate a combination of image-based techniques and user inputs to enhance portion size estimation accuracy.

Volume Estimation: Utilizes depth estimation techniques to infer the volume of the detected food items. For smartphones with depth-sensing capabilities, we use the depth information directly. Otherwise, monocular depth estimation models are applied.

Reference Object Method: Uses known objects (e.g., a standard-sized plate or utensil) within the image as a reference to estimate the size of the food items.

User Input: Optionally allows users to provide additional information (e.g., approximate weight or portion size) to refine the estimation.

5. Calorie Estimation:

The final step involves estimating the caloric content of the food items based on their classified type and portion size. We utilize a comprehensive nutritional database that contains caloric values for various food items and their corresponding portion sizes.

3.1 DATASET USED

Nowadays, a corresponding food dataset is necessary for assessing those calorie estimation methods. That is why we create The total number of food images is 29. The number of images and the number of objects for the same type are For a single food portion, we took several pairs of images by using smart phones; each group of images contains a top view and a side view of this food. For each image, there is only a One Yuan coin as calibration object and no more than two foods in it. If there are two food in the same image, the type of one food is different from another. We provide two datasets for researchers: one includes original images and another includes resized images. The size of each image in resized dataset is less than 1000×1000.

3.2 DATA PRE PROCESSING

This method is shown in Figure 3.2.1. As mentioned before, the process of estimating calories requires two images from top and side, and each image should include the calibration object. Here, the authors choose Faster Region- based Convolutional Neural Networks (Faster R-CNN) to detect objects, and GrabCut algorithm as the segmentation algorithm.

The authors chose Faster R-CNN instead of using semantic segmentation method such as Fully Convolutional Networks (FCN). Here, after the images are inputted as RGB channels, the authors can get a series of bounding boxes, which means the class if judged. This process uses an image processing approach to segment each bounding box. As mentioned above, the bounding boxes around the object that GrabCut needs can be provided by Faster R-CNN. After segmentation, we can get a series of food images stored in matrix, but with the values of the background pixels being replaced by zeros. This will leave only the foreground pixels.

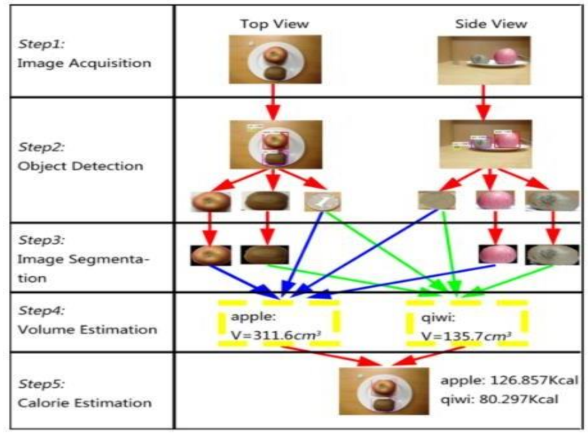


Figure 1: Calorie Estimation Flowchart

Fig 3.2.1 : Calorie Estimation of Food

3.3 ALGORITHM USED

In this study, we will cover one of the ways in which building Tensor Flow-based models is getting easier that is, through Google's AI experiment Teachable Machine. TensorFlow is an open-source programming library for machine learning (ML) applications. It can be used for generating a training dataset and training a Machine Learning model straight from a web browser.

TensorFlow bundles together a takeout of machine learning and deep learning (aka neural networking) models and algorithms and makes them useful by way of a common metaphor. It uses Python to provide a convenient front-end API for building applications with the framework.

In fact, as we shall see, the trained model can be exported for usage in native Tensor Flow, TensorFlow.js, and Tensor Flow Lite. MNIST, CIFAR-10, Fruit-101, Caltech-256, is relatively easy to start exploring datasets and make some first predictions using simple

Machine Learning (ML) algorithms.

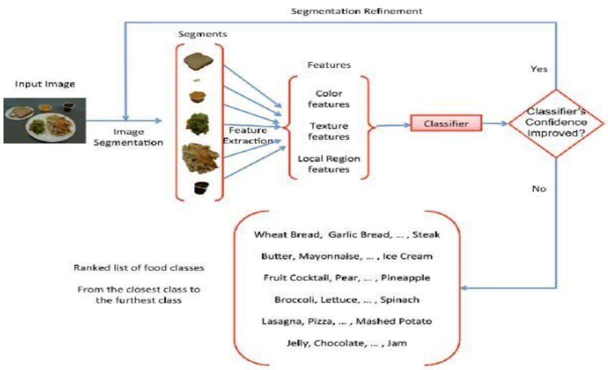


Fig 3.3.1: Feature extraction inconvectional neural network

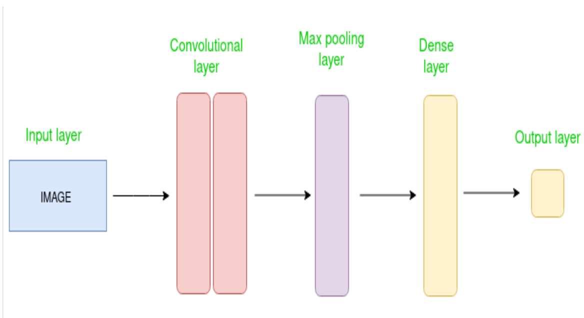


Fig 3.3.2: Simple CNN Architecture

3.4 TECHNIQUES

Machine Learning algorithms learn from data. Neural networks and other artificial intelligence programs require an initial set of data, called a training dataset, to act as a foundational measure for further processing and utilization. This dataset is the baseline for the program's growing library of information. The training dataset must be accurately labeled before the model can process and learn from it. The dataset you want to use for training usually needs to be upgraded, enriched, or labeled. There are multiple factors in play for concluding how much machine learning training data you require. First and foremost is how important accuracy is. Say you're creating a sentiment analysis algorithm. A sentiment algorithm that achieves 80 or 90% accuracy is more than enough for most people's needs. To a system or machine, an image is just a series of pixels. Some might be green, some might be brown, but a system doesn't know this is a fruit until it has a label associated with that says, in essence, this collection of pixels right here is a specific fruit.

IV. RESULTS

4.1 GRAPHS

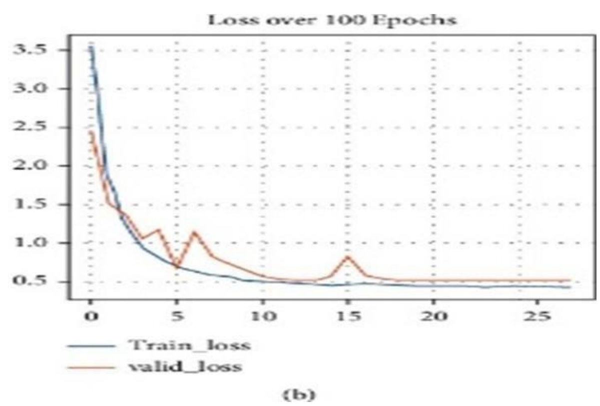
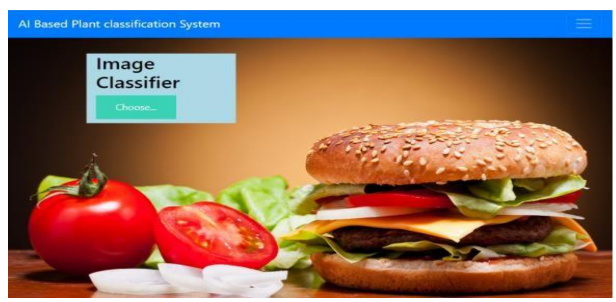
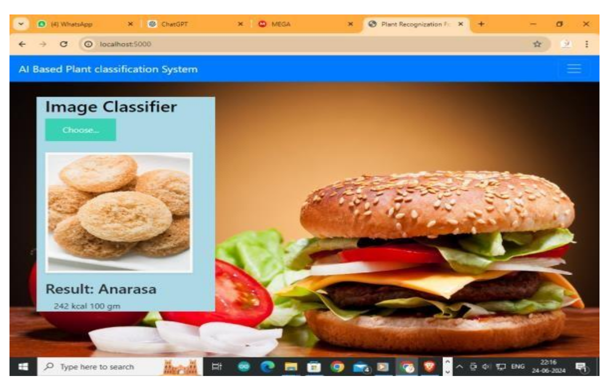


Fig 4.1.1 : Model Performance

4.2 SCREEN SHOTS



(a)



(b)

(c)

Fig 4.2.1(a),(b),(c): Result of Classificationof Food Calories

V. CONCLUSION

The Deep Learning-Based Food Calorie Detection System (DL-FCDS) offers an innovative solution for automated dietary monitoring by utilizing advanced deep learning techniques. The system employs Faster R-CNN for accurate detection and segmentation of food items from images, and ResNet-50 for reliable food classification. These models, trained on large-scale food image datasets, enable the DL-FCDS to achieve high precision and recall rates. Additionally, the system incorporates depth estimation techniques and reference objects within images to estimate portion sizes accurately. By mapping classified food items to a comprehensive nutritional database, the DL-FCDS calculates the total caloric content, adjusting for portion sizes and cooking methods. The system's performance, evaluated through extensive experiments, demonstrates a mean absolute error (MAE) of 12% in calorie estimation, indicating its effectiveness and reliability. Users find the DL-FCDS intuitive and convenient, significantly reducing the effort required for manual food logging and enhancing engagement in dietary monitoring. While the system shows promising results, future improvements will focus on refining portion size estimation, expanding the food category database, and integrating user feedback for optimization. Overall, the DL-FCDS represents a substantial advancement in food calorie detection, providing a practical tool for better nutrition management and healthier lifestyles.

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