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Food Processing and Calorie Detection

Shubhangi Solanke
Department of Computer Engineering,
Jayawantrao Sawant college of engineering, Pune, India
shubhangimalas1@gmail.com

Bhushan Patil
Department of Computer Engineering,
Jayawantrao Sawant college of engineering, Pune, India
bhushanpatil0348@gmail.com

Keshav Shelar
Department of Computer Engineering,
Jayawantrao Sawant college of engineering, Pune, India
ksshelar30@gmail.com

Vishwajeet Patil
Department of Computer Engineering,
Jayawantrao Sawant college of engineering, Pune, India
vishwajeetpatil2111@gmail.com

Suraj Raut
Department of Computer Engineering,
Jayawantrao Sawant college of engineering, Pune, India
surajraut1434@gmail.com

***Abstract*— Abstract: Food is one of the most basic needs of all living things on Earth. People want the food they eat to be pure, fresh, and of a standard quality. The food processing industry's automation and standards-setting mechanisms ensure the quality of the food. Worldwide, people are becoming increasingly sensitive to food these days. An unbalanced diet can result in weight gain, obesity, diabetes, and other problems. As a result, numerous algorithms were developed to assess food images and calculate calories. This method proposes a powerful deep Convolutional Neural Network (CNN) architecture to locate and recognize local food photographs. Food is available in a wide range of flavors, textures, and shapes, which emphasizes how challenging it is to recognize food in pictures. Conversely, deep learning has become more and more well-liked as a successful picture-recognition method. We created a system for identifying foods and estimating calories, which uses a picture of a meal as input to determine a person's daily caloric intake. We provide a fresh dataset of the most well-liked foods, collected from publicly available web resources. Convolutional neural networks, or CNNs, are used as classifiers to identify foods, and we can determine a food's calorie content based on its gram weight.**

Keywords — Calorie estimation, deep learning, convolutional neural networks, and food detection and recognition.

I. INTRODUCTION

When it comes to food identification, food classification still mostly depends on time-consuming and costly manual evaluation. In order to persuade increasingly sensitive consumers, it is imperative that food commodities be classified with greater accuracy. Food categorization that is done automatically can reduce production costs by improving production speed and efficiency while maintaining classification accuracy.

Computer vision systems have been used much more in food identification and classification methods in recent years. In the parts that follow, we will briefly go over food detection and recognition techniques. Color and texture are the main components of natural images and are essential to visual perception. Color has been used to differentiate objects for a long time. Color classification initially retrieves the spectral properties of object surfaces. Next, it will be compared against a set of widely recognized descriptions or class models to see which match is the best. The things we eat control our bodies. Because of this, a diet plan needs to continuously take into consideration the total number of calories required to maintain a healthy and fit lifestyle. However, most of the time people find it challenging to estimate and measure the amount of food they eat because of a lack of nutritional information, which includes a laborious process of writing down this information, among other issues. Thus, a mechanism for keeping an eye on and maintaining caloric intake should be in place. Therefore, it is equally important to precisely estimate meal calories in such circumstances.

Thanks to advances in deep learning and convolutional neural networks, the capacity to identify and classify objects has grown dramatically over the past three years. To live a healthy and active life, one must effectively classify and recognize food objects using this technology. Still, it would take an inordinate amount of time to keep bringing up the nutritional content of every single food item. Food image recognition provides a quick and easy method to determine an individual's dietary caloric intake and evaluate their eating patterns by using cameras to track food consumption. A precise estimation of daily food consumption is a useful strategy for preserving health and preventing illness.

II. LITERATURE REVIEW

The various existing food detection and calorie estimation and their standards are discussed below:

1: Meng-Lin Chiang, Jiankai Feng, Chia-An Wu, Chiung-Yao Fang, et al. [4] To give health information on the food we eat, this paper introduces a system that takes advantage of the widespread use of mobile devices. To identify food classes, and food masks, and label food calories and nutrients, this work employs food photos as input to a system based on Mask R-CNN. The system uses a Mask Region-based Convolutional Neural Network (R-CNN) with union post-processing to improve the results of analysis and visualization by modifying the generated bounding boxes and masks without using non-maximum suppression (NMS). Villa Cafe and the Food-256 Datasets together had a recognition accuracy of 99.86% and an intersection over union (IOU) of 97.17%. Eight meal classes made up the food weight estimation experiment: salad, fruit, bread, sausage, bacon, ham, patties, and French fries. Using the linear regression model, these classes included a total of 320 data points, which were divided among 40, 40, 44, 40, 41, 49, 26, and 40 data points, respectively. The average absolute error was 8.22 in the experimental results, while the average relative error was 0.13.
FHIR Chain, designed to meet the criteria set by the Office of the National Coordinator (ONC), adheres to Health Level 7 (HL7) and Fast Health Interoperability Resource (FHIR) standards. This framework ensures decentralized storage and preserves data ownership rights. FHIR Chain utilizes trustless decentralized storage for metadata, facilitating data exchange without the need for data downloads or uploads. Identity and authentication are secured through encrypted reference pointers.

2: Shika Gupta, Priya Gupta, et al. [2], in this paper, To determine or estimate calorie intake, an effort has been made in this paper to determine or classify food using image processing in conjunction with other intelligent algorithms. Our study serves as the foundation for contemporary remote, computer-assisted dietary management systems. Our approach consists of segmenting the food in the image, extracting image attributes from the segmented food area, such as area, major axis, and minor axis convex area, & then utilizing an artificial neural network that has already been trained to categorize the food based on these parameters. Food segmentation has been accomplished using a combination of techniques, including the detection of surface features and bags of features, the removal of the background using HCV processing, etc. By combining several image processing methods with a leven-barg Marquardt function flitting neural network, high detection accuracy can be achieved.

3: Haoyu Hu, Zihao Zhang, Yulin Song [3], in this paper the detailed explanation of CNN – (Convolution Neural Network) is given. CNN is made up of an input layer and a hidden layer. The hidden layer consists of the following sublayers 1. Convolution layer, 2.The pooling layer, 3.The fully connected layer, 3.Output layer. This paper gives the idea of working with CNN. This paper teaches us how to improve the accuracy of our model. It uses multiple mathematical methods to increase its accuracy.

III. PROPOSED SYSTEM

A novel algorithm for food recognition is introduced, taking into account the attributes of food such as size, shape, color, and feel. A more accurate classification will be made by combining different combinations of these features. A potent and adaptable supervised deep learning algorithm for both regression and classification is CONVOLUTIONAL NEURAL NETWORK. An existing concept that uses the input image to identify and detect food items is called "food recognition." 101 different food categories are used to train our model. Additionally, the goal is to calculate the food item's estimated calorie content. To identify the food item, a convolutional neural network (CNN) is employed. We have included the standard calorie value for one gram of each food item in order to further estimate the number of calories. The precise calorie value of the food item is computed using the weight of the food item as an input and standard calorie value.

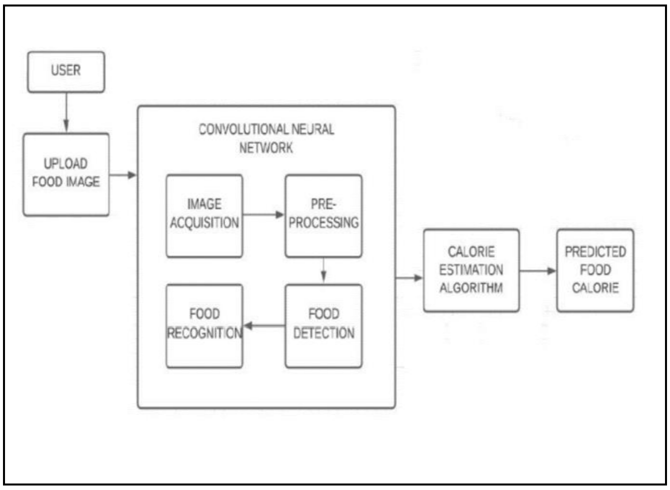

Fig. 1. Proposed System

The following features are included in the system we are suggesting for food processing and calorie detection:

1. Identification of Foods

2. Calorie Identification

3. Meal Schedule

4 Meal Intake Record

Utilizing CNN approaches, the suggested system is constructed in Python and has the ability to anticipate gestures, including the alphabet or number that a user is attempting to express. The methods employed in the suggested system is listed below.

- Kaggle was the source of the image data.
-The gathered dataset is split into two sections. for example: 20% for testing and 80% for training.
-A variety of methods are used, including feature extraction and pre-processing.
-A web application was constructed with Vue for the front end and Django for the back end. -Classification was done using CNN.
-The captured image feature is extracted and the user-taken image is passed.
-The trained model will be compared with the extracted features, and the anticipated output will be determined by the proximity of the match.

IV. METHODOLOGY

A method for several common image bracket problems is provided by the convolutional neural network (CNN). Applying it to food brackets has resulted in a good delicacy. In comparison to traditional methods, CNN performs better and is therefore frequently used in the food recognition industry. The sophistication of identifying and retrieving food photographs has grown over the past many years as a result of developments in deep literacy, particularly in convolutional neural networks. This is due to improved deep infrastructures and novel techniques in addition to larger datasets. Because Le Net was its creator, Convolutional Neural Network (CNN) is sometimes known by that name. Information Technology Department, Savitribai Phule Pune University JSCOE. Convolutional, pooling, and sub-sampling layers make up the majority of CNN, with fully connected layers coming last. The CNN applies subsampling and convolution on an input image. The data is passed into the fully connected neural network, which executes the bracket task, after two comparable computations. CNN's key benefit is its robustness against minor reels and shifts, and its capacity to learn the high-position effective features.
Three layers make up a convolutional neural network: an input layer, a hidden layer, and an output layer.

Input Layer
Multi-dimensional data can be handled by the convolutional neural network's input subcaste. This design takes RGB channels and two-dimensional image pixels as input data since it makes use of convolutional neural networks for computer vision operations.

The Convolutional Layer
Several complication kernels in the convolutional layer can be utilized to extract features from the input data. Each member of the complexity kernel correlates to a weight measure and a bias, much like feed-forward neural network neurons. Near the antedating sub-caste, each neuron has connections to several other neurons. In order to create a dependable affair, the complication kernel at work will periodically ignore the input features, multiply and sum the input features by matrix rudiments, and add bias.

Pooling layer
Point selection and information filtering of affair point mapping will be carried out by the pooling subcaste following the completion of the convolutional subcaste's point birth. The preset pooling function, which is a part of the pooling subcaste, substitutes the statistics of the conterminous areas of a point chart for the results of a single point in the point chart. The complication kernel examines the point chart that is governed by the stuffing, step size, and pool size concurrently with the pooling subcaste selection.

Fully connected layer
In a convolutional neural network, the fully connected subcaste is positioned similarly to the retired subcaste in a feed-forward neural network. A convolutional neural network's retired subcaste's final segment only communicates with the other subcaste that is fully linked. The point chart translates the activation function and expands the spatial topology into a vector in the entirely linked subcaste.

Output Layer
The construction and operation of the completely connected subcaste are similar to those of the affair subcaste of a conventional feed-forward neural network since it is typically located upstream of the affair subcaste of a convolutional neural network. Because of the affair subcast, the object's central equals, size, and bracket are affair in this design.

V. CONCLUSION

The research findings indicate that it is possible to achieve automatic food image recognition and feature extraction. The existing food recognition methods based on color and shape attributes are not robust and effective enough. Consequently, a new system for determining food quality is proposed, which combines texture, shape, and size analysis methods to improve recognition accuracy more quickly. This method enables the classification and recognition of food images based on the obtained feature values.
We will apply a basic CNN method to locate and identify food items together with their calorie content. We classified foods and non-foods using the FOOD-101 dataset. We will utilize highly deep convolutional networks (24 weight layers) for food image categorization. The big kernel size at the top of the layers preserves shape features during the learning process. Accurate classification will benefit from having this depth. Prior research confirms that network depth is crucial for training visual representations.

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