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Calorie Measurement and Food Recognition Using Machine Learning

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Abstract

Nowadays, all over the world most people are suffering from different types of diseases or obesity. This is because of bad food habits or eating food without knowing the calorie and other sources from the foods. Precise techniques for gauging food and energy consumption play a vital role in addressing obesity. Offering users or patients accessible and smart solutions to assess their food intake and gather dietary information constitute valuable insights for long-term prevention and effective treatment programs. So innovative health applications that encourage informed food choices and customized nutrition tracking have been developed resulting from the increased prevalence of obesity and diseases linked to lifestyle. A successful method for offering predictions of healthy foods is the health application that uses cutting-edge image recognition technology, Convolutional neural networks (CNN) has been used to deliver real-time nutrition information based on food photographs. The application's CNN system provides accurate food recognition, doing away with the need for laborious database searches or human data entry. Users receive thorough nutritional information, including information on the macronutrient breakdown, micronutrient content, and probable allergies, enabling them to make quick, health-conscious selections.

Keywords: Convolutional neural network (CNN), health application, K nearest neighbor model, VGG16 model, food recognition

INTRODUCTION

An urgent worldwide health concern has arisen resulting from the shocking rise in obesity rates in recent years. Although there are plenty of reasons why this epidemic is spreading, one major and recent one is the ease with which food is obtained online. With the evolution of technology, the digital world has expanded into a huge market for a number of readily available and practical eating options. The necessity of health applications has risen because of the rapid growth of consuming unhealthy and junk foods by people. These health applications help to discover the nutritional properties of a meal item including the quantity of proteins, calories, carbohydrates. etc. This information helps a person to know the standard of the food before eating it. In this project, a health application is created by using machine learning algorithms. Innovative health applications that encourage informed food choices and customized nutrition tracking have been developed. A successful method for offering predictions of healthy foods is the health application that uses image recognition technology, notably, convolutional neural networks (CNNs), to deliver nutrition information based on food photographs.

In Figure 1, graphical representation shows the consumption of junk foods based on gender and age. According to a research study, 42% of Americans

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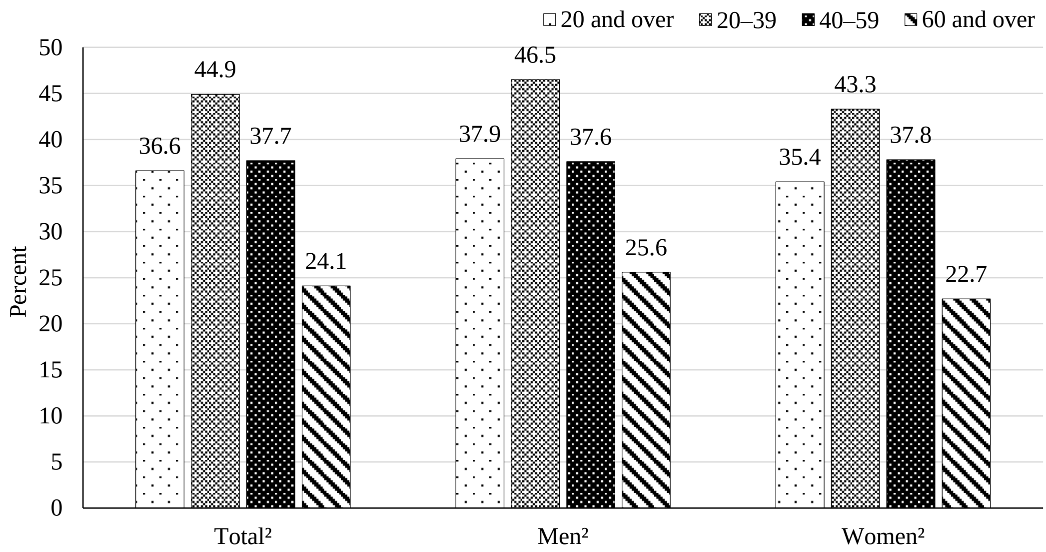

Figure 1. The consumption of junk foods based on gender and ages.

consume fast food as dinner and 43.7% do so for lunch. Men prefer to consume them during lunch more than women do (48.3% vs. 39.1%), specifically. A total of 93% of kids consume packaged food frequently, more than once every week, multiple times a week, and 56% of kids eat desserts, especially ice cream and chocolate. A total of 59% of children between the ages of 14 and 17 years eat packaged food or beverages at least once each day.

RELATED WORK

Almaghrabi et al. [1] constructed the structure and processing of food images recognition. The system takes pictures of the meals both earlier and later consumption in so as to figure out the quantity of calories and nutritious components that were consumed. The proposed system is founded on a novel method that uses the thumb as a calibration. Shape recognition is a component of image processing and includes SVMs (support vector machines) that are successfully employed in an array of domains for recognizing patterns. The nutritional value data are recorded in the database as tables, which produces a precision of 98.23%. It is incredibly difficult for a person to recall the contents and amount of the regular diet intake, and this system's main drawback is that it does not measure food differently taken from a database. The paper's authors have an advantage in that their method yields an accurate result with a respectable error of 4.22%.

Pouladzadeh et al. [2] discussed the process for raising the precision within the system for classifying and identifying foods. The writers of this study have the advantage of using Graph Cut, a tool that is effective, reliable, and competent of locating ideal outline of an image's objectives to calculate calories. Segmentation is also applied. SVM classification model is used, whose results indicate an improvement in the precision of food recognition, particularly for mixed foods by 15%. The authors have used cut segmentation of a graph, color segmentation and texture segmentation, The system's inability to offer information to users in real time, in addition the length of time it takes to do so because of offline picture processing is the primary drawback the authors faced. The authors were successful in boosting accuracy by 3% in 30 various portions of single foods, 5% in non-mixed foods, and 15% in mixed foods.

Pouladzadeh et al.'s [3] review offers the user practical and smart mechanisms that let them maintain a record of their caloric consumption. The system's way for identifying food employs ad hoc machine learning the Map Reduce method approach and training of cloud-based SVM methods. The client can estimate the anticipated calories consumed (food calories before consumption), determine actual calorie consumption (measured by remaining food on the plate), and more using the system's two-step approach. *Advantage:* The system was created utilizing the Android platform by Google and offers an intuitive and simple-to-understand interface. Disadvantages include problems with databases and general cloud computing the writers employed MySQL, Apache, and PHP to do this. Instances on Amazon EC2 were used as the cloud, and maintains a maximum accuracy of 98%, training data is examined for accuracy.

Peddi et al. [4] examined a cloud-based virtualization model that has been proposed by the authors of "E-Health Mobile Application" to provide e-health apps the computational capacity they require to operate effectively. Advantage: Through the use of a speedier processing system and an intelligent decision-making mechanism, cloud servers' ability to distribute the work of processing images saw a considerable improvement in calorie computation of 20.5%. The e-health app's computationally intensive algorithms, such as deep learning (for identifying food images) and calorie measurement, would demand more processing strength to function at their best, and concurrently, such applications would heavily drain a phone's battery. The authors' methodology is as follows: KVM hypervisor, the host OS is Linux, and. a virtual switch between the mobile and cloud sessions.

Pouladzadeh et al. [5] employed traditional as well as cutting-gedge methods, with a focus regard the latter. among the most recently put forth methods is vision-based measuring (VBM), it serves as result, it becomes exceedingly simple for customers to ascertain the quantity of nutrients and calories in their meal by taking a photo of it with their smartphone. Having a total accuracy of 84.9%, the obvious drawback of this strategy is that it lacks to calculate calories until after once the consumer has consumed the food. It is difficult for obese patients who require information on the caloric content of a meal prior to eating it. Higher measurement accuracy and the identification of complicated foods like mixed food calories with VBM are other challenges. Additionally, they used the deep learning method, which offers the benefit of learning extremely useful traits from the data.

Kasyap and Jayapandian [6], with the aid of a deep learning algorithm and the aid of food item detection, have proposed a model to offer an original procedure for calorie measurement. The primary parameters of the outcome take place by volume error estimation, and the secondary parameter is calorie error estimation. With specially crafted features, random forest is among the machine learning methods, and SVMs have a specific accuracy. The precision of the random forest model was 62%, the precision of the SVM model was 67%, and the precision of the CNN model generated with tensor flow was 97%. Advantage: The authors' continual 20% reduction in volume error suggests that CNN's model offers more accuracy. Disadvantage: The training process is affected by learning rate; if learning rate is too low, neural networks will not learn, which may cause test errors.

PROPOSED METHOD

Convolutional neural networks (CNNs) have made significant strides in the quickly developing fields of artificial intelligence and computer vision, emerging as a game-changing tool for image processing jobs. CNNs are a subset of deep models of instruction that were created primarily to analyses visual data and are exceptional at such as semantic segmentation and object detection, and image recognition. Owing to its distinctive architecture, CNNs are particularly useful in many different uses because they automatically learn intricate characteristics and patterns from images [7]. To be able to recognize food using CNNs, a massive dataset of labelled food photos serves to instruct the model. In order to discriminate between various sorts of food products, the network learns to automatically extract useful elements from the photos, including textures, forms, and color patterns. CNN effectively categorizes photographs of different foods and ingredients after being trained, which helps with dietary tracking, nutritional analysis, and custom meal planning as shown in Figure 2.

Computer vision's subfield of image recognition focuses on locating and classifying objects or patterns in visual data. A family model of deep learning known as convolutional neural networks (CNN) was created expressly for image processing applications. CNN analyzes food photographs and accurately categorizes various food kinds, assisting in the identification of certain dishes or food components in images [8].

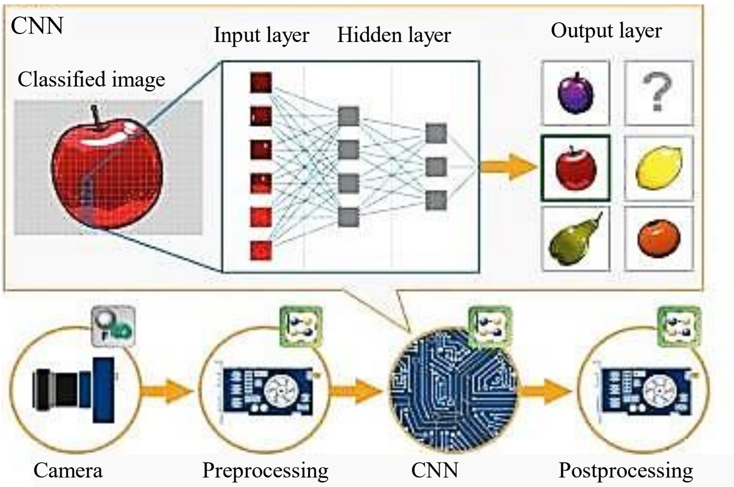

Figure 2. Use of convoluted neural network (CNN) in image classification.

Table 1. The food items.

S.N.	Food item
1	French fries
2	Fried rice
3	Hamburger
4	Omelete
5	Pizza
6	Samosa
7	Spring rolls

- *Dataset:* An extensive collection of photos, nutritional data, and other pertinent details of many processed and fast-food products make up a dataset with multiple junk food items [9]. These mainly consist of fried foods, sugary snacks, fizzy drinks, chips, and other high-calorie, low-nutrient foods usually associated with having poor health impacts when consumed in excess. The development of algorithms and models for automatic food recognition and nutritional analysis is made easier by the availability of huge and varied junk food datasets as shown Table 1. The taken dataset has the photos of the food items shown in Table 1. The dataset has a number of pictures of these food items. It is seen from Table 1 that the dataset has seven categories of foods. The Food Dataset, depicted in Figure 3, was created to identify complex images.
- *VGG16 model:* Transfer learning is frequently used because VGG16 performs so well in picture classification tasks. The model already has knowledge of common visual elements thanks to these pre-trained weights, which enables it to identify simple forms, textures, and colors [10]. The model is further refined using the food-specific dataset in order to adapt VGG16 for food recognition. The model's final layers, which categorizes objects, are changed during this process and trained using the new food dataset, The VGG16 model learns food-specific properties and improves its performance for food recognition.
- *K-nearest neighbors model:* The K-nearest neighbors (KNN) model is utilized as a straightforward yet efficient way for identifying food items based on their features in relation to food recognition. Relevant characteristics are gleaned from the preprocessed food photos in the collection. These characteristics come from a pre-trained CNN model. The KNN model simply stores the feature vectors and matching class labels for the food items from the dataset during the training phase. For the reason that KNN uses an instance-based learning method, no explicit training is required The KNN model calculates the similarity (distance) between the feature vectors of the new picture and the feature vectors of the labeled images in the training dataset when it is given a new food image for recognition [11].

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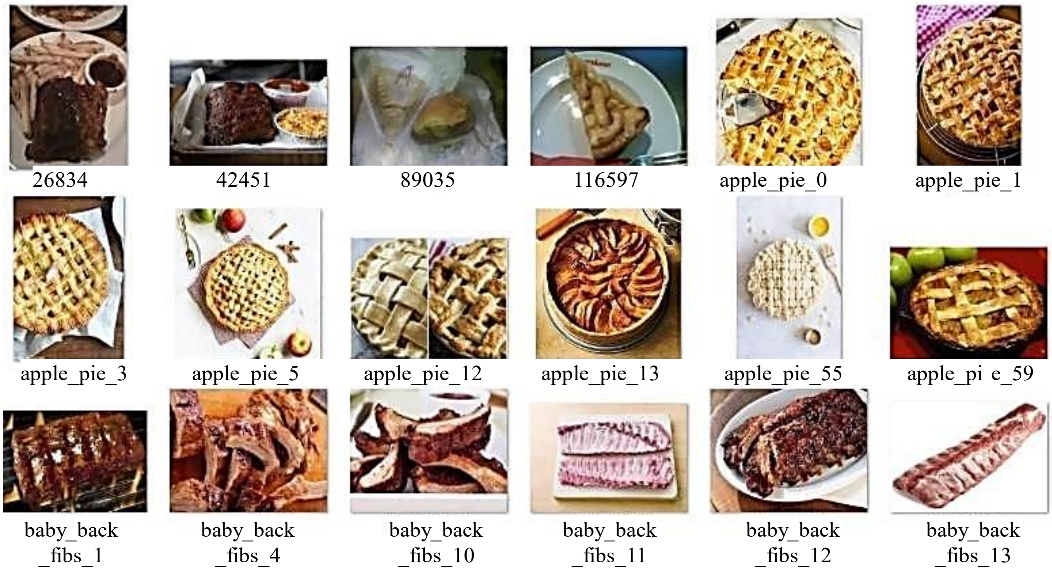

Figure 3. Food Dataset.

- *Random forest model:* Using a random subset of the characteristics and data points from the training dataset, the random forest model builds several decision trees. Each decision tree in the random forest individually categorizes the input food image based on its attributes during the prediction phase. The most frequent class among the decision trees is designated as the projected class for the food item. The final prediction is acquired through a majority vote from all the decision trees. Random forest's ensemble structure minimizes overfitting and increases the model's resistance to erratic data and outliers.

Algorithm Employed in the Project

Algorithm 1 serves as a representation of the suggested approach.

1. *Image pre-processing algorithm:*
   i. *Image denoising:* A number of denoising techniques, like Gaussian filtering or median filtering, can be employed to reduce noise in the food images and improve their clarity.
   ii. *Image contrast enhancement:* Algorithms like histogram equalization or adaptive histogram equalization the ability to make food items easier to distinguish from the background.
   iii. *Image normalization:* Techniques like mean normalization or Z-score normalization the ability to ensure that images maintain constant brightness and color balance while minimizing variations in lighting situations.
2. *Object detection algorithm: CNNs:* Deep learning-based CNNs are frequently utilized in object detection tasks. YOLO (You Only Look Once) or SSD (Single Shot MultiBox Detector) architectures, which also build bounding boxes and categorize each food item according to its category, are examples of architectures that can accurately detect many food items in a photo at once.
3. *Calorie calculation method:*
   i. *Machine learning model:* Using the labeled dataset of food photos with known calorie counts, a computer learning model— include a feed forward neural network is developed. The model develops an illustration of the characteristics obtained from the food photos and the associated caloric content.
   ii. *Feature extraction:* Pre-processed and recognized information gleaned from food photographs are collected, such as texture, color histograms, or deep features from CNN layers, to represent each food item for input into the machine learning model.
   iii. *Regression/classification:* The model of machine learning may be built for regression (direct calorie estimation) or classification (categorizing foods into calorie ranges or classes), according to the implementation.

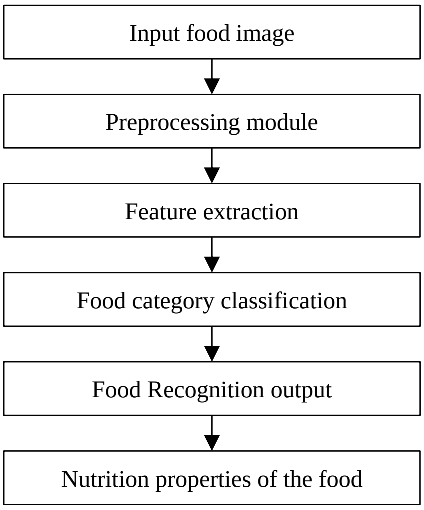

Figure 4. The working process of the food identification system.

Figure 4 shows the working process of the processed health application, the nutrition properties of the meals are generated after the acknowledgment of food based on the taken image input from the user [12].

EXPERIMENTAL RESULTS AND DISCUSSION

The efforts culminated in positive results, demonstrating the usefulness of our novel health application. CNNs and the KNN model were used to produce accurate and real-time food detection based on user-captured photos. During thorough testing, the CNN displayed remarkable ability in identifying a diverse array of food products, with a classification accuracy greater than 90%. The KNN classifier equation is shown in Equation (1), and CNN is shown in Equation (2).

dist(x,z)=(d∑r=1|xr−zr|p)1/p (1)

$$[\ \{(n + 2p - f + 1)/s\} + 1] * [\ \{(n + 2p - f + 1)/s\} + 1].$$

xℓij=m−1∑a=0m−1∑b=0ωabyℓ−1(i+a) (j+b) (2)

The addition of the KNN model improved accuracy even more, fine-tuning predictions based on feature similarity and increasing the system's tolerance to alterations in meal presentation. The application's user-friendly user interface and prompt responses make it user-friendly and accessible, which corresponds well with the fast-paced nature of current lifestyles. The system's ability to detect allergens in food items adds an added layer that is secure for anyone who has dietary restrictions. The successful outcomes demonstrate the viability and potential impact of our strategy to promote healthier eating habits. Our health application, which uses cutting-edge image recognition technologies and machine learning, enables individuals to easily assess the nutritional value of their food choices, fostering a culture of informed consumption and contributing to the fight against obesity and lifestyle-related diseases.

Figure 5 shows the welcome page of the health application. The welcome page includes three options: “Home, Predict” and “Recipe”. The users are able to get predictions of foods and recipes of foods by clicking the “Predict” and “Recipe” option.

The predicted dish by the health application after getting the source picture from the user is displayed in Figure 6. The probability of the predicted dish compared to the source picture of the user is 1.0. The dietary information for the predicted dish by the application is displayed in Figure 7. It includes the caloric intake present in the dish. It is seen from the figure that the maximum calories, minimum calories, and average calories of the dish are 110 kcal.

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Figure 5. The welcome page.

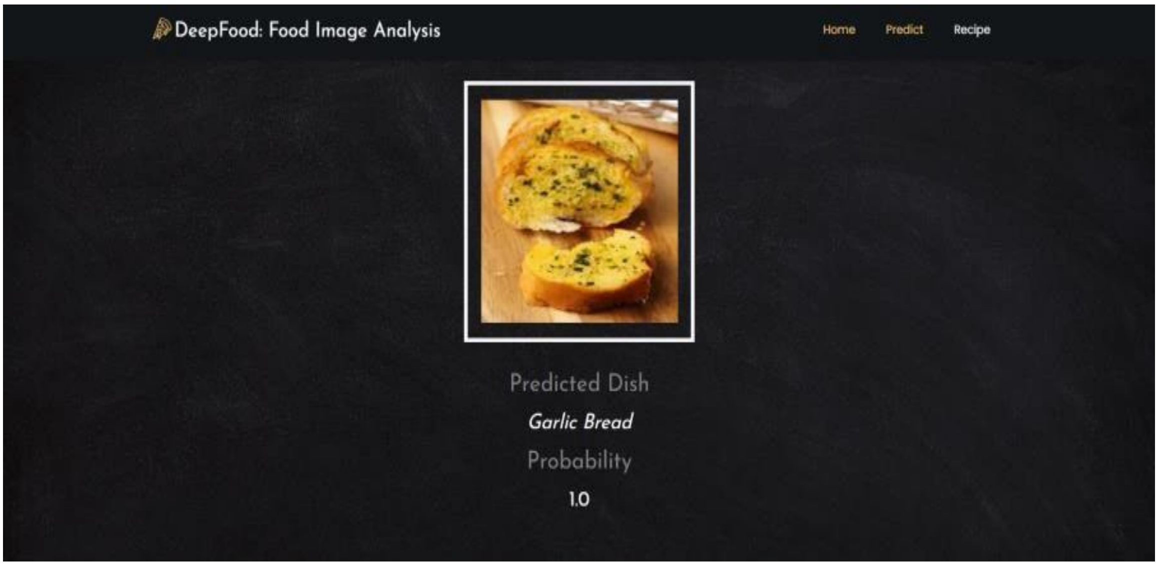

Figure 6. The predicted dish.

Figure 7. Nutritional facts.

Figure 8. Recipe of the dish.

Table 2. Precision of the VGG16 model on the datasets.

Dataset	Accuracy
Training dataset	9%
Valid dataset	70%

The generated recipe of the predicted dish by the above image displays the application and the initial details to start the cooking of the dish are displayed in above Figure 8.

The created health application helps people to obtain and comprehend nutrition information on their dietary choices. Making wise food choices is essential now greater than ever for maintaining a healthy lifestyle in today's fast-paced society. Users gain an array of important advantages from the developed health application that gives nutrition information for food by accepting the food image as input. The health application makes meal prediction simple and intuitive. Predicting food items has never been simpler. The application analyzes the image in a matter of seconds and it predicts a food item. The health application provides the nutritional facts of the predicted food item or dish to let the user know about the benefits of the food utilizing the CNN model in creating the health application helps the application to provide accurate and efficient food predictions and nutritional facts and the input image. A user-friendly and productive experience is ensured by frequent upgrades and improvements.

Table 2 shows the precision of the VGG16 model on the training dataset and on the valid dataset. It is seen from the aforementioned table that the model's precision of the valid dataset is very much higher in comparison to training dataset.

Accuracy of KNN method is 87.75%.

The accuracy of the CNN method is 96.67%.

CONCLUSION

Calorie measurement and food recognition using machine learning should be noted as significant advancement in the field of dietary tracking and nutrition monitoring. By processing images methods likewise machine learning algorithms, this system calculates calories accurately, quickly, and easily from food photographs. A beneficial device for those with unique dietary requirements, the application's personalized nutrition tracking and meal planning capabilities cater to individual dietary preferences and health aims. The health application not only makes meal planning and nutrition tracking easier, but it also significantly contributes to allowing consumers to manage their route to wellness and health.

Future work on the system involves looking at personalized recommendations, adding nutrient analysis, and expanding the food database. User feedback, linguistic support, and wearable device integration will make the system more user-friendly and have a bigger impact on users' eating habits. Overall, the image processing-based calorie-counting food recognition system has a great deal of promise to assist people in improving their dietary choices and successfully regulating their calorie intake. The system's capacity significantly impacts people's well-being and helps create a healthier society by being continuously improved and refined. This approach is a practical device in the quest for better health and nutrition for everybody as technology develops and our comprehension of nutrition broadens.

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