

Implementing Deep Learning to Estimate Food and Beverage Nutrients

Presented by Kalyanamma Bawage.

Dept. Of Computer Science and Engineering (MCA) VTU CPGS Kalaburagi. kalyanibawage@gmail.com

Under the guidance of Prof.Shobha s biradar

Dept. Of Computer Science and Engineering (MCA) VTU CPGS Kalaburagi. baichabal@gmail.com

Abstract— Obesity, a serious chronic disease, is on the rise as a result of how easily food can be brought to our door steps. People's need for food grew, and at the same time, their anxiety about their nutrition also grew. This study offers an image-based calorie estimation system that asks the user to upload an image of a food item in order to calculate the estimated number of calories in the image. It is a multitasking system that displays weekly information on a user's calorie consumption and the number of calories that must be ingested to prevent obesity related illnesses like cancer, heart attack, etc. To recognize complex pictures, a collection of food images with 20 classes and 500 images are built in each class. This study has developed a six-layer Convolutional Neural Network (CNN) architecture for the purpose of extracting the traits and identification trials had an accuracy of 78.7% during testing and 93.29% throughout training.

Keywords: Convolutional Neural Network (CNN), Calorie calculation.

INTRODUCTION

The field of computer vision and deep learning has witnessed remarkable advancements in recent years, revolutionizing various industries and applications. One such application is food recognition and calorie estimation, which plays a pivotal role in intelligent diet monitoring and nutrition management. Accurately identifying and quantifying food items is crucial for individuals seeking to make informed decisions about their dietary intake and maintain a healthy lifestyle. With the proliferation of smartphones and the increasing prevalence of food-related health concerns, the development of robust and efficient systems for food recognition and calorie estimation has become an area of significant research interest. The aim of this project is to propose and develop a comprehensive and advanced system, called "SmartBite: Deep Learning-driven Food Recognition and Calorie Estimation for Intelligent Diet Monitoring," that leverages state-of-the-art deep learning techniques to address the challenges associated with accurate food recognition and calorie estimation.

Literature Survey

State recognition of food images is a recent topic that is gaining a huge interest in the Computer Vision community. Recently, researchers presented a dataset of food images at different states where unfortunately no information regarding the food category was included. In practical food monitoring applications it is important to be able to recognize a peeled tomato instead of a generic peeled item. To this end, in this paper, we introduce a new dataset containing 20 different food categories taken from fruits and vegetables at 11 different states ranging from solid, sliced to creamy paste. We experiment with most common Convolutional Neural Network (CNN) architectures on three different recognition tasks: food categories, food states, and both food categories and states. Since lack of labeled data is a common situation in practical applications, here we exploits deep features extracted from CNNs combined with Support Vector Machines (SVMs) as an alternative to the End-to-End classification. We also compare deep features with several hand-crafted features. These experiments confirm that deep features outperform hand-crafted features on all the three classification tasks and whatever is the food category or food state considered.

BACKGROUND/OBJECTIVES

The aim of this study was to develop Korean food image detection and recognition model for use in mobile devices for accurate estimation of dietary intake.

SUBJECTS/METHODS

We collected food images by taking pictures or by searching web images and built an image dataset for use in training a complex recognition model for Korean food. Augmentation techniques were performed in order to increase the dataset size. The dataset for training contained more than 92,000

images categorized into 23 groups of

Korean food. All images were down- sampled to a fixed resolution of 150×150 and then randomly divided into training and testing groups at a ratio of 3:1, resulting in 69,000 training images and 23,000 test images. We used a Deep Convolutional Neural Network (DCNN) for the complex recognition model and compared the results with those of other networks: AlexNet, GoogLeNet, Very Deep Convolutional Neural Network, VGG and ResNet, for large-scale image recognition.

outperforms other approaches in pixel accuracy, and since it is the first automatic solution for recognizing the images of fake foods, the results could be used as a baseline for possible future studies using the mask. The surface area along with the calorie per square inch value of the food item is used to estimate the calories present in the food.

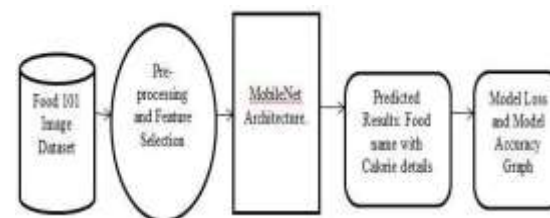


Fig 1. Proposed architecture

EXISTING WORK

The earlier system was designed using a six- layer Convolutional Neural Network (CNN) architecture for food recognition. It aimed to classify food images into 20 distinct food classes. The system utilized a dataset consisting of food images specifically categorized into these 20 classes.

During the training phase, the system achieved an impressive accuracy of 93.29%. This high accuracy indicated that the system effectively learned and recognized various food items within its limited set of classes. The training process involved the

optimization of network parameters through backpropagation and gradient descent algorithms.

The six-layer CNN architecture employed in the existing system played a vital role in achieving the achieved accuracy levels. CNNs are specifically designed for image recognition tasks, utilizing multiple layers of convolutional and pooling operations to extract hierarchical features from input images. The architecture's ability to capture spatial dependencies and learn complex patterns in images contributed to the system's success in food recognition.

PROPOSED METHODOLOGY

The proposed system, "SmartBite: Deep Learning-driven Food Recognition and Calorie Estimation for Intelligent Diet Monitoring," introduces a comprehensive and advanced approach to food recognition and diet monitoring. By leveraging deep learning methodologies and incorporating innovative features, the proposed system aims to address the limitations of the existing system and offer improved accuracy, functionality, and usability.

The core component of the proposed system is the utilization of a deeper and more sophisticated MobileNet architecture for food recognition. This architecture has demonstrated exceptional performance in image classification tasks, enabling the system to achieve higher accuracy rates. With its increased capacity to learn intricate patterns and features, the proposed system can deliver more precise and reliable food recognition results. The proposed system emphasizes adaptability and scalability. It is designed to handle larger datasets and accommodate expanding food class categories as needed. With its flexible architecture and advanced deep learning techniques, the system can meet the increasing demands for comprehensive food

recognition and diet monitoring. This adaptability ensures the system's ability to keep pace with evolving dietary trends and user requirements.

The proposed system features a user-friendly interface that integrates a web framework with the proposed model. Users can effortlessly analyze food images, with the system providing clear and organized displays of recognized food items and their corresponding calorie estimations. The intuitive design of the user interface aims to enhance the user experience and encourage sustained engagement with the system.

IMPLEMENTATION

Modules

- Dataset
- Importing the necessary libraries
- Retrieving the images
- Splitting the dataset
- Building the model
- Apply the model and plot the graphs for accuracy and loss
- Accuracy on test set
- Saving the Trained Model

MODULES DESCRIPTION:

Dataset:

In the first module of Food Recognition and Calorie Estimation, we developed the system to get the input dataset. Data collection process is the first real step towards the real development of a machine learning model, collecting data. placed in the project and it's located in the model folder. The dataset is referred from the popular standard dataset repository kaggle where all the researchers refer it. The dataset consists of 37,046 food images. The following is the URL for the dataset referred from kaggle.

Link: <https://www.kaggle.com/datasets/jayaprak>

[ashpondy/food-101-dataset](#)

A classic Mobile Net model which contains only two convolution layers. The latter layer we are convolving, the more high-level features are being searched. It works similarly to human perception. To give an example, below is a very descriptive picture with features which are searched on different CNN layers.

Mobile Net | CNN model Architecture:

Mobile Nets:__Efficient Convolutional Neural Networks for Mobile Vision Applications paper from Google. They developed a class of efficient models called Mobile Nets which mainly focuses on mobile and embedded vision applications. In one word the main focus of their model was to increase the efficiency of the network by decreasing the number of parameters by not compromising on performance.

Results

Calorie estimation of food and beverages using deep learning is an emerging area that leverages advanced neural networks to predict the nutritional content of various items. By training models on vast datasets of food images and nutritional information, these systems can identify food items and estimate their calorie content with considerable accuracy. Convolutional Neural Networks (CNNs), in particular, have been effective due to their ability to recognize and process visual patterns and features in images. Researchers use annotated food datasets where each image is labeled with its corresponding calorie count. These models typically involve several

stages, including food recognition, portion size estimation, and nutritional value prediction. Some advanced methods combine CNNs with other techniques, such as Recurrent Neural Networks (RNNs) or attention mechanisms, to improve the

estimation by considering context and multiple factors like ingredients and cooking methods. The applications of such technology are vast, ranging from personal dietary management tools to aiding in medical nutrition therapy and enhancing food monitoring systems in various industries. While the field is promising, challenges remain, such as the need for more comprehensive and diverse datasets, handling variations in food presentation, and improving the model's ability to generalize across different cuisines and preparation styles.

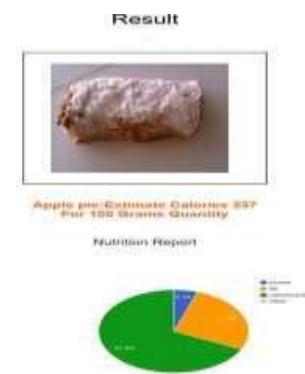


Fig:2 Result Chart

CONCLUSION

The project, "SmartBite: Deep Learningdriven Food Recognition and Calorie Estimation for Intelligent Diet Monitoring," has successfully developed an advanced system that combines deep learning techniques, an extensive food dataset, and innovative features to enable accurate and comprehensive food recognition and calorie estimation. Through the implementation of a deeper and more sophisticated MobileNet architecture, the system achieves enhanced accuracy in food recognition, ensuring reliable identification of a wide variety of food items. The integration of the Food 101 dataset, consisting of 101 food classes, expands the system's recognition capabilities, enabling it to classify a diverse range of food items accurately. The project's success can be

attributed to the careful implementation of deep learning methodologies, rigorous training on the Food 101 dataset, and the integration of user-friendly interfaces. The user-friendly interface allows seamless capture and analysis of food images, making the system accessible to users of varying technical backgrounds. The proposed system demonstrates adaptability and scalability, allowing for future expansion and integration with larger datasets or additional food class categories.

REFERENCES

1. Bray, G.; Bouchard, C. (Eds.) andbook of Obesity-Volume 2: Clinical Applications; CRC Press: Boca Raton, FL, USA, 2014.
2. Prentice, A.M.; Jebb, S.A. Beyond body mass index. *Obes. Rev.* 2001, 2, 141–147.
3. Petimar, J.; Ramirez, M.; RifasShiman, S.L.; Linakis, S.; Mullen, J.; Roberto, C.A.; Block, J.P.
4. Health Canada. Health Canada Nutrient Values. November 2011. Available online: <https://www.canada.ca/en/healthcanada/services/foodnutrition/healthy-eating/nutrientdata/nutrient-value-some-ommonfoods-booklet.html> (accessed on 31 August 2022).
5. Kasar, M.M.; Bhattacharyya, D.; Kim, T.H. Face recognition using neural network: A review. *Int. J.*
6. Li, G.Z.; Bu, H.L.; Yang, M.Q.; Zeng, X.Q.; Yang, J.Y. Selecting subsets of newly extracted features from PCA and PLS in microarray data analysis. *BMC Genom.* 2008, 9, S24.