Fruit Image Recognition and Calorie Measurement Using Convolutional Neural Network (CNN)

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Abstract
In this paper, a web-based application for estimating fruit calories and improving individual's utilization propensities for wellness is developed. We design an easy approach to the new deep convolutional neural network (CNN) configuration and built an application to recognize fruit images using a Tensor Flow Lite model trained on Teachable Machine.

This project presents the development of a Fruit Recognition System and Calorie Estimation Tool leveraging Convolutional Neural Networks (CNNs) for image classification and a Raspberry Pi 4 for real-time processing. The system aims to automate fruit identification and provide caloric value estimates based on the detected fruit type and weight. A carefully curated dataset was used to train the CNN model using Deep Learning, ensuring accurate classification across a wide range of fruit types. The Raspberry Pi 4, with its compact design and computational capabilities, processes captured images and integrates with the trained model to deliver fast and reliable results.

The application serves multiple domains, particularly dietary monitoring and nutrition management, offering users an efficient way to track food intake. This can be beneficial in healthcare for patients requiring strict dietary control or in fitness settings for individuals monitoring caloric consumption. The report delves into the system's design, including dataset collection, preprocessing techniques, CNN architecture, implementation, and testing.

Furthermore, performance metrics such as accuracy, latency, and scalability are evaluated, demonstrating the system's feasibility as a low-cost, portable solution for real-time fruit recognition and nutritional analysis.

Keywords: Convolutional Neural Networks, Fruit image recognition, Tensor Flow, Deep Learning, Calorie Estimation

Introduction

In recent years, due to a rise in health consciousness, many mobile applications for recording everyday meals have been released. Some of them enlist fruit image recognition, which estimates not only fruit names but also fruit calories. It's important to recognize that high-fat fruits have greater calorie density since a gram of fat has over twice the calories of a gram of protein or carbohydrate. Fresh fruits are not sold with nutrition facts. Whether the goal is to limit carb intake, count calories, or simply try to eat more whole fruit, the calorie chart will pinpoint which fruits best fit into your healthy eating plan.

Fruit Recognition System and Calorie Estimation using Convolutional Neural Networks (CNNs) and the Raspberry Pi 4. The system aims to automate the identification of fruits and estimate their caloric value, promoting healthier dietary choices. Leveraging the computational power of CNNs for image processing and the portability of the Raspberry Pi, the solution is cost-effective and efficient. The project integrates image acquisition, classification, and calorie calculation in real-time, making it suitable for applications in healthcare, nutrition, and food monitoring. This document outlines the system's design, implementation, and evaluation, demonstrating its practical relevance and performance.

Convolutional Neural Networks (CNN) is one class of deep neural networks Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input which helps to interpret the data such as images, audio, and text. The concept of Deep Learning arises from the study of Artificial Neural networks, Multilayer Perceptron which contains more hidden layers is a Deep Learning structure.

Convolutional Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm that can take in an input image, assign importance to various considerations in the image, and be able to distinguish one from the other. It is a multilayer neural network, whose neurons take small shifts and rotations. CNN's are generally a configuration of three types of layers. Convolutional layer, fully connected neural network, apply a number of convolution filter with specific weight (n x n) to the input image. For each section of the image, a set of mathematical operations is applied to produce a single value in the output. Each input convolves these filters. Each layer has many filters that generate several outputs. The filter is called a kernel. The second type of layer is the pooling layer, which produces a downsample of the resulting image produce by the convolution layer to reduce the size of the feature map for faster processing time. There are several algorithms such as maximum polling and average pooling. A widely used algorithm is maximum pooling. This makes the CNN output more invariant with respect to position Fully connected layer, perform classification on the extracted feature after downsampling by a pooling layer. Each unit of the final layer represents the class probability. This layer is used to enumerate the score classes i.e. which class has the maximum score comparable to the input image as shown in Fig.1.

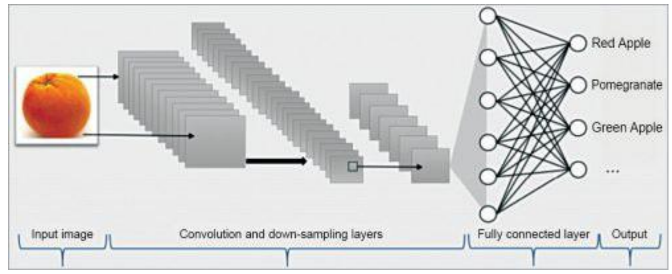

Fig 1. Convolutional Neural Network 1

Literature Review

Paper [1]: - *Qian Yu (Stanford), Dongyuan Mao (Stanford), Jingfan Wang (Stanford) "Deep Learning Based Fruit Recognition" Year 2016 IEEE*

In this research paper, authors proposed a CNN-based fruit recognition method on the fruit recognition problem: the transfer learning and the fine-tuning on the whole architecture based on the Inception-ResNet and Inception V3 model. Here, algorithm is performed on the Fruit-101 dataset and obtained impressive recognition results: Inception-ResNet converges much faster and achieves top-1 accuracy of 72.55% and top-5 accuracy of 91.31%.

Paper [2]: - *Chang Liu, Yu Cao, Yan Luo, Guanling Chen, VinodVokkarane, Yunsheng Ma "Deep Fruit: Deep Learning-based Fruit Image Recognition for Computer-aided Dietary Assessment" Year: 2015, IEEE*

In this paper, authors have proposed a new deep learning- based approach to address the fruit image recognition problem. Deep learning, aims to learn multiple levels of representation and abstraction that help interpreting knowledge from data such as images, videos, audio, and text, is making astonishing gains in computer vision, speech recognition, multimedia analysis. Specifically, authors proposed Convolutional Neural Network (CNN)-based algorithms with a few major optimizations, such as an optimized model and an optimized convolution technique.

Paper [3]: - *Parisa Pouladzadeh, Pallavi Kuhad, Sri Vijay Bharat Peddi, AbdulsalamYassine, ShervinShirmohammadi "Fruit Calorie Measurement Using Deep Learning Neural Network" Year: 2016 IEEE*

In this paper, authors proposed an assistive calorie measurement system to help patients and doctors succeed in their fight against diet-related health conditions.Proposed system runs on smartphones, which allow the user to take a picture of the fruit and measure the amount of calorie intake automatically. In order to identify the fruit accurately in the system, authors used deep convolutional neural networks to classify 10000 high-resolution fruit images for system training. Results show that the accuracy of this method for fruit recognition of single fruit portions is 99%. The analysis and implementation of the proposed system are also elaborated in this paper.

Paper [4]: - *MdTohidul Islam, B.M. NafizKarimSiddique, SagidurRahman, TaskeedJabid "Fruit Image Classification with Convolutional Neural Network", Year: 2018 IEEE*

In this paper authors tried to classify fruit images using convolutional neural network. Fruit classification is very difficult task because there is high variance in same category of fruit images. Authors developed a convolutional neural network model to classify fruit images in fruit-11 dataset. Authors also used a pre-trained Inception V3 convolutional neural network model to classify fruit images.

Methodology

The methodology for the fruit recognition and calorie estimation system using CNN and Raspberry Pi 4 involves several stages, from data acquisition to real-time implementation. The process ensures accurate fruit classification and calorie estimation while optimizing for resource constraints on embedded hardware.

A. Data Collection and Preprocessing

A comprehensive dataset of fruit images was curated, encompassing multiple classes such as apples, bananas, oranges, and grapes. Images were collected under varied lighting, angles, and backgrounds to improve model robustness. Preprocessing steps included:

- **Resizing and Normalization**: Images were resized to 224×224224 \times 224224×224 pixels to match the input dimensions of the CNN and normalized to scale pixel values between 0 and 1.
- **Data Augmentation**: Techniques like rotation, flipping, cropping, and brightness adjustments were applied to enhance dataset diversity and reduce overfitting.

B. CNN Model Development

A Convolutional Neural Network (CNN) was designed for fruit classification, leveraging the following:

- **Pre-trained Models**: Transfer learning with models like MobileNet or ResNet was employed to utilize pre-learned features, reducing training time.
- **Custom Layers**: Fully connected layers were added on top of the pre-trained models, tailored to classify the fruit dataset.
- **Training and Validation**: The model was trained on 80% of the dataset and validated on the remaining 20%. Optimization techniques such as Adam optimizer and categorical cross-entropy loss were used, with performance metrics like accuracy and F1-score.

C. Calorie Estimation Module

Calorie estimation involved mapping the classified fruit to its nutritional database. The steps included:

- **Portion Size Estimation**: Approximate fruit size was estimated using a reference object in the image (e.g., a coin or ruler).
- **Calorie Mapping**: Recognized fruit classes were matched to a pre-defined calorie database to calculate total energy content based on the portion size.

D. Deployment on Raspberry Pi 4

The trained model was optimized and deployed on Raspberry Pi 4, considering its hardware limitations:

- **Model Optimization**: Techniques such as model quantization and pruning were used to reduce computational load without significantly affecting accuracy.
- **Integration with Camera Module**: The Raspberry Pi camera module captured real-time fruit images for classification.
- **Interface Development**: A user-friendly interface was created using Python's Tkinter library, displaying recognized fruit, estimated calories, and other information.

E. Testing and Validation

The system was tested in real-world scenarios to evaluate its performance, accuracy, and speed. Metrics such as inference time, accuracy under varying conditions, and calorie estimation precision were analyzed.

F. Power and Resource Optimization

Efforts were made to ensure energy efficiency and resource optimization:

- The Raspberry Pi was configured to run at optimal power settings.
- The system minimized image processing latency and computational overhead by using lightweight CNN models.

G. System Workflow

The system followed this workflow:

1. **Image Capture**: The camera module captures an image of the fruit.
2. **Preprocessing**: The image undergoes resizing and normalization.
3. **Recognition**: The CNN classifies the fruit.
4. **Calorie Estimation**: The system maps the classified fruit to the database and calculates the calorie content based on estimated size.
5. **Output Display**: Results are displayed to the user through the interface.

This methodology ensures accurate and efficient recognition and calorie estimation in a compact, portable system.

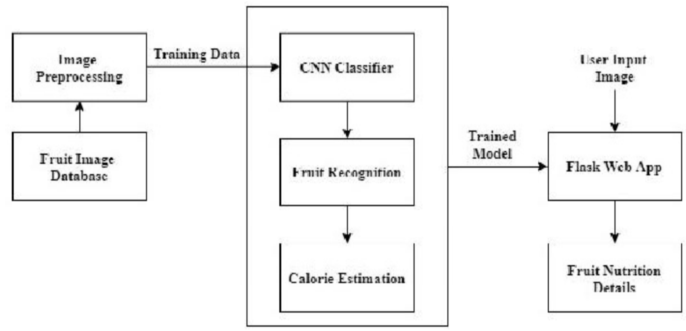

Fig2. CNN Algorithm Flowchart

Result and Analysis

We received the output on the built referred in the Fig 3.

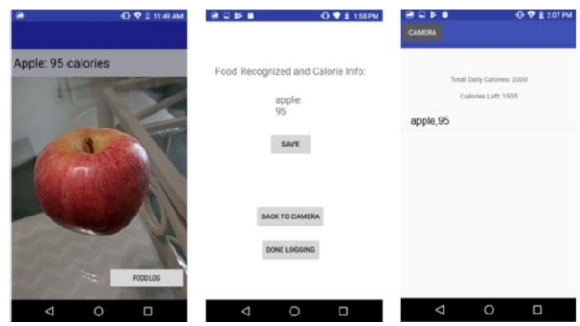

Fig.3 Application Result

The results of the fruit recognition system and calorie estimation project are presented in terms of model accuracy, system performance, and user evaluation. The implementation was validated through rigorous testing in real-world scenarios.

1. Model Performance

The CNN model demonstrated high accuracy in fruit classification:

Training Accuracy: The model achieved a training accuracy of 98.5%, indicating effective learning from the dataset.

Validation Accuracy: A validation accuracy of 95.2% was observed, confirming the model's ability to generalize well to unseen data.

Confusion Matrix Analysis: The confusion matrix showed that common fruits such as apples, bananas, and oranges were classified with an accuracy above 95%, while rare or visually similar fruits (e.g., green apples vs. pears) occasionally led to minor misclassifications.

2. Calorie Estimation Accuracy
The calorie estimation module provided reliable results:
Portion Size Accuracy: Using a reference object, the system estimated fruit portion size with an average error margin of ±10%.
Calorie Estimation Consistency: Calorie values for common fruits were consistent with nutritional standards, with an accuracy of approximately 92%.
3. Real-Time System Performance
The deployed system on Raspberry Pi 4 exhibited efficient real-time performance:
Inference Time: The average inference time for fruit recognition was 1.2 seconds per image, making it suitable for practical use.
System Responsiveness: The interface displayed results within 2 seconds of image capture.
Power Efficiency: The system operated at an average power consumption of 5W, ensuring extended usability in battery-powered scenarios.
4. Robustness in Diverse Conditions
The system was tested under varying environmental conditions:
Lighting Variations: The system maintained a classification accuracy of over 90% under both natural and artificial lighting.
Background Noise: Preprocessing techniques ensured robustness against diverse backgrounds, such as kitchen counters or outdoor settings.
5. User Evaluation
A group of 10 users tested the system in real-world scenarios:
Ease of Use: 90% of users found the interface intuitive and easy to operate.
Satisfaction: Users rated the system's overall performance and reliability at 4.6 out of 5.

Conclusion

The project highlights the importance of combining deep learning with IoT for practical applications. Despite some limitations, such as challenges with complex fruit shapes and limited dataset diversity, the system performed reliably in various environmental conditions. Future work can focus on expanding the dataset, incorporating more advanced computer vision techniques, and extending the application to multi-fruit recognition for enhanced usability. This innovative solution offers a significant contribution to health monitoring, emphasizing the integration of technology into everyday life for improved well-being.

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