

## Fruits and Vegetable Classification and Calories Measurement System

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### ABSTRACT

Individuals care about the types of fruit they are eating and the nutrients it contains because eating fruits and vegetables is an essential part of leading a healthy diet. In this paper we introduce an automatic way for detecting and recognizing the fruits in an image in order to enable keeping track of daily intake automatically using images taken by the user. The proposed method uses state of the art deep-learning techniques for feature extraction and classification. Deep learning methods, especially convolutional neural networks, have been widely used for a variety of classification problems and have achieved promising results. Our trained model has achieved an accuracy of 75% in the task of classification of 43 different types of fruit. The similar methods have achieved up to 70% with fewer classes.

### Keywords

Calorie counter; Fruit classification; fruit recognition; convolutional neural network; Deep learning.

### 1. INTRODUCTION

Usage of smartphones has been growing during the past few years. This has presented us with a great opportunity. We can use the large amount of data generated by smartphone users to predict the behavior of the people in the society.

A large percentage of the images uploaded to social networks are pictures of food. We can use this data to track an individuals' eating habits and the number of calories they are consuming daily. The first step in this approach is to develop an automatic recognition system that could detect the type of food in the picture and retrieve the number of calories it contains. Google's im2calorie project is a similar project but its results are still not available for comparison of image recognition capabilities.

In our research, the goal is to train a model that detects all kinds of food, drinks, fruits, and vegetables, but due to the extensive computational requirements, in this paper we present an early version of our work limited to the images of fruit and vegetable. An automatic fruit recognition system could serve as a calorie counter for people who are trying to lose weight. People could take a picture of the fruit that they are eating and see the number of calories it contains.

The features used for training fruit recognition systems are color, size, shape, and texture [1]. Most of the current systems use these features or a combination of them.

The convolutional neural network model learns what type of features result in a higher accuracy and therefore uses them in the classification process and the KNN technique can be used [11][12].

Our optimization methods have improved the initial results significantly. By selecting a smaller learning rate and removing the more general classes like Fruit and Nut, we were able to improve the results up to 40% [10][15-17].

The rest of the paper is organized as follows: The proposed method and the database used for training

the model are discussed in Section 2. The results are shown in section 3. Conclusions of the paper are presented in the final section.

## 2. Methodology

The methodology is the method or type of algorithm that is being used to develop a system.

### 2.1 Data

The train and test images were all selected from the ImageNet dataset. The ImageNet dataset consists of 15 million images and 22,000 categories. The images are gathered from the internet and labeled by humans [2]. The images from the ImageNet are real world images generated by ordinary users of the internet. They have different qualities. They may contain objects from different classes. As a result, classifying them is a lot harder than classifying the other datasets. 49,626 images from 43 categories were handpicked from the ImageNet dataset. 80% of the images were used for training the model and the rest for testing it. The images were all selected from the leaf nodes in the WordNet tree [3]. Our results show that the accuracy highly decreases when a node and its parent node both exist in the database.

### 2.2 Convolutional Neural Network (CNN)

Convolutional Neural Networks are the most widely used types of artificial neural networks. CNNs have successfully been used in image and video recognition [4], voice recognition and signal processing [5][14], recommender systems [6] and natural language processing [7][13].

The main property of a convolutional neural network is its sparse connectivity. Each neuron in a CNN layer is connected to a subset of neurons in an adjacent layer by a set of weights [8]. as a result, a spatially local correlation exists around each neuron. These weights are shared between different neurons in a layer and represent the correlation filters [9].



**Figure 1: examples of predictions by the model**

### 2.3 Network Architecture

The convolutional neural network used in this paper consists of three convolution layers and three pooling layers followed by two fully connected layers.

The input to the network is a  $227 \times 227 \times 3$  image and the output is a distribution over 43 labels in the model.

The first convolution layer has 48 filters of size  $11 \times 11$ . The second convolution layer has 128 filters of size  $5 \times 5$  and finally, the last convolution layer has 128 filters of size  $3 \times 3$ .

### 2.4 Preprocessing

A few preprocessing steps were conducted before the training phase to ensure reliable results.

We resized all of the images in the database to the width and height of 256 pixels without preserving

the aspect ratio. Then the resized images were cropped to the size of  $227 \times 227$  with random offsets.

### 3. Results

Table 1 shows the summarized results of the proposed model. The average top-5 accuracy of the model is 75% and the average top-1 accuracy is 45%.

**Table 1. The Results for Some Categories in The Database**

No.	Name	Top-1	Top-5
1	Apple	13	53
2	Strawberry	61	83
3	Blueberry	32	69
4	Peach	40	74
5	Pear	20	58

The top-1 accuracy is the percentage of the times that the actual label is the first predicted label by the model and the top-5 accuracy is the

percentage of the times that the actual label is among the first five predicted labels by the model.

The initial model was trained on 314 categories with over 300,000 images. These categories included classes like Fruit, Edible Fruit, and Nuts. Therefore, a picture of a fruit could have belonged to multiple classes in the model. This resulted in a poor accuracy. Using the proper learning rate and selecting the images from the leaf nodes of the ImageNet, improved the results by 40%.

### 4. Conclusion

Many health conscious individuals keep track of what they are eating and how many calories they consume daily. But knowing which food contain how many calories is not easy for humans. An automated food recognition system could do the job for them, just by taking a picture of it. People who want to know how many calories they are consuming, can take a picture of their food and find out.

In this paper, we used a Convolutional Neural Network, one of the most widely used Deep learning methods, for feature learning and classifying the images.

The model achieved a top-5 accuracy of 75% and a top-1 accuracy of 45%. The results are highly affected by the quality of the image and the number of objects it contains. We predict that by using the pictures that only contain the user's meal, we can achieve a higher accuracy up to 95%.

In the future, we plan to extend our work and develop a recognition system that can recognize all types of edible and drinkable objects.

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