

# Food Recognition for Dietary Assessment Using Deep Convolutional Neural Networks

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## Introduction

Diet management is a key factor for the prevention and treatment of diet-related chronic diseases. Computer vision systems aim to provide automated food intake assessment using meal images. We propose a method for the recognition of food items in meal images using a deep convolutional neural network (CNN) followed by a voting scheme. Our approach exploits the outstanding descriptive ability of a CNN, while the patch-wise model allows the generation of sufficient training samples, provides additional spatial flexibility for the recognition and ignores background pixels.

## Materials & Methods

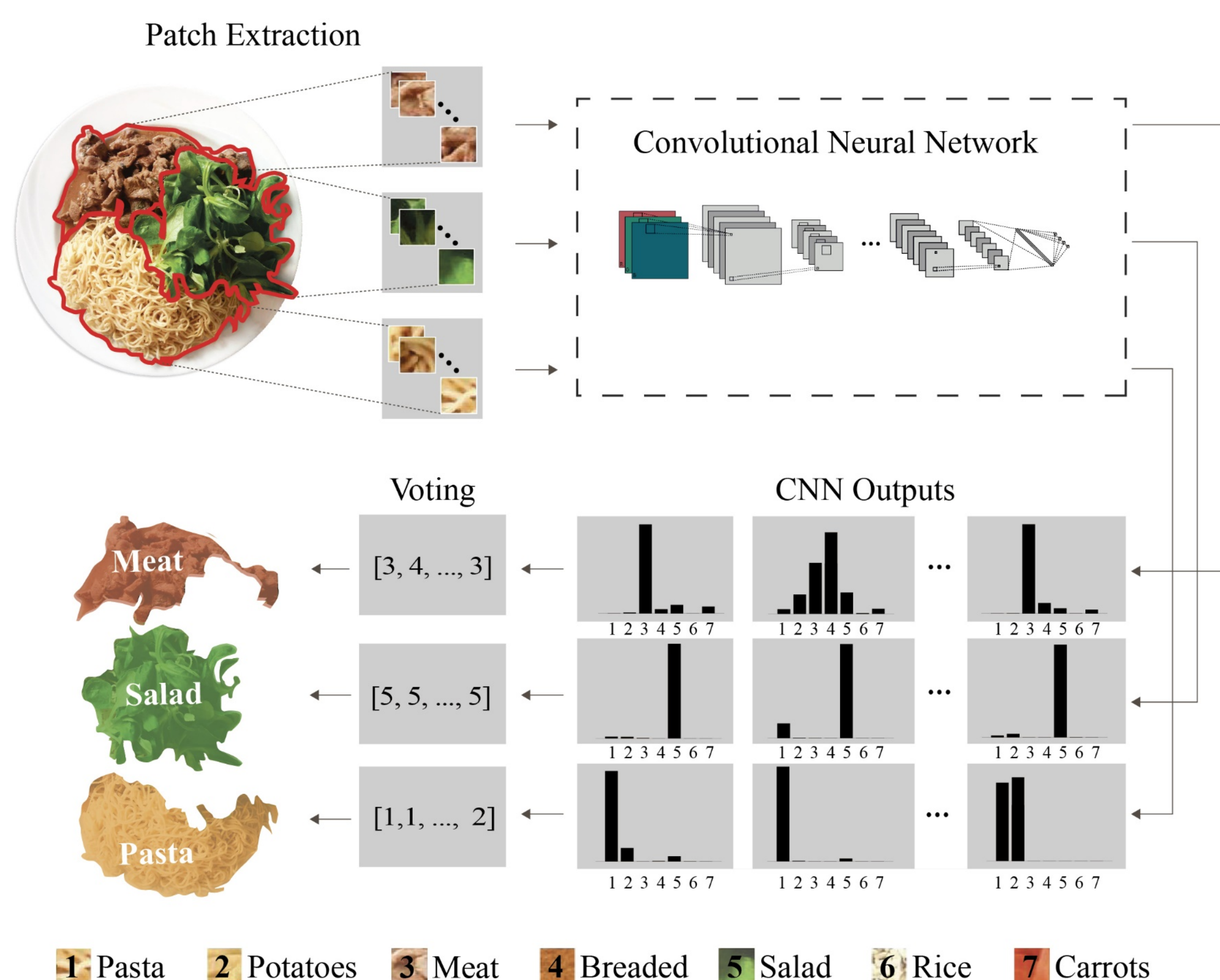


Figure 1 – The proposed system overview

## Results

### Evaluation:

- 60% of the data was used for training 20% for validation and 20% for testing.
- The best configuration of the network was identified by a trial and error procedure
- The performance was assessed in terms of the average F-score over the different classes on a patch basis ( $pF_{avg}$ ) and food item basis ( $iF_{avg}$ )
- Average classification times for food items are also given

The overall  $iF_{avg}$  of the proposed system was **84.9%**. **Table 1** provides the accuracy of the patch-wise classification for the different CNN architectures. **Table 2** shows the results of the food-item classification for a number of different schemes as well as a comparison with a method from the literature. **Figure 2** illustrates the learned kernels of the first layer convolutional layer of the CNN.

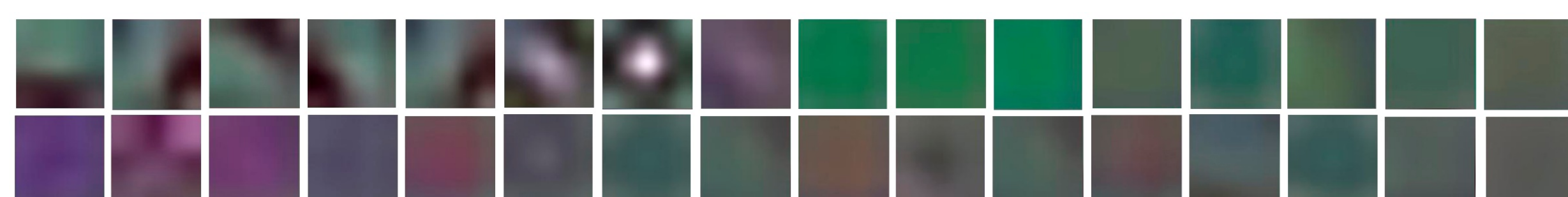


Figure 2 – The kernels from the first layer of the proposed CNN

## Conclusions

We proposed a method for the recognition of already segmented food items using a CNN. The classification is applied in a patch-wise manner and a voting technique was used to determine the class of each food item. Future work should include a more thorough investigation on the optimal architecture as well as the training parameters of the network.

The proposed system recognizes already segmented food items using an ensemble learning model (**Figure 1**).

### Materials:

- 12,500 patches were extracted from 573 food items
- Seven (7) broad food classes: pasta, potatoes, meat, breaded food, rice, green salad and carrots.

### Preprocessing:

- Zero mean normalization for every patch
- Data augmentation with 16 label preserving transformations leading to 200,000 patches

### Network Training:

A deep CNN was trained with:

- Four convolutional layers with 5×5 kernels
- Two fully connected layers at the end
- Rectified linear units (ReLU) as activation functions
- Dropout in the fully connected layers

### Food Recognition:

For each food item:

- Image patches are extracted on a grid
- Patches are preprocessed and fed to the CNN
- The most frequent class is assigned to the food item

Table 1 – Results for the different architectures investigated

CNN architecture	$pF_{avg}$
32cp – 32cp – 128fc – 7fc	66.5
32cp – 32cp – 64cp – 128fc – 7fc	68.7
32cp – 32cp – 32cp – 64cp – 128fc – 7fc	69.5
32cp – 32cp – 32cp – 64cp – 64cp – 128fc – 7fc	67.1
32cp – 32cp – 32cp – 64cp – 128fc – 7fc + LRN	70.4
<b>32cp – 32cp – 32cp – 64cp – 128fc – 7fc + Dropout</b>	<b>71.79</b>
32cp – 32cp – 32cp – 64cp – 128fc – 7fc + LRN + Dropout	71.28

Table 2 – Results of the proposed method for different voting schemes and variants compared to a method from the literature

Classification Method	Accuracy	$iF_{avg}$	Time (sec/item)
CNN+Weighted voting+step=16	84.6	82.8	0.28
CNN+Max voting+step=32	83.5	81.4	0.11
<b>CNN+Max voting+step=16</b>	<b>84.9</b>	<b>82.7</b>	<b>0.28</b>
CNN+Max voting+step=8	84.7	82.5	0.92
Learned histogram+LBP+SVM <sup>1</sup>	82.2	79.7	0.1

<sup>1</sup>M. Anthimopoulos, J. Dehais, P. Diem, S. Mougiakakou, "Segmentation and recognition of multi-food meal images for carbohydrate counting", 2013 IEEE 13th International Conference on Bioinformatics and Bioengineering (BIBE), 10-13 Nov. 2013

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