

# Food For Machine Learning Dataset

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## Abstract

We introduce and describe a dataset with 1282 images of 423 foods taken from 3 angles. We also present the strengths and weaknesses of our database and encourage researchers to use it for testing the image analysis algorithms.

<i>CONTENTS</i>	2
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## **Contents**

<b>1</b>	<b>Introduction</b>	<b>3</b>
<b>2</b>	<b>Related datasets</b>	<b>3</b>
<b>3</b>	<b>The proposed Food For Machine Learning dataset</b>	<b>4</b>
<b>4</b>	<b>Future work</b>	<b>9</b>

## 1 Introduction

We introduce a new dataset of images containing some of the most common Romanian food dishes.

The dataset is named **Food For Machine Learning Dataset** (Food For Machine Learning) and can be downloaded from the addresses pointed by references [1] and [2], and it is constantly updated with images of new foods as soon as possible.

Unlike the datasets mentioned in section 2, the FFML covers a larger variety of foods, 423 to be more exact, divided into main courses, international dishes, traditional dishes, desserts (birthday cakes, sweets, ice cream, cookies), snacks, soups, salads, fast-foods, grills, garnishes, aperitifs and pizzas.

Instead of just covering a single category of foods, we choose to gather as many as we could get our hands on, that include all types of ingredients, in different forms: fruits, vegetables, meat, sauces, carbohydrates, pasta and so on.

As a second reason why our dataset is of a better quality is because all the images have been taken by us, carefully curated, modified to remove all the background noise and resized to a 512x512 format. This is a big plus, because most other datasets contain images that have both the dishes and the surrounding objects (like plates and tables) in them. If the background is clean, then an algorithm have a higher chance of detecting the correct type of food even if the surrounding objects are different.

The paper is structured as follows: Section 2 describes other existing datasets with images of foods. Section 3 explains, in great detail, the ways in which the images of the dataset were selected, processed and stored. Section 4 concludes our paper.

## 2 Related datasets

This section describes similar attempts of creating databases with food images. Also mentions some attempts to train them.

Paper [3] contains a dataset of 101 standardized fast food categories, randomly sampling 750 images from `foodspotting.com`, and an additional 250 test images collected from each class, that were manually cleaned.

Paper [4] mentions the use of three image datasets, the first one (named *Food-5K*) containing 2,500 food images and 2,500 non-food images, the second one (named *Food-11*) 16,643 images grouped into 11 categories (Bread, Dairy Products, Dessert, Egg, Fried food, Meat, Noodles/Pasta, Rice, Seafood, Soup and Vegetable/Fruit), and the third one (named *IFD*) 4,230 food 5,428 non-food images. The food images, in the first two datasets, were selected from already existing and publicly available food image datasets.

Paper [5] describes a dataset of 251 prepared food categories split into 158,00 images gathered from the internet. For the training set, it uses 118,000 images and, for validation, it provides human verified labels for 40,000 images.

The website referred by [6] contains photos of 100 categories of some of the most popular foods in Japan. "Each food photo has a bounding box indicating the location of the food item in the photo."<sup>1</sup>

Paper [7] introduces 4,545 still images, 606 stereo pairs, 303 360-degrees videos, and 27 videos of eating events as a part of a visual dataset. 101 different foods (including burgers, pizza, burgers, salads, etc.) from 11 popular fast food restaurants were gathered for use in this dataset.

[8] uses a 50-category food images set (aptly named *Food50*), built by gathering 100 relevant food images from the internet by hand for each category.

[9] features a dataset (*Food85*) of 85 kinds of foods, with a total of 100 images per category. Paper [10] details a dataset of food images taken in 10 restaurants across 5 different types of food (American, Indian, Italian, Mexican and Thai).

[11] is a large collection of Chinese food images. It contains 145,065 images for training, 20,253 images for validation and 20,310 images for testing.

Dataset	Images	Classes	Background Noise
<b>Food-101</b> [3]	101,000	101	Yes
<b>Food-5k</b> [4]	5000	2	Yes
<b>Food-11</b> [4]	16,643	11	Yes
<b>FoodX-251</b> [5]	158,000	251	Yes
<b>UEC FOOD 100</b> [6]	9,060	100	Yes
<b>PFID</b> [7]	1,098	61	Yes
<b>Food50</b> [8]	5,000	50	Yes
<b>Food85</b> [9]	8,500	85	Yes
<b>CHO-Diabetes</b> [10]	5000	6	Yes
<b>ChineseFoodNet</b> [11]	185,628	208	Yes
<b>Food For Machine Learning (FFML)</b>	<b>1282</b>	<b>423</b>	<b>No</b>

**Table 1:** Datasets for food recognition. The *Food For Machine Learning* datasets includes more classes compared to most of the prior work and and features background noise-free images.

### 3 The proposed Food For Machine Learning dataset

A good dataset is very important to the construction of an image recognition algorithm. It must contain a large number of high quality images to obtain an excellent performance for the algorithm.

As of now (11.28.2019) our dataset contains a number of 423 types of foods with a total of 1282 images.

<sup>1</sup><http://foodcam.mobi/dataset100.html> [Online, accessed on 05.02.2020]

From the beginning we discussed the methods in which we would approach the creation of the dataset, mainly the ways in which we could obtain the images for a potential training algorithm. The options were to either search and download them from the internet or to take the pictures by ourselves. After all of this we reached the conclusion that in order to have full control over the angles and brightness, which are very important also for a high quality image, we would need to take the pictures whenever we cook or go in other places with food.

In photographing the dishes we captured them from different angles like:

- Above view
- Sides view
- Section view

For the above view we could have a perfect background preferably white or green but anyway not floral or drawings to capture the shapes of our food. Also we had to take into account the borders of our food, meaning that they have to be well defined and that they don't cut into the subject of the image. Thus, we will have a perfect above view of our dish.

Because one picture is not sufficient for the training algorithm, we also had to take side-view pictures. Depending on the type of the food, we like to choose the perfect side of view in order to capture the shape and all the ingredients included in the dishes.

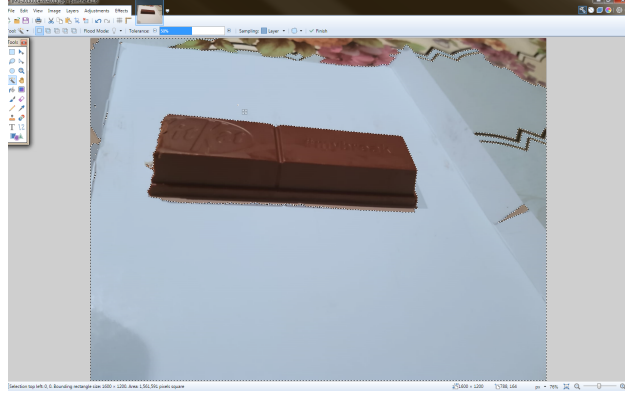
The section view is important to capture the interior of the foods because the exterior can vary in its color, texture, shape or decorations. Even if these variations are small they count for the recipe of the dish.

After we defined all the rules for taking excellent pictures of a dish, we moved on to processing the images. But before we could begin this process we had to choose the best picture for each angle mentioned above from the collection of images taken. So now, we have a minimum of three images for each category of food, which means that we are now ready to modify the pictures.

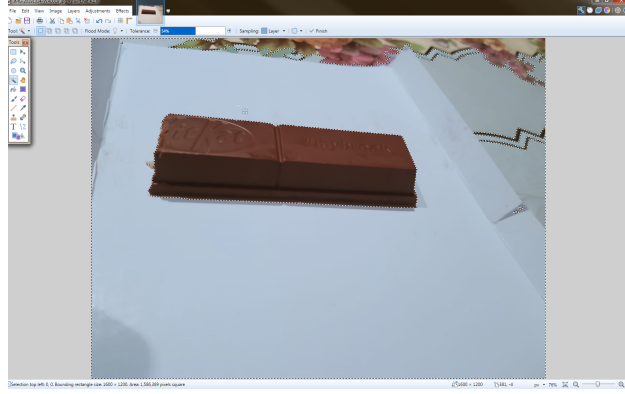
We chose to use *Paint.net* in order to separate very well the food from the background and also because it's a very common application. The tools provided by this program are sufficient to make this process possible and easy:

- *Magic Wand*: we use this to select and remove easily most of the background. (See Figures 1 and 2)
- *Ellipse Select*: can help when we have a rounded shape of food like in the case of soups when they are served in bowls.
- *Eraser*: this tool is used to remove the pixels of the background left out by the previous tools and polish the borders. (See Figures 3 and 4)

After extracting the main subject of the images from the background, we had to trim the margins, by bringing them as close to the food as possible, applying a square aspect ratio and keeping the dish centered. The next step is to resize the



**Figure 1:** Roughly applying the *Magic Wand* tool.



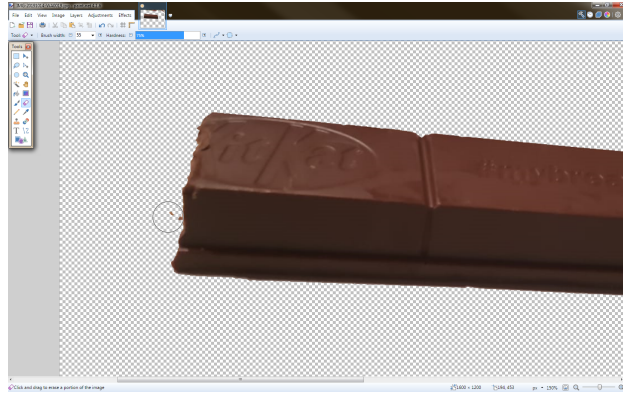
**Figure 2:** Fine tuning the range of selection for the *Magic Wand* tool.

images to 512x512 pixels, for uniformity. These steps are very crucial so that the performance of the algorithm increases. We found that the best application in order to achieve this would be *Adobe Photoshop*, mainly because of its *Scripting* feature, which allows us to automate these repetitive tasks. The tools, settings and the order in which to apply them are written in a code form in a JavaScript file and placed into the *Presets/Scripts* folder in the application directory. The script is then binded to the *Open Document* Photoshop event, in the *Script Events Manager*, so that when opening the images in a food type, the steps mentioned above apply automatically, without any user input. The code of the script is given in Listing 1, and the results of applying it can be observed in Figure 5.

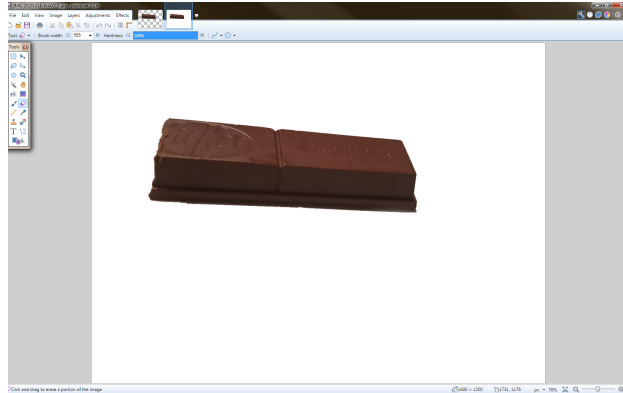
```

1  // Store the active document in a variable
2  doc = app.activeDocument;
3  // Trim the edges of the document
4  doc.trim();
5  // Apply a square ratio

```



**Figure 3:** Using the *Eraser* tool to remove left out pixels.



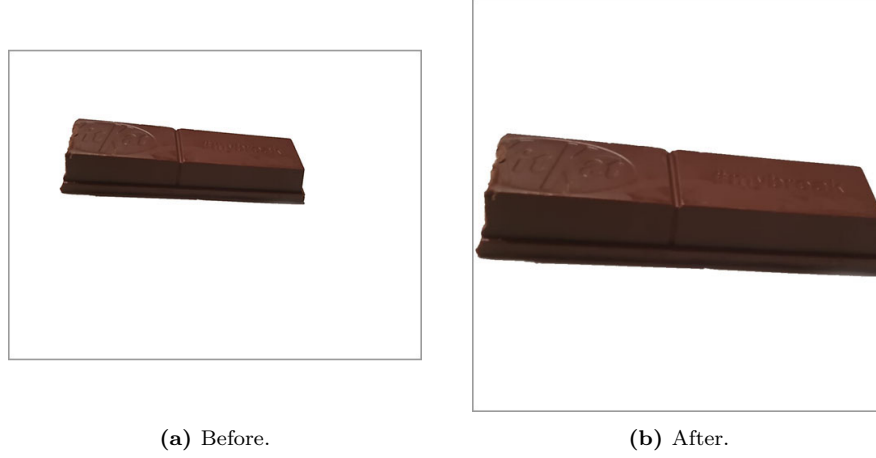
**Figure 4:** Final result of the process of separating the dish from the background.

```

6   if( doc.height > doc.width ) {
7       // If the height is greater than the width
8       // then set the width equal to the height
9       var size = UnitValue(doc.height, 'px');
10      doc.resizeCanvas(size, size);
11  } else {
12      // If the width is greater than the height
13      // then set the height equal to the width
14      var size = UnitValue(doc.width, 'px');
15      doc.resizeCanvas(size, size);
16  }
17  // Resize the document to a 512x512 pixels
18  doc.resizeImage(UnitValue(512, 'px'), UnitValue(512, 'px'));
19  // Save the document
20  doc.save();
21  // Close the document
22  doc.close(SaveOptions.DONOTSAVECHANGES);

```

**Listing 1:** The code for the Photoshop script.



**Figure 5:** The results of applying the Photoshop script.

The final images are put into their respective folders named after the type of food that they represent (see Figure 6). These types of foods are then grouped by the category of which they belong to (i.e. main courses, soups, deserts, etc.). We chose to adopt a two-digit increment number convention for the images, which starts with *01.jpg*, continues with *02.jpg*, *03.jpg* and so on, and then resets with each new folder.

Name
BAKED BISCUITS WITH SEEDS AND CHIVES
BAKED POTATO CHIPS WITH YOGURT & HERBS
BISCUITS WITH BUTTER (TED)
BROWN RICE CHIPS WITH PAPRIKA
CEREALS WITH SUGAR AND SOUR CHERRY
CHILI POTATO CHIPS
CHURP PAKI WITH BACON
CHURP PAKI WITH CHEESE
CHURP PAKI WITH SALT
COCOA WAFERS CUBES
COVERED PUFFS WITH CHOCOLATE
CRISPY PEANUTS COATED WITH PAPRIKA
EXPANDED CHIPS WITH SOUR CREAM AND DILL
EXTRUDED MAIZE GRITS FLIPS IN TUBE SHAPE WITH CHEESE FLAVOUR

**Figure 6:** Folder structure.

A public GitHub repository (see reference [1]) has been created to store the dataset and also to make it accessible for anyone wishing to use it in their own projects. The repository's structure is made up of:

- A *FOOD* folder, which contains all the categorized images.
- A *README.md* file that has a full list of food types, and also some basic information related to the dataset properties, description and history of updates.





**Figure 7:** File structure.

- A *LICENSE.txt* file that details the preservation of copyright and license notices.

Whenever a new set of types of foods is added to the GitHub repository, we refresh the *History* section of the *README.md* file by entering the date and also a full list of the dishes included in the update.

## 4 Future work

In the future we plan to improve the dataset by adding more images of new classes of food. In the near future we will start testing various machine learning algorithms on the FFML dataset.

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