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# BBM 416 Computer Vision Project Final Report


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# Food Recognition for Calorie Management


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**Abstract**

Our paper address the issue of how much calorie food is. For this purpose, we propose a CNN-based food classification and food detection model using Pytorch to estimate the number of calories in an image of food taken; based on the average calorie value of each detected category. Our dataset contains 101.000 images of 101 different types of food.


## 1 Introduction

Obesity in the world is increasingly rising. One of the biggest reasons is an unawareness of calorie of those what people eat. People do not know calories of their meal so that they eat unconsciously and gain weight readily. We aim to address this issue by means of Deep Learning and Convolutional Neural Network. Our solution is recognize food in a meal and calculate calories.

There are a few big challenges to solve this problem. First one is to identify food or ingredients in it. Identifying ingredients would give more precise results to calculate calorie. But it is immensely hard to identify due to the smallness of those. Hence, we have ended up with classifying food instead. However, a new problem comes out. Although food recognizing is easier, calculating the calorie is hard. Because it is not known the portion of food on the plate and most time we do not even what exists in meal, for example soup. We do not know how the cooker cooks, what she

includes into food. But averagely gives more precise results and we have to make these assumptions. That is why we have chosen food based classification.

Main task is to calculate calorie. However, it is not a big problem. Because we just map the food name to its amount of calorie in 100 gram food.

## 2 Related Works:

- Pouladzadeh et al.(4) proposed an approach that segments the image and predicts the calorie of the food in the given image. They used K-Mean clustering for the image segmentation and find the food portions in the image. For classification Support Vector Machines(SVM) is used. The SVM model was trained in order to classify the food that given. SVM model took Color Features(10 categories), Size Features(6 categories), Shape Features(5 categories), Texture Features(5 categories) and classify the food. They needed two images(one is from the side and other is from the top) which are contains food and the user's thumb for the volume estimation. They reached 92.21% of accuracy.

- Chokr et al.(2) used a dataset of fast-food images based on the Pittsburgh Fast-Food Image Dataset. Mathworks Image Processing Toolbox is used for extracting features. Total of 11,868 raw features extracted from RGB representation of the image. Raw features reduced using Principal Component Analysis(PCA) and Information Gain(InfoGain) to 23 features. Using these features and Sequential Minimal Optimization(SMO) they classified the food. Size prediction is done by using Random Forest in grams. Finally, the calorie of the food is predicted using Multilayer Perceptron. They experiment on different types of representation of an image such as Averaged RGB, Gray Scale, BW 0.7 and BW 0.5 but they get the best results with RGB representation.

- Liang et al. (3) used a dataset of 2978 images of 19 different food with a single yuan coin. They used Faster CNN for object detection. Each bounding box that created by Faster CNN is classified. They used the GrabCut algorithm for image segmentation. They divided food into 3 categories ellipsoid, column and irregular. Using the coin as a reference point they calculate the volume of the food depending on its shape. Knowing the volume mass can be easily calculated using the density of the food. With the mass is known they calculated the calorie of the food.

# 3 Method:

- During pre-process of project, we had to design a solution for the classification problem. After a brief search, we came up with a solution which uses neural networks because neural networks give outputs which refer to scores of all the classes.Also, in state-of-art they are pretty successful classifiers, and are broadly used. Moreover, with convolutional neural network layers, we finalized our solution in a perfect fit. Thus, we decided the architecture of our neural network as sequentially contains convolutional and fully connected layers.

- We end up the number of convolutional layers as 3 because in the progress period, we wanted to have some feedback and results from what we had designed so we chose a number which provides as quickly as possible and also successful training phase for the layers of neural network. Thus, the number of fully connected layers was also decided as 1. The architecture of the our neural network is shown in figure 1.
- Convolutional layers provide a role which extracts features of images by the help of kernels. These features enter into the fully connected layers as inputs.
- In this progress period, we have used cross entropy loss and Adam optimizer for now, however until the final report, we set our minds to implement various optimizer and loss functions as well.

## 3.1 Experiments

## 3.2 Experimental Setup:

We used data set of 101 food categories, with 101.000 images. (1).For each class, 250 manually reviewed test images are provided as well as 750 training images. Those images are from "foodspotting.com" which is one of the well-known sites in which people share the images of what they eat and give information about.
our parameters:
Epochs: 15
Classes: 101
Batch size: 64

Learning rate: 0.001
Also we resized images to 128x128.

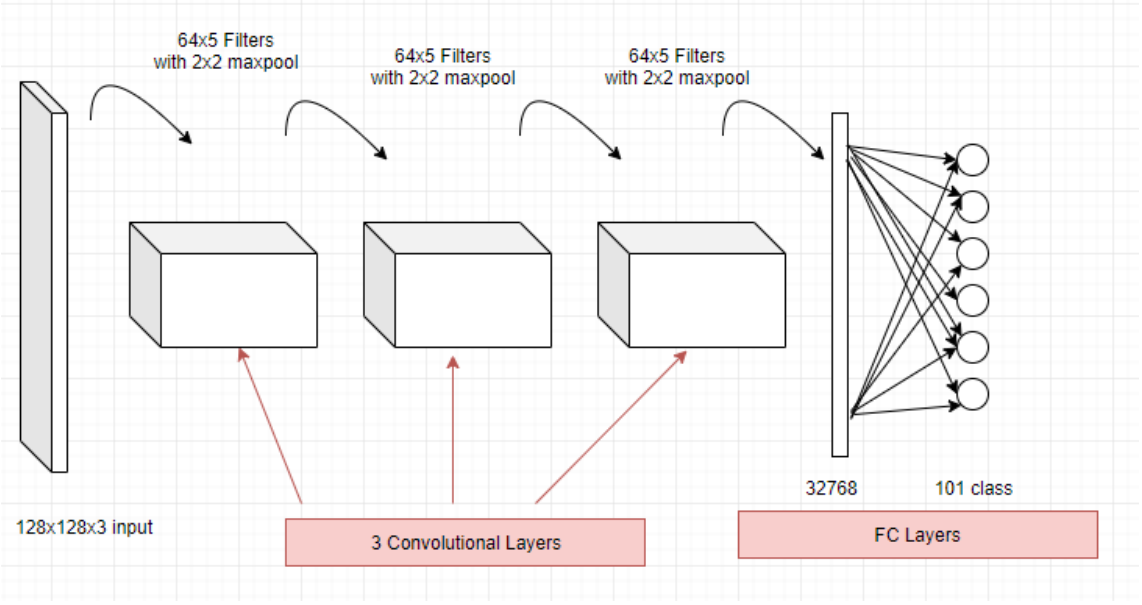
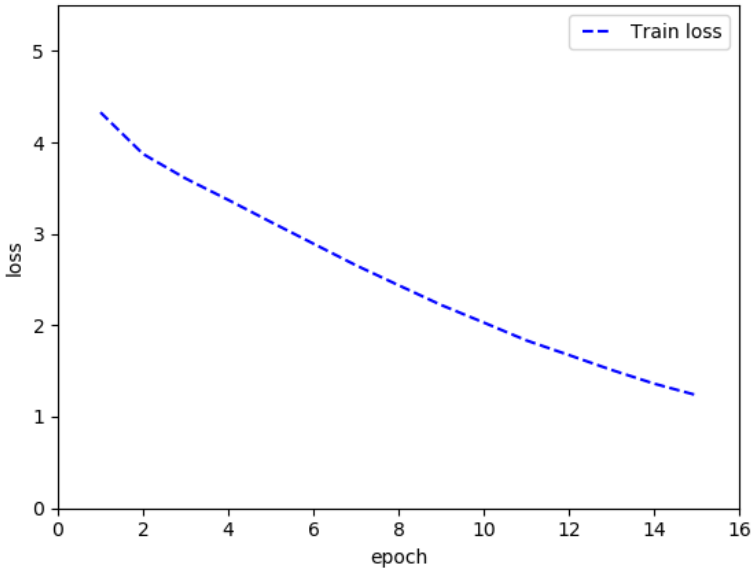


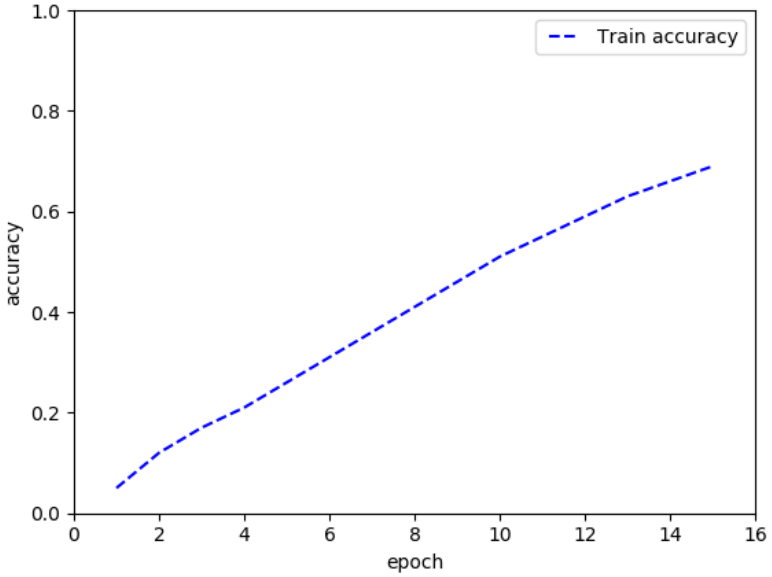

Figure 1: **Our Neural Network**

## 3.3 Experimental Results:

**Train loss:**




**Train accuracy:**




As it is seen from accuracy and loss graphs, results are getting better according to increase of epoch number.

**Overall accuracy and parameters:**

| | **Epoch**: 15<br>**Batch Size**: 64<br>**Learning Rate**:0.001 |
|---|---|
| **Train Accuracy:** | %77 |
| **Test Accuracy:** | %69 |
| **Loss** | 1.21 |

Overall test accuracy is good. But higher epoch number and convolutional, fc layers are may gives us better results. 15 epoch took approximately 4.5 hours.
**Now here are demonstrated example images classified correctly and calorie is found beneath the images:**

Figure 2: **Spaghetti carbonara: 191 kcal per 100g**

Figure 3: **Steak: 150 kcal per 100g**

Figure 4: **Donuts: 452 kcal per 100g**

**Here are the incorrectly classified examples:**

Figure 5: **Predicted: Tiramisu-283 kcal per 100g, GT: bread pudding**

Figure 6: **Predicted: Macaroni and cheese-164 kcal per 100g, GT: Grilled Chesee Sandwich**

# 4 Conclusion

As seen in the results, the predictions are pretty good for the most images. The results are more accurate in clear images as well. However, the results would be better if we could estimate ingredients, masses or volumes of food. We just assume that the mass of food is constant and 100 gram and that there is only one kind of food on the plate. Thus, our prediction is based on 100-gram food. Eventually, the results are satisfactory that we could improve with a larger database and different neural network.

# References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