

Identification and Classification in Food Images

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Abstract

Final Year Project focused on identification and classification of food images. A background of previous work done on the subject is outlined, followed by experiments in creating neural networks to perform classifications and segmentations. These experiments will be applied to food images and evaluated.

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Chapter 1

Introduction

1.1 Overview

This project explores the use of identification and classification of food images for use in a calorie measurement android application. Food calorie consumption is a huge problem in the modern world. Over 25% of the population in Ireland is obese and this figure is likely to rise over the coming years. A mobile application that could help keep track of a user's calorie intake by taking pictures of their meals would be a great help. The area of Machine Vision is a very difficult topic to address as it is a very hard task for computers to undertake. We, as humans, take vision for granted as we can soon see, from the study of Machine Vision, that there are many difficult steps that have to be made for full identification and classification of an image.

When looking into calorie measurement using an image, there are three questions that have to be answered:

- Where are the Regions of Interest (ROI) in this food image?
- What food types are in these ROI's?
- What is the portion size of each food type?

In this project, my main focus will be on the first question, 'Where are the Regions of Interest (ROI) in this food image?'.

Many researchers in various machine vision labs have attempted to solve this problem using different methodologies. There has been promising results from some papers but these are mostly under highly constrained circumstances. When mixed foods are introduced to the problem, many of the methods fail. Convolution Neural Networks (CNN) have had very promising results in the field of image classification in the recent years but to get to the classification step, image segmentation is first needed, otherwise known as image identification.

I have researched many different methods of image segmentation but it seems that CNN's have had the best results for multiple objects in one image and I hope to apply these results for many foods in an image.

The application that I am proposing to solve the problem statement above is an easy to use Android mobile phone application. The idea is, that when a user is about to eat their meal, they can simply take a picture of their meal for computation. From here, the application would take the image, find the objects (ROI) in the image and take note of them. Concurrently, the application would attempt to classify each object detected. Once this is done, the size of each food type would be measured and through this an overall calorie count would be displayed for the user. This could be logged for user metrics. I will focus on finding the objects for this application as I would not be able to implement the full system due to time constraints.

1.2 Objectives

I have a few objectives for this project and I will explain each one in detail.

Understanding of Convolutional Neural Networks

In the project, I will be using Convolutional Neural Networks (CNN's) for object identification in Food Images. I will be using an API for this due to time

constraints but it is a key objective for me to develop a deep understanding of CNN's as they are quite pivotal in the current Machine Vision Industry and I find bio-inspired systems very interesting.

Learn about different image identification and classification techniques

Although, I will be using CNN's for my implementation, I will not be turning a blind eye to other methods of identification and classification. I have done extensive research on many different methods prior to my decision to use CNN's. I think it is very important to learn about other methods as different methods are better suited for some situations and it would be best to know about these methods due to the inevitability of their use.

Develop real world skills in Machine Vision

Machine Vision is a growing field in computer science and I think it is a very interesting field to study. My main objective is develop the skills necessary in order to partake in Machine Vision projects in industry or to do further research in academia.

1.3 Methodology

The following methodology were adapter for this project:

1.3.1 Define the research question

The first step to this project was to define the research question. I knew that I wanted to look into the general area of 'Food Identification and Classification' but the scope of this is too broad for an FYP. Therefore I decided that the research question would be to look at the food identification aspect ie. region of interest detection.

1.3.2 Literature Review

Once I had defined the question, finding related work was the next milestone. There are many attempts at Food Image Classification and these were not difficult to find, using Google Scholar, but many of these papers glossed over the segmentation aspect and relied on third parties for this step. Because of this, I had to follow quite a few references to different papers that focused solely on image segmentation.

1.3.3 Explore different image identification methods

I had collected various image identification from the literature review that I carried out so there were many options to evaluate. I wanted to try something with Convolutional Neural Networks so more traditional methods of identification using colour and texture was not so strenuously explored.

1.3.4 Select an image identification method

1.3.5 Research technologies and develop skills in these technologies

As I used a Convolutional Neural Network (CNN) in this project, I leveraged many resources to enrich my understanding of the process. I decide to use Tensorflow as my main resource in creating a CNN so I followed online tutorials for this technology. I also enrolled in a Deep Learning Course on Udacity to enhance my understanding and skills.

1.3.6 Build a prototype of the application

1.3.7 Compare and analyse results to other implementations

1.4 Overview of Report

This report is broken down into various main headings:

Introduction

This section is to give an overview of what this project is about, how I will approach this project and why I am doing it.

Background

I will be giving some information on the background of the subject that I am focusing on.

Experiments

In this part of the report I will carry out various experiments using tensorflow.

Empirical Studies with Food Images

This section will analyse the results I have obtained and compare them against various metrics and other implementations.

Discussion and Conclusion

In this section, I will discuss my results from the empirical studies and conclude my findings.

1.5 Motivation

I find the topic of Computer Vision a very interesting one. It excites me, to be able to 'teach' a machine how to see as we do. For this reason, I really wanted to learn about Neural Networks and this was a large motivator for this project.

Once I had a topic that I wanted to research, I needed a focus or problem statement for this research. I find that it is much more rewarding to work on something that positively impacts both myself and other people so I decided that I wanted to research something that fit this requirement.

Food calorie consumption is a very big problem in the modern world. Over 25 percent of the population in Ireland are obese. A mobile application that could help keep track of a user's calorie intake by taking a picture of their meals would be a big help to combat this problem. This problem statement works very well for me because of its application use and because of its complexity. Identifying and recognising food is much more difficult than say recognising faces as it has no uniform shape. Therefore, this problem would also be very beneficial to developing skills in the computer vision area.

Chapter 2

Background

2.1 Introduction to Machine Learning

In Mitchell [6], Machine Learning is defined as "the question of how to construct computer programs that automatically improve with experience". Machine Learning has blossomed in recent years with applications across multiple domains using vastly different paradigms and technologies.

There are many ways in which Machine Learning can be used in the modern world, many of which are being utilised to great affect. Some of these applications, are image recognition, natural language processing, medical diagnosis and many more. There may be fear that Machine Learning will start to take away many jobs from humans but this may not be the case. Imagine a doctor, having to diagnose a patient, a machine can offer suggestions based on very large datasets of what the diagnosis is. This is not to say that a Machine would be perscribing patients, but merely act as an assistant to the doctor.

Machine Ethics is a large problem that comes hand in hand with Machine Learning. There is a very important question of who takes the blame when things go wrong, that is why I think it is important that we only use Machine Learning to advise and not to determine but this can be very difficult in a world where, for example, an autonomous car has to decide between crashing into a vehicle beside them with an unknown number of people inside or the

two children playing in the street.

One of the most exciting avenues in Machine Learning, in my opinion, is Computer Vision. Computer Vision can be used in many areas to improve our lives. As mentioned earlier, autonomous cars are only possible when a machine can determine what objects are around it. Computer Vision can allow a machine to recognise skin diseases in an image. The applications are nearly limitless and that is without taking into account other uses.

2.2 Machine Learning Paradigms

There are many Machine Learning paradigms, all of which I will discuss briefly below, but the main area of my focus for this project is in Artificial Neural Networks (ANN). This is because I have researched extensively into Convolutional Neural Networks which are based on ANN's.

2.2.1 Artificial Neural Networks

An Artificial Neural Network is a bio-inspired system that is used to model the human brain in how it learns from experience. The ANN uses this model to build a very complex web of connected units called artificial neurons. These neurons are connected by certain weights which determines the processing capacity of the network and these weights are created by learning a dataset. (Malachy) An ANN has a set of inputs that take in a value, sometimes from network outputs and produce a single result or classification. While an ANN is bio-inspired from the human brain, there are many elements of the brain that are not present in ANN and many new elements in ANN that are not modelled from the human brain.

Before I can talk about Convolution Neural Networks which are vital the image processing, I will have to talk about the perceptron learning algorithm, the multi layer perceptron, and backpropagation.



Figure 2.1: Perceptron

Perceptron Learning - Artificial Neuron

In our Artificial Neural Network a Perceptron is an Artificial Neuron. It is called an Artificial Neuron because it is a bio-inspired neuron which models a neuron in the human brain in terms of inputs and output.

In Perceptron learning, we can take two inputs which are put towards an activation function with a bias attached as seen in 2.1. These inputs are multiplied by the weights that connect the input to the activation function and depending on the result, the activation function may fire an output.

This Perceptron Learning Rule assumes that there are two sets of instances, a positive and negative set, and each of these has an input and output domain.

Multi Layered Perceptron

Multi Layer Perceptrons (MLP) are made up of multiple layers of perceptrons connected together. Firstly, we have an input layer, followed by one or more hidden layers and then finally an output layer. Any Neural Network with more than three hidden layers is categorised as a deep layer.

Multi Layer Perceptrons are a class of feed forward Artificial Neural Networks. This means that the output of each perceptron feeds into an input in the next layer of the network.

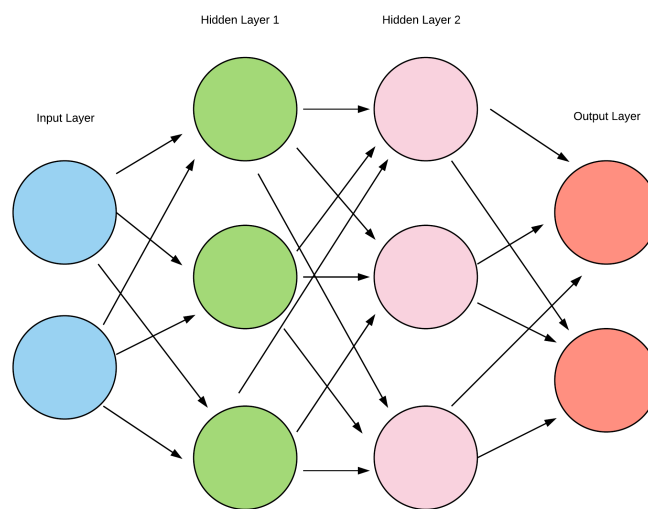
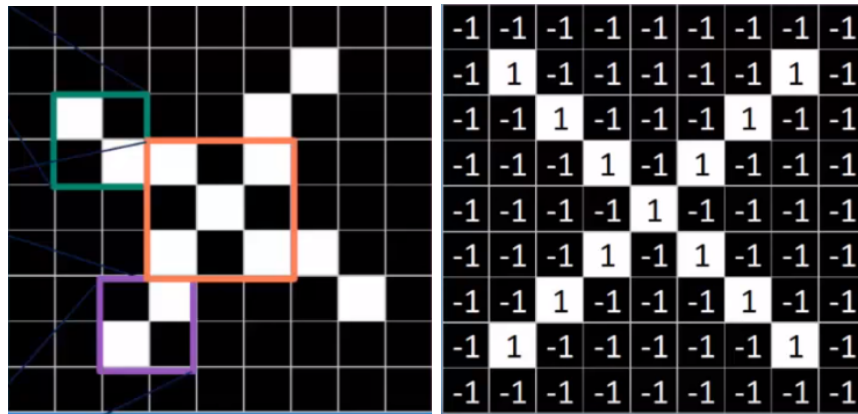


Figure 2.2: Multi Layer Perceptron



(a) Image to Classify

(b) Image to Compare

Gradient Descent and Backpropagation

Gradient Descent is an algorithm used to find the optimal weights to produce the smallest prediction error.

Backpropagation is used to calculate the error for each neuron.

Convolutional Neural Networks

Convolutional Neural Networks (CNN's) are essentially a Multi Layered Percetron with a special structure. CNN's have one major difference from a MLP, they have extra layer of convolution and pooling.

Figure ?? show an image that we want to compare against Figure ??. For humans, it is quite easy to determine that these images are very similar but for a computer this task is surprisingly difficult.

So what a CNN does, to combat this problem, is to take a small feature from Figure ?? and compare it to a subsection of Figure ??. The CNN multiplies the feature and a section of Figure ??, adds up the results and divides by 9. This then gives a decimal value of how likely it is that the feature is in the part of the image, as seen in Figure 2.4b. This is called filtering. The Convolutional layer is composed of carrying out this filtering for every single possible location in Figure ??.

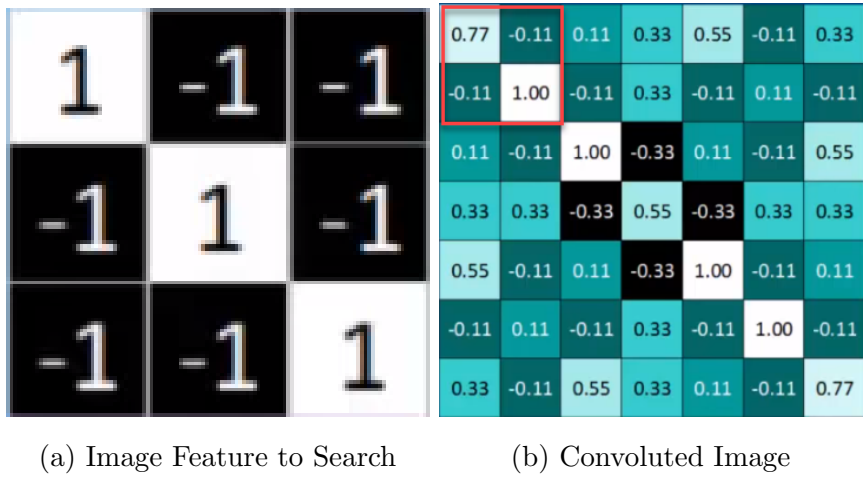


Figure 2.5: Pooled Image

Next is the Pooling Layer, what this layer does, is it takes the convoluted layer output, you can use Figure 2.4b as reference, and from a user defined size ie. 2x2, gets either the highest decimal value (Max pooling) or the average value (Mean pooling) and records that as the new value for the section. This is then applied to the entire image. As we can see in Figure 2.5 we know have a much smaller image stack in which to classify, thus making the computation easier. In between the Convolution and Pooling layer, there is sometimes a Normalization layer. This Normalization layer creates Rectified Linear Units (RLU's). In other words, if we take Figure 2.4b, it changes all minus values to zero.

Fully Convolutional Networks

A Fully Convolutional Network is one that does not have a fully connected layer and in a fully connected layers place is another convolution layer.

2.2.2 Other Paradigms

There are many other Machine Learning paradigms apart from Neural Networks, each of which I will give a brief introduction.

Decision Trees

"Decision tree learning is method for approximating discrete-valued target functions, in which the learned function is represented by a decision tree" Mitchell [7]. There are many different classification algorithms that can create decision trees from supervised learning.

Bayesian Learning

Instance Based Learning

Logistic Regression

Support Vector Machine

Regression Analysis

Unsupervised Learning

Reinforcement Learning

2.3 Overview of Machine Vision Approaches to Identification and Classification

There have been many attempts of identification and classification by many different researchers over the last number of years. There some approaches that decouple the two tasks of identification and classification from one another but mostly, researchers have attempted the two together. Sometimes, by semantic segmentation and in others simply building a classifier for the image without taking into account, the need for object identification.

2.3.1 Region Based Convolutional Neural Networks

Ross Girshik and other contributors had some very positive results in the area of object detection using region based convolutional neural networks. There were four iterations of papers based on this work by Ross and groups in UC Berkley, Microsoft and Facebook. A PHD student at the time of Ross's first paper also completed his dissertation on the subject. I will analyse this papers, their results (2.1) and the changes made through each iteration.

RCNN

In the first paper written by Ross Girshik, while researching at UC Berkeley, focused on two main insights. These were that "one can apply high-capacity convolutional neural networks (CNNs) to bottom-up region proposals in order to localize and segment objects" and that "when training data is scarce, supervised pre-training for an auxiliary task, followed by domain-specific fine-tuning, yields a significant performance boost" Girshick et al. [3].

The system that they developed followed these steps:

- Take image as input
- Extract approximately 2000 region proposals from the image
- Compute fixed length vectors of features for the regions using a convolutional neural network
- Use a Support Vector Machine (SVM) to classify these regions
- Bounding box regression for final region proposals

This system utilised selective search to gather these region proposals but they mention that a sliding-window detector is also an option. Ross Girshik and his team used the open source Caffe CNN library for this system. The system is quite efficient and scalable. It is scalable because of the fixed length vector of features which will remain constant regardless of inputs and additional outputs.

The team evaluated their results on a few metrics and test sets as seen in 2.1.

Fast RCNN

Ross Girshik's next iteration of work on region based convolution neural networks took place in Microsoft Research. This paper was titled "Fast R-CNN" as its aim was to decrease training and testing time "while also increasing detection accuracy" Girshick [2].

This paper analyses why RCNN Girshick et al. [3] was slow and therefore how it could be improved. RCNN was classified to be slow because of three main factors:

- There are multiple stages to training as both a CNN and a SVM need to be trained.
- In training of the SVM, each region proposal must be written to disk and is therefore expensive.
- Object detection takes 47s per image Girshick [2].

Due to these problems with RCNN, a new algorithm, titled Fast RCNN was proposed. The architecture is as follows. An image is taken as input along with a proposals for regions. The image is pushed through convolutional and pooling layers (using max pooling). A fixed-length vector of features is then extracted from each region proposal. These vectors are inputted to fully connected layers for bounding box location prediction Girshick [2].

At detection time, a pass through of the net is all that is needed so this runtime is significantly less than RCNN.

Faster RCNN

Due to the success of RCNN and Fast RCNN, Faster RCNN was introduced to combat the problem of region proposal computation Ren et al. [8].

The architecture for this system comprises of two modules. These consist of a convolutional neural network for region proposals (RPN) which the feeds into a Fast RCNN detector. These combine to produce a single neural network for object detection.

Instead of training these networks separately, the team had to look at how to share layers between the two networks. There were three option available:

- Alternating training whereby RPN is trained, and then used to train Fast RCNN. The Fast RCNN network is then used to initialise RPN and the process is iterated Ren et al. [8]. This paper follows this approach.

Table 2.1: Results from Region Based CNN Research

	VOC07	VOC10	VOC11	VOC12	COCO15	COCO16
RCNN	58.5%	53.7%	47.9%	N/A	N/A	N/A
Fast RCNN	70.0%	68.8%	N/A	68.4%	N/A	N/A
Faster RCNN	78.8%	N/A	N/A	75.9%	42.7%	N/A
Mask RCNN	N/A	N/A	N/A	N/A	N/A	63.1%

- Approximate joint training.
- Non- approximate joint training.

Mask RCNN

The most recent paper on this topic was also written by Ross Girshik while working with Facebook AI Research He et al. [4]. Mask RCNN ”extends Faster RCNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box regression” He et al. [4].

Mask RCNN has two modules, similar to Faster RCNN, where the first module is the Region Proposal Network. In the second module, in parallel to classification, a binary mask is outputted for each region. Bounding box regression and classification are done in parallel.

2.3.2 Fully Convolutional Neural Networks for Semantic Segmentation

There has been a very interesting paper from UC Berkeley focused on using Full Convolutional Networks for semantic segmentation Shelhamer, Long, and Darrell [9]. Fully Convolutional Networks (FCN) do not have any fully connected layers. They are replaced with more filtering layers. Nvidia Digits have a semantic segmentation implementation based off the work of this paper.

They took this approach because ”feedforward computation and backpropagation are much more efficient when computer layer-by-layer over an entire image

Table 2.2: FCN Results Shelhamer, Long, and Darrell [9]

	FCN
VOC11 mean IU	62.7
VOC12 mean IU	62.2
PASCAL VOC10 pixel acc.	67.0
PASCAL VOC10 mean acc.	50.7
PASCAL VOC10 mean IU	37.8
PASCAL VOC10 f.w. IU	52.5

instead of independently patch-by-patch” Shelhamer, Long, and Darrell [9]. This was also because they were focused on object detection. Normal classifiers do not work very well when they are to classify more than one subject in an image and image segmentation was a way to solve this.

There are a set of steps you can follow to turn a CNN into a FCN for semantic segmentation as follows ie. change to a convolutional layer from a fully connected one:

- The size of the filters must be set to the size of the input layers.
- For every neuron in the fully connected layer, have a filter.

2.3.3 Image Segmentation

Graph Based Segmentation

Sift/Surf

2.3.4 Convolutional Neural Networks for Classification

2.4 Technologies

2.4.1 Tensorflow

2.4.2 Jupyter

2.4.3 OpenCV

2.5 Evaluating the Output

There are various different metrics that can be used for evaluating the output of a classifier or segmentation algorithm, many of which we have seen in previous sections. I will analyse a few of these evaluations of results so that I can use them as a reference to apply to my own experiments. I will also look into some problems associated with evaluating models.

2.5.1 Research into Diagnosing Errors in Object Detectors

There has been some research into the question of how to evaluate object detectors, one of which I will discuss in detail Hoiem, Chodpathumwan, and Dai [5]. This paper in question "analyzes the influences of object characteristics on detection performance and the frequency and impact of different types of false positives" Hoiem, Chodpathumwan, and Dai [5]. They found that there were many effects that had influence on detectors as follows:

- occlusion
- size
- aspect ratio
- visibility of parts
- viewpoint
- localization error
- confusion with semantically similar objects
- confusion with other labeled objects
- confusion with background

The research team goes on to analyse false positives in object detectors. Localization errors were a large factor. This is where bounding boxes overlap to other objects in the image. Confusion with similar objects had a large influence on false positives also by which, for example, a dog detector had a high score for a cat Hoiem, Chodpathumwan, and Dai [5]. Confusion with dissimilar objects and confusion with background are the categories of the rest of the false positives they measured.

In conclusion the team would that "Most false positives are due to misaligned detection windows or confusion with similar objects" Hoiem, Chodpathumwan, and Dai [5]. They had some recommendations towards improves detectors as follows:

- Smaller objects are less likely to be detected
- Localization could be improved
- Reduce confusion with similar categories
- Robustness to object variation
- More detailed analysis

VOC 2010 test	aero	bike	bird	boat	bottle	bun	car	cat	chair	cow	table	dog	horse	motor	person	plant	sheep	sofa	train	tv	mAP
DPM v5 [Chen et al. 2013]	49.2	53.8	13.1	15.3	35.5	53.4	49.7	27.0	17.2	28.8	14.7	17.8	46.4	51.2	47.7	10.8	34.2	20.7	43.8	38.3	33.4
UVA [Ullrich et al. 2013]	56.2	42.4	15.3	12.6	21.8	49.3	36.8	46.1	12.9	32.1	30.0	36.5	43.5	52.9	32.9	15.3	41.1	31.8	47.0	44.8	35.1
Regionlets [Wang et al. 2013a]	65.0	48.9	25.9	24.6	24.5	56.1	54.5	51.2	17.0	28.9	30.2	35.8	40.2	55.7	41.5	14.3	43.9	32.6	54.0	45.9	39.7
SegDPM [Fidler et al. 2013]	61.4	53.4	25.6	25.2	35.5	51.7	50.6	50.8	19.3	33.8	26.8	40.4	48.3	54.4	47.1	14.8	38.7	35.0	52.8	43.1	40.4
R-CNN	67.1	64.1	46.7	32.0	30.5	56.4	57.2	65.9	27.0	47.3	40.9	66.6	57.8	65.9	53.6	26.7	56.5	38.1	52.8	50.2	50.2
R-CNN BB	71.8	65.8	53.0	36.8	35.9	59.7	60.0	69.9	27.9	50.6	41.4	70.0	62.0	69.0	58.1	29.5	59.4	39.3	61.2	52.4	53.7

Figure 2.6: Detection Average Precision Donahue [1]

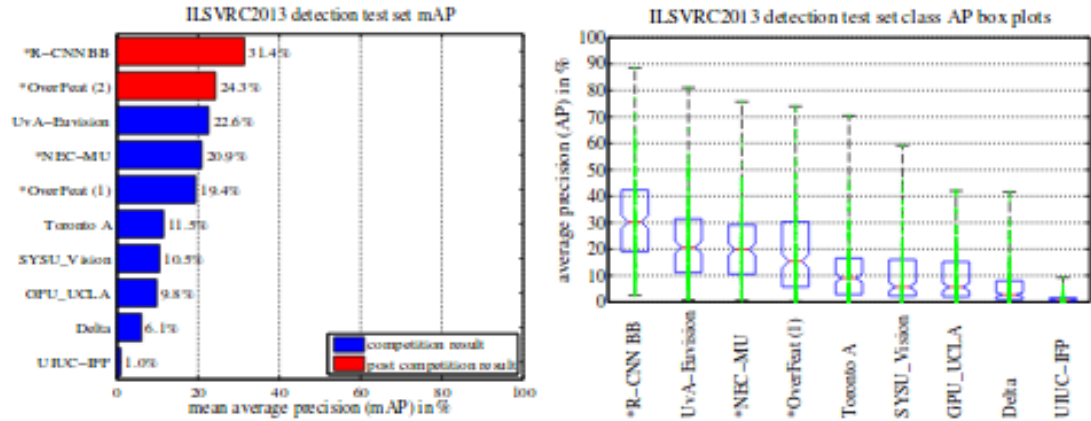


Figure 2.7: Mean Average Precision Donahue [1]

2.5.2 Detection Average Precision

See 2.6.

2.5.3 Mean Average Precision

See 2.7.

2.5.4 Distribution of top-ranked false positives

See 2.8.

2.5.5 Segmentation Mean Accuracy

See 2.9.

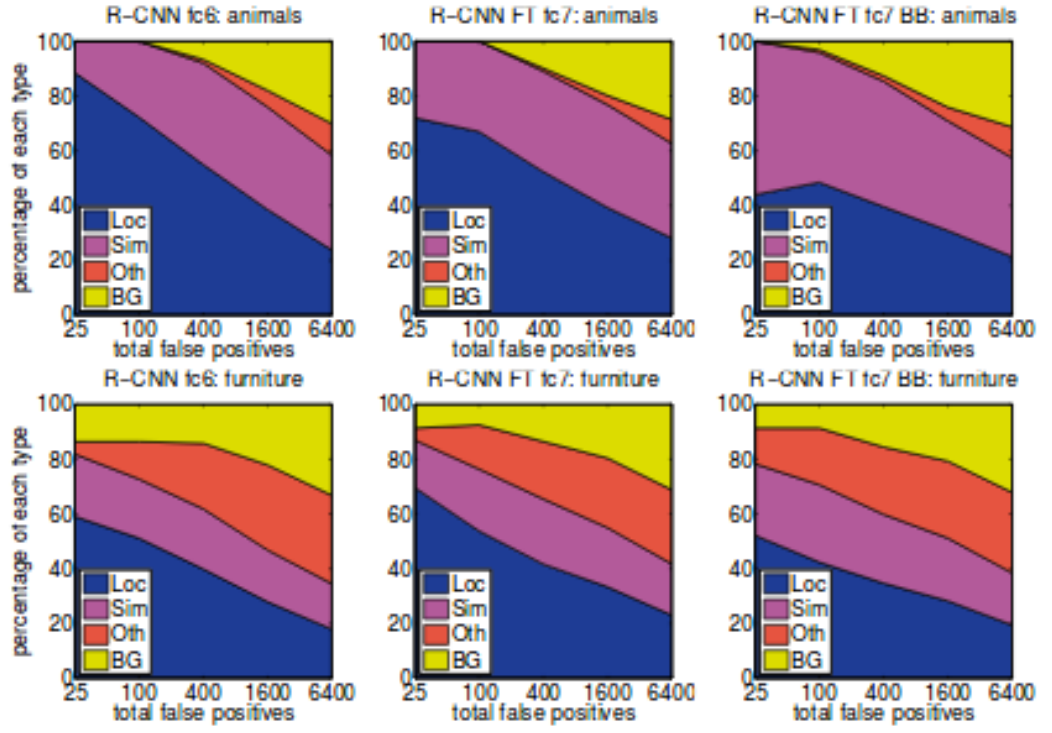


Figure 2.8: Distribution of top-ranked false positives Donahue [1]

O_2P (Carreira et al., 2012)	<i>full</i> R-CNN		<i>fg</i> R-CNN		<i>full+fg</i> R-CNN	
	fc_6	fc_7	fc_6	fc_7	fc_6	fc_7
46.4	43.0	42.5	43.7	42.1	47.9	45.8

Figure 2.9: Segmentation Mean Accuracy Donahue [1]

VOC 2011 val	bg	aero	bike	bird	boat	bottle	bun	car	cat	chair	cup	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mean
O ₂ P [Carrreira et al., 2013]	84.0	69.0	21.7	47.7	42.2	42.4	64.7	65.8	57.4	12.9	37.4	20.5	43.7	35.7	52.7	51.0	35.8	51.0	28.4	59.8	49.7	46.4
full R-CNN \hat{c}_a	81.3	56.2	23.9	42.9	40.7	38.8	59.2	56.5	53.2	11.4	34.6	16.7	48.1	37.0	51.4	46.0	31.5	44.0	24.3	53.7	51.1	43.0
full R-CNN \hat{c}_7	81.0	52.8	25.1	43.8	40.5	42.7	55.4	57.7	51.3	8.7	32.5	11.5	48.1	37.0	50.5	46.4	30.2	42.1	21.2	57.7	56.0	42.5
f_{R} R-CNN \hat{c}_a	81.4	54.1	21.1	40.6	38.7	53.6	59.9	57.2	52.5	9.1	30.5	23.6	46.4	38.1	53.2	51.3	32.2	38.7	29.0	53.0	47.5	43.7
f_{R} R-CNN \hat{c}_7	80.9	50.1	20.0	40.2	34.1	40.9	59.7	59.8	52.7	7.3	32.1	14.3	48.8	42.9	54.0	48.6	28.9	42.6	24.9	52.2	48.8	42.1
full+ f_{R} R-CNN \hat{c}_a	83.1	60.4	23.2	48.4	47.3	52.6	61.6	60.6	59.1	10.8	45.8	20.9	57.7	43.3	57.4	52.9	34.7	48.7	28.1	60.0	48.6	47.9
full+ f_{R} R-CNN \hat{c}_7	82.3	56.7	20.6	49.9	44.2	43.6	59.3	61.3	57.8	7.7	38.4	15.1	53.4	43.7	50.8	52.0	34.1	47.8	24.7	60.1	55.2	45.7

Figure 2.10: Per-category segmentation accuracy Donahue [1]

class	AP	class	AP	class	AP	class	AP	class	AP
accordion	50.8	centipede	39.4	hair spray	13.8	pencil box	11.4	snowplow	69.2
airplane	50.0	chain saw	14.1	hamburger	34.2	pencil sharpener	9.0	soap dispenser	16.8
ant	31.8	chair	19.5	hammer	9.9	perfume	32.8	soccer ball	43.7
antelope	53.8	chime	24.6	hamster	46.0	person	41.7	sofa	16.3
apple	30.9	cocktail shaker	46.2	harmonica	12.6	piano	20.5	spatula	6.8
armadillo	54.0	coffee maker	21.5	harp	50.4	pineapple	22.6	squirrel	31.3
artichoke	45.0	computer keyboard	39.6	hat with a wide brim	40.5	ping-pong ball	21.0	starfish	45.1
axe	11.8	computer mouse	21.2	head cabbage	17.4	pitcher	19.2	stethoscope	18.3
baby bed	42.0	corkscrew	24.2	helmet	33.4	pizza	43.7	stove	8.1
backpack	2.8	cream	29.9	hippopotamus	38.0	plastic bag	6.4	strainer	9.9
bagel	37.5	croquet ball	30.0	horizontal bar	7.0	plate rack	15.2	strawberry	26.8
balance beam	32.6	crutch	23.7	horse	41.7	pomegranate	32.0	stretcher	13.2
banana	21.9	cucumber	22.8	hotdog	28.7	popsicle	21.2	sunglasses	18.8

Figure 2.11: Per-class segmentation accuracy Donahue [1]

2.5.6 Per-category segmentation accuracy

See 2.10.

2.5.7 Per-class segmentation accuracy

2.11.

Chapter 3

Experiments

3.1 Experiment 1

3.1.1 Network Architecture

3.1.2 Dataset

3.1.3 API's

3.1.4 Script

3.1.5 Results

3.1.6 Analysis

Chapter 4

Empirical Studies with Food Images

Chapter 5

Discussion and Conclusion

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