Development of criteria suitable for machine learning based on morphological hierarchical trees

A Degree Thesis

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by

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Advisor: Laurent Najman and Philippe Salembier

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Abstract

Nowadays the technology is changing the way of performing and it is adapting towards Artificial Intelligence. However this technique is still being introduced and is not common in the domain of image processing based on morphological trees. This thesis focuses on the creation of a criterion based on machine learning to be assigned into morphological tree. The developed criterion is based on a Convolutional Neural Network, called Overfeat, which runs in to the nodes of a Binary Partition Tree, in order to be able to detect traffic signs. It has turned out to be a suitable criterion to identify traffic sings in images but it has room of improvement due to its performance is lower than 70% of success.

Resum

Avui en dia la tecnologia esta canviant la seva forma d'actuar i s'està adaptant cap a la Intel·ligència Artificial. Tot i que aquesta tècnica s'està introduint no és gaire comú en el domini del processament d'imatge basat en arbres morfològics. Aquesta tesis es centra en la creació d'un criteri basat en machine learning que s'assigna a un arbre morfològic. El criteri desenvolupat en aquest projecte es basa en una Xarxa Neuronal Convolucional, anomenada Overfeat, que treballa sobre els nodes d'un arbre de partició binaria, per ser capaç d'identificar senyals de transit. El criteri ha resultat ser adequat per identificar senyals de transit però encara te marge de millora ja que els resultats obtinguts no son superiors al 70% d'encert.

Resumen

Hoy en día la tecnología está cambiando su forma de actuar y se está adaptando hacia la Inteligencia Artificial. Aunque esta técnica se está introduciendo, no es muy común en el dominio del procesamiento de imagen basado en arboles morfológicos. Esta tesis se centra en la creación de un criterio basado en Machine learning que se asigna a un árbol morfológico. El criterio desarrollado en este proyecto se basa en una Red Neuronal Colvolucional, llamada Overfeat, que trabaja sobre los nodos de un árbol de partición binaria, para ser capaz de identificar señales de tráfico. El criterio ha resultado ser adecuado para identificar señales de tráfico pero aún tiene margen de mejora ya que los resultados obtenidos no son superiores al 70% de acierto.

To all my family, especially my parents Pilar and Jesús,
you are my unconditional support.

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Moreover, I would want to show my gratitude to Nguyen Xuan Thanh, for his patience when guiding me and helping me every time I needed.

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1. Introduction

1.1. Statement of purpose

The purpose of this project is to study and develop image criteria to be assigned to morphological trees, which are a way of representing the hierarchical nature of an image in a graphical form.

A classical approach to object detection in images is the sliding window approach, which as its name suggests, uses a window to that runs through the entire image searching for objects of interest.

The idea of this technique is explained in the Fig. 1. Firstly it is needed to select the size of the window according to the searched object, in the Fig. 1 example the size of the window is 3x3 pixels. Once the size has been chosen, the window runs through the image form left to right and from top to bottom and, at each particular location, it is decided if the desired object is in the window or not.

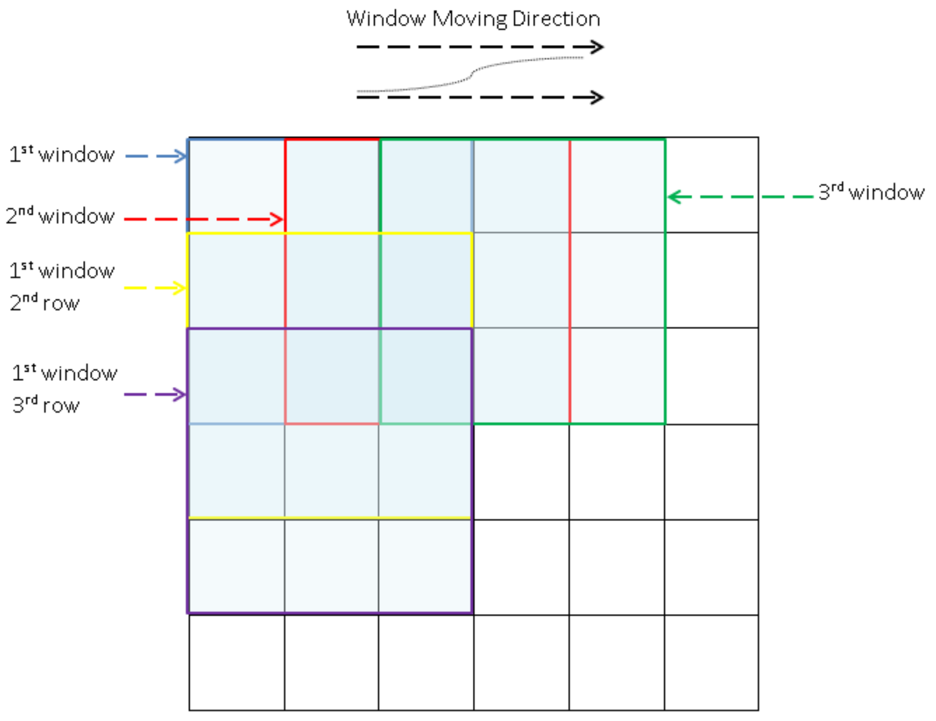

Figure 1: Sliding window technique.

The searched object can have different sizes in the same image, so it is necessary to scan the entire image with different size of windows (keeping the aspect ratio) or keep the window size and make the image smaller, so the area contained by the window would be bigger.

In this way, the image is scanned several times to identify all the objects of interest, but with the morphological tree representation only one scan is needed to build the tree representation.

In morphological trees, pixels are grouped in a natural way, forming shapes, and these shapes are represented by the nodes of the tree and the link between nodes represents the inclusion relationship. So with the tree representation, the detection of the objects of interest becomes easier as the focus is now on tree nodes instead of raw pixels.

Machine learning is the ability of a computer system to learn to perform a task without being explicitly programmed, in other words, it is the way to represent the human brain behaviour in a computer system. Every machine learning system requires a two-step process: training and test. During the training phase the system is provided with a large amount of data, the desired result and the optimization criterion. With all these inputs the system creates a mapping between the input data and the desired result by optimizing the criterion given, which provides the system with the ability to "learn". Finally when the training phase has ended, this mapping is used in the test phase with new input data to predict their result.

Machine learning is really helpful because it is not necessary to program a whole process with a purpose, but instead, with some machine learning algorithms, you can achieve the same results and hopefully even better ones.

Nowadays the object detection with morphological trees has been implemented by using programmed functions specifically adapted to the object which is being identified. What we want to do is to adapt this process by introducing a classifier based on machine learning, which will work on the nodes of a morphological three, and the result of this classification will be used to identify traffic signs in the images.

The main goals of the project are:

1- Study and learn about morphological trees.

2- Develop and test different criteria based on machine learning to be assigned to morphological trees.

3- Identify particular elements in images, such as traffic signals.

1.2. Requirements and specifications

The requirements of this project are the following:

- Machine learning should be included in the criteria.

- The results based on [2] must been improved by using the machine learning criteria.

The project specifications are the following:

- Use Python as a programming language.

- The system must detect the traffic signal on German Traffic Sign Detection Benchmark (GTSDB) dataset images with at least 90% accuracy.

1.3. Methods and procedures

The project has been carried out at ESIEE Paris in Noisy-le-Grand, France.

This project uses OverFeat Neural Network software [1] and simplified algorithms from Playing with Kruskal [4]. It is developed in Python and it uses Scikit-Learn module for Python [6].

1.4. Work plan

The work plan is described in the following work packages and Gantt diagram. During its development it has been modified and all the modifications are explained below:

1.4.1. Work packages

- WP 1: Previous information
- WP 2: Machine learning criteria
- WP 3: Software development
- WP 4: Integration and test
- WP 5: Thesis writing

1.4.2. Gantt diagram

	Nombre	Inicio	Terminado
1	⊟**Previous information**	**9/02/18 8:00**	**9/03/18 17:00**
2	Morphologicatl tree	9/02/18 8:00	9/03/18 17:00
3	Machine learning	9/02/18 8:00	9/03/18 17:00
4	⊟**Machine learning criteria**	**12/03/18 8:00**	**27/04/18 17:00**
5	Criteria selection	12/03/18 8:00	27/04/18 17:00
6	Point of application selection	12/03/18 8:00	27/04/18 17:00
7	⊟**Software building**	**27/04/18 8:00**	**1/06/18 17:00**
8	Development	27/04/18 8:00	18/05/18 17:00
9	Individual testing	21/05/18 8:00	1/06/18 17:00
10	⊟**Integration and test**	**1/06/18 8:00**	**20/06/18 17:00**
11	Integration	1/06/18 8:00	8/06/18 17:00
12	Training	8/06/18 8:00	12/06/18 17:00
13	Test	8/06/18 8:00	12/06/18 17:00
14	Adjustments	12/06/18 8:00	20/06/18 17:00
15	⊟**Thesis writing**	**1/06/18 8:00**	**29/06/18 17:00**
16	Thesis writing	1/06/18 8:00	29/06/18 17:00
17	Feedback	1/06/18 8:00	29/06/18 17:00

Figure 2: Gantt diagram

1.4.3. Incidences and modifications

While we were developing the project there were issues that caused delays and meant that we had to modify the initial Work plan.

Firstly, in work package 2 there was a misunderstanding about the notion of machine learning criterion and how to implement it in the project. After some discussion, we decided to focus on a single and simple criterion.

After this, work package 3 turned out to be heavier than we thought due to the fact that the programming language in the criteria development is Python, and that I had no prior knowledge about this programming language. As a result, it was necessary to devote time to learn the language and adapt to the programming framework.

The decision to focus on a single criterion, has also been reached because while developing work package 4 we have realized that the integration was more difficult than we expected, because of the architecture of our neural network and our tree, which were not easily compatible until we had developed the code to connect them.

In addition, in the initial Work plan, we did not specify a specific work package related to the thesis writing so we had to add it to our work plan.

2. State of the art

The project has two different topics on which it depends, morphological trees and machine learning.

2.1. Morphological trees

Morphological trees are a way of representing the hierarchical nature of an image in graphical form. There are different approaches but in this project the morphological tree we are working with is the Binary Partition Tree.

A Binary Partition Tree is a structured representation of regions that can be obtained from an initial partition. This initial partition can be obtained by a segmentation procedure or it can be provided by the user.

The tree leaves represent regions that belong to an initial partition while the remaining nodes represent regions that are obtained by merging two child regions.

In the example shown in Fig. 4, it can be seen that the initial partition corresponds to each single pixel of the original image (Fig.4.a), so each leaf corresponds to a pixel. The Binary Partition Tree is built by merging two of these regions resulting in a new region which contains both children regions. If the process is followed until the end, the entire image will be represented in the root node of the Binary Partition Tree (Fig.4.b).

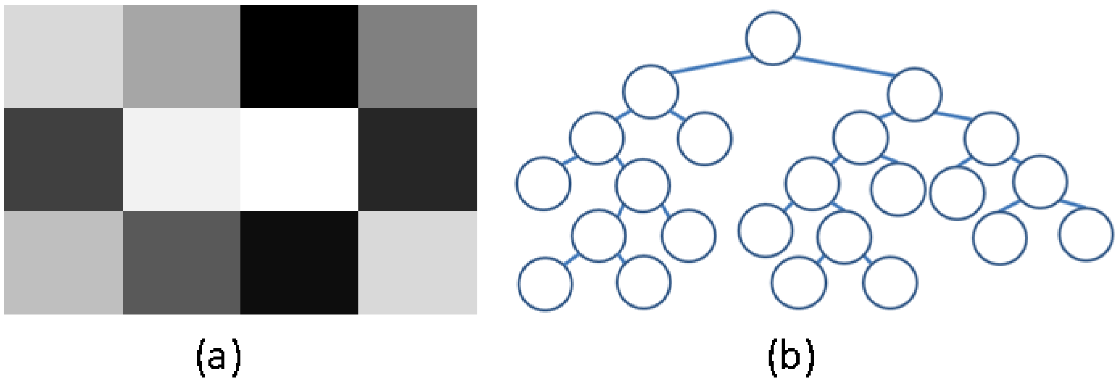

Figure 3: (a) Original image; (b) Example of Binary Partition Tree.

2.2. Machine learning

Machine learning is a subset of artificial intelligence in the field of computer science that creates computer systems which “learn” automatically. This learning can result in the identification of complex patterns in millions of data or it can be a progressive improvement on the performance of a specific task but what the machine really learns is an algorithm which looks into the data and is capable of predicting future behaviours. Every machine learning system, as well as a biological brain, has two phases, training and test. The training phase comprises the creation of a mapping between the input data and the desired outcome by optimising a previously specified optimization criterion. And then, when the mapping has been optimized, it can be used to predict results from new input data.

In other words, it is the way of representing the human brain behaviour in a computer system.

There are a lot of different approaches such as:

- Decision trees
- Association rule
- Support vector machines
- Bayesian networks
- Artificial neural networks

These are not the only ones however.

In this project we worked with a Neural Network called OverFeat so now we are going to explain what it is.

2.2.1. Neural Network

Neural Networks are computing systems inspired by the animal brains. These systems learn to perform tasks by taking examples. They generally use a database with labelled information in order to know what has to be done, and by the optimization of a specific criterion they generate automatically a mapping between the input data and the desired result, usually specified in the labels. The resulting mapping will be used to predict future results of new input data.

A Neural Network is based on a set of connected units or nodes which are called artificial neurons. This set of artificial neurons are connected and due to these connections, which model the synapse in a biological brain and are called edges, the information can be transmitted from one to another.

Usually in Neural Networks implementations a real number is the signal transmitted between the artificial neurons and the output of every artificial neuron is computed by some non-linear function of the sum of the inputs. To implement the learning process, each artificial neuron and edge has a weight that increases or decreases the strength of the signal and which is adjusted in the training process of the Neural Network.

Typically artificial neurons are aggregated into layers and every layer performs different transformations to their inputs. A Neural Network can be formed by lots of layers or very few, depending on the task that must be performed.

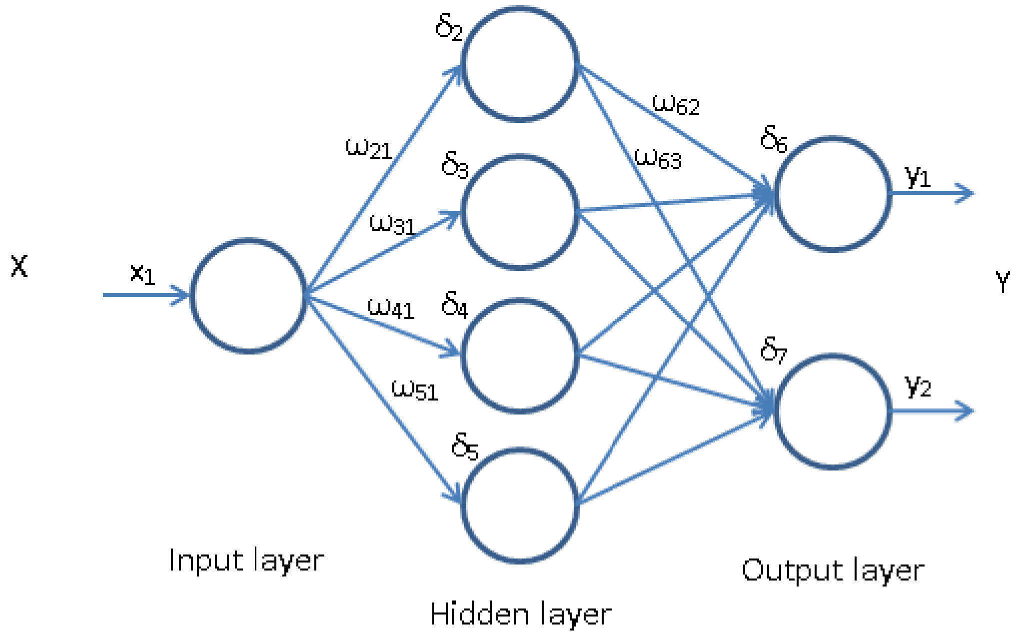

Figure 4: Neural network example where ω is the weight of the edge and δ is the weight of the node.

Particularly, OverFeat is a Convolutional Neural Network, which is a class of deep, feed-forward Neural Network, most commonly applied to analysing visual imagery.

2.2.2. Convolutional Neural Network

As Neural Network, CNNs consist of an input layer, an output layer and multiple hidden layers. The main difference lies in the minimal pre-processing required, the shared-weights architecture and the hidden layers, which can be convolutional, ReLU, pooling and fully connected.

2.2.2.1. Convolutional layer:

The convolutional layer is the basic element of a CNN. It has a set of filters which can be learnt and have a small receptive field but extend through all the input size. While the data go through the layer, each filter produces a two dimensional activation map of that filter. At the end of the process, the network have had learnt different filters that it will activate when it detects some particular feature in a precise position in the input.

2.2.2.2. ReLU layer:

The ReLU layer, or Rectified Linear Units layer, uses a non-saturating activation function to decide if a neuron is activated or not. Nowadays this is the most common used function because trains faster the neural network, but there are others such as the saturating hyperbolic tangent or the sigmoid function.

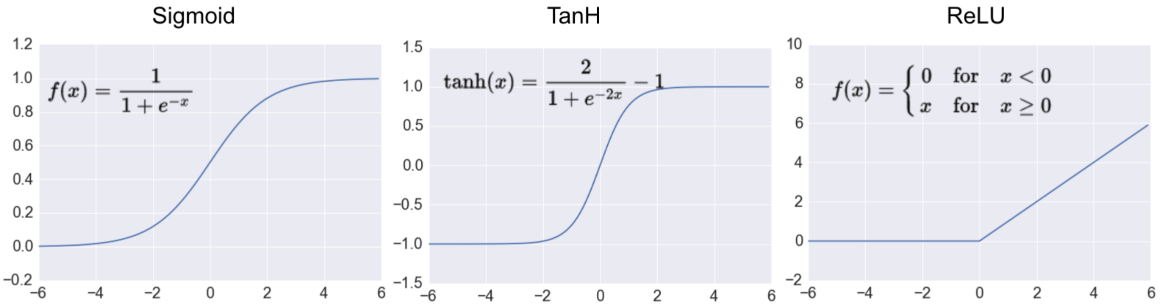

Figure 5: Activation functions, from left to wright, Sigmoid, hyperbolic tangent and Rectified Linear Units. [Source: http://adilmoujahid.com/images/activation.png]

2.2.2.3. Pooling layer:

The pooling layer performs a non-linear down-sampling to reduce progressively the amount of parameters and computation in the network. There are several functions to implement pooling but max pooling is the most common.

Max pooling function is based on the idea that the exact location of a feature is less important than its approximate location relative to other features. It partitions the input image into a set of non-overlapping rectangles from where the maximum value is calculated and given as an output.

This kind of layer is commonly inserted periodically between successive convolutional layers.

2.2.2.4. Fully connected layer:

The fully connected layers are the layers which perform the high-level reasoning in the neural network. The neurons of the fully connected layer are connected to all activations in previous layers so their activation can be computed with a matrix followed by a bias offset.

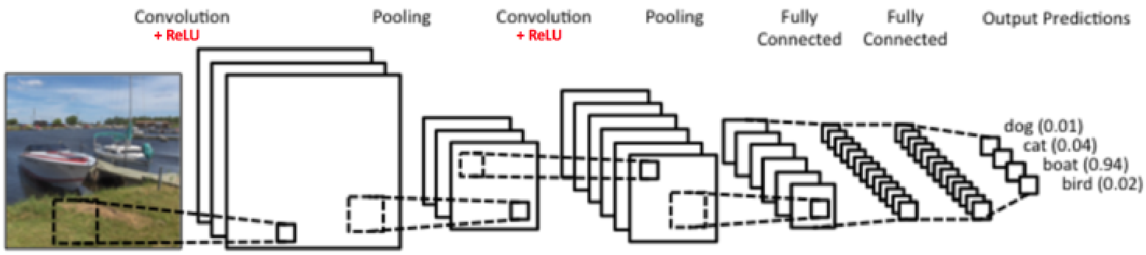

Figure 6: Architecture of a typical Convolutional Neural Network [7]

OverFeat is a Convolutional Neural Network which detects, recognises and locates objects in an integrated approach. It uses multiscale and sliding window approach to locate the objects and predict the boundaries of the object. Then it accumulates bounding boxes to increase the detection confidence.

It is a pre-trained Neural Network with 1000 classes (see appendix 1) which include traffic signals (street sign or traffic light, traffic signal, stoplight). It has no limitation of input image size and the computational time is short. For this reasons it feats perfectly in our project.

3. Methodology:

The aim of the project is to identify traffic signals in images by using a machine learning classifier working on morphological tree nodes. According to our database and the needs of the system the project has been divided into three phases which each depends on the previous phase to perform its task.

Figure 7: General diagram of the project.

3.1. Database

The German Traffic Sign Detection Benchmark (GTSDB) dataset is composed by 900 images (1360x800 pixels) in PPM format. The training dataset contains 600 images and the test dataset contains 300.

The images contain zero to six traffic signs which sizes vary from 16x16 to 128x128.

Traffic signs may appear in every perspective and under every lighting condition.

3.2. Pre-processing

The first phase of this project consists in a previous processing of the input image as well as a quick image scan to discard images which not contains traffic signals.

The size of the dataset image is too big to build a Binary Partition Tree which initial partition is each single pixel, so it is needed a reduction of the image to analyse.

The initial idea was to make smaller the image and work with a rescaled image but as traffic signals are not really big (16x16-128x128) the needed information was even more difficult to find, because traffic signs were smaller than before.

So then, the original image size needed to be kept but also make smaller the image to analyse. The resulting idea was to scan the image with smaller windows with which the morphological tree can be built.

The pre-processing block starts cropping the image in 9 different images. Each cropped image is sent to the Neural Network to analyse if there is some traffic signal or not. This analysis has two parts. First one, the 30 better rated classes from the Neural Network are selected and the second one, the classes street sign and traffic light are checked if their rating is higher than the average OverFeat ratting, obtained from the training dataset images containing traffic signs.

Figure 8: Cropping process of the pre-processing phase. On the left, the original image with some of the cropped windows. On the wright, a particular cropped window.

If the cropped image satisfies both conditions it will be sent to the next phase. However, if the image does not satisfy the conditions it is rejected.

3.3. Tree construction and analysis

Once the image has been scanned, the smaller images that satisfy the previous conditions are sent to next phase.

From every image, a Binary Partition Tree is built by using a simplified version of Playing with Kuskal [4]. In this building process the bounding box[1] of each node is stored in it as well as the initial pixel value. When the tree has been built Overfeat analyses each bounding box which size is compressed between 50x50 and 150x150 pixels. The sizes have been chosen because of the dataset specifications (see 3.1.) and some experiments showing that little images have not good results in their classification.

Image size	Overfeat traffic sign detection (detected/labelled) %
16x16	0
30x30	0
50x50	8,6

Table 1: Comparison of the minimum size of the images to analyse.

From each bounding box fitting the size specifications Overfeat gives 15 classes. As it has been done previously in the scanning process, to agree that the image contains a traffic signal the class street sign or traffic sign should be between the 15 better options of the neural network classification. If the class exists, the node is saved to its later processing.

[1] Bounding box: Area defined by two points, (x_{min},y_{min}), (x_{max},y_{max}), which encloses a sort of objects. In this project the bounding box is enclosing pixels and it is the smaller box which contains all the pixels in the node.

3.4. Image recovery

This is the last phase of the project and it consists in returning the original image with the different traffic signals highlighted by their own bounding box.

Once the Neural Network has confirmed that exist a traffic signal in the image this traffic sign should be highlighted and showed later to the user. Using the information provided by the last phase and the information contained in the Binary Partition Tree, the image can be recovered by using the pixel value, and the traffic sign will be highlighted due to the bounding box of the selected node.

Finally the image containing the signal bounding boxes will be saved to its later visualization.

4. Results

4.1. Evaluation metric

The evaluation in image processing is usually done with Precision and Recall metrics. Precision is a metric which analyses the ratio of correct identifications inside the set of positive identifications and Recall is the metric which analyses which ratio of positive identifications are correctly identified. As well as this two metrics it is usually computed the balanced F-score metric, which is a metric that combines both previous metrics performing the harmonic mean of them.

$$Precision = \frac{TP}{TP+FP} \qquad Recall = \frac{TP}{TP+FN} \qquad F-score = 2 * \frac{Pres*Rec}{Pres+Rec}$$

Where,

- TP: True Positives, samples correctly identified as positives.
- FP: False Positives, samples wrong identified as positives.
- FN: False Negatives, samples wrong identified as negatives.

4.2. Experiment analysis

To perform the evaluation of the system it has been used the test dataset of the GTSDB database. It contains 300 images which can contain up to six traffic signs each one.

The results of the analysis have been the following ones.

True Positives	False positives
420	207
True Negatives	**False Negatives**
285	198
Precision (%)	**Recall (%)**
66,99	67,96
F-score (%)	
67.75	

Table 2: Results obtained by the system developed from test dataset of GTSDB.

To be able to interpret these results is it is needed to compare the system with the performance of Overfeat, in order to know if the new developed system is improving the task done by Overfeat.

Analysing the same database, test dataset of GTSDB, with Overfeat the results obtained have been the ones which are described below.

True Positives	False positives
192	68
True Negatives	**False Negatives**
12	28
Precision (%)	**Recall (%)**
73,85	87,27
F-score (%)	
80,00	

Table 3: Results obtained by Overfeat from test dataset of GTSDB.

As it has been explained in 2.2.2., Overfeat is a CNN which analyses image identifying object on it but it does not identify the amount of the object. Due to this fact the evaluating set is composed by 300 images while the evaluating set of the developed system is composed by all the different traffic signals contained in the dataset images.

4.3. Examples

Figure 9: Predicted results of the system.

In Fig.9 are shown some examples of the results obtained by the system. Looking at them it can be seen that the system is able to analyse and identify traffic signals but sometimes other objects are wrongly identified as a traffic signal (Fig.9 top) and sometimes it misses some of the traffic signals present in the image (Fig 9 middle).

5. Budget

Whilst the purpose of this thesis is not to develop a product prototype to be sold, certain costs must still be taken into account.

Name	Nº hours	Cost/hour (€) [2]	Total (€)
Junior engineer	720	12,76	9187,20
Senior engineer	36	20,05	721,80
		TOTAL	9909

Table 4: Approximate cost of the project.

This project has been carried out at École Supérieure d'Ingénieurs en Electrotechnique et Electronique (ESIEE) as a degree thesis and there have not been any investment.

The software used in the project was all Open Source and as well as the database which was Open Data. So no cost must be taken into account from the software part.

[2] Costs based on the average salary in Spain in 2018. [Source: http://espana.jobtonic.es/]

6. Conclusions and future development:

This project started very enthusiastically and so our requirements reflect, but in the end is has turned out to be so ambitious according to the prior knowledge. It has focused on the research and learning about the involved concepts rather than develop a sort of criteria. However, the main goals of the project have been accomplished.

According to the results obtained, it can be seen that the project still has room of improvement because the classification of the traffic signal performed by Overfeat can be improved

The OverFeat neural network seemed to be ideal as it is explained in point 2.2.1. but truly the neural network has been too specific, even distinguishing between kinds of cars. For this reason we think that another pre-trained Neural Network would have been better.

On the other hand we could have trained a neural network from the scratch but it requires time which we did not have due to all the issues happened while the developing of the project.

With more time, or a better communication and understanding, it could have been possible to train a network from the scratch which would have improved the project performance.

For further development the project can be adapted using a neural network built from the scratch and it can be orientated in following the idea of shape-space described in [2, 3] which has a good improving potential introducing machine learning criteria as shape-space enhance object shapes in the image and the detection can be improved.

Bibliography:

[1] Pierre Sermanet, David Eigen, Xiang Zhang, Michael Mathieu, Rob Fergus, Yann LeCun. "OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks ".

[2] Yongchao Xu, Edwin Carlinet, Thierry Géraud, Laurent Najman. "Hierarchical Segmentation Using Tree-Based Shape Spaces”. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Institute of Electrical and Electronics Engineers, 2017, 39 (3), pp.457-469.

[3] Yongchao Xu, Thierry Géraud, Laurent Najman. "Connected Filtering on Tree-Based Shape-Spaces”. *IEEE Transactions on Pattern Analysis and Machine Intelligenc*e, Institute of Electrical and Electronics Engineers, 2016, 38 (6), pp.1126 - 1140.

[4] Laurent Najman, Jean Cousty, Benjamin Perret. "Playing with Kruskal: algorithms for morphological trees in edge-weighted graphs”. *C.L. Luengo Hendriks, G. Borgefors, R. Strand. International Symposium on Mathematical Morphology*, May 2013, Uppsala, Sweden. Springer, 7883, pp.135-146, 2013, Lecture Notes in Computer Science.

[5] Philippe Salembier, Luis Garrido. “Binary Partition Tree as an efficient representation for filtering, segmentation and information retrieval”. *IEEE Transactions on Image Processing*, April 2000, 9(4), pp.561-576.

[6] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. “Scikit-learn: Machine learning in Python”. *Journal of Machine Learning Research (JMLR)*, 2011, 12, pp. 2825–2830.

[7] Ujiwalkman, An Intuitive Explanation of Convolutional Neural Networks, *The data science blog*, August 2016. Available at: https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/ [Accessed: 18 June 2018]

[8] Convolutional Neural Network, *Unsupervised Feature Learning and Deep Learning tutorial*. Available at : http://ufldl.stanford.edu/tutorial/supervised/ConvolutionalNeuralNetwork/ [Accessed: 18 June 2018]

[9] Python 2.7 documentation. Available at http://docs.python.org/org/2.7/

[10] Curso intensivo de aprendizaje automático, *Google developers*. Available at https://developers.google.com/machine-learning/crash-course/ [Accessed: 3 April 2018]

Appendices:

Appendix 1: OverFeat classes

abacus	crayfish, crawfish, crawdad, crawdaddy	lawn mower, mower	safe
abaya	crib, cot	leaf beetle, chrysomelid	safety pin
academic gown, academic robe, judge's robe	cricket	leafhopper	Saint Bernard, St Bernard
accordion, piano accordion, squeeze box	Crock Pot	leatherback turtle, leatherback, leathery turtle, Dermochelys coriacea	saltshaker, salt shaker
acorn	croquet ball	lemon	Saluki, gazelle hound
acorn squash	crossword puzzle, crossword	lens cap, lens cover	Samoyed, Samoyede
acoustic guitar	crutch	Leonberg	sandal
admiral	cucumber, cuke	leopard, Panthera pardus	sandbar, sand bar
affenpinscher, monkey pinscher, monkey dog	cuirass	lesser panda, red panda, panda, bear cat, cat bear, Ailurus fulgens	sarong
Afghan hound, Afghan	cup	letter opener, paper knife, paperknife	sax, saxophone
African chameleon, Chamaeleo chamaeleon	curly-coated retriever	Lhasa, Lhasa apso	scabbard
African crocodile, Nile crocodile, Crocodylus niloticus	custard apple	library	scale, weighing machine
African elephant, Loxodonta africana	daisy	lifeboat	schipperke
African grey, African gray, Psittacus erithacus	dalmatian, coach dog, carriage dog	lighter, light, igniter, ignitor	school bus
African hunting dog, hyena dog, Cape hunting dog, Lycaon pictus	dam, dike, dyke	limousine, limo	schooner
agama	damselfly	limpkin, Aramus pictus	scoreboard
agaric	Dandie Dinmont, Dandie Dinmont terrier	liner, ocean liner	scorpion
aircraft carrier, carrier, flattop, attack aircraft	desk	lion, king of beasts, Panthera leo	Scotch terrier, Scottish terrier,

carrier			Scottie
Airedale, Airedale terrier	desktop computer	lionfish	Scottish deerhound, deerhound
airliner	dhole, Cuon alpinus	lipstick, lip rouge	screen, CRT screen
airship, dirigible	dial telephone, dial phone	little blue heron, Egretta caerulea	screw
albatross, mollymawk	diamondback, diamondback rattlesnake, Crotalus adamanteus	llama	screwdriver
alligator lizard	diaper, nappy, napkin	Loafer	scuba diver
alp	digital clock	loggerhead, loggerhead turtle, Caretta caretta	sea anemone, anemone
altar	digital watch	long-horned beetle, longicorn, longicorn beetle	sea cucumber, holothurian
ambulance	dingo, warrigal, warragal, Canis dingo	lorikeet	sea lion
American alligator, Alligator mississipiensis	dining table, board	lotion	sea slug, nudibranch
American black bear, black bear, Ursus americanus, Euarctos americanus	dishrag, dishcloth	loudspeaker, speaker, speaker unit, loudspeaker system, speaker system	sea snake
American chameleon, anole, Anolis carolinensis	dishwasher, dish washer, dishwashing machine	loupe, jeweler's loupe	sea urchin
American coot, marsh hen, mud hen, water hen, Fulica americana	disk brake, disc brake	lumbermill, sawmill	Sealyham terrier, Sealyham
American egret, great white heron, Egretta albus	Doberman, Doberman pinscher	lycaenid, lycaenid butterfly	seashore, coast, seacoast, sea-coast
American lobster, Northern lobster, Maine lobster, Homarus americanus	dock, dockage, docking facility	lynx, catamount	seat belt, seatbelt
American Staffordshire terrier, Staffordshire terrier, American pit bull terrier, pit bull terrier	dogsled, dog sled, dog sleigh	macaque	sewing machine
amphibian, amphibious vehicle	dome	macaw	Shetland sheepdog, Shetland sheep dog, Shetland
analog clock	doormat, welcome mat	Madagascar cat, ring-	shield, buckler

		tailed lemur, Lemur catta	
anemone fish	dough	magnetic compass	Shih-Tzu
Angora, Angora rabbit	dowitcher	magpie	shoe shop, shoe-shop, shoe store
ant, emmet, pismire	dragonfly, darning needle, devil's darning needle, sewing needle, snake feeder, snake doctor, mosquito hawk, skeeter hawk	mailbag, postbag	shoji
apiary, bee house	drake	mailbox, letter box	shopping basket
Appenzeller	drilling platform, offshore rig	maillot	shopping cart
apron	drum, membranophone, tympan	maillot, tank suit	shovel
Arabian camel, dromedary, Camelus dromedarius	drumstick	malamute, malemute, Alaskan malamute	shower cap
Arctic fox, white fox, Alopex lagopus	dugong, Dugong dugon	malinois	shower curtain
armadillo	dumbbell	Maltese dog, Maltese terrier, Maltese	siamang, Hylobates syndactylus, Symphalangus syndactylus
artichoke, globe artichoke	dung beetle	manhole cover	Siamese cat, Siamese
ashcan, trash can, garbage can, wastebin, ash bin, ash-bin, ashbin, dustbin, trash barrel, trash bin	Dungeness crab, Cancer magister	mantis, mantid	Siberian husky
assault rifle, assault gun	Dutch oven	maraca	sidewinder, horned rattlesnake, Crotalus cerastes
Australian terrier	ear, spike, capitulum	marimba, xylophone	silky terrier, Sydney silky
axolotl, mud puppy, Ambystoma mexicanum	earthstar	marmoset	ski
baboon	echidna, spiny anteater, anteater	marmot	ski mask
backpack, back pack, knapsack, packsack, rucksack, haversack	eel	mashed potato	skunk, polecat, wood pussy
badger	eft	mask	sleeping bag

bagel, beigel	eggnog	matchstick	slide rule, slipstick
bakery, bakeshop, bakehouse	Egyptian cat	maypole	sliding door
balance beam, beam	electric fan, blower	maze, labyrinth	slot, one-armed bandit
bald eagle, American eagle, Haliaeetus leucocephalus	electric guitar	measuring cup	sloth bear, Melursus ursinus, Ursus ursinus
balloon	electric locomotive	meat loaf, meatloaf	slug
ballplayer, baseball player	electric ray, crampfish, numbfish, torpedo	medicine chest, medicine cabinet	snail
ballpoint, ballpoint pen, ballpen, Biro	English foxhound	meerkat, mierkat	snorkel
banana	English setter	megalith, megalithic structure	snow leopard, ounce, Panthera uncia
Band Aid	English springer, English springer spaniel	menu	snowmobile
banded gecko	entertainment center	Mexican hairless	snowplow, snowplough
banjo	EntleBucher	microphone, mike	soap dispenser
bannister, banister, balustrade, balusters, handrail	envelope	microwave, microwave oven	soccer ball
barbell	Eskimo dog, husky	military uniform	sock
barber chair	espresso	milk can	soft-coated wheaten terrier
barbershop	espresso maker	miniature pinscher	solar dish, solar collector, solar furnace
barn	European fire salamander, Salamandra salamandra	miniature poodle	sombrero
barn spider, Araneus cavaticus	European gallinule, Porphyrio porphyrio	miniature schnauzer	sorrel
barometer	face powder	minibus	soup bowl
barracouta, snoek	feather boa, boa	miniskirt, mini	space bar
barrel, cask	fiddler crab	minivan	space heater
barrow, garden cart, lawn cart, wheelbarrow	fig	mink	space shuttle
baseball	file, file cabinet, filing cabinet	missile	spaghetti squash
basenji	fire engine, fire truck	mitten	spatula
basketball	fire screen, fireguard	mixing bowl	speedboat
basset, basset hound	fireboat	mobile home, manufactured home	spider monkey, Ateles geoffroyi
bassinet	flagpole, flagstaff	Model T	spider web,

			spider's web
bassoon	flamingo	modem	spindle
bath towel	flat-coated retriever	monarch, monarch butterfly, milkweed butterfly, Danaus plexippus	spiny lobster, langouste, rock lobster, crawfish, crayfish, sea crawfish
bathing cap, swimming cap	flatworm, platyhelminth	monastery	spoonbill
bathtub, bathing tub, bath, tub	flute, transverse flute	mongoose	sports car, sport car
beach wagon, station wagon, wagon, estate car, beach waggon, station waggon, waggon	fly	monitor	spotlight, spot
beacon, lighthouse, beacon light, pharos	folding chair	moped	spotted salamander, Ambystoma maculatum
beagle	football helmet	mortar	squirrel monkey, Saimiri sciureus
beaker	forklift	mortarboard	Staffordshire bullterrier, Staffordshire bull terrier
bearskin, busby, shako	fountain	mosque	stage
beaver	fountain pen	mosquito net	standard poodle
Bedlington terrier	four-poster	motor scooter, scooter	standard schnauzer
bee	fox squirrel, eastern fox squirrel, Sciurus niger	mountain bike, all-terrain bike, off-roader	starfish, sea star
bee eater	freight car	mountain tent	steam locomotive
beer bottle	French bulldog	mouse, computer mouse	steel arch bridge
beer glass	French horn, horn	mousetrap	steel drum
bell cote, bell cot	French loaf	moving van	stethoscope
bell pepper	frilled lizard, Chlamydosaurus kingi	mud turtle	stingray
Bernese mountain dog	frying pan, frypan, skillet	mushroom	stinkhorn, carrion fungus
bib	fur coat	muzzle	stole
bicycle-built-for-two, tandem bicycle, tandem	gar, garfish, garpike, billfish, Lepisosteus osseus	nail	stone wall
bighorn, bighorn sheep, cimarron, Rocky	garbage truck, dustcart	neck brace	stopwatch, stop watch

Mountain bighorn, Rocky Mountain sheep, Ovis canadensis			
bikini, two-piece	garden spider, Aranea diademata	necklace	stove
binder, ring-binder	garter snake, grass snake	nematode, nematode worm, roundworm	strainer
binoculars, field glasses, opera glasses	gas pump, gasoline pump, petrol pump, island dispenser	Newfoundland, Newfoundland dog	strawberry
birdhouse	gasmask, respirator, gas helmet	night snake, Hypsiglena torquata	street sign
bison	gazelle	nipple	streetcar, tram, tramcar, trolley, trolley car
bittern	German shepherd, German shepherd dog, German police dog, alsatian	Norfolk terrier	stretcher
black and gold garden spider, Argiope aurantia	German short-haired pointer	Norwegian elkhound, elkhound	studio couch, day bed
black grouse	geyser	Norwich terrier	stupa, tope
black stork, Ciconia nigra	giant panda, panda, panda bear, coon bear, Ailuropoda melanoleuca	notebook, notebook computer	sturgeon
black swan, Cygnus atratus	giant schnauzer	obelisk	submarine, pigboat, sub, U-boat
black widow, Latrodectus mactans	gibbon, Hylobates lar	oboe, hautboy, hautbois	suit, suit of clothes
black-and-tan coonhound	Gila monster, Heloderma suspectum	ocarina, sweet potato	sulphur butterfly, sulfur butterfly
black-footed ferret, ferret, Mustela nigripes	goblet	odometer, hodometer, mileometer, milometer	sulphur-crested cockatoo, Kakatoe galerita, Cacatua galerita
Blenheim spaniel	go-kart	oil filter	sundial
bloodhound, sleuthhound	golden retriever	Old English sheepdog, bobtail	sunglass
bluetick	goldfinch, Carduelis carduelis	orange	sunglasses, dark glasses, shades
boa constrictor, Constrictor constrictor	goldfish, Carassius auratus	orangutan, orang, orangutang, Pongo pygmaeus	sunscreen, sunblock, sun blocker
boathouse	golf ball	organ, pipe organ	suspension bridge
bobsled, bobsleigh, bob	golfcart, golf cart	oscilloscope, scope, cathode-ray oscilloscope, CRO	Sussex spaniel

bolete	gondola	ostrich, Struthio camelus	swab, swob, mop
bolo tie, bolo, bola tie, bola	gong, tam-tam	otter	sweatshirt
bonnet, poke bonnet	goose	otterhound, otter hound	swimming trunks, bathing trunks
book jacket, dust cover, dust jacket, dust wrapper	Gordon setter	overskirt	swing
bookcase	gorilla, Gorilla gorilla	ox	switch, electric switch, electrical switch
bookshop, bookstore, bookstall	gown	oxcart	syringe
Border collie	grand piano, grand	oxygen mask	tabby, tabby cat
Border terrier	Granny Smith	oystercatcher, oyster catcher	table lamp
borzoi, Russian wolfhound	grasshopper, hopper	packet	tailed frog, bell toad, ribbed toad, tailed toad, Ascaphus trui
Boston bull, Boston terrier	Great Dane	paddle, boat paddle	tank, army tank, armored combat vehicle, armoured combat vehicle
bottlecap	great grey owl, great gray owl, Strix nebulosa	paddlewheel, paddle wheel	tape player
Bouvier des Flandres, Bouviers des Flandres	Great Pyrenees	padlock	tarantula
bow	great white shark, white shark, man-eater, man-eating shark, Carcharodon carcharias	paintbrush	teapot
bow tie, bow-tie, bowtie	Greater Swiss Mountain dog	pajama, pyjama, pj's, jammies	teddy, teddy bear
box turtle, box tortoise	green lizard, Lacerta viridis	palace	television, television system
boxer	green mamba	panpipe, pandean pipe, syrinx	tench, Tinca tinca
Brabancon griffon	green snake, grass snake	paper towel	tennis ball
brain coral	greenhouse, nursery, glasshouse	papillon	terrapin
brambling, Fringilla montifringilla	grey fox, gray fox, Urocyon cinereoargenteus	parachute, chute	thatch, thatched roof
brass, memorial tablet, plaque	grey whale, gray whale, devilfish, Eschrichtius gibbosus, Eschrichtius	parallel bars, bars	theater curtain, theatre curtain

	robustus		
brassiere, bra, bandeau	grille, radiator grille	park bench	thimble
breakwater, groin, groyne, mole, bulwark, seawall, jetty	grocery store, grocery, food market, market	parking meter	three-toed sloth, ai, Bradypus tridactylus
breastplate, aegis, egis	groenendael	partridge	thresher, thrasher, threshing machine
briard	groom, bridegroom	passenger car, coach, carriage	throne
Brittany spaniel	ground beetle, carabid beetle	patas, hussar monkey, Erythrocebus patas	thunder snake, worm snake, Carphophis amoenus
broccoli	guacamole	patio, terrace	Tibetan mastiff
broom	guenon, guenon monkey	pay-phone, pay-station	Tibetan terrier, chrysanthemum dog
brown bear, bruin, Ursus arctos	guillotine	peacock	tick
bubble	guinea pig, Cavia cobaya	pedestal, plinth, footstall	tiger beetle
bucket, pail	gyromitra	Pekinese, Pekingese, Peke	tiger cat
buckeye, horse chestnut, conker	hair slide	pelican	tiger shark, Galeocerdo cuvieri
buckle	hair spray	Pembroke, Pembroke Welsh corgi	tiger, Panthera tigris
bulbul	half track	pencil box, pencil case	tile roof
bull mastiff	hammer	pencil sharpener	timber wolf, grey wolf, gray wolf, Canis lupus
bullet train, bullet	hammerhead, hammerhead shark	perfume, essence	titi, titi monkey
bulletproof vest	hamper	Persian cat	toaster
bullfrog, Rana catesbeiana	hamster	Petri dish	tobacco shop, tobacconist shop, tobacconist
burrito	hand blower, blow dryer, blow drier, hair dryer, hair drier	photocopier	toilet seat
bustard	hand-held computer, hand-held microcomputer	pick, plectrum, plectron	toilet tissue, toilet paper, bathroom tissue
butcher shop, meat market	handkerchief, hankie, hanky, hankey	pickelhaube	torch
butternut squash	hard disc, hard disk, fixed disk	picket fence, paling	totem pole
cab, hack, taxi, taxicab	hare	pickup, pickup truck	toucan

cabbage butterfly	harmonica, mouth organ, harp, mouth harp	pier	tow truck, tow car, wrecker
cairn, cairn terrier	harp	piggy bank, penny bank	toy poodle
caldron, cauldron	hartebeest	pill bottle	toy terrier
can opener, tin opener	harvester, reaper	pillow	toyshop
candle, taper, wax light	harvestman, daddy longlegs, Phalangium opilio	pineapple, ananas	tractor
cannon	hatchet	ping-pong ball	traffic light, traffic signal, stoplight
canoe	hay	pinwheel	trailer truck, tractor trailer, trucking rig, rig, articulated lorry, semi
capuchin, ringtail, Cebus capucinus	head cabbage	pirate, pirate ship	tray
car mirror	hen	pitcher, ewer	tree frog, tree-frog
car wheel	hen-of-the-woods, hen of the woods, Polyporus frondosus, Grifola frondosa	pizza, pizza pie	trench coat
carbonara	hermit crab	plane, carpenter's plane, woodworking plane	triceratops
cardigan	hip, rose hip, rosehip	planetarium	tricycle, trike, velocipede
Cardigan, Cardigan Welsh corgi	hippopotamus, hippo, river horse, Hippopotamus amphibius	plastic bag	trifle
cardoon	hog, pig, grunter, squealer, Sus scrofa	plate	trilobite
carousel, carrousel, merry-go-round, roundabout, whirligig	hognose snake, puff adder, sand viper	plate rack	trimaran
carpenter's kit, tool kit	holster	platypus, duckbill, duckbilled platypus, duck-billed platypus, Ornithorhynchus anatinus	tripod
carton	home theater, home theatre	plow, plough	triumphal arch
cash machine, cash dispenser, automated teller machine,	honeycomb	plunger, plumber's helper	trolleybus, trolley coach, trackless trolley

automatic teller machine, automated teller, automatic teller, ATM			
cassette	hook, claw	Polaroid camera, Polaroid Land camera	trombone
cassette player	hoopskirt, crinoline	pole	tub, vat
castle	horizontal bar, high bar	polecat, fitch, foulmart, foumart, Mustela putorius	turnstile
catamaran	hornbill	police van, police wagon, paddy wagon, patrol wagon, wagon, black Maria	tusker
cauliflower	horned viper, cerastes, sand viper, horned asp, Cerastes cornutus	pomegranate	typewriter keyboard
CD player	horse cart, horse-cart	Pomeranian	umbrella
cello, violoncello	hot pot, hotpot	poncho	unicycle, monocycle
cellular telephone, cellular phone, cellphone, cell, mobile phone	hotdog, hot dog, red hot	pool table, billiard table, snooker table	upright, upright piano
centipede	hourglass	pop bottle, soda bottle	vacuum, vacuum cleaner
chain	house finch, linnet, Carpodacus mexicanus	porcupine, hedgehog	valley, vale
chain mail, ring mail, mail, chain armor, chain armour, ring armor, ring armour	howler monkey, howler	pot, flowerpot	vase
chain saw, chainsaw	hummingbird	potpie	vault
chainlink fence	hyena, hyaena	potter's wheel	velvet
chambered nautilus, pearly nautilus, nautilus	ibex, Capra ibex	power drill	vending machine
cheeseburger	Ibizan hound, Ibizan Podenco	prairie chicken, prairie grouse, prairie fowl	vestment
cheetah, chetah, Acinonyx jubatus	ice bear, polar bear, Ursus Maritimus, Thalarctos maritimus	prayer rug, prayer mat	viaduct
Chesapeake Bay retriever	ice cream, icecream	pretzel	vine snake
chest	ice lolly, lolly, lollipop, popsicle	printer	violin, fiddle
chickadee	impala, Aepyceros	prison, prison house	vizsla, Hungarian

	melampus		pointer
chiffonier, commode	Indian cobra, Naja naja	proboscis monkey, Nasalis larvatus	volcano
Chihuahua	Indian elephant, Elephas maximus	projectile, missile	volleyball
chime, bell, gong	indigo bunting, indigo finch, indigo bird, Passerina cyanea	projector	vulture
chimpanzee, chimp, Pan troglodytes	indri, indris, Indri indri, Indri brevicaudatus	promontory, headland, head, foreland	waffle iron
china cabinet, china closet	iPod	ptarmigan	Walker hound, Walker foxhound
chiton, coat-of-mail shell, sea cradle, polyplacophore	Irish setter, red setter	puck, hockey puck	walking stick, walkingstick, stick insect
chocolate sauce, chocolate syrup	Irish terrier	puffer, pufferfish, blowfish, globefish	wall clock
chow, chow chow	Irish water spaniel	pug, pug-dog	wallaby, brush kangaroo
Christmas stocking	Irish wolfhound	punching bag, punch bag, punching ball, punchball	wallet, billfold, notecase, pocketbook
church, church building	iron, smoothing iron	purse	wardrobe, closet, press
cicada, cicala	isopod	quail	warplane, military plane
cinema, movie theater, movie theatre, movie house, picture palace	Italian greyhound	quill, quill pen	warthog
cleaver, meat cleaver, chopper	jacamar	quilt, comforter, comfort, puff	washbasin, handbasin, washbowl, lavabo, wash-hand basin
cliff dwelling	jackfruit, jak, jack	racer, race car, racing car	washer, automatic washer, washing machine
cliff, drop, drop-off	jack-o'-lantern	racket, racquet	water bottle
cloak	jaguar, panther, Panthera onca, Felis onca	radiator	water buffalo, water ox, Asiatic buffalo, Bubalus bubalis
clog, geta, patten, sabot	Japanese spaniel	radio telescope, radio reflector	water jug
clumber, clumber spaniel	jay	radio, wireless	water ouzel, dipper
cock	jean, blue jean, denim	rain barrel	water snake
cocker spaniel, English cocker spaniel, cocker	jeep, landrover	ram, tup	water tower

cockroach, roach	jellyfish	rapeseed	weasel
cocktail shaker	jersey, T-shirt, tee shirt	recreational vehicle, RV, R.V.	web site, website, internet site, site
coffee mug	jigsaw puzzle	red fox, Vulpes vulpes	weevil
coffeepot	jinrikisha, ricksha, rickshaw	red wine	Weimaraner
coho, cohoe, coho salmon, blue jack, silver salmon, Oncorhynchus kisutch	joystick	red wolf, maned wolf, Canis rufus, Canis niger	Welsh springer spaniel
coil, spiral, volute, whorl, helix	junco, snowbird	red-backed sandpiper, dunlin, Erolia alpina	West Highland white terrier
collie	keeshond	redbone	whippet
colobus, colobus monkey	kelpie	red-breasted merganser, Mergus serrator	whiptail, whiptail lizard
combination lock	Kerry blue terrier	redshank, Tringa totanus	whiskey jug
comic book	killer whale, killer, orca, grampus, sea wolf, Orcinus orca	reel	whistle
common iguana, iguana, Iguana iguana	kimono	reflex camera	white stork, Ciconia ciconia
common newt, Triturus vulgaris	king crab, Alaska crab, Alaskan king crab, Alaska king crab, Paralithodes camtschatica	refrigerator, icebox	white wolf, Arctic wolf, Canis lupus tundrarum
computer keyboard, keypad	king penguin, Aptenodytes patagonica	remote control, remote	wig
conch	king snake, kingsnake	restaurant, eating house, eating place, eatery	wild boar, boar, Sus scrofa
confectionery, confectionary, candy store	kit fox, Vulpes macrotis	revolver, six-gun, six-shooter	window screen
consomme	kit fox, Vulpes macrotis 1.12342e-41	rhinoceros beetle	window shade
container ship, containership, container vessel	kite	Rhodesian ridgeback	Windsor tie
convertible	knee pad	rifle	wine bottle
coral fungus	knot	ringlet, ringlet butterfly	wing
coral reef	koala, koala bear, kangaroo bear, native bear, Phascolarctos	ringneck snake, ring-necked snake, ring snake	wire-haired fox terrier

	cinereus		
corkscrew, bottle screw	Komodo dragon, Komodo lizard, dragon lizard, giant lizard, Varanus komodoensis	robin, American robin, Turdus migratorius	wok
corn	komondor	rock beauty, Holocanthus tricolor	wolf spider, hunting spider
cornet, horn, trumpet, trump	kuvasz	rock crab, Cancer irroratus	wombat
coucal	lab coat, laboratory coat	rock python, rock snake, Python sebae	wood rabbit, cottontail, cottontail rabbit
cougar, puma, catamount, mountain lion, painter, panther, Felis concolor	Labrador retriever	rocking chair, rocker	wooden spoon
cowboy boot	lacewing, lacewing fly	rotisserie	wool, woolen, woollen
cowboy hat, ten-gallon hat	ladle	Rottweiler	worm fence, snake fence, snake-rail fence, Virginia fence
coyote, prairie wolf, brush wolf, Canis latrans	ladybug, ladybeetle, lady beetle, ladybird, ladybird beetle	rubber eraser, rubber, pencil eraser	wreck
cradle	Lakeland terrier	ruddy turnstone, Arenaria interpres	yawl
crane	lakeside, lakeshore	ruffed grouse, partridge, Bonasa umbellus	yellow lady's slipper, yellow lady-slipper, Cypripedium calceolus, Cypripedium parviflorum
crane	lampshade, lamp shade	rugby ball	Yorkshire terrier
crash helmet	langur	rule, ruler	yurt
crate	laptop, laptop computer	running shoe	zebra
			zucchini, courgette

Table 5: OverFeat Neural Network classes

Glossary

CNN: Convolutional Neural Network.

GTSDB: German Traffic Sign Detection Benchmark.