FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

A study of ensemble methods for vehicle classification on motorways

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DISSERTATION REPORT

Mestrado Integrado em Engenharia Informática e Computação

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May 7, 2019

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Abstract

Computer Vision and Machine Learning are areas with many applications, with sensors based on the most diverse methods of image capture and video streaming being used more and more. From industrial processes to autonomous vehicles, from the identification of individuals to the monitoring of cities, there are several applications.For the specific case of Intelligent Transportation Systems we are assisting to an increasing interest in such methodologies since highways are usually equipped with cameras and so they can be used to perform in autonomous and automatic tasks such as: vehicle counting by class, incident detection, the identification of vehicles in irregularity, among others.

We are now faced with the consequences of numerous traffic occurrences, with negative implications to both businesses and citizens. This results from an ineffective and subjective traffic control system, carried out by records conditioned by environmental factors, among which the quality of the image, the intensity of light, noise caused by the conditions of available light, camera positioning, occlusion of objects and the subjectivity of human reasoning.

In this dissertation we applied an ensemble learning architecture for classifying vehicles. We propose a Bagging architecture with You Only Look Once, Single Shot MultiBox Detector and Background Subtraction as level 0 classifiers. To combine the output of the algorithms we implemented 2 options, namely: a Majority Voting algorithm and an Avg Best algorithm. In order to validate the proposed solution, the ensemble of classifiers was tested on three different highway datasets with different characteristics (size of the vehicles, angle of view, number of lanes and different number of classes, different lighting scenarios).

The proposed ensemble solution detected and classified more vehicles than any singular classification algorithm on 5 out of 6 tests. Single Shot MultiBox Detector proved very stable regardless of the test scenarios while You Only Look Once proved to have a better generalization with less samples of a class. Background Subtraction detects the fewest vehicles but classifies those objects almost as well as the other algorithms with faster prediction times.

Keywords:

Computing methodologies→ Computer-Vision

Computing methodologies → Machine learning → Machine learning approaches → Neural networks

Computing methodologies → Machine learning → Machine learning algorithms → Ensemble methods

Resumo

Visão computacional e aprendizagem máquina são áreas com inúmeras aplicações, com sensores baseados nos mais diversos métodos de captura de imagem e streaming de vídeo sendo cada vez mais usados. De processos industriais a veículos autônomos, desde a identificação de indivíduos até à monitorização de cidades. Para o caso específico da área dos Sistemas Inteligentes de Transporte estamos a assistir a um interesse crescente em tais metodologias, já que as vias rodoviárias são geralmente equipadas com câmeras e elas podem ser usadas para executar tarefas autônomas e automáticas como: contagem de veículos por classe, detecção de incidentes, identificação de veículos em irregularidades, entre outros.
Somos agora confrontados com as consequências de numerosas ocorrências de tráfego, com implicações negativas para as empresas e para os cidadãos. Isto é o resultado de um sistema de controle de tráfego ineficaz e subjetivo, realizado por registos condicionados por fatores ambientais, de entre os quais figuram a qualidade da imagem, a intensidade da luz, o ruído provocado pelas condições de luz disponível, posicionamento da câmera, oclusão de objetos e a subjetividade do raciocínio humano.
Nesta dissertação aplicámos uma arquitetura de 'Ensemble Learning' para classificar veículos. Propomos uma arquitetura de 'Bagging' com 'You Only Look One', 'Single Shot MultiBox Detector' e Subtração de Fundo como classificadores de nível 0. Para combinar a saída dos algoritmos, implementámos 2 opções: um algoritmo de votação maioritária e um algoritmo de melhor média. Para validar a solução proposta, o conjunto de classificadores foi testado em três diferentes conjuntos de dados de rodovias com diferentes características (dimensão dos veículos, ângulo de visão, número de faixas, número de classes diferentes e diferentes cenários de iluminação).
A solução proposta detectou e classificou mais veículos do que qualquer algoritmo de classificação singular em 5 de 6 testes. Single Shot MultiBox Detector mostrou-se muito estável, independentemente dos cenários de teste, enquanto 'You Only Look Once' provou ter uma melhor generalização com menos amostras de uma classe. Subtração de Fundo detecta o menor número de veículos, mas classifica esses objetos quase tão bem quanto os outros algoritmos com tempos de previsão considerávelmente mais rápidos.

Acknowledgements

My sincere thanks to Professor Rosaldo Rossetti and Catarina Santiago for all the support and guidance during the writing of this thesis. I also thank them for all the lessons that they taught me and that will stay with me throughout to the next challenges of my life. Also a thanks to Joel Carneiro for brainstorming help and for sharing his experience of his dissertation.

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Abbreviations

SSD	Single Shot Multi-box Detector
YOLO	You Only Look Once
ITS	Intelligent Transport System
CNN	Convolutional Neural Network
R-CNN	Regions with Convolutional Features
mAP	mean Average Precision
RoI	Regions of Interest
RPN	Region Proposals Networks
FPN	Feature Pyramid Networks
R-FCN	Region based Fully Convolutional Networks
SVM	Support Vector Machine
LDA	Linear Discriminant Analysis
HMM	Hidden Markov Model
KNN	K-Nearest Neighbour
AUC	Area Under the Curve
OpenCV	Open Source Computer Vision Library
TPU	Tensor Processing Unit
IOU	Intersection Over Union

Chapter 1

Introduction

1.1 Motivation

Computer Vision and Machine Learning are areas with many applications, with sensors based on methods of image capture and video streaming being used more and more. The result has many uses: the counting of vehicles by class, the detection of incidents, the identification of vehicles in irregularity, among others.
At ARMIS ITS (Intelligent Transport System) they apply information and communication technologies to the transport area, through intelligent solutions that reduce accidents, CO2 emissions and improve traffic conditions, ensuring values such as sustainability, efficiency and safety.
ARMIS has been working on the area of detection and tracking of vehicles and currently has a solution. This suggests that the company might have an interest in the findings of this thesis in the ITS area.
According to [Toroyan, 2015] more than 1.2 million people die each year on the world's roads, making road traffic injuries a leading cause of death globally. In [ITS, 2018] "The ITS market in roadways is expected to be worth USD 23.35 billions in 2018 and USD 30.74 billions by 2023, at a Compound Annual Growth Rate (CAGR) of 5.65% between 2018 and 2023." This increase is attributed to an increase in traffic congestion, concerns of public safety and government initiatives for effective and modern traffic management. In the Portuguese landscape, some news also confirm the interest of government infrastructures in modern traffic management systems as reported in [Lusa, 2018] which shows also a positive approach to the area and the environment in which our problem is inserted since the input video data used in this work will be from the Porto area.
Currently counting of vehicles is done manually, where humans classify vehicles while watching the video so there is also the motivation to ease the work for humans but not necessarily relieving them from the process entirely.

1.2 Problem Definition

Current approaches to classifying vehicles on highways with a single model have lead to inconsistencies in the results, as some methods overfit on the training set and do not classify some of the vehicles of the test set.

1.3 Objectives and Contributions

With this dissertation, we intend to feature traffic management systems with intelligent functionalities, using computer vision algorithms. Some video cameras from Portuguese highways will be used for the implementation, proof of concept and tests of the classification algorithms by computer vision.
The objectives defined for this thesis are the following:

1. achieve a more accurate output than single model prediction
2. show from each model the features that get valued the most

1.4 Document Structure

The next section, Literature Review, is divided in two parts, namely the methods part that provides an overview of the algorithms that are mostly used on the context of this thesis problem and the second part, Related Work, where the related solutions are described.
In the third chapter, Methodological Approach, our solution to the problem is explained with the scope, proposed solution details and support technology.
In the fourth chapter, we present the Test Procedures and Results as well as a description of each dataset and the implications of each. The fifth and final chapter includes the conclusions and provides some guidelines for future work.

Chapter 2

Literature Review

This chapter attempts to be a two part guide. The first part presents a guide to algorithms for Detection and Classification, methods for combining different classification algorithms and metrics for evaluating them. The first attempts featured approaches based on detection and classification in separate phases while newer applications do detection and classification at the same stage. The second part presents a review of what has been done in the area of vehicle detection, classification and ensemble systems.

2.1 Methods

In order to understand more recent approaches to detection, we must first know what is a CNN, a convolutional neural network, this explanation is based on [A. Krizhevsky, 2012] and [Y. Lecun, 2015]. A CNN takes four steps: convolution, Pooling, Flattening and Full connection.
Convolution is a mathematical operation that multiplies two functions (dot product) creating a third that expresses how one influences the other, on the case of computer vision, convolution is a small filter that goes through the entire image computing the dot product between the entries of the filter and the input image. A network is convolutional if it has at least a convolutional layer that builds feature maps from the input image.
Pooling reduces the complexity, by reducing the number of bytes taken from the feature map by using a mask. Flattening transforms the pooling maps into an input layer for the network. Full connection means that every neuron in a layer is connected to all the neurons in the immediate previous and immediate next layers. From here a CNN is just like any Neural Network it has an input layer, some hidden layers that compute weights based on training and an output layer that provides a prediction.

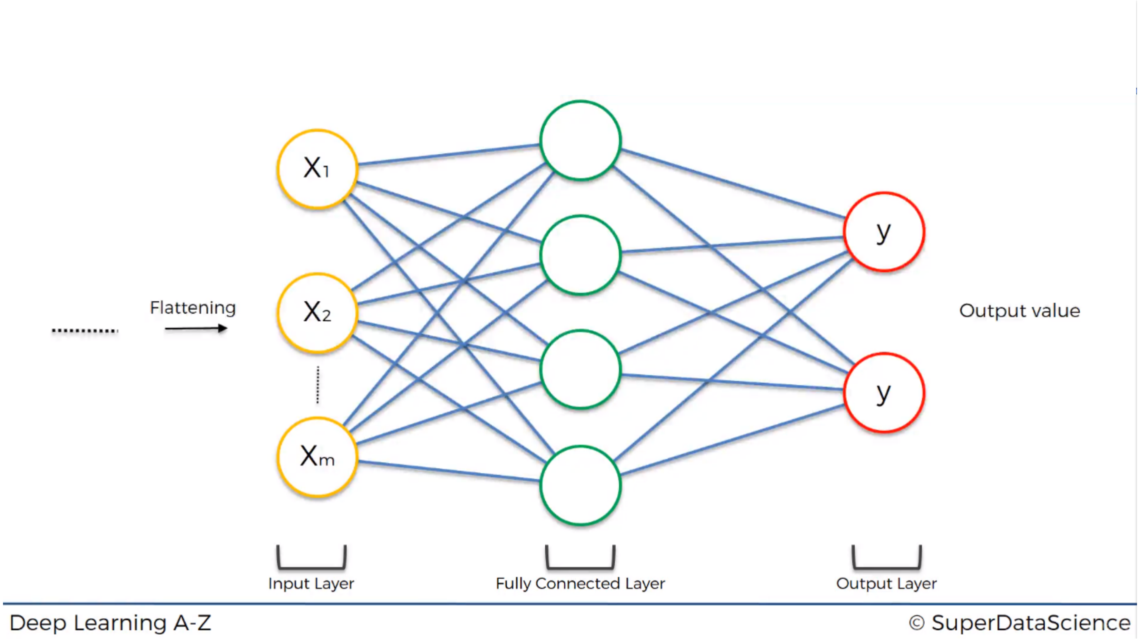


Figure 2.1: Taken from Udemy paid course about Deep Learning[Eremenko, 2018] Example of a CNN in the fully connection step.

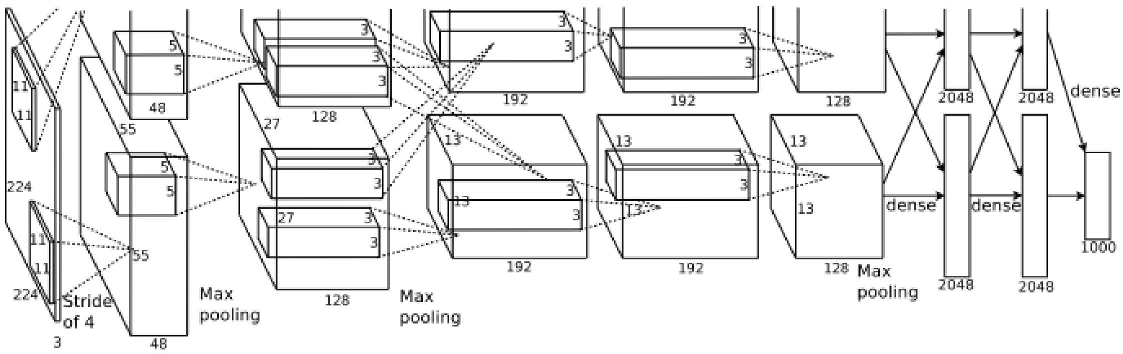


Figure 2.2: Taken from [A. Krizhevsky, 2012] Example of architecture of a CNN

Some CNNs, as presented next, use Softmax functions for the output of predictions. As explained more thoroughly in[Nasrabadi, 2007], Softmax is a function that takes a K-dimensional vector z and transforms it into a K-dimensional vector of real values, where each entry is in the range [0, 1].

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$

Figure 2.3: Softmax function

The final concept to understand is logistic regression that to put it very simple is what allows for an approximation to a binary result, pass or fail, based on the value it either outputs 0 or 1.

2.1.1 Detection

Detection is the method in which key-points or groups of key-points, are qualified according to an objective, in the case of object detection in which vehicle detection is a part of, the method focuses on finding groups of key-points to determine where there are objects. In 2003 the Scale Invariant Feature Transform(SIFT) was presented in the "Distinctive Image Features from Scale-Invariant Keypoints" paper, [Lowe, 2004]. This technique consisted in four stages: first a search over all scales and image regions finding the candidate points; second, for each candidate region, a model is used to determine location and scale of keypoints; third at least one orientation is assigned to each keypoint location using image gradient directions; fourth image gradients are measured at the selected scale in the region around each keypoint.
From here on a lot of different methods came to light, as of late detection algorithms that integrate classification with detection have been heating up. Currently three types of detectors exist as categorized in [T.-Y Lin, 2018] and will be explained resorting to examples: Classic Object Detectors, Two-stage Detectors and One-stage Detectors.

2.1.1.1 Classic Object Detectors

Classic Object Detectors consist in a classifier being applied to a dense image grid. Yann Lecun regarded as the father of Convolutional Neural Networks (CNN), is responsible for the earliest implementation by applying a classifier (CNN) on handwritten digit recognition.[Y. LeCun, B. Boser, J. S. Denker, D.
Even though sliding window methods were mostly used in object detection as said in [T.-Y Lin, 2018], the revival of deep learning allowed the appearance of two other types of detectors Two-Stage and One-Stage detectors.

2.1.1.2 Two-Stage Detectors

As the name indicates, two-stage dectetors are composed by two stages, the first stage, detects and the second classifies. Two stage detectors came to dominate the paradigm, in the first phase the set of candidate locations (locations of images with a probable image in it) get generated, this separates most of the non object locations from the object locations (99%), in the second phase the set of candidates get classified into background and foreground. The first to use this methodology were [J. Uijlings, 2013] in Selective Search paper and upgraded upon the launch of R-CNN[R. Girshick, 2014] with a convolutional neural network (CNN) for for the second phase classification which brought with it an increase of accuracy.

The R-CNN [R. Girshick, 2014] abbreviation comes from the use of Region proposal with a CNN. The technique is composed by three modules, the first generates category-independent region proposals. These proposals define the set of candidate detections available to the detector. The second module is a large convolutional neural network (CNN) that extracts a fixed-length feature vector from each region. The third module is a set of class-specific linear Support Vector machines (SVMs).

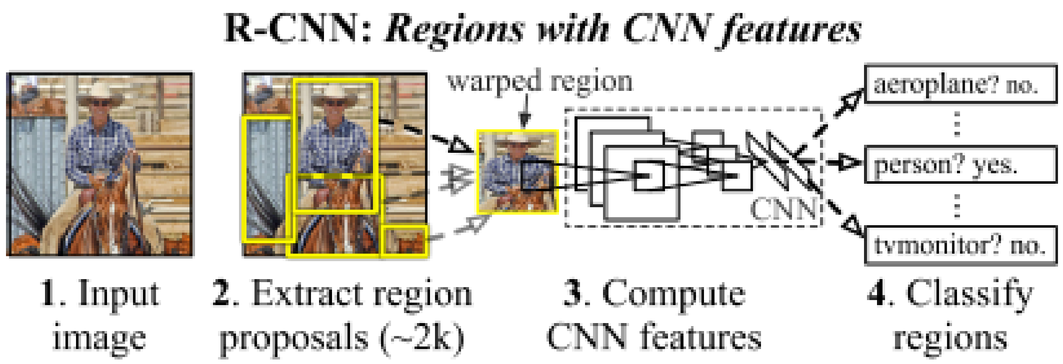


Figure 2.4: Taken from [R. Girshick, 2014] Object detection system overview. System (1) takes an input image, (2) extracts around 2000 bottom-up region proposals, (3) computes features for each proposal using a large convolutional neural network (CNN), and then (4) classifies each region using class-specific linear SVMs

After the R-CNN, an improvement was made called the fast R-CNN[Girshick, 2015] that featured a new trained network that was faster at test time and more accurate (mAp). Furthermore, training became single stage using a multi-task loss. The network first processes the whole image with several convolutional and max pooling layers to produce a convolutional feature map. Then, for each object proposal a region of interest pooling layer extracts a fixed-length feature vector from the feature map. Each feature vector is fed into a sequence of fully connected layers that finally branch into two sibling output layers: one that produces softmax probability estimates over K object classes (the number of classes of objects) plus a catch-all "background" class and another layer that outputs four real-valued numbers for each of the K object classes, those values are encoded refined bounding box positions.

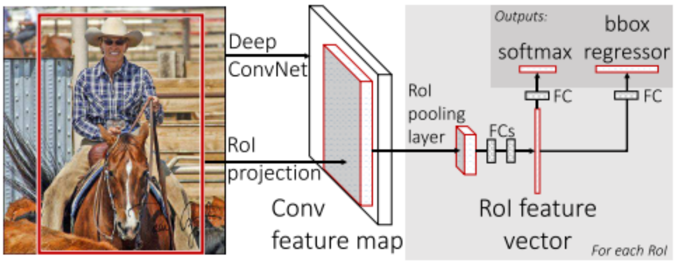


Figure 2.5: Taken from [Girshick, 2015] Fast R-CNN architecture. An input image and multiple regions of interest (RoIs) are input into a fully convolutional network. Each RoI is pooled into a fixed-size feature map and then mapped to a feature vector by fully connected layers (FCs). The network has two output vectors per RoI: softmax probabilities and per-class bounding-box regression offsets. The architecture is trained end-to-end with a multi-task loss

Upgrades to Fast R-CNN have been made in the past few years with learned object proposals and Region Proposals Networks (RPN) like the faster R-CNN [S. Ren, 2015] where a RPN takes an image (of any size) as input and outputs a set of rectangular object proposals, each with an objectness score (probability of being an object), an RPN is a fully convolutional network that simultaneously predicts object bounds and objectness scores at each position. RPNs are trained end-to-end to generate high-quality region proposals. The Faster R-CNN is an upgrade using the aforementioned RPN that shares full image convolutional features with the detection network. Extensions and small upgrades have been made more recently.

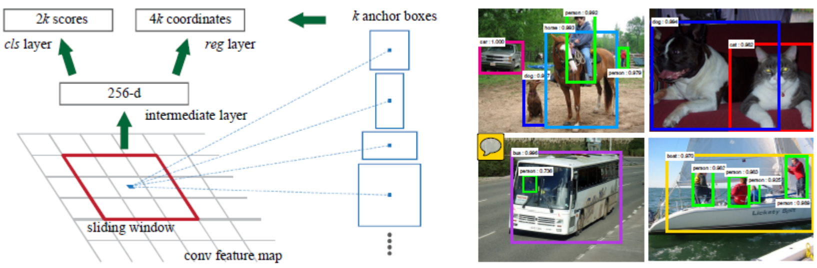


Figure 2.6: Taken from [S. Ren, 2015] Left: Region Proposal Network (RPN). Right: Example detections using RPN proposals on PASCAL VOC 2007 test. This method detects objects in a wide range of scales and aspect ratios

Feature Pyramid Networks for Object Detection is one of those extensions to faster R-CNN[T.-Y Lin, 2017] where these pyramids are scale-invariant in the sense that an object's scale change is offset by shifting its level in the pyramid. Intuitively, this property enables a model to detect objects across a large range of scales by scanning the model over both positions and pyramid levels.

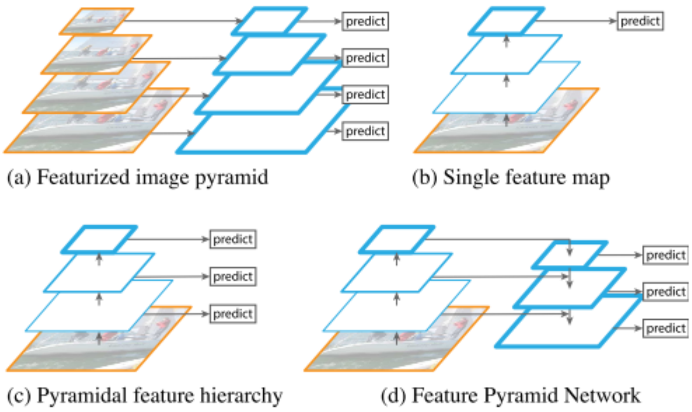


Figure 2.7: Taken from [T.-Y Lin, 2017]Figure 1. (a) Using an image pyramid to build a feature pyramid. Features are computed on each of the image scales independently, which is slow. (b) Recent detection systems have opted to use only single scale features for faster detection. (c) An alternative is to reuse the pyramidal feature hierarchy computed by a ConvNet as if it were a featurized image pyramid. (d) their proposed Feature Pyramid Network (FPN) is fast like (b) and (c), but more accurate. In this figure, feature maps are indicated by blue outlines and thicker outlines denote semantically stronger features

Another extension is R-FCN [Y. Li, 2016] following R-CNN, R-FCN adopts the two-stage object detection strategy that consists of: (i) region proposal, and (ii) region classification. It extracts candidate regions by the Region Proposal Network [S. Ren, 2015] and as described above which is a fully convolutional architecture in itself. The approach shares the features between RPN and R-FCN. The figure 2.8 this text shows an overview of the system.
Given the proposal regions (RoIs), the R-FCN architecture is designed to classify the RoIs into object categories and background. In R-FCN, all learnable weight layers are convolutional and are computed on the entire image. The last convolutional layer produces a bank of k2 position-sensitive score maps for each category, and thus has a k2$(C+1)$-channel output layer with C object categories (+1 for background). The bank of k2 score maps correspond to a $k \times k$ spatial grid describing relative positions. R-FCN ends with a position-sensitive RoI pooling layer. This layer aggregates the outputs of the last convolutional layer and generates scores for each RoI.

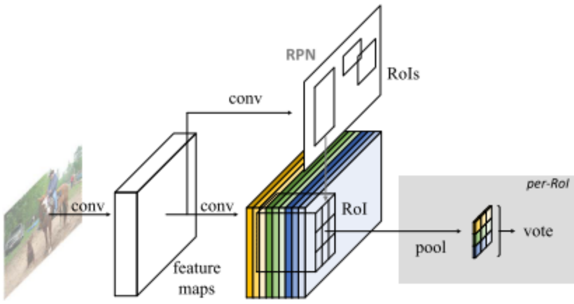


Figure 2.8: Taken from [Y. Li, 2016] Overall architecture of R-FCN. A Region Proposal Network (RPN)[S. Ren, 2015] proposes candidate RoIs, which are then applied on the score maps. All learnable weight layers are convolutional and are computed on the entire image;

2.1.1.3 One-Stage Detectors

One-stage detectors have existed for some time, Overfeat [P. Sermanet, 2014] has kick-started newer developments as one of the first one-Stage detectors, using a single CNN to detect, classify, locate in that order and using a shared feature learning base. In Classification, each image is assigned a single label corresponding, to the main object in it, it uses five guesses to find the correct labeling. In Localization a bounding box for the predicted object is returned with each of the five guesses. In Detection the task differs from localization because there can be any given number of objects in the image (even zero) and false positives are penalized by mean average precision measure (mAP).

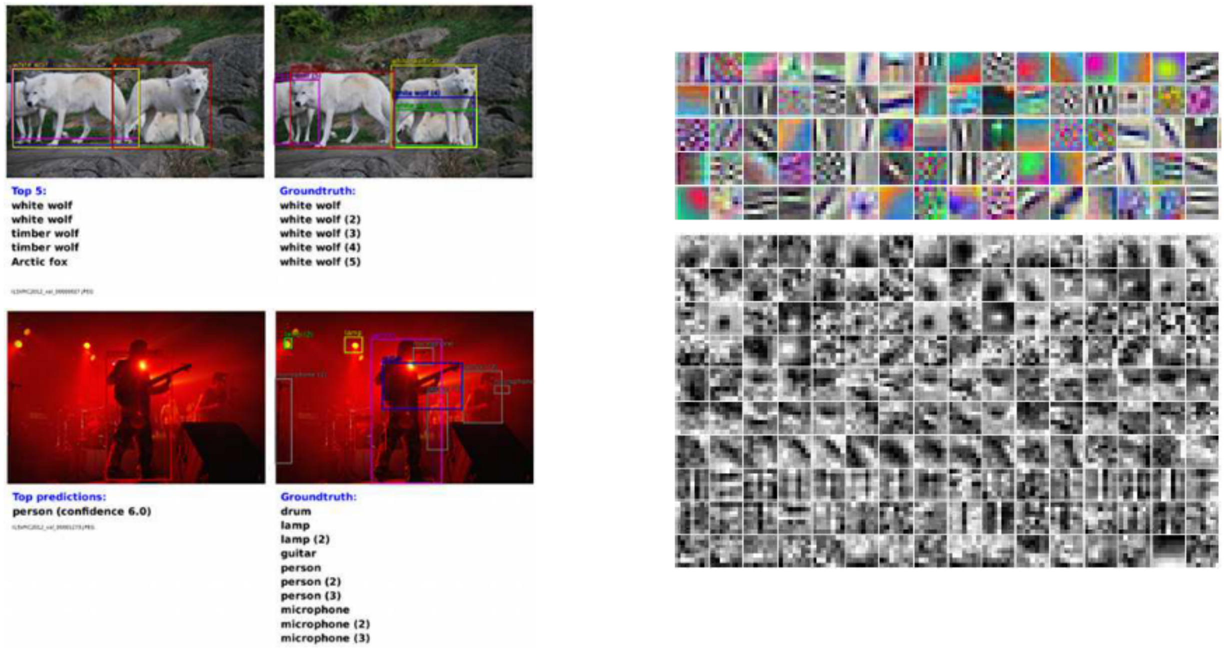


Figure 2.9: Taken from [P. Sermanet, 2014]Localization (left top) and detection tasks (left bottom). The most left images contain predictions (ordered by decreasing confidence) while the left right images show the groundtruth labels. The detection image (left bottom) illustrates the higher difficulty of the detection dataset, which can contain many small objects while the classification and localization images typically contain a single large object. To the right the images are Layer 1 filters (right top) of features and the layer 2 filters (right bottom)

Recently the interest in creating a fast detector to allow real time detection has brought new developments of accuracy and speed. Like YOLO [J. Redmon, 2015, J. Redmon, 2018], SSD[W. Liu, 2016], RetinaNet [T.-Y Lin, 2018].

YOLO, meaning You Only Look Once, uses a regression problem approach (classification aims at predicting a label while regression is about predicting a quantity) to spatially separate bounding boxes and object class probabilities using a single CNN in a single evaluation of a full image as written in [J. Redmon, 2015].

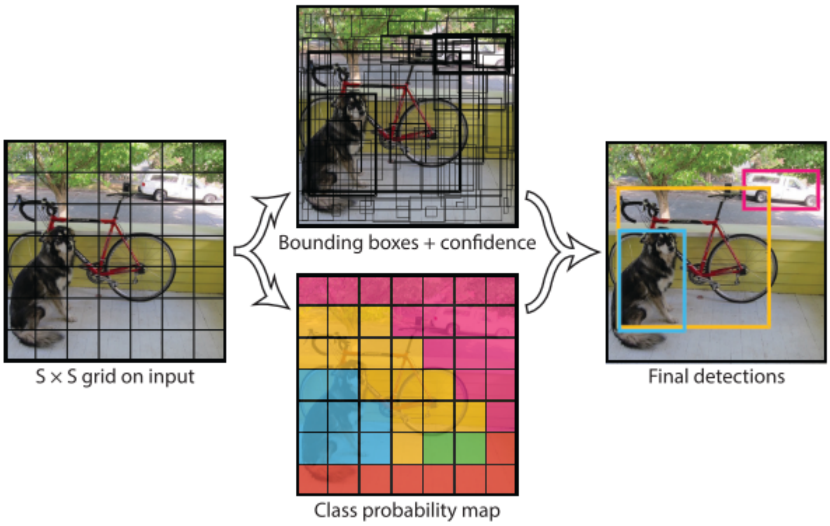


Figure 2.10: Taken from [J. Redmon, 2015]YOLO divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities

SSD as described in [W. Liu, 2016], splits the output bounding boxes into a set of default boxes per different image ratios, scales and per feature map location. During prediction time the algorithm's network scores the presence of each object category in each default box and produces adjustments to the box more closely match the object shape. Additionally, the network combines predictions from multiple feature maps with different resolutions to naturally handle objects of various sizes.

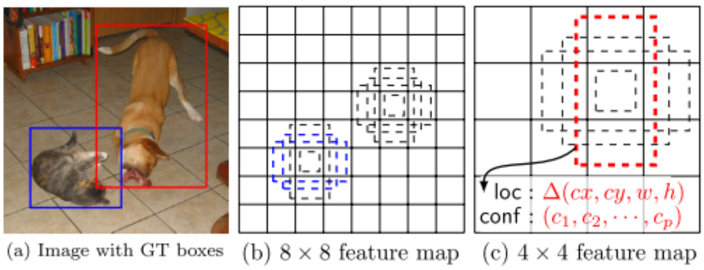
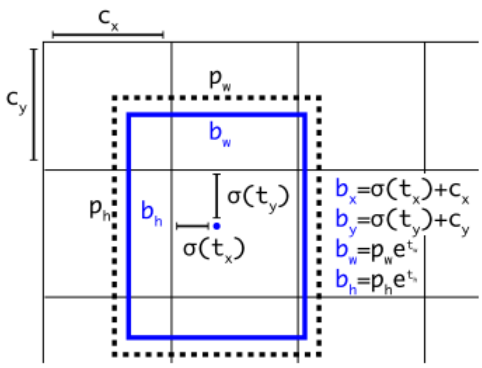


Figure 2.11: Taken from [W. Liu, 2016]SSD framework. (a) SSD only needs an input image and ground truth boxes for each object during training. In a convolutional fashion, it evaluates a small set of default boxes of different aspect ratios at each location in several feature maps with both the shape offsets and the confidences for all object categories ((c1, c2, · · · , cp)) different scales (e.g. 8×8 and 4×4 in (b) and (c)). For each default box, it predicts At training time, the algorithm first matches these default boxes to the ground truth boxes. For example, if there has been matched two default boxes with the cat and one with the dog, which are treated as positives and the rest as negatives. The model loss is a weighted sum between localization loss and confidence loss (e.g. Softmax).

Recently, a third updated version of YOLO, YOLOv3 [J. Redmon, 2018], was released. In this version YOLO predicts bounding boxes using dimension clusters as anchor boxes. The network predicts 4 coordinates for each bounding box and then predicts an objectness score for each bounding box using logistic regression. Each box predicts the classes in the bounding box. YOLOv3 predicts boxes at 3 different scales, system extracts features from those scales using a similar concept to feature pyramid networks (FPN). Then they take the feature map from 2 layers previous and upsample it two times. They also take a feature map from earlier in the network and merge it with upsampled features using concatenation to get more meaningful semantic information from the upsampled features and finer-grained information from the earlier feature map. A new network for feature extraction was also created and trained, it was called Darknet 53, because of it's 53 convolutional layers. In this version there is also a smaller version of yolo, tiny-yolo which is extremely fast in training, the architecture is similar but with less convolutional layers.



	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Figure 2.12: Taken from [J. Redmon, 2018]Left:Bounding boxes with dimension priors and location prediction. Predicts the width and height of the box as offsets from cluster centroids. Predicts the center coordinates of the box relative to the location of filter application using a sigmoid function. Right:Architecture of the convolutional neural network Darknet-53

RetinaNet, or as the paper is called, Focal Loss for Dense Object Detection [T.-Y Lin, 2018], is the final detector in this chapter and the second most recent one. RetinaNet is a single, unified network composed of a backbone network and two task-specific subnetworks. The backbone is responsible for computing a convolutional feature map over an entire input image. The first subnet performs convolutional object classification on the backbone's output; the second subnet performs convolutional bounding box regression. They built a FPN[T.-Y Lin, 2017] on top of the ResNet[K. He, 2016] as the backbone network the pyramid has levels P3 through P7, where l indicates pyramid level (Pl has resolution 2^l lower than the input). Preliminary experiments using features from only the final ResNet[K. He, 2016] layer yielded low AP. The algorithm uses translation-invariant anchor boxes similar to those in the RPN variant in FPN [T.-Y Lin, 2017].

The anchors have areas of 32^2 to 512^2 on pyramid levels P3 to P7, respectively.
The classification sub-network predicts the probability of object presence at each spatial position for each of the A anchors and K object classes. This subnet is a small FCN (fully convolutional network) attached to each FPN level; parameters of this subnet are shared across all pyramid levels. It is designed to taking an input feature map with C channels from a given pyramid level, the subnet then applies four 3×3 conv layers, each with C filters and each followed by ReLU activations, followed by a 3×3 conv layer with KA filters. Finally sigmoid activations are attached to output the KA binary predictions per spatial location. In parallel with the object classification subnet, another small FCN is attached to each pyramid level for the purpose of regressing the offset from each anchor box to a nearby ground-truth object.

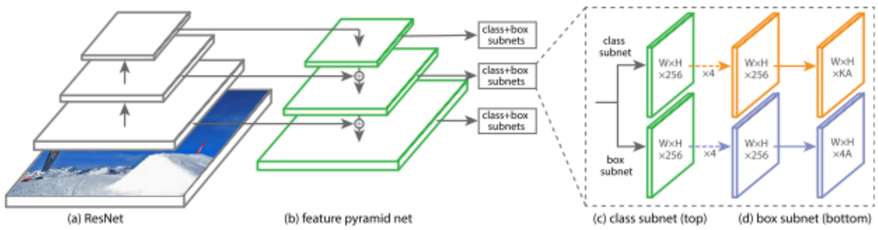


Figure 2.13: Taken from [T.-Y Lin, 2018] The one-stage RetinaNet network architecture uses a Feature Pyramid Network (FPN) backbone on top of a feedforward ResNet[K. He, 2016] architecture (a) to generate a rich, multiscale convolutional feature pyramid (b). To this backbone RetinaNet attaches two subnetworks, one for classifying anchor boxes (c) and one for regressing from anchor boxes to ground-truth object boxes (d). The network design is intentionally simple, which enables this work to focus on a novel focal loss function that eliminates the accuracy gap between the one-stage detector and state-of-the-art two-stage detectors like Faster R-CNN with FPN

2.1.2 Classification

Current object detectors based on neural networks already integrate classification with detection but for the purpose of presenting a bigger picture, many classification algorithms will be presented here, not only neural networks.

2.1.2.1 Linear Discriminant Analysis(LDA)

LDA's aims at utilizing hyperplanes to split the different classes. To do that it is necessary to find the expression of a plane that maximizes the distance between two classes and minimizes the interclass variance. The more classes the more planes are necessary to separate each of the classes from the others.

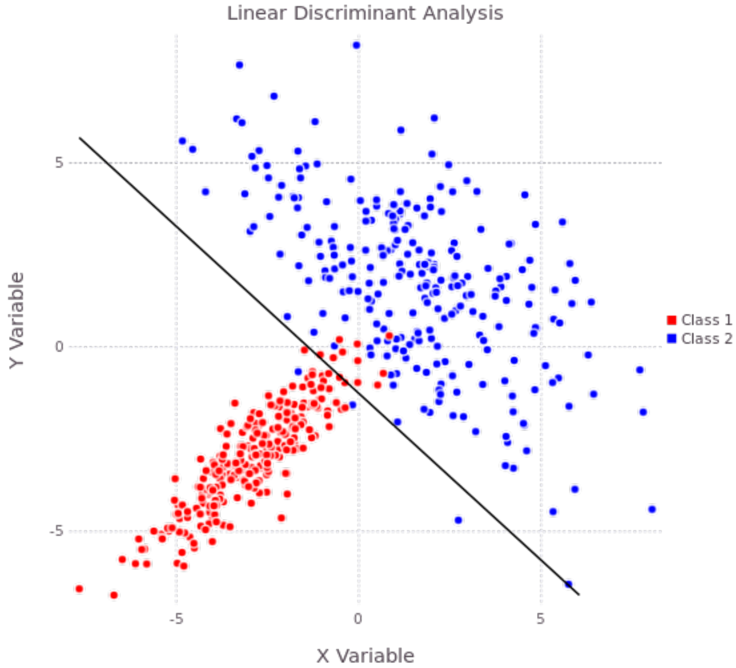


Figure 2.14: taken from [F. Lotte, 2007] A hyperplane which separates two different classes

2.1.2.2 Support Vector Machines(SVM)

SVM is a supervised learning algorithm that just like LDA the idea is to also define a hyperplane to separate classes but the most important criterion is the maximum margin hyperplane.

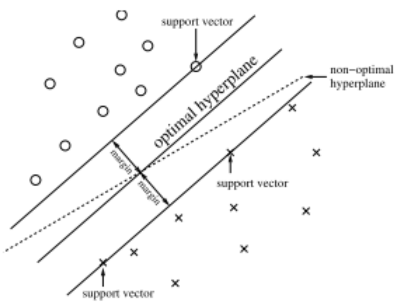


Figure 2.15: taken from [F. Lotte, 2007] the optimal hyperplane for generalization

2.1.2.3 Hidden Markov Model(HMM)

The mindset of Hidden Markov Model is to compute in the best way, given the parameters of the model, the probability of a particular output sequence. This requires summation over all possible state sequences. Each state of the automaton can estimate the probability of observing a given feature vector.

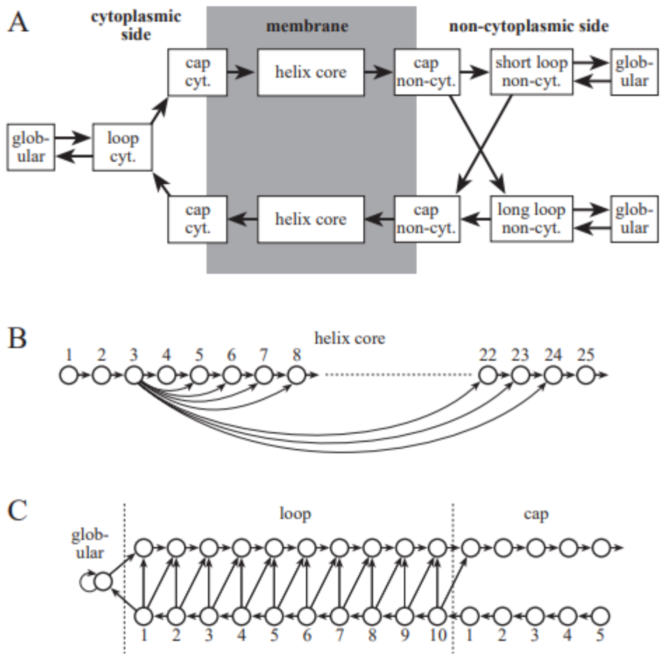


Figure 2.16: taken from [E. Sonnhammer, 1998] The structure of the model used in TMHMM(Transmembrane Helix Hidden Markov Model). A) The overall layout of the model. Each box corresponds to one or more states. Parts of the model with the same text are tied, i.e. their parameters are the same. Cyt. means the cytoplasmic side of the membrane and non-cyt. the other side. B) The state diagram for the parts of the model denoted helix core in A. From the last cap state there is a transition to core state number 1. The first three and the last two core states have to be traversed, but all the other core states can be bypassed. This models core regions of lengths from 5 to 25 residues. All core states have tied amino acid probabilities. C) The state structure of globular, loop, and cap regions. In each of the three regions the amino acid probabilities are tied. The three different loop regions are all modelled like this, but they have different parameters in some regions

2.1.2.4 K Nearest Neighbor classification(KNN)

KNN is based on the input of the k closest training sets in the feature space. An object is classified by a majority vote of its neighbors and k is the number of neighbors that vote to classify that object. The object is assigned to the class most common among its k nearest neighbors. If k = 1, then the object is simply assigned to the class of that single nearest neighbor. The bigger the k the lesser the noise, but also there is a risk of less separation between classes.

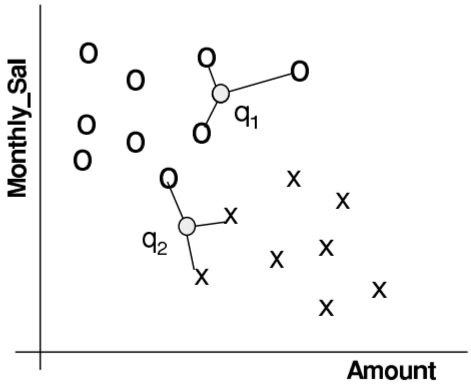


Figure 2.17: Example of K-Nearest Neighbours [P. Cunningham, 2007]

2.1.2.5 Decision trees

A Decision Tree is a diagram where each branch represents a test or as it is called in [Aggarwal, 2014] a split criterion, whose objective is to try splitting the training data in order to maximize the discrimination among the different classes over different nodes.

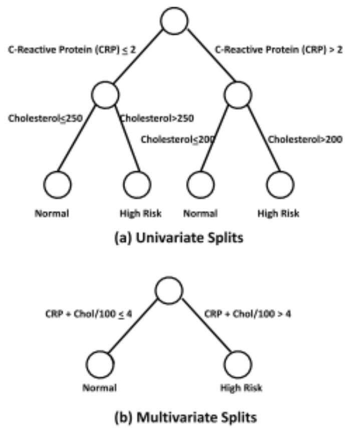


Figure 2.18: taken from [Aggarwal, 2014] Univariate is when the criterion is on a single attribute. Multivariate is when the split criterion uses conditions on multiple attributes.

2.1.2.6 Neural networks

In the start of this chapter a type of neural networks, the convolutional neural networks, were described to serve as introduction to the detection section.
In the book ”Data classification: algorithms and applications” [Aggarwal, 2014] the author states: ”Neural networks attempt to simulate biological systems, corresponding to the human brain. In the human brain, neurons are connected to one another via points, which are referred to as synapses. In biological systems, learning is performed by changing the strength of the synaptic connections, in response to impulses.” In computer science, Neural networks are supervised learning method composed by a group of layers of neurons, an input layer and an output layer. Each of those

neurons on the output layer get the information that was inserted in the input layer with some weights associated, those weights are the strength of the synapses. It is by adjusting the weights associated with each input that the algorithm "learns" how each part of the data influences the output classification.

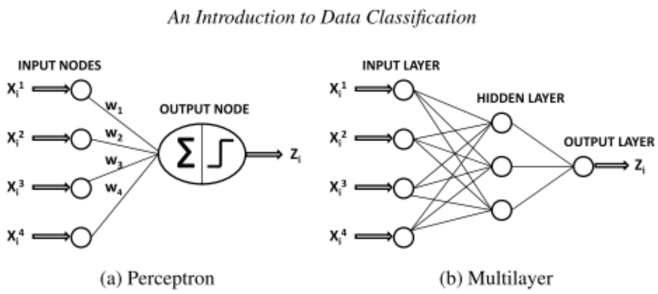


Figure 2.19: taken from [Aggarwal, 2014] Perceptron and Multilayer Perceptron

2.1.3 Ensemble Learning

Ensemble Learning consists in combining predictions of multiple different models to increase performance. Some of these techniques are described next based on what was found in [Polikar, 2006] and [M. Galar, 2011]. As a matter of introduction, three very simple ensemble methods exist: max voting, averaging and weighted average.

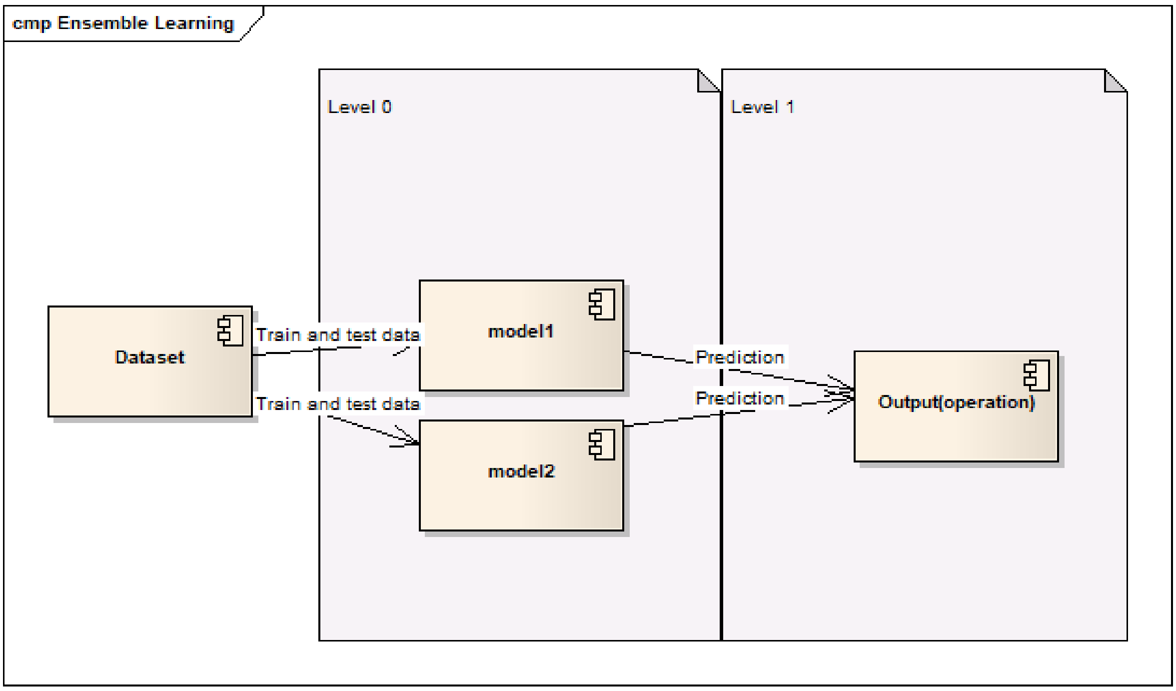


Figure 2.20: Example diagram to explain the most basic idea of Ensemble learning.

In figure 2.20 a dataset is used to train and test the models in the level 0 then the output of the models gets fed forward to an operation or another model in the next level, this is the most basic idea behind ensemble.

Starting with max voting the output operation in the example is the mode of the predictions from the models. In weighted average each model gets an associated weight based on importance and the weighted average gets calculated as this $(p1*w1+p2*w2)/2$ where p1 is the prediction of model1 and w1 is the weight given to model1. The average method implies the calculation of the normal average to combine the outputs. Other more advanced approaches are Stacking, Bagging and Boosting.

2.1.3.1 Stacking

Stacking is an ensemble learning technique that takes predictions from multiple models to build a new model and then that model outputs the final predictions on the test set. The train set is used for the training of the level 0 models and for their predictions as well, those predictions are then used to build the next level model.

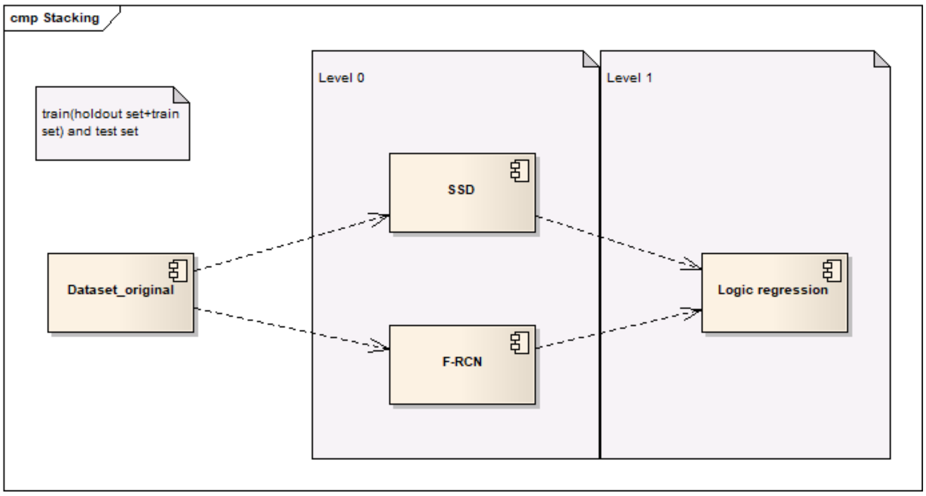


Figure 2.21: In this example SSD and F-RCN are the models of level 0, they make the predictions on the train set and those predictions are used to build the Logistic Regression model in level1 that makes predictions on the original test set

2.1.3.2 Bagging

Bagging or bootstrap aggregation consists in creating subsets from the original dataset and using each of these subsets to train different independent models. The predictions of each of these independent models are then combined using voting for classification or average.

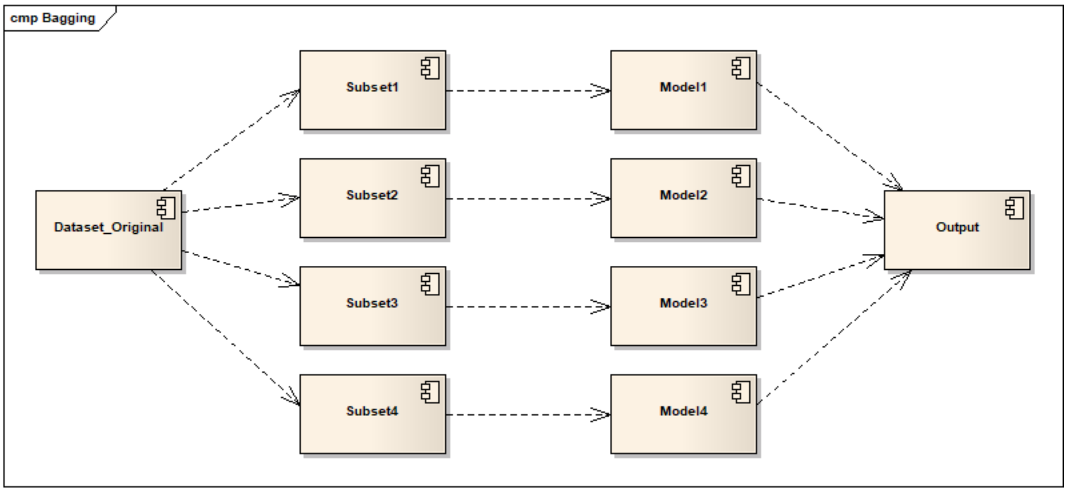


Figure 2.22: four random subsets from the original data go through four independent models that output predictions. Those predictions are combined to make the final the output.

Bagging has two variations according to [Polikar, 2006]: Random forests and Pasting small votes. Random forests are created from decision trees with varying training parameters and said parameters can be bootstrapped versions of the train data or different feature subsets. Pasting small votes on the other hand uses large data partitioned into smaller subsets used to train different classifiers, the data subsets can be created at random, called "Rvotes", or can be created consecutively based on importance of instances (those that improve diversity), called "Ivotes".

2.1.3.3 Boosting

The idea behind boosting is to use weak models (barely better than random guessing) by training them on small subsets and then make predictions on the whole dataset. The wrong predictions are weighted with bigger weights, then another model is created and fed the weighted data to attempt to correct the mistakes from the previous model this happens on a sequential loop with N iterations. The final model uses a weighted mean of all the weak models.

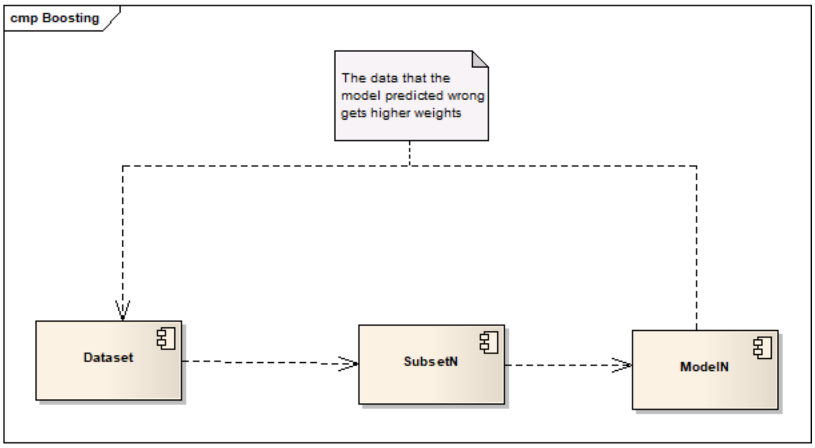


Figure 2.23: In the first iteration all the data has the same weight, a subset is sampled from the whole dataset. A model is trained on the subset and makes predictions on the whole dataset. The data that the model predicted incorrectly get higher weights and the cycle restarts with the updated data weights.

2.1.4 Metrics for Evaluating Classification Algorithms

Classification algorithms fall under the category of machine learning algorithms. The most common metrics for machine learning algorithms are: Classification Accuracy, Logarithmic Loss, Confusion Matrix, Area under Curve, F1 Score, Mean Absolute Error and Mean Square Error.

2.1.4.1 Classification Accuracy

Classification Accuracy is the ratio between the correct predictions and total predictions.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions Made}} \tag{2.1}$$

It only evaluates well when there is the same amount of samples for each class.

2.1.4.2 Logarithmic Loss

The Logarithmic Loss metric penalizes the wrong classifications. It requires the classifier to assign a probability to each class. N samples, M classes, y_{ij} indicates whether sample i belongs to class j or not, p_{ij}, indicates the probability of sample i belonging to class j

$$\text{Logarithmic Loss} = \frac{-1}{N} \sum_{i=1}^{N} \sum_{j=1}^{M} y_{ij} * log(p_{ij}) \tag{2.2}$$

It works well for multi-class classification. The lower the log loss the higher accuracy.

2.1.4.3 Confusion Matrix

A Confusion Matrix describes the performance in more detail. It looks at each of the predictions and the actual class. So it is easier to understand, [A. Mishra, 2018] has a very simple example:

Table 2.1: Example of a confusion matrix, TP means True Positive, FN means False Negative, FP means False Positive and TN True Negative, these concepts will be explained further and used in the next metrics

	Predicted: Class1	Predicted: Class2
Actual: Class1	100 (TP)	10 (FN)
Actual: Class2	5 (FP)	50 (TN)

What this means is that the algorithm predicted Class1 a hundred times and that was the actual class (TP), so the right prediction, fifty times predicted Class2 and it was the actual class (TN). The classification accuracy can be calculated from this since Number of Correct Predictions $=$ $100+50$ and the Total Number of Predictions Made $= 100+5+10+50$ so as written above

$$Accuracy = 150/165$$

2.1.4.4 Area Under the Curve(AUC)

AUC works well only with binary classification (where there is only Class1 or Class2) problems since it is the probability of the classifier ranking a random chosen positive higher than a random chosen negative. To define the AUC it is necessary to calculate True Positive Rate and False Positive Rate.

$$\text{True Positive Rate} = \frac{\text{True Positive}}{\text{False Negative} + \text{True Positive}} \tag{2.3}$$

$$\text{False Positive Rate} = \frac{\text{False Positive}}{\text{False Positive} + \text{True Negative}} \tag{2.4}$$

The area under the curve of plot False Positive Rate vs True Positive Rate is the AUC.

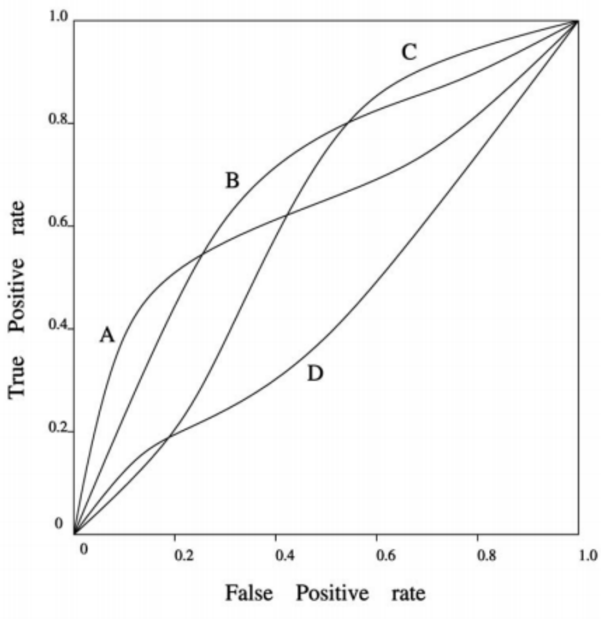


Figure 2.24: Example of an area under the curve taken from [J. Huang, 2005] A,B,C,D are classifiers

2.1.4.5 F1 Score

This metric evaluates how precise and robust the classifier is, the greater the value of F1 the better.

$$F1 = 2 * \frac{1}{\frac{1}{precision} + \frac{1}{recall}} \tag{2.5}$$

Precision is the fraction of the Positives predicted that were correctly classified.

$$\text{Precision} = \frac{\text{True Positives}}{\text{False Positives} + \text{True Positives}} \tag{2.6}$$

Recall is the fraction of actual Positives that existed and that the model predicted correctly.

$$\text{Recall} = \frac{\text{True Positives}}{\text{False Negatives} + \text{True Positives}} \tag{2.7}$$

High precision means that it is accurate, but lower recall means that misses too many of difficult to classify instances.

2.1.4.6 Mean Absolute Error

As the name says Mean Absolute Error is the mean of difference between the Actual Values and the Predicted Values it can also be described as the distance between the Values.

$$\text{Mean Absolute Error} = \frac{1}{N} \sum_{j=1}^{N} \mid y_j - y2_j \mid \tag{2.8}$$

y_j and $y2_j$ one represents the actual value for class j and the other the predicted for class j

2.1.4.7 Mean Squared Error

This metric is similar to the Mean Absolute Error except for the fact that it uses the square of the difference. The error gets squared so it becomes larger and more significant.

$$\text{Mean Squared Error} = \frac{1}{N}\sum_{j=1}^{N}(y_j - y2_j)^2 \tag{2.9}$$

y_j and $y2_j$ one represents the actual value for class j and the other the predicted for class j

2.2 Related Work

In this section the current related solutions are explored. This is done to achieve better understanding of what has been done in the area and what technologies are indispensable for the work.

2.2.1 Detection and Classification

In 1998, an approach to a traffic surveillance system based on vehicle tracking called "A real-time computer vision system for vehicle tracking and traffic surveillance" [B. Coifman, 1998] was introduced. In this solution the authors proposed a feature-based tracking system for detecting vehicles under the challenging conditions. Instead of tracking entire vehicles, vehicle's most salient features are tracked to make the system robust to partial occlusion. Leaving out the camera calibration that was done at that time, in the detection module corner features are defined as regions in the gray level intensity image where brightness varies in more than one direction. The corner features are tracked over time in the tracking module using Kalman filtering [Gelb, 1974] (using a mean weighted measure predicts the state of the system with a new value) to predict a given corner's location and velocity in the next frame. This approach is very old but the theoretical idea of feature based tracking is very good which will be thought for the tracking approach of our solution.

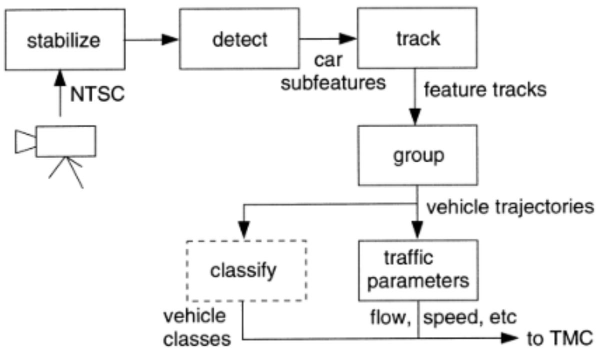


Figure 2.25: Taken from [B. Coifman, 1998] Overview of the system. To clarify the classification model was not implemented.

In 2008 the Institute of systems and Robotics of the FCT from the University of Coimbra Created a funded Project by Brisa [Monteiro, 2008] that included Robust Vehicle Segmentation, Stopped Vehicles Detection, Wrong Way Drivers Detection, Vehicle Counting, Vehicle Velocity Estimation project by Brisa. Describes a sliding window paradigm and it is not an integrated solution since that project is more of an experiment of solving each sub-problem independently than to solve the three sub-problems of detection, classification and tracking, simply solves each problem separately together.

In 2015 [P. Barcellos, 2014] "A novel video based system for detecting and counting vehicles at user-defined virtual loops" was presented. As written in [P. Barcellos, 2014], the proposed method used motion coherence and spatial adjacency to group sampling particles in urban video sequences. A foreground mask is created using Gaussian Mixture Models and Motion Energy Images to determine the preferable locations that the particles must sample, and the convex particle groups are then analyzed to detect the vehicles. After a vehicle is detected, it is tracked using the similarity of its colors in adjacent frames. The vehicles are counted in user-defined virtual loops, by detecting the intersections of the tracked vehicles with these virtual loops.

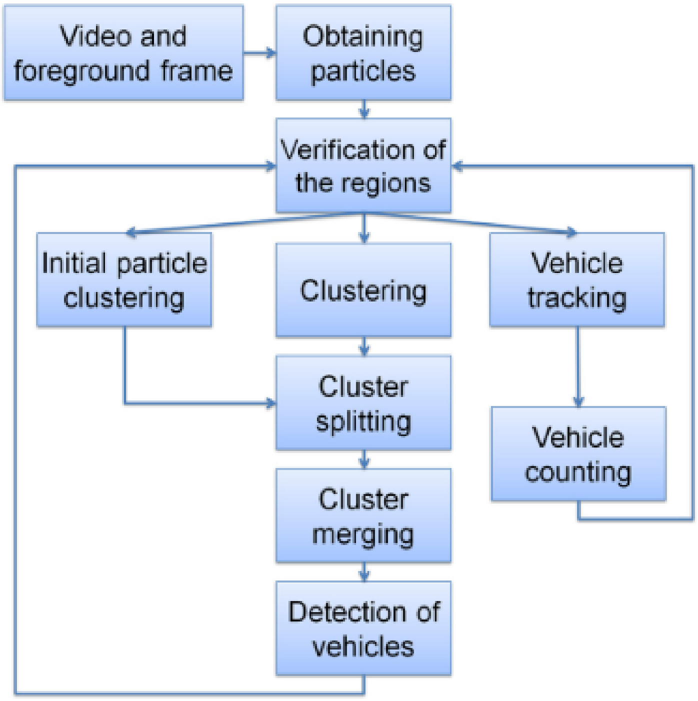


Figure 2.26: Taken from [P. Barcellos, 2014] Overview of the method

This program however is still inefficient as it was written in [P. Barcellos, 2014]:"However, the proposed method may have a worse vehicle counting performance when the traffic flow is interrupted to be later resumed. Also, vehicle occlusions tend to worsen the vehicle counting performance of the proposed method. Small vehicles may be missed by the proposed method (...)" . Also since it is from 2015 none of the newer algorithms for detection and classification have been used.
Data from sky [Dat, 2018] uses aerial images to detect, classify and track providing the end user with detailed information like speed, counting and detecting anomalies. Uses drones to collect the video feed, does not use common traffic surveillance feeds. Only works with very high resolution aerial images and can not be used with current installation of cameras. There is not a paper or anywhere where to see the details of the implementation so the analysis is more on what features it provides and what requirements it has. This competing solution appears mentioned here as more of a curiosity of the applications since it can not be of use given that there is no information on the theory or implementation behind the product.

2.2.2 Ensemble Learning

"A Review on Ensembles for the Class Imbalance Problem: Bagging-, Boosting-, and Hybrid-Based Approaches", [M. Galar, 2011], is not a specific scenario where there was used a fusion of classifiers applied to vehicle classification, but actually it is focused on experiments done on many

different implementations of methods of ensemble but not in the field of vehicles specifically. Although there is a metric of accuracy of each algorithm tested on three vehicle datasets.
In these experiments each of the algorithms is compared with the other algorithms that are similar, belong to the same family, from there the better performing algorithms of each family are selected to be compared with the better performing algorithms of other families. The study provides some interesting conclusions, namely that ensemble based algorithms improve the results of single classifiers, more complex methods do not outperform simpler ones and presents a good idea behind the experimentation method and which algorithms might be better.

In "Ensemble of Exemplar-SVMs for Object Detection and Beyond" [T. Malisiewicz, 2011], the author uses a bagging like ensemble approach to vehicle detection and classification even though it does not mention it as bagging. This approach featured an ensemble of SVMs trained on different vehicles.

Adaboost has been reported in uses for vehicle classification in a pipeline for rear view vehicle detection system based on monocular vision[Wang and Cai, 2015] and [Wen et al., 2015] where there is an approach to increasing Adaboost training speed for vehicle classification.

2.2.3 Previous Approaches

This work was done in Artificial Intelligence and Computer Science Lab Faculty of Engineering, University of Porto where there were already previous approaches in the ITS area we present some next: In ”Video Processing Techniques for Traffic Information Acquisition Using Uncontrolled Video Streams” [P. Loureiro, 2009], this paper presents a survey to the first attempts at monitoring transportation systems in order to provide information useful to the community. Adding to the survey there is an analysis of the issues that may arise and the best methods to solve them.
In ” A computer-vision approach to traffic analysis over intersections” [G. Lira, 2016], this paper presents an approach using computer vision algorithms on videos obtained with drones of vehicles crossing intersections. This is done to identify and track vehicles, with the finality of extracting a statistical model.
In ”Computer-vision-based surveillance of intelligent transportation systems” [Neto et al., 2018], this paper describes the development of a video analytics server to detect and classify vehicles on motorways. This approach features Background Subtraction for detection and a fuzzy set for classification.

2.3 Summary

A lot of development has been done in the are of detection and classification, some was described in this chapter other has been left out since it was not in consideration for our solution. Some solutions solve one problem and leave another unsolved, some are faster but with worse accuracy, others the opposite. Some methods require more data, others require weak learners but more computational power. The metrics vary, a few only work for binary classification problems while the others can be applied to anything, a combination of many is the best way to evaluate the classification.

Even though many similar applications have been made there is still space for further developments in order to improve the solutions by using different algorithms and different approaches.

Chapter 3

Methodological Approach

As written in the first chapter, our problem is to solve inconsistencies of single model predictions when classifying vehicles on highways. From this problem a set of questions have emerged:

1. Which algorithms classify vehicles better on their own?
2. How to fix the inconsistencies of single models to achieve a better result of classification?

3.1 Scope

Scope is defined as either Project Scope or Product scope.
According to [Kerzner, 2017], the work that needs to be accomplished to deliver a product, service, or result with the specified features and functions (hows) compose the project scope.
Also according to [Kerzner, 2017], the features and functions that characterize a product, service or result (whats) is the product scope.

At first, the isolated classification algorithms will be evaluated in order to assess their strong and weak points. Afterwards, based on the findings, create an hypothesis that defines which algorithms will be used to solve which problems and what are their constraints. Finally solve the problem using that hypothesis.

The product scope associated is to deliver a module integrated on the existing pipeline with the fusing of different classifying algorithms allowing to see the independent accuracy of each algorithm and the combined predictions as output. These are the two scopes that can be defined in this work.

3.2 Support Technologies

Taken from [OpenCV, 2018],OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. Being a BSD-licensed product, OpenCV makes it easy for businesses to utilize and modify the code.

As it can bee found in [Ten, 2018], TensorFlow™ is an open source software library for high performance numerical computation. Its flexible architecture allows easy deployment of computation across a variety of platforms (CPUs, GPUs, TPUs), and from desktops to clusters of servers to mobile and edge devices. Originally developed by researchers and engineers from the Google Brain team within Google's AI organization, it comes with strong support for machine learning and deep learning and the flexible numerical computation core is used across many other scientific domains.

Taken from [Chollet, 2015], Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK [CNT, 2017], or Theano [The, 2017]. It was developed with a focus of enabling fast experimentation. Being able to go from idea to result with the least possible delay is key to doing good research. Allows for easy and fast prototyping (through user friendliness, modularity, and extensibility). Supports both convolutional networks and recurrent networks, as well as combinations of the two. Runs seamlessly on CPU and GPU.

The scikit-learn [sci, 2017] provides API to calculate metrics like F1, accuracy, AUC and other algorithms for optimization.

3.3 Proposed Solution

In the next sections we will first analyze the existing solution and then we will present the proposed changes to that solution. It is important to analyze the existing solution in order to find what can be done to improve it.

3.3.1 Existing Solution

In this thesis we intend to improve the classification part of the pipeline shown in the next figure.

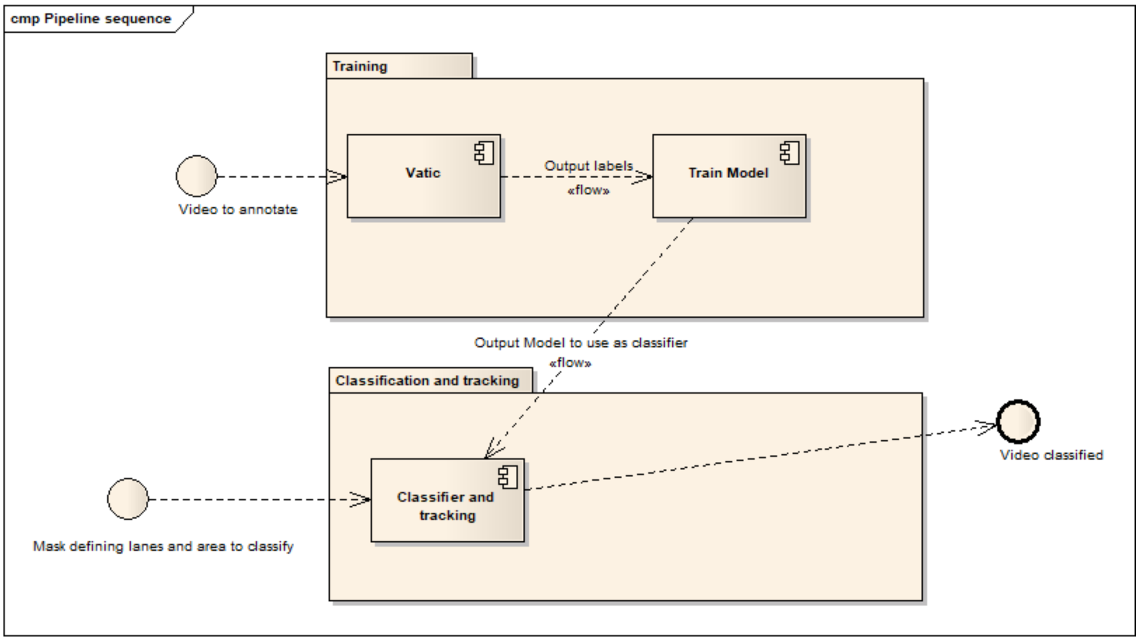


Figure 3.1: Basic Implementation pipeline

This pipeline comprises training and annotation of videos that can serve as dataset.
The tensorflow object detection pipeline for training [Ten, 2018] is used for the neural network classifier. Detection and classification is achieved with a single one-stage model SSD, discussed in the Background section and described in [W. Liu, 2016].
Currently SSD is running with three classes: light vehicles, motorcycles and heavy vehicles and performs quite well on vehicle classification, 68% of the bounding boxes, as will be described in more detail on the results chapter. This model is a pre-trained SSD, with the COCO dataset (implementation in tensorflow that can be found in `http://download.tensorflow.org/models/object_detection/ssd_inception_v2_coco_2018_01_28.tar.gz`).
The classification has done some good outputs but also some missed classifications, the data available is small which is less than optimal for training neural networks, which might be one of the reasons of the not so good predictions.
To fix these problems, an Ensemble approach to the classification task is chosen based on the following reasons: ensemble methods work well with little data as can be found in [Polikar, 2006], ”In the absence of adequate training data, re-sampling techniques can be used for drawing overlapping random subsets of the available data, each of which can be used to train a different classifier, creating the ensemble. Such approaches have also proven to be very effective.” So that solves the small amount of data, as for the inconsistencies in accuracy of the classification, the same article, states ”Readers familiar with neural networks or other automated classifiers are painfully aware that good performance on training data does not predict good generalization performance (...). A set of classifiers with similar training performances may have different generalization performances. In fact, even classifiers with similar generalization performances may perform differently in the field, particularly if the test dataset used to determine the generalization performance is not

sufficiently representative of the future field data. In such cases, combining the outputs of several classifiers by averaging may reduce the risk of an unfortunate selection of a poorly performing classifier."

3.3.2 Proposed System Architecture

Figure 3.2, below, represents our ensemble pipeline and the possible combinations:

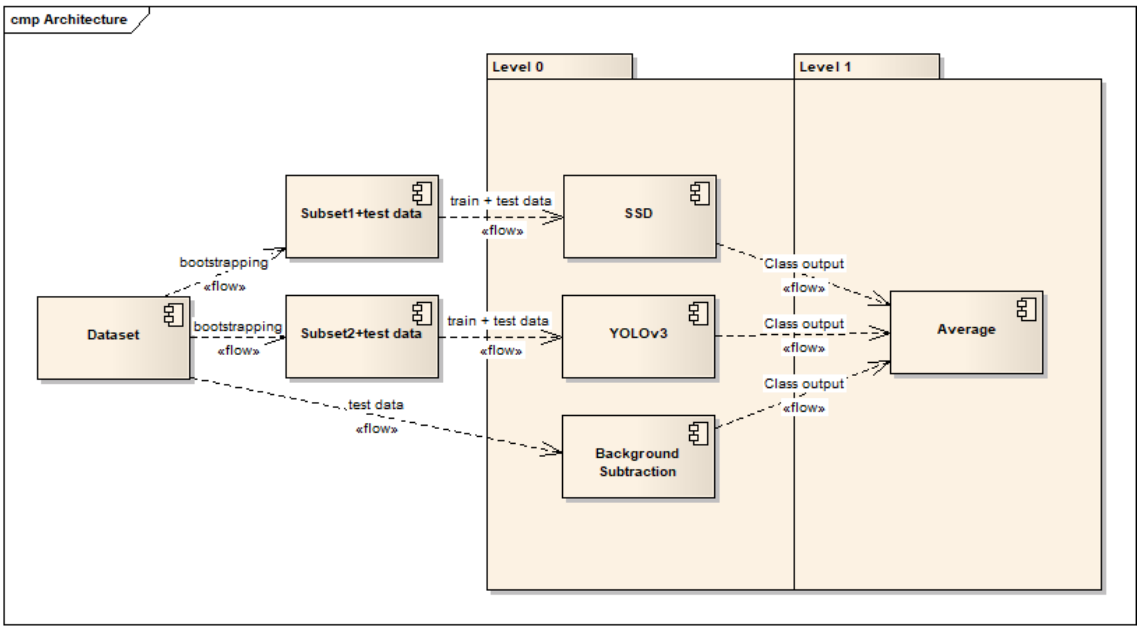


Figure 3.2: Architecture of the ensemble solution with average as combination

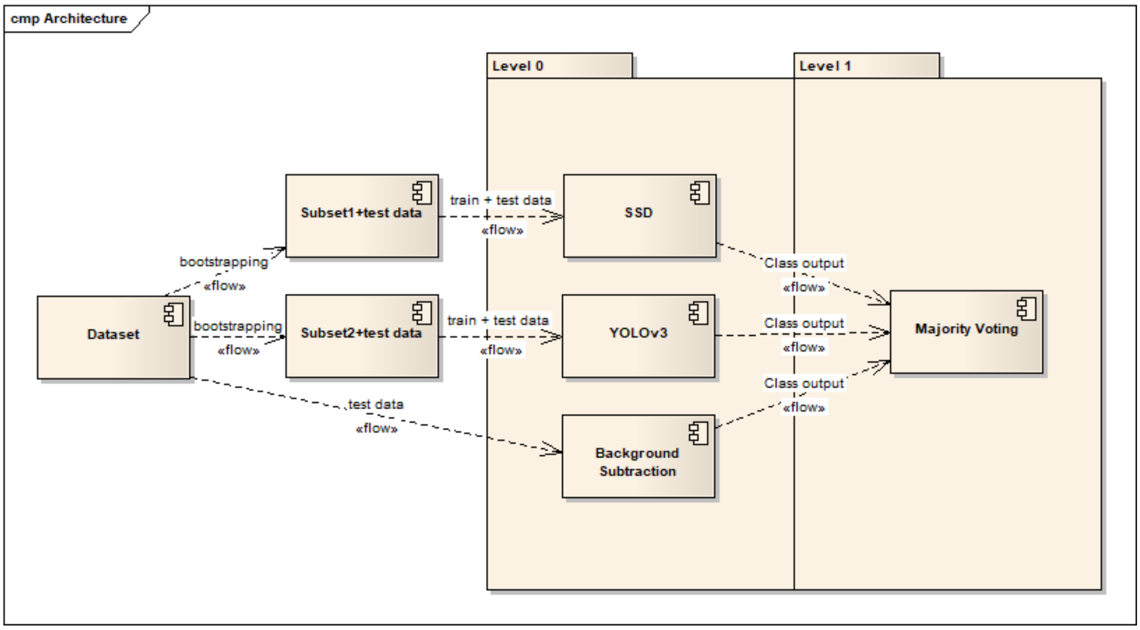


Figure 3.3: Architecture of the ensemble solution with majority voting as combination

We propose a Bagging strategy with the pasting small votes variation, since according to [Polikar, 2006] it is a good approach when available data is of limited size and also when there are unstable models to help ensure diversity (neural networks are unstable models). Although Boosting is also an ensemble methodology that can achieve good classification results, it is not suitable for our proposed solution since, as can be seen on the following paragraph, we are using computationally heavy learners(YOLO and SSD) and Boosting is based on weak learners that can be trained over and over.

The classification algorithms that compose the proposed ensemble are SSD, YOLO and Background Subtraction. SSD performs well with vehicle datasets, as it is presented in figure 3 of [W. Liu, 2016], while being faster to train than the two-stage approaches like faster-RCNN that take a long time to train and it is already integrated in the current pipeline so it is important to have for comparison with the newer solution.

YOLOv3 the latest iteration of YOLO, has the quickest inference times of current classification algorithms as can be found in [J. Redmon, 2018] and for classification with mobility applications it is important to have the fastest algorithms possible. Finally background subtraction is a weak algorithm that was one of the first attempts of classifying vehicles and for comparison purposes it is interesting to have with the other two more recent methods.

3.3.2.1 SSD

The version existing in the original pipeline and chosen to be a part of the ensemble is SSD Inception which is a SSD model architecture with an inception network. So we can only assume that the application behind the inception theory [Szegedy et al., 2015] with the SSD model. Normal SSD has densely connected layers while SSD Inception has sparsely connected layers, while densely layers connect to every next layer, sparsely does not connect to all layers but instead connect to a concatenation layer.

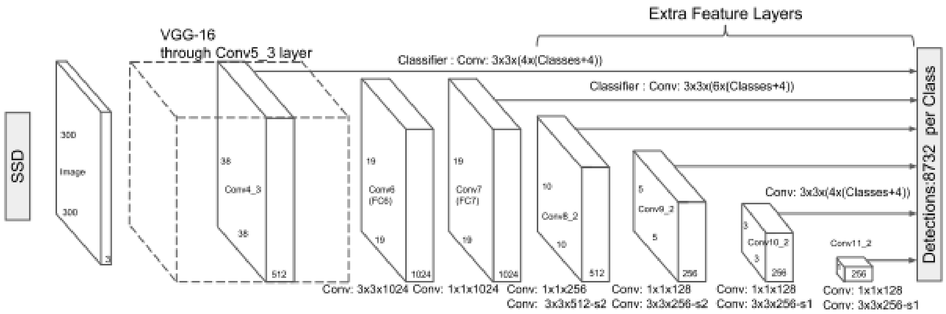


Figure 3.4: Architecture of normal SSD taken from [W. Liu, 2016]

In Figure 3.4, above, there are fully connected convolutional layers. With inception those fully connected become sparsely connected with a filter concatenation at the end.

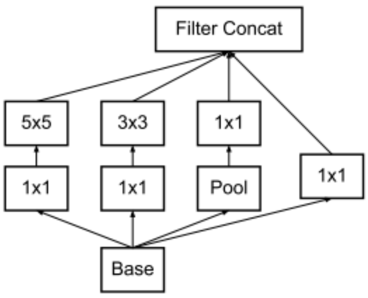


Figure 3.5: Diagram of the idea behind inception [Szegedy et al., 2015]

SSD was trained with 3 classes motorcycles, light vehicles and heavy vehicles. It uses 2 data augmentation options, random cropping and random horizontal flip. We mostly trained SSD for 50 000 iterations per dataset. Acceptance threshold for detection and classification was 50%.

3.3.2.2 YOLO

For the used datasets, YOLOv3 would require 1900MB of VRAM and the training time for all 3 datasets would not be within the thesis time frame, therefore we chose to perform the training with tiny YOLOv3 which has less convolutional layers therefore uses 400MB of VRAM.
Tiny YOLO is composed of 13 convolutional layers and 2 YOLO output layers, each of the first 6 convolutional layers is followed by a maxpooling operation of size 2. We trained yolo on 3 classes, so each of the convolutional layers before the YOLO layers has a filter of size 24 as presented in the guide for YOLO and in SSD's paper [W. Liu, 2016] $(classes+5)*3$. YOLO downsamples by a factor of 32 so every image size has to be a multiple of 32.

Table 3.1: Architecture of YOLO tiny based of [J. Redmon, 2018]

Type	Filters	Size/Stride	Output
Convolutional	16	3x3	256x256
Maxpool		2x2/2	128x128
Convolutional	32	3x3	128x128
Maxpool		2x2/2	64x64
Convolutional	64	3x3	64x64
Maxpool		2x2/2	32x32
Convolutional	128	3x3	32x32
Maxpool		2x2/2	16x16
Convolutional	256	3x3	16x16
Maxpool		2x2/2	8x8
Convolutional	512	3x3	8x8
Maxpool		2x2/2	4x4
Convolutional	256	1x1	4x4
Convolutional	512	3x3	4x4
Convolutional		1x1	4x4
AvgPool		Global	
Connected		1000	
Softmax			

We trained YOLO with a learning rate of 0.0004 and batch size of 64. The acceptance threshold for detection and classification was 50%.

3.3.2.3 Background Subtraction

This classifier is the simplest and the fastest, it is based on MOG (mixture of gaussians)[T. Bouwmans, 2008].To the resulting foreground image we applied the algorithm for edge detection [Suzuki and Be, 1985].

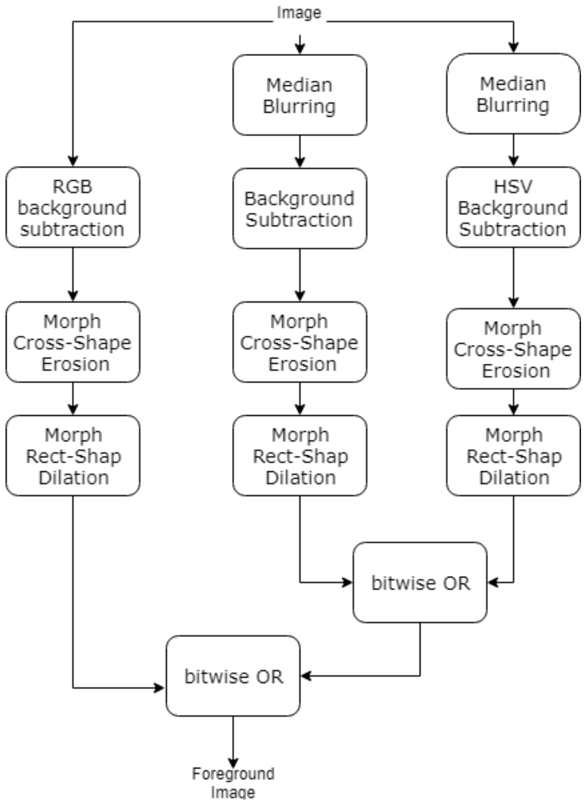


Figure 3.6: Flow chart of the operations for extracting the background. Each of the background subractors are MOG background subractors

Finally we used dimension heuristics to remove contours that do not represent vehicles. For each camera a region for classification on each lane is selected. The region for each camera is a critical part of the method since class is given based on area threshold, everything above the threshold is a heavy and everything below is a light vehicle.
The next figure shows the region coded for the classification in the first dataset.

Figure 3.7: Regions chosen for background subtraction classification on dataset 1,area threshold is 1890 pixels

The next figure shows the region coded for the classification in dataset 2.

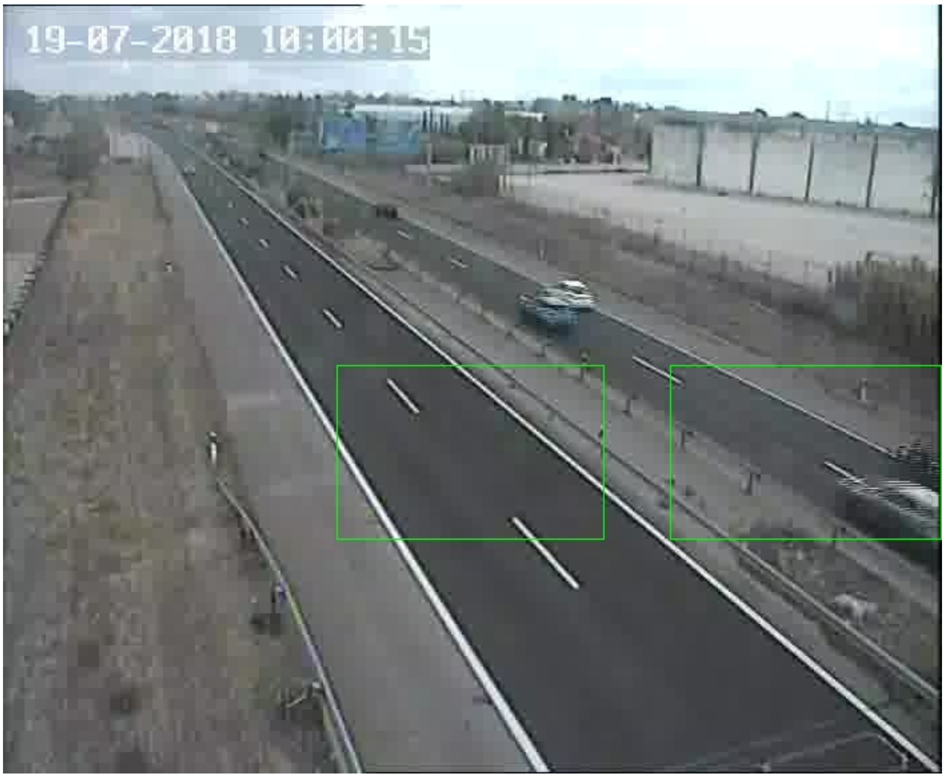


Figure 3.8: Regions chosen for background subtraction classification on dataset 2

The next figure shows the region chosen for the classification in dataset 3.

Figure 3.9: Regions chosen for background subtraction classification on dataset 3, area threshold is 60 000 pixels

Since background subtraction only classifies objects based on area and does not use any features then we associated a probability with each class. Light vehicles and motorcycles have 0.5 probability since the area of the contour boxes is not very different and this probability affects combination as we explain in the next subsection. Heavy vehicles have a higher probability of 0.7 since they have a more distinctive area.

3.3.2.4 Combination

For the combinational part, each dataset is divided into two parts, 70% of the vehicle samples are used for training while the remaining 30% are used for testing. The training part, is further divided into two halves that are fed into the two classifiers (SSD and YOLO).
The test set is the same for all the learners and will be used to serve as the data for combining the predictions of the different learners, in order to retrieve an evaluation of the single and combined predictions over the same data.
Background subtraction is implemented in a way that only classifies certain regions closer to the camera where we know the area threshold between the different classes of vehicles. Even though both learners, SSD and YOLO, output classification for the full image, doing the same on background subtraction would result in a complete randomness of predictions since the area of a vehicle box depends on how far of the camera it is.
It must be stated that Background subtraction is not a learning algorithm so it does not receive a dataset to train only the one to test.
Each algorithm is different and outputs classification differently but in order to compare all the algorithms a uniformization of output is required. To that end, for each frame or image of the test set, each model writes a predictions file <frame>-<model>.txt. Each line of the file is composed of <class> <probability> <x> <y> <width> <height> all the models output a file in that format at the end of the test phase. x, y, width, height are all aspect ratios and x and y are centroid coordinates, some of the models output the format in centroids and others in coordinates of the bounding box corners so for those we calculated the centroids.
To combine the outputs a python script was implemented, which goes frame by frame opening the output files of each model and compare each line to see which are similar since being similar means that they classify the same object. We find similarity by calculating the IOU(Intersect over Union) between the boxes which definition is shown next.

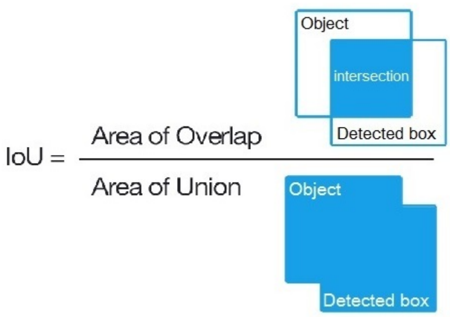


Figure 3.10: Definition of IOU, image taken from PyImageSearch an Image Search engines blog [Rosebrock, 2018]

Two methods for calculating the final prediction were implemented Max Voting also known as Majority Voting and Best Average . For Best Average if the similar lines have the same class prediction then we sum probability, x, y, width and height then divide it by number of similar lines, the final classification is the one with higher probability.

Algorithm 1 Best Average

box ▷ list that has the bounding box probability, centroid coordinates in aspect ratios, width and height
Z_c ▷ number of classifiers that predicted for this frame with class c
$listAverages$ ▷ list to store the averages for each class
$sum_c \leftarrow \sum_{n=1}^{Z_c} box_n$
$listAverages.append(sum_c/Z_c)$
return $max(listAverages)$

We also created a max voting combination method as a second option. Each classification algorithms has the same vote weight in the case that there is a tie in the number of votes then the tiebreaker is having the highest probability. A classifier votes towards a class for an object by predicting for it.

Algorithm 2 Max Voting also known as Majority Voting

$dictionaryVotes$ ▷ dictionary of votes per class ordered from the most voted to the least voted
$dictionaryProb$ ▷ dictionary of best(highest probability) per class list with outputed by classifier bounding box and associated probability
$maxelem \leftarrow dictionaryVotes.key(0)$
$i \leftarrow 0$
for $i < dictionaryVotes.length$ **do**
    $elem \leftarrow dictionaryVotes.key(i)$
    if $dictionaryVotes.get(elem) == dictionaryVotes.get(maxelem)$ **then**
        if $dictionaryProb.get(elem) > dictionaryProb.get(maxelem)$ **then**
            $maxelem \leftarrow elem$
        end if
    end if
    $i \leftarrow i + 1$
end for
return $maxelem, dictionaryProb.get(maxelem)$ ▷ The Majority voted class is maxelem and the box associated is dictionaryProb.get(maxelem)

In the scenario that only one model has a prediction for a given object, then we used a threshold of 50% of class probability to trust the prediction, in order to reduce the situations of a single model introducing miss classifications.

For evaluating the methods we chose the average precision, F1 score and the hit rate, by hit rate we mean the percentage of annotations that the models and combination predicted correctly. We excluded the classification accuracy metric since there is a large class imbalance between heavy and light vehicles. This is even worse when there are motorcycles. The hit rate is the most useful one since it is the main comparison point between classifiers to evaluate if there are more or less vehicles being missed and the gain between the individual models and the combination.

The evaluation is run on a test set that also has a xml with the annotations for it. To find the box predicted for an annotation we use the scipy linear sum assignment, this function of the optimize module finds the best of assignment between the bounding boxes predicted and the ground-truths annotated. The cost matrix is $1 - similarity$ because the algorithm looks to minimize cost.

3.4 Summary

In this chapter we defined the questions that we must address to fix the problem. Which algorithms classify vehicles better on their own? How to fix the inconsistencies of single models to achieve a better result of classification? Then we analyzed the existing pipeline, that pipeline had SSD as the only classifier. After exploring different classification methods we chose YOLO due to its high inference speed and background subtraction due to being a very fast classifier, not taking any training time and one of the first approaches to classification on images. Based on the existing solution and the questions that we wanted to address we chose an ensemble learning approach. There were multiple options to choose from Stacking, Boosting, Bagging and multiple mathematical combination methods like Averaging and Majority voting or a classifier for the Stacking approach.

We chose a Bagging architecture due to being the best fit since it works well with smaller datasets and the total training time necessary as well as the classifiers chosen. The Bagging complete architecture was defined as 50% split of the training samples for each class of vehicle among the learning classifiers. Then the output of all the classifiers for each frame goes through a combination algorithm (we implemented best avg and Majority voting also know as Max voting) that outputs the final predictions.

Chapter 4

Results

This chapter describes the datasets and tests performed in order to validate the proposed solution as well as the initial hypothesis. After that, analyses the results obtained in the tests.

4.1 Dataset Specifications

Using the most common practice of splitting data, the datasets were divided in the form of 70% for training and 30% for testing [M. Shahin, 2004]. Three datasets, each from a different camera were available. One obvious flaw in this approach is that only dataset 2 of all the dataset has motorcycles so the training is almost always done with only 2 classes, light vehicles and heavy vehicles.

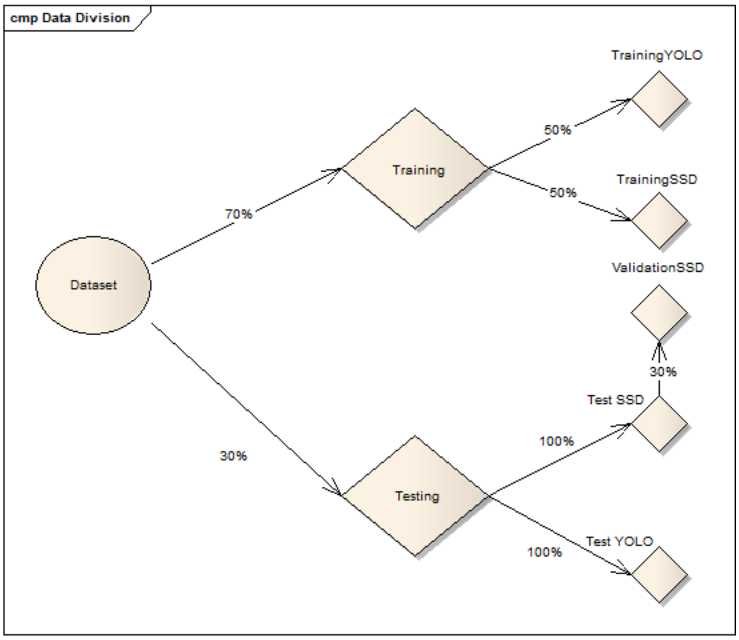


Figure 4.1: Diagram of the division of the data

YOLO does not run validation while training unlike SSD. So SSD uses 30% of the test data for validation when training and 100% when testing. Algorithms test the same data in order to compare the metrics.

4.1.1 Dataset 1

The first dataset that we called dataset 1 has 413 light vehicles and 70 heavy vehicles. The video has 352x288 pixels and a frame rate of 24.000038. One obvious flaw is that it does not have motorcycles.
The training part is composed of 289 light vehicles and 49 heavy vehicles, which were divided as follows: 145 light vehicles and 24 heavy vehicles were used to train YOLO, 144 light vehicles and 25 heavy vehicles to train SSD. The test set has 124 light vehicles and 21 heavy vehicles.

Figure 4.2: Frame of training that has a heavy that is difficult to classify

Figure 4.3: Frame of a lightweight vehicle

4.1.2 Dataset 2

The second dataset, called dataset 2, has 227 light vehicles, 39 heavy vehicles and 4 motorcycles. The video has 704x576 pixels and a frame rate of 25 frames per second. The training part is composed of 159 light vehicles, 27 heavy vehicles and 3 motorcycles. YOLO was trained with 80 light vehicles, 13 heavy vehicles and 1 motorcycle. SSD was trained with 79 light vehicles, 14 heavy vehicles and 2 motorcycles. The test set contains 68 light vehicles, 12 heavy vehicles and 1 motorcycle.

Figure 4.4: Frame of lightweight vehicles and a motorcycle

Figure 4.5: Frame of lightweight vehicles and a heavy vehicle

4.1.3 Dataset 3

The third dataset, called dataset 3 has 199 light vehicles and 56 heavy vehicles, frame size is 586x480 pixels and the frame rate is 15 frames per second. The training part is composed of 139 light vehicles and 39 heavy vehicles. YOLO was trained with 69 light vehicles and 19 heavy vehicles. SSD was trained with 70 light vehicles and 20 heavy vehicles. The test set is composed of 60 light vehicles and 17 heavy vehicles.

Figure 4.6: Frame of light vehicle

4.2 Test Procedures

As described above both learners got different parts of the training as the bagging method suggests. Using the 70% of the original dataset for training purposes each model got 50% of those 70% for each camera. SSD is trained on 54 000 iterations for each experiment and YOLO on 10 000 which was equivalent to 1 day of training on a 940MX Nvidia GPU.

Our experiments consisted on performing the neural networks training with SSD and YOLO using the training and validation subsets of the dataset then we predicted the vehicles on each test set and finally we ran both combination algorithms. In order to evaluate we decided to use every frame so the annotated groundtruth used for comparison has the frame and the box corner points. When we refer to the number of boxes, we refer to the total number of boxes that exist in the groundtruth. So one vehicle will have more than one corresponding box depending on the number of frame where it appears.

Table 4.1: training dataset on the left testing set on the right

training \ testing	1	2	3
1	X		
2		X	
3			X
1+2+3	X	X	X

This table means that for training on dataset 1 we tested with the test set 1, for dataset 2 we tested on test set 2 and so on.
For clarification when we mention bounding boxes in any of the tests we are using the term for detection. Even though for YOLO and SSD there is no method to separate detection from classification we can evaluate it based on the predicted bounding box and the algorithm can predict the object is in a correct area or similar to it and output a wrong classification for it.

4.3 Test Results

In order to evaluate the results the following metrics were used with each of the chosen classifiers (SSD, YOLO and background subtraction): AP is the average precision of the bounding boxes, Avg Recall is the the average recall of the bounding boxes, Hit rate represents the percentage of boxes annotated that were correctly classified.
In order to classify a vehicle it must also be detected, both learning algorithms do detection and classification in the same stage so there is no classification without detection and vice-versa. Detecting boxes means that the algorithm found a box of variable size with a certain classification. A non detection means a non classification which is seen in the hit rate.

Test set 1 has 3145 boxes that correspond to 124 light and 21 heavy vehicles.

Table 4.2: Evaluation Set 1 Results

	Detection			Classification		
Model-#Iterations	#Correct Detect	AP	AvgRecall	#Correct Class	Hit rate	F1 Score
SSD-54457	2210	0.7985	0.7140	2138	0.6798	0.9670
v3tiny-10000	1798	0.8087	0.7762	1755	0.5580	0.9762
bsub	1267	0.6576	0.8010	1129	0.3590	0.9104
combined best avg	2706	0.7853	0.7798	2582	0.8210	0.9550
combined max voting	2706	0.8065	0.7574	2586	0.8223	0.9569

Figure 4.7: Example of prediction of SSD for dataset 1

SSD's prediction is correct. The classifier seems to value the area of the bounding box heavily making more squared detection boxes. Also seems that the predictions for this dataset values every contour of the vehicle making the boxes bigger to accommodate ever corner.

Figure 4.8: Example of prediction of YOLO for dataset 1

YOLO's prediction is correct and closer to the groundtruth box having less background in the bounding box. It seems YOLO valued the back and side of the car more so box was closer to those features.

Figure 4.9: Background Subtraction for dataset 1

Background subtraction also predicted correctly, this test has this particular quality of having all three methods working as expected. Background Subtraction classifies based completely of area of the bounding box.

Figure 4.10: Majority voting prediction for dataset 1

The Majority Voting chose, the box of SSD as the best one of all the 3, since they all voted for the same class the next heuristic is the highest probability.

The angle of the camera in the dataset 1 scenario, allows for vehicles to appear in a lot of frames so there are more samples for the training, also there is not a big flow of traffic so there are almost no obstruction by multiple vehicles being close to each other. This dataset got the best performance overall, all learners had a good classification accuracy so there were not that many mistakes to be corrected among the ensemble combination.

We can see from the AP that YOLO in terms of localization is better while SSD misses a smaller number of vehicles. As expected the classifiers ensemble has a better results than individual classifiers. Among the combination algorithms, max voting outperforms best avg in everything outside of avg recall. This means that for this camera using the ensemble combination with max voting would be more favorable regarding the number of vehicles missed.

Test set 2 has 3782 boxes that correspond to 68 light vehicles, 12 heavy vehicles and 1 motorcycle.

Table 4.3: Evaluation Set 2

	Detection			Classification		
Model-#Iterations	#Correct Detect	AP	AvgRecall	#Correct Class	Hit rate	F1 Score
SSD-54789	1007	0.4835	0.4182	899	0.2377	0.8943
v3tiny-10000	1618	0.5064	0.3320	1514	0.4003	0.9315
bsub	391	0.5838	0.4317	301	0.0796	0.7625
combined best avg	1740	0.4765	0.3465	1580	0.4178	0.9082
combined max voting	1740	0.4744	0.3532	1601	0.4233	0.9067

Figure 4.11: Example of SSD's prediction for dataset 2

SSD valued the features of the vehicle but could not determine where one vehicle started and ended so it grouped both vehicles together. The motion blur of the vehicle the closest probably is responsible for the lack of prediction since if we compare the previous tests SSD values all the features of the contour, here it probably can not resolve the contour.

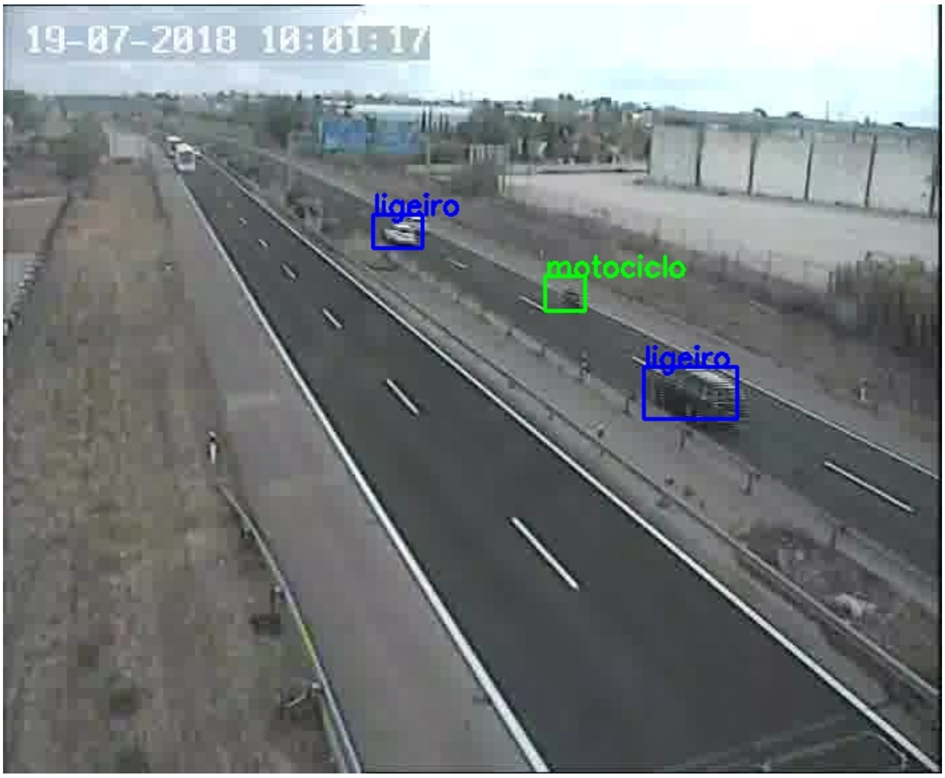


Figure 4.12: Example of YOLO's prediction for dataset 2

YOLO seems to use more background here as a feature to classify the motorcycle. To classify the light vehicles it uses more the side of the vehicle. This is exhibited by bounding box for the vehicle closer to the camera, since it does not include the tail end.

Figure 4.13: Example of Background Subtraction's prediction for dataset 2

Background Subtraction included a lot more than the vehicle, since the blur unites the contour with the separator and part of the road.

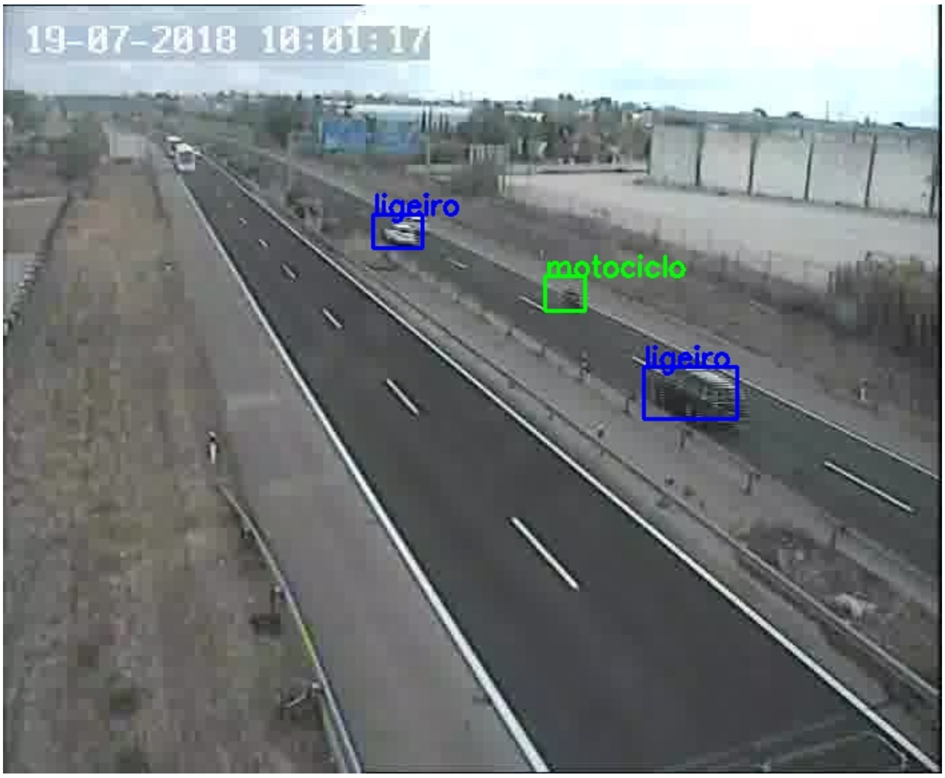


Figure 4.14: Example of Majority voting prediction for dataset 2

This dataset has the most traffic flow, so our combination algorithm misses some boxes due to being very close to each other and the threshold for treating the boxes as classifying the same object eliminates boxes that are too similar. For this scenario, YOLO is the one that performs better in everything but recall, considering only the classifiers. SSD does not detect a single motorcycle, while YOLO does, which exhibits that YOLO generalizes better with less samples, since it trained on 1 motorcycle and SSD trained on 2. Between the two ensemble approaches max voting outperforms best avg in everything except recall. In this situation the difference between a single model and the combination does not bring a lot of gain in hit rate for the execution costs. Even though the hypothesis that the combination decreases the loss of vehicles still holds. If we look at grand picture, in the previous test SSD performed better than YOLO so if we had just used SSD instead of the ensemble then in this scenario we would not have any motorcycles being classified.

Test set 3 has 512 boxes, 60 light vehicles and 17 heavy vehicles.

Table 4.4: Evaluation Set 3

	Detection			Classification		
Model-#Iterations	#Correct Detect	AP	AvgRecall	#Correct Class	Hit rate	F1 Score
SSD-54037	311	0.7512	0.8951	298	0.5820	0.9622
v3tiny-10000	332	0.2531	0.4309	257	0.5019	0.7736
bsub	131	0.5248	0.9035	111	0.2168	0.8661
combined best avg	360	0.4378	0.6966	316	0.6172	0.8771
combined max voting	360	0.5556	0.7281	319	0.6230	0.8868

This dataset has several problems, first it does not have any motorcycles, second it has a low frame rate (15 fps) which means less frames for training, third the top part is obstructed with text that confuses the classifier since some vehicles get obstructed by them, finally the camera's angle only allows to see a small portion of the road and therefore vehicles are only inside the camera's field of view for short periods of time. Additionally, the low frame rate associated with the vehicles high speed causes motion blur, which means the edges of the vehicles become somewhat transparent impacting negatively the bounding boxes detection.

Figure 4.15: Example of prediction of SSD for dataset 3

The detection and classification of SSD is really good here.

Figure 4.16: Example of prediction of YOLO for dataset 3

We can see that the detection of the bounding box is quite wrong but the classification is correct. The detection seems to be looking for the text as a feature. Since in this dataset most vehicles pass through the lane that gets obstructed by the text.

Figure 4.17: Example of Majority Voting combination algorithm for dataset 3

For this frame there is no detection from Background Subtraction so the ensemble output is based on just the 2 learners. Majority Voting takes the best of the 2 bounding boxes if they predicted the same so the best one was SSD's. The majority voting algorithm performs better than the best avg among the ensemble. As expected the ensemble combination outperforms all the single classifiers. Regarding the classifiers, SSD is the better one.

Finally, we wanted to verify how well does a global classifier perform on each camera. Using a global classifier would be more useful for a commercial solution since it would not be needed to perform so many trainings and it would be easier to manage information needed for the classification.
In order to accomplish this, a global dataset, with all the training images from datasets 1 to 3, was created. This dataset was used to train the SSD and Yolo classifiers.
The number of iterations used for training each of these classifiers was 150 000 and 30 000, respectively, which corresponds to the sum of iterations for the specific camera classifiers. The results are next: Full training on 1+2+3 datasets and evaluation on test set 1.

Table 4.5: Evaluation Set 1 trained with all the cameras: 3145 boxes, 124 light and 21 heavy vehicles

	Detection			Classification		
Model-#Iterations	#Correct Detect	AP	AvgRecall	#Correct Class	Hit rate	F1 Score
SSD-152024	2558	0.8581	0.7753	2472	0.8394	0.9497
v3tiny-30000	356	0.9112	0.6843	31	0.0099	0.0140
bsub	1267	0.6576	0.8010	1129	0.3590	0.9104
combined best avg	2754	0.8344	0.8033	2440	0.7758	0.8829
combined max voting	2754	0.8557	0.7633	2455	0.7806	0.8761

Figure 4.18: Example of prediction of SSD trained on all the datasets for dataset 1

SSD detected and classified both vehicles exemplary.

Figure 4.19: Example of prediction of YOLO trained on all the datasets for dataset 1

YOLO detected something but not the right vehicle, both the box and the class are wrong.

Figure 4.20: Example of prediction of Background Subtraction for dataset 1

Background Subtraction only detected the light vehicle.

Figure 4.21: Example of prediction of Majority voting combination for dataset 1

Here is a case of where the combination persisted the good prediction of SSD and ignored the one from YOLO. In this experiment with the all training sets, YOLO is not working well, the precision of the boxes is very good but the classification is very bad and only classified correctly 31 boxes this could be due to YOLO on a global training that is not incremental re-sizes all the frames for the same size and the frames of this test set are the smallest with 352x288. In this case SSD is better than the combination.

SSD is the best single model and also outperforms the combination in this situation this is due to YOLO having a high probability in some wrong predictions like the following example:

Figure 4.22: SSD prediction for heavy vehicle

SSD predicted correctly with a probability of 58% while YOLO did what we see next

Figure 4.23: YOLO predicted incorrectly

YOLO predicted incorrectly with 98% confidence which influences the combination

Figure 4.24: Final combination prediction

The combination could not ignore a 98% probability so the error of YOLO propagates to the ensemble output.
The best combination method in this case is the max voting. This is the real issue of combination

is when a classifier is miss classifying with a high probability and there is only another prediction to vote against it. The advantage in this case, of the ensemble, is that the analyst does not know which algorithm will work with each camera and which one will not and the ensemble will always guarantee that detection and classification do not miss many vehicles without having to test every algorithm for each case and then have to choose one.
The cameras of all the three training sets that are combined for these experiments have different angles and this one has the furthest away viewpoint so the feature points are the less distinctive.
SSD overfitted to the dataset 1 which is the one with the most samples of different vehicles and since the global training has more iterations than the training adapted to the each dataset it was able to get better extremely high results.
Full training on 1+2+3 datasets and evaluation on test set 2.

Table 4.6: Evaluation Set 2 trained with all the cameras: 3782 boxes, 68 light vehicles, 12 heavy vehicles and 1 motorcycle

	Detection			Classification		
Model-#Iterations	#Correct Detect	AP	AvgRecall	#Correct Class	Hit rate	F1 Score
SSD-152024	1588	0.2532	0.2350	1400	0.3702	0.8659
v3tiny-30000	1227	0.2408	0.2186	886	0.2343	0.6757
bsub	391	0.5838	0.4317	301	0.0796	0.7625
combined best avg	1809	0.2529	0.2396	1494	0.3950	0.8110
combined max voting	1809	0.2507	0.2355	1464	0.3871	0.8120

Figure 4.25: Example of prediction of SSD trained on all the datasets for dataset 2

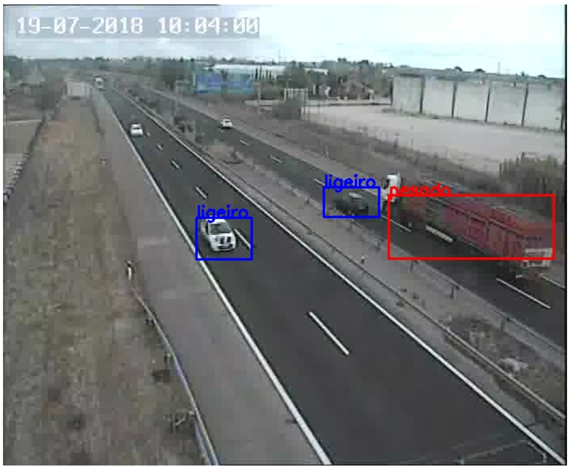


Figure 4.26: Example of prediction of YOLO trained on all the datasets for dataset 2

YOLO seems to take into account the trailer more than the front of the truck or the tail end.

Figure 4.27: Example of prediction of Background Subtraction for dataset 2

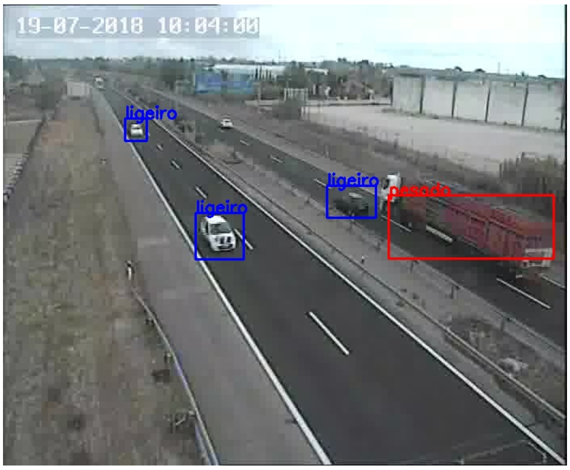


Figure 4.28: Example of prediction of Best Avg combination for dataset 2

We can see that the best average uses the average of the bounding boxes since the 2 boxes that were classified by more than one classifier appear as a average on the ensemble result.

For the evaluation set 2 none of the models had a great result, with SSD being the better single model and best avg the better combination. The results in this experiment are still better than the next ones that is because this dataset has a similar perspective to the first dataset. Still, the results in this experiment are worse than the first ones due to the fact that only this dataset has motorcycles so in the training there is an extreme class imbalance regarding the motorcycles. No motorcycles were classified, by any classifier so none was classified by the ensemble.

Full training on 1+2+3 datasets and evaluation on test set 3.

Table 4.7: Evaluation Set 3 trained with all the cameras: 512 boxes, 60 light vehicles and 17 heavy vehicles

	Detection			Classification		
Model-#Iterations	#Correct Detect	AP	AvgRecall	#Correct Class	Hit rate	F1 Score
SSD-152024	64	0.6044	0.5118	60	0.1172	0.9414
v3tiny-30000	63	0.7950	0.6283	57	0.1113	0.9194
bsub	131	0.5248	0.9035	111	0.2168	0.8661
combined best avg	141	0.6987	0.5693	115	0.2246	0.9539
combined max voting	141	0.6987	0.5693	115	0.2246	0.9539

Figure 4.29: Example of prediction of SSD for dataset 3 trained with all cameras

Figure 4.30: Example of prediction of YOLO trained globally for dataset 3

Figure 4.31: Example of prediction of Background Subtraction trained for dataset 3

Figure 4.32: Example of prediction of Majority Voting trained globally for dataset 3

We can see that the best of the voted boxes was the SSD one that's why the previous result of the combined using the majority voting algorithm is the same as the SSD.

Background Subtraction is the best individual performing method in regard to hit rate, while YOLO has better detection precison and recall. Just as the experiments with the training adapted to the camera, more specifically experiment 3, this third test set has the worst hit rate. Coincidentally both combinations have the same results and both are better than any individual algorithm. This dataset has the fewest share of boxes for training so it is expected that this one has the worse hit rate. Also, this viewpoint has nothing in common with the previous 2 datasets since the angle catches the side and top of the vehicle unlike the other 2. When we trained YOLO on the dataset 3 only it's detection was very off, looking for the text as a feature to classify vehicles. On this case even though it misses a lot of detections the fact it trained on vehicles with no text on top meant the detection worked more cleanly.

4.4 Summary

From the result tables of the training for only each dataset we created summarized graphics to be easier to compare.

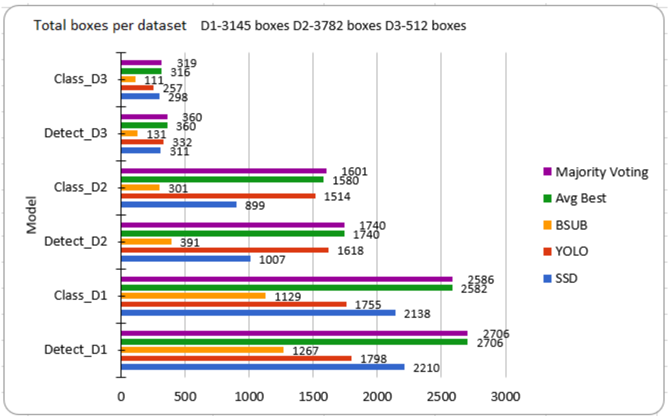


Figure 4.33: Total boxes correct detections and classifications for each dataset

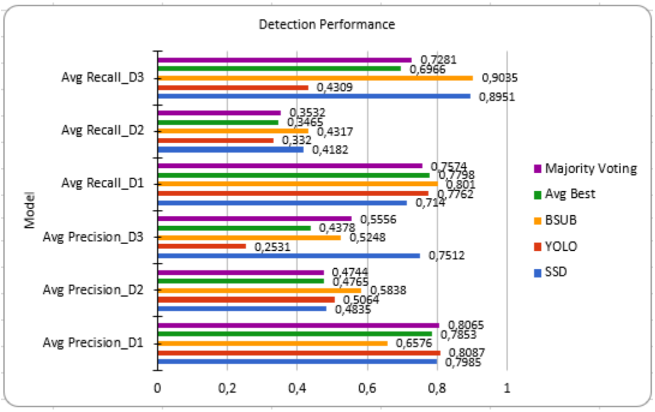


Figure 4.34: Detection Performance per dataset

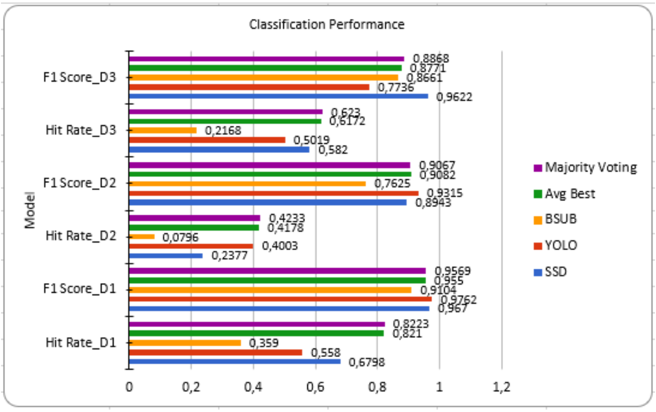


Figure 4.35: Classification Performance for the predicted boxes per dataset

We also summarized the experiments with all the training sets.

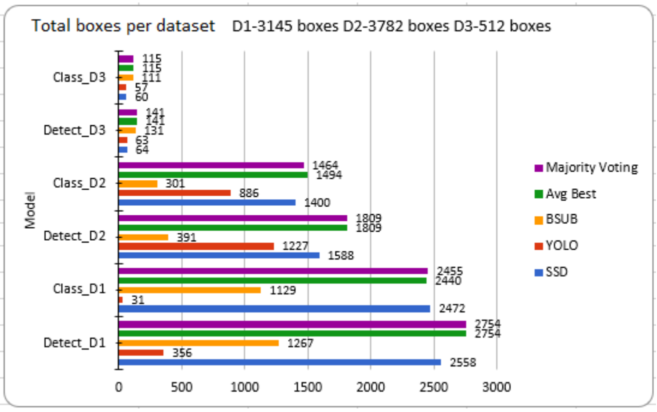


Figure 4.36: Total boxes correct detections and classifications per each test set for training with all datasets

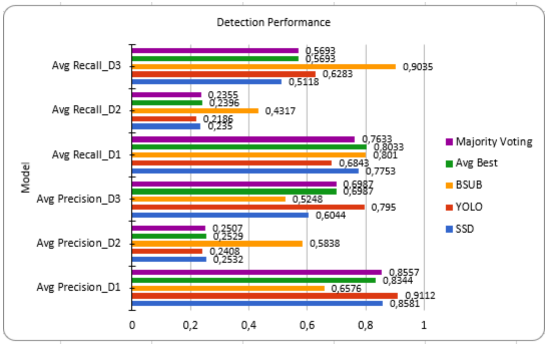


Figure 4.37: Detection Performance per test set trained with all the datasets

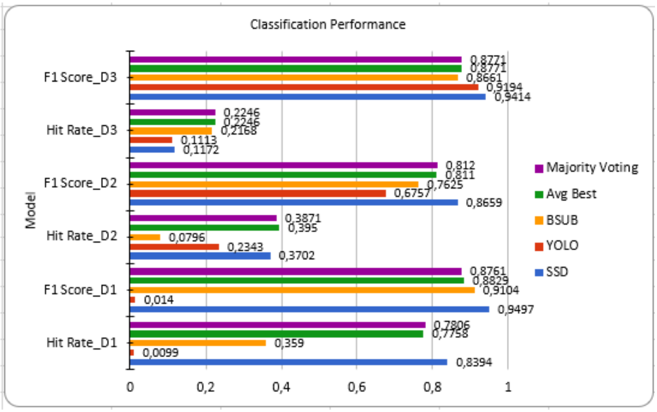


Figure 4.38: Classification Performance per test set trained with all the datasets

Concerning the initial hypothesis, that an ensemble classifier performs better than single classifiers, it was possible to validate it, since on every experiment but one(test set 1 trained with all the training sets 1+2+3), the combination proved to be better. Among the used ensemble methods max voting performed better than best avg on 3 of the 3 tests on the adapted testing(training with only a dataset). That is because, the bounding boxes get less influenced by a wrong classification having a high probability which would swing the average to its side.
In the scenarios that the combination does not perform well(worse than a single classifier), the majority of the algorithms is not performing well and then vote for a incorrect class so the max voting outcome is more influenced than the best avg which explains not outperforming best avg, this happens only on global training.

From the previous tests it is possible to verify that a global classifier does not benefit the classification since it implies a decrease on AP, Hit rate. The main reason behind this is that the characteristics of the vehicles for the same class are quite different between the different datasets. One exception is SSD's results. On dataset 1, which indicate that SSD overfitted to the dataset 1 and since the global training had more iterations than the training adapted to the each dataset it was able to get extremely high results. It also performed better on dataset 2 due to the fact that is similar to dataset 1 and together, dataset 1 and 2, have the most samples.

Analyzing the features for each classifier from the predictions for each dataset, it seems that SSD needs more features to classify a vehicle than YOLO, and uses the area as an important feature since none of its bounding boxes exclude parts of the vehicle. Vehicles where there is a big effect of motion blur, particularly for dataset 2, where the features are very small, SSD fails to detect and classify the vehicles. YOLO values each single feature more since we see some features be excluded on its bounding boxes and the area of the box does not seem to be valued much. From these findings we would recommend using YOLO when the training samples are really small as exhibited in dataset 2 that has only 3 total motorcycles for training and use SSD when there is obstruction of features common to most training samples like seen in the dataset 3. Background Subtraction is better for scenarios comparable with dataset 3 where the difference in area between the classes is more significant.

Chapter 5

Conclusions

In the Introduction we explained Motivation behind the dissertation, that Computer Vision and Machine Learning are increasingly being used. There are news of increased investment in the ITS(Intelligent Transport System) area. ARMIS ITS has been working on the area of detection and tracking of vehicles and currently has a solution. Their current approach to classifying vehicles on highways with a single model has lead to inconsistencies in the results, as some methods overfit on the training set and do not classify some of the vehicles of the test set.

In the Literature Review we elicited different algorithms possible for detection and classification that looked appropriate to address the problem, one stage detectors like SSD and YOLO and two stage detectors like R-CNN. We went in some detail through each algorithm to see which we could use on our methodological approach. From our study it was possible to identify that ensemble is a suitable technique to address classification problems, therefore we perform a study on the existing ensemble methods. Finally we analyzed common metrics for evaluating the literature algorithms.

In Methodological Approach we analyzed in depth the existing solution of ARMIS and chose an ensemble architecture to fix the inconsistencies seen on the classification of vehicles. We chose a bagging architecture with YOLO, SSD and Background Subtraction as level 0 classifiers and 2 combination options, Best Avg and a Majority voting. To evaluate each of the classifiers and the ensemble combinations we decided upon calculating the average precision of the bounding boxes, average recall of the bounding boxes, hit rate (the fraction of bounding boxes predicted of the total groundtruth bounding boxes) and F1 score for the classification.

To prove the hypothesis that an ensemble of classifiers provides better results than single classifiers we trained and tested our solution on three different datasets from cameras with different angles and different traffic flow. The hypothesis holds for the 3 datasets trained individually so we decided to add a new experiment, we trained each of the learners on all datasets together from scratch. In this experiment the results where inconsistent with the hypothesis only on one of the

tests, the test with dataset 3, the hypothesis holds true.
Results also showed that ensemble is better, particularly Majority voting since it is less influenced by a wrong classification with high probability. Even with a very simple ensemble approach it is possible to obtain good results.
Moreover it was possible to verify that an adapted training for each dataset provides a better solution than the global training on almost all of the datasets. The exception to this was the test on the dataset 1 which is the one with the most training samples and SSD training on 150 000 iterations achieves better results than trained with 50 000 adapted to only it.
From the feature analysis that was done with each test we can take that there are similarities between the boxes of the Background Subtraction and the boxes of SSD which supports the theory that SSD seems to value more the contour of the object, while YOLO seems to value more singular features. SSD's bounding boxes always include the full contour of the vehicles just like Background Subtraction. On the other hand, in some of YOLO's predictions there are vehicles which contour is not fully included on the bounding box.

5.1 Further Developments

The outcome of this thesis showed some points that would be interesting to address, however it was not possible to do so due to the thesis time frame.

1. It would be interesting to change the ensemble from a combination algorithm to a learner or classifier and verify if it would be beneficial.
2. As for centralizing data, there is a lot of redundancy in the data: same videos and test sets used by different classifiers copied among different folders, that if centralized would save more disk space. The current thought was to keep the folders with everything used by the experiment so to be easier to evaluate and store.
3. With multiple GPUs there would be the possibility of running the training phase for both learners concurrently which would allow for a more automatic pipeline.
4. Annotation part of the pipeline re-sizes videos with frames bigger than 586x480 to that size which means on the training the classifiers could train with better resolution but not with these settings.
5. The solution is not completely integrated, there is a script for converting annotations from the annotation to YOLO or Tensorfow record for SSD but YOLO also needs ffmpeg to be run to split the video in frames for testing.
6. Each classifier outputs a .txt file with predictions for each frame that has predictions, a better idea would be to have just one file with all the predictions for the classifier, that way it would be easier for a human to read.

5.2 Future Work

This work could serve as the basis, for instance, to perform vehicle tracking and evaluate speed and flow which would allow for improved traffic management.
It would also be interesting to use the same approach on cameras placed inside the vehicles to aid on autonomous driving, since this is an application field that is gaining more and more relevance in today's society.

5.3 Final Remarks

A training for each dataset achieves better results than a global training with all the samples together. Ensemble improves the number of detections and classifications for 5 out 6 tests. It is valuable to have different algorithms that classify based on different aspects of the class. We can see with the obstructions on the dataset 3 that do not influence SSD and with YOLO classifying the motorcycle and detecting more vehicles in an ambient with dense traffic flow in dataset 2. From our findings the recomendation would be to use YOLO when the training samples are really small as exhibited in dataset 2 that has only 3 total motorcycles for training and use SSD when there is obstruction of features common to most training samples like seen in the dataset 3. Background Subtraction is better for scenarios comparable with dataset 3 where the difference in area between the classes is more significant. Ensemble proves a good approach to classification problems but currently is not usable for autonomous vehicles or real time applications since the inference takes too long. YOLO and Background Subtraction on their own would be fast enough for real time but with current hardware the ensemble is not fast enough.

Machine learning and hardware come hand in hand. When the available hardware is not top shelf every mistake or small inconsistency, be it on wrong dimensions of images or any re-sizes required, has to be studied in detail because it will force a re-train and re-test which take a long time. Programming is the smallest part of the work. Data analysis and annotation take most of the time and the rest goes to checking on the training and testing.

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