Kaunas University of Technology

Faculty of Electrical and Electronics Engineering

Technical University of Cartagena

School of Industrial Engineering

Human motion estimation and analysing feasible collisions between individuals in real settings by using conventional cameras an Deep Learning-based algorithms

Bachelor's Final Degree Project

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Cartagena, Kaunas 2022

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Intelligent Robotics Systems (6121EX013)

Industrial Electronics and Automation Engineering (5071)

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2022 05 04

TASK OF FINAL PROJECT OF UNDERGRADUATE (BACHELOR) STUDIES

Issued to the Student:	*Rafael Sojo García*	Group ERB8/2

1. Project Subject:

Lithuanian Language:	Žmogaus judėjimo įvertinimas ir galimų susidūrimų analizė tarp asmenų realiomis sąlygomis, naudojant įprastą kamerą ir giliojo mokymosi algoritmus
English Language:	Human motion estimation and analysing feasible collisions between individuals in real settings by using conventional cameras and Deep Learning-based algorithms

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2. Goal of the Project: To develop a collision prevention system

3. Specification of Final Project: The work must meet the methodological requirements for the preparation of final projects of KTU Faculty of Electrical and Electronics Engineering.

4. Project's Structure. *The content is concretized together with supervisor, considering the format of the final project, which is listed in 14 and 15 points of Combined Description of Preparation , Defence and Keeping of Final Projects Methodical Requirements*

4.1 Analyse computer visio, object detection, object tracking algorithms
4.2 Create human detection and tracking algorithm
4.3 Make experimental testings of created algorithm

5. Economical Part. *If economical substantiation is needed; content and scope is concretized together with supervisor during preparation of final projects*

none

6. Graphic Part. *If necessary, the following schemes, algorithms and assembly drawings; content and scope is concretized together with supervisor during preparation of final projects*

Show experimental results and explane them

5. This Task is Integral Part of Final Project of Undergraduate (Bachelor) Studies

6. The Term of Final Project Submission to Defense Work at a Public Session of Qualification Commission. *until 2022-05-13* *(date)*

I received this task:	***Rafael Sojo García***	*2022-02-08*
	(student's name, surname, signature)	*(date)*
Supervisors:	**Assoc. Prof. Nieves Pavón Pulido** **Assoc. Prof. Dr. Virginijus Baranauskas**	*2022-02-08*
	(position, name, surname, signature)	*(date)*

Sojo García, Rafael. Human motion estimation and analysing feasible collisions between individuals in real settings by using conventional cameras and Deep Learning-based algorithms. Bachelor's Final Degree Project / supervisors: Prof. Dr. Nieves Pavón Pulido, Assoc. Prof. Dr. Virginijus Baranauskas; School of Industrial Engineering; Technical University of Cartagena; Faculty of Electrical and Electronics Engineering, Kaunas University of Technology.

Study field and area (study field group): electronics and electrical engineering, technological science, engineering.

Keywords: Artificial Intelligence, object detection, object tracking, collision prevention, YOLOv5, DeepSORT.

Kaunas, Cartagena, 2022, 93 pages.

Summary

The aim of the final project is to develop a collision prevention system. This project includes: an introduction, which the reader is made aware of the problematic to be addressed; theoretical foundation, with which to provide the necessary knowledge required by the models used, with special emphasis on their mathematical foundations; the proposed method section. Experimental section develops the four main steps 1) camera calibration, 2) correction of possible distortion during image acquisition, 3) detection and tracking of the people involved in the images obtained and 4) obtention of alerts in potentially dangerous situations throughout the test. The experimental section show the results obtained in the process of detection, tracking and obtention of alerts. Conclusions and a list of the bibliographical references are given.

Sojo García, Rafael. Estimación del movimiento humano y analizador de posibles colisiones entre individuos en entornos reales usando cámaras convencionales y algoritmos de Deep Learning. Trabajo de Fin de Grado / supervisores: Prof. Dr. Nieves Pavón Pulido, Prof. Dr. Virginijus Baranauskas; Universidad Politécnica de Cartagena, Facultad de Ingeniería Industrial; Universidad Tecnológica de Kaunas, Facultad de Ingeniería Eléctrica y Electrónica.

Campo de estudio y área: ingeniería electrónica e ingeniería eléctrica, ciencia tecnológica, ingeniería.

Keywords: Inteligencia artificial, detection de objetos, seguimiento de objetos, prevención de colisiones, YOLOv5, DeepSORT

Kaunas, Cartagena 2022, 93 páginas.

Sumario

El objetivo del proyecto final es desarrollar un sistema de prevención de colisiones. Este proyecto incluye: una introducción, con la que se hace partícipe al lector de la problemática que se pretende abordar; una fundamentación teórica, con la que se aportan los conocimientos necesarios que requieren los modelos utilizados, haciendo especial hincapié en sus fundamentos matemáticos; la sección del método propuesto. La sección experimental desarrolla los cuatro pasos principales 1) calibración de la cámara, 2) corrección de la posible distorsión durante la adquisición de la imagen, 3) detección y seguimiento de las personas implicadas en las imágenes obtenidas y 4) obtención de alertas en situaciones potencialmente peligrosas a lo largo de la prueba. El apartado experimental muestra los resultados obtenidos en el proceso de detección, seguimiento y obtención de alertas. Se presentan las conclusiones y una lista de referencias bibliográficas.

Sojo García, Rafael. Žmogaus judėjimo įvertinimas ir galimų susidūrimų analizė tarp asmenų realiomis sąlygomis, naudojant įprastą kamerą ir giliojo mokymosi algoritmus. Bakalauro baigiamasis projektas / vadovai / doc. dr. VIrginijus Baranauskas, doc. dr. Nieves Pavón Pulido; Kauno technologijos universitetas, Elektros ir elektronikos fakultetas, Universidad Politécnica de Cartagena, Pramonės inžinerijos fakultetas.

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Reikšminiai žodžiai: dirbtinis intelektas, objektų aptikimas, objektų sekimas, susidūrimų vengimas, YOLOv5, DeepSORT.

Kaunas, Cartagena 202. p. 93

Santrauka

Baigiamojo projekto tikslas – sukurti susidūrimų prevencijos sistemą. Darbą sudaro: įvadas, kuriame skaitytojas supažindinamas su problema, kurią reikia spręsti; teorinis pagrindimas, kuris suteikia reikiamų žinių, reikalingų naudojamiems modeliams, ypač pabrėžiant jų matematinius pagrindus; autoriaus siūlomas metodas. Praktinėje dalyje išplėtoti keturi pagrindiniai žingsniai: 1) kameros kalibravimas, 2) galimų iškraipymų koregavimas vaizdo gavimo metu, 3) žmonių, dalyvaujančių gautuose vaizduose, aptikimas ir sekimas ir 4) įspėjimų gavimas, testuojant potencialiai pavojingas situacijas. Eksperimentinėje dalyje rodomi perspėjimų aptikimo, sekimo ir gavimo rezultatai. Pateikiamos išvados ir naudotų literatūros šaltinių sąrašas.

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List of abbreviations and terms

Terms:

AGV – Autonomous Guided Vehicles

AMR – Autonomous Mobile Robot

ANN – Artificial Neural Network

CmBN – Cross mini-Batch Normalization

CNN – Convolutional Neural Network

CSPNet – Cross Stage Partial Network

DPM – Deformable Parts Model

FPN – Feature Pyramid Network

FPS – Frames Per Second

HSV – Hue Saturation Value

IOU – Intersection Over Union

mAP – Mean Average Precision

PANet – Path Aggregation Network

R-CNN – Region-based Convolutional Neural Network

ReLU – Rectified Lineal Unit

RGB – Read Green Blue

ResNet – Residual Network

SKU – Stock-Keeping Unit

SORT – Simple Online Real-time Tracking

SSE – Sum-Squared Error

SSP – Spatial Pyramid Pooling

VOC – Visual Object Classes

YOLO – You Only Look Once

1. Introduction

Nowadays, Computer Vision (CV), has become a very powerful tool since technological improvements done in recent years are bringing a strong rise in the use and popularity of Artificial Intelligence (AI) systems. Moreover, CV systems have a lot of different possible applications in many fields typically led to the human responsibility, like Health Care or Security Industries. Thus, allowing us to focus our attention in the task of increasing productivity, whereas these systems take care of those aspects in which we are either more likely to commit errors, or just more expensive than the robotization of the job in the long term.

On the other hand, in industrial environments where vehicles are constantly sharing space with pedestrians, any distraction or visibility reduction can end into a forklift-related accident. This is either an economic and a work safety problematic due to the risk for the worker and the subsequent hospitalization costs, which in many cases might end into serious injuries.

Therefore, the aim of this project is to address this problematic through a CV-based human trajectory estimation for collision preventions. This solution takes advantage of some CV and models based on Deep Learning (DL), focused on performing real-time object detections, as well as a mathematical and statistical object tracking implementation with a deep association metric.

This project is entirely focused on human-to-human interactions, but the results are completely extrapolable for human-to-vehicle and vehicle-to vehicle-situations.

1.1. Objectives

This project aims to develop a collision prevention system, whose function is to contribute to the work safety in the manufacturing industry. For that reason, this system should be able to return warnings depending on the location of several individuals within a predefined area.

To accomplish this goal, the following partial objectives are set:

- Camera calibration: for the camera parameters extraction.
- Image undistortion: for the correct data acquisition.
- Object detection and tracking: based on YOLOv5 and DeepSORT.
- Security area definition: setting the angle, radius and orientation of a circular sector in front of each human at each frame.
- Warning system definition: the alerts are given depending on the trajectories and locations of the individuals.

2. State of Art

2.1. Accidents involving Forklifts.

Industrial environments are characterized by the fact that work safety has an important role in every task, since the machinery is capable of causing enormous amounts of energy. However, the workers and vehicles moving around are something that may go unnoticed, but according to the Occupational Safety and Health Administration (OSHA) in 1995, up to 34.900 serious injuries, 61.800 non-serious injuries and around 85 fatalities, were caused by forklifts trucks in the United States since 1981 on annual average. At least a 10% of the fatal accidents as a result of people being struck by a forklift, see Table 1.

Type accident	Percent
Crushed by tipping vehicle	42
Crushed between vehicle and a surface	25
Crushed between two vehicles	11
Struck or run over by vehicle	10
Struck by falling material	8
Fall from platform on forks	4
Accidental activation of controls	2

Table 1. Fatal accident causes involving forklifts. [1]

More recently, the Bureau of Labor Statistics, U.S. Department of Labor, shared in 2019 that more than 8.500 nonfatal injuries involving forklifts still occurring on average every year, resulting in several days out of work. Furthermore, with barely no change in the number of fatal injuries and nearly the 20% of them as a direct cause of forklift struck, see Fig 1 and Fig 2.

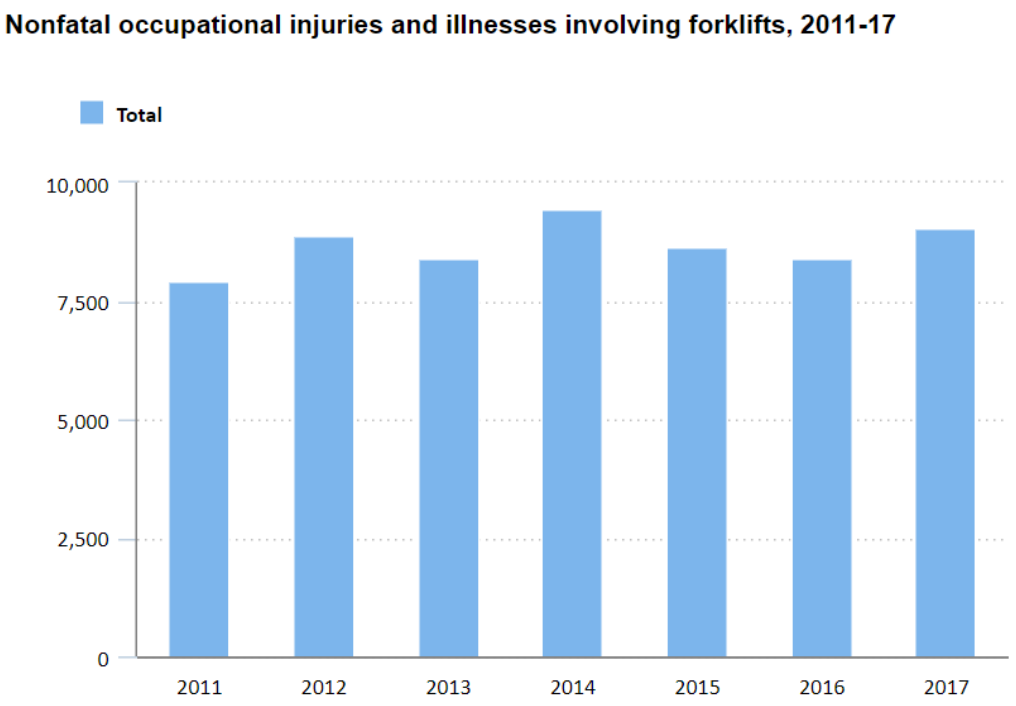


Fig. 1. Nonfatal injuries involving forklifts, 2011-2017. [2]

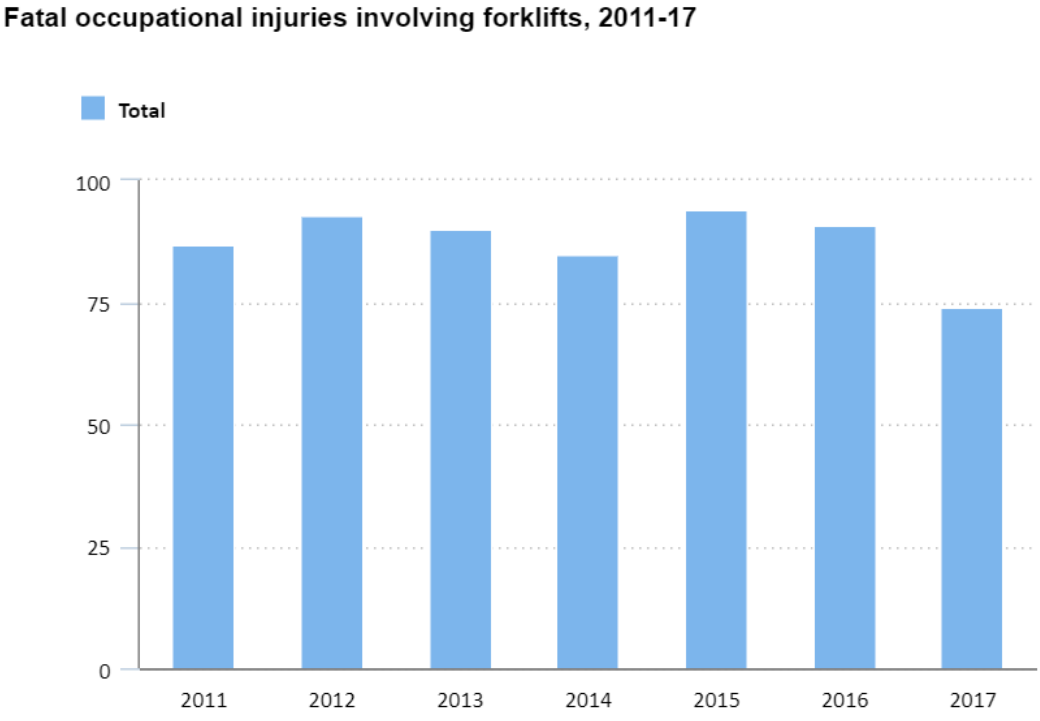


Fig. 2. Fatal injuries involving forklifts, 2011-2017. [2]

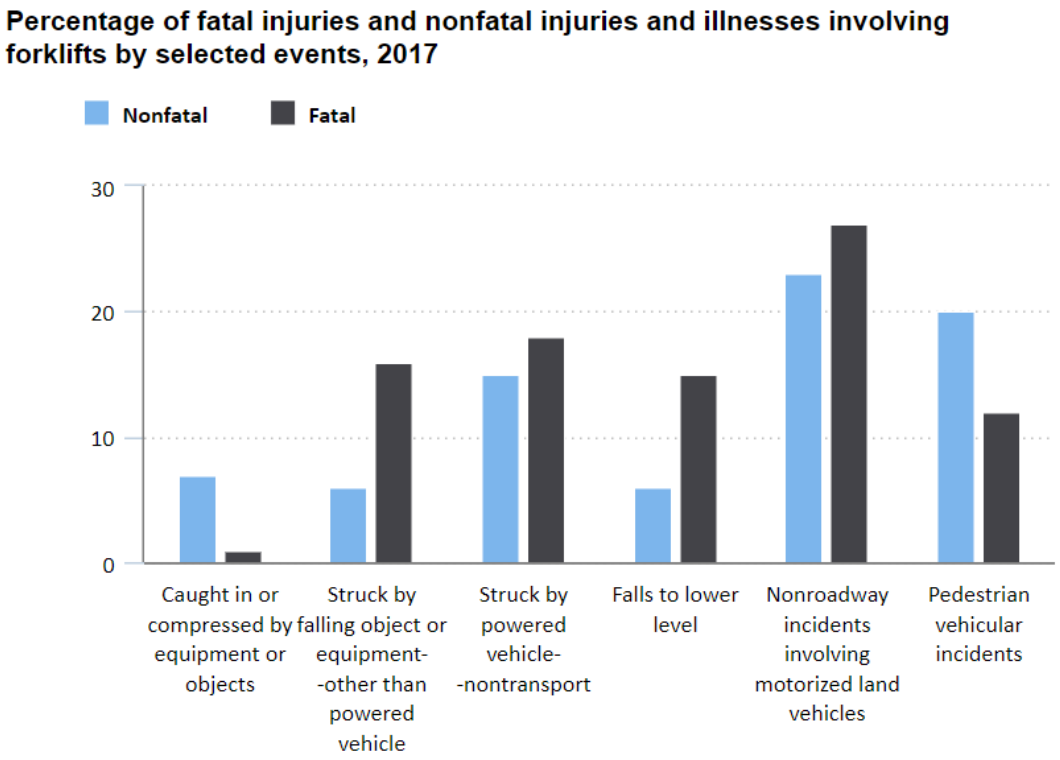


Fig. 3. Accident causes involving forklifts, 2017. [2]

2.2. Strategies for addressing the problem

Forklifts struck are one of the principal cause of accidents in the manufacturing industry as it was shown above. However, there are different ways of addressing the problem for reducing the number of injuries. Some of the most promising strategies are the use of autonomous robots and the application of CV approaches.

2.2.1. Autonomous Mobile Robots

According to Intel‘s description, “an autonomous mobile robot is a type of robot that can understand and move through its environment independently” [3]. These robots, use artificial intelligence systems to calculate the best route based on the environmental inputs received from their sensors and cameras. This behavior increases the fluency of travelling, since they are able to avoid obstacles and find faster routes depending on the situation without the need of an operator, as with the classical AGVs, which independency was subject to the conditions of the tracks and the correct oversight.

Furthermore, an AMR can be used for different tasks than simply moving inventory, like assisting in the picking process or performing sortation, thus, increasing productivity and order accuracy. Due to the fact that an AMR model can be equipped with different handling technologies, the sortation usability is managed by a barcode reader on the robot, and a rapid displacement to the storage location, where the item is tilted.

For the assistance in the picking process, there are two ways of using the AMRs:

- Conventional picking.

- Goods-to-Person Picking.

In the picking process, an operator must move from location to location, lossing a big amount of time. When using an AMR, it is possible to equip the robot with an order basket, so that the robot can perform these movements while the operator of every location takes the inventory. The Goods-to-Person Picking, on the contrary, consist on the movement of the entire shelve to the pick station. Then, the robot indicates the correct picks and quantities.

In any case, a fleet of AMRs can significantly reduce the number of forklift-related accidents within a warehouse if the number of SKUs is big enough [4].

2.2.2. Computer Vision approaches

2.2.2.1. VIA Mobile360

The company VIA Technologies, Inc., announced in October of 2021 the VIA Mobile360 Forklift Safety System [5]. The system uses voice and sounds alerts to warn the forklift driver of possible collisions through three IP67 HD cameras, two of them wide-angle cameras situated in front and rear of the forklift, and one inside the cabin.

According to the company, the area coverture has a radius of 4-5 meters far, which can be configured with either two or one warning zones. The alert is given if either a pedestrian is to close of the forklift safety zone (see Fig. 4), or the cabin camera detects signs of fatigue, smartphone usage or smoking.

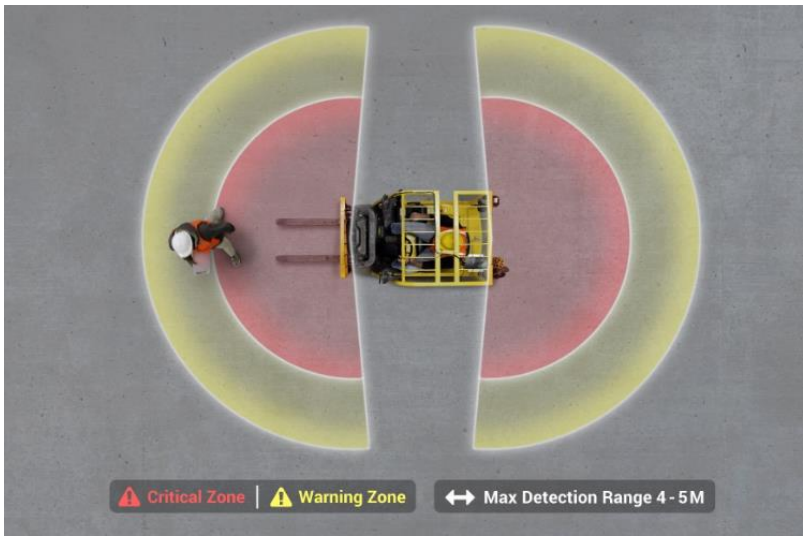


Fig. 4. VIA Mobile360 Warning and Critical Zones.

2.2.2.2. Warny

Warny [6] is a product developed by the Australian computer vision company Bigmate, focused on reducing the number of heavy vehicles-related accidents, as well as unexpected situations. They provide a full ecosystem to enhance work safety through three applications:

- Vehicle collision avoidance
- Safety zone alerting
- Thermal analysis of people and industrial systems

Warny (see Fig. 5), is capable of detecting combustions, fires, equipment overheating, and especially, a real time movement analysis, for example, alerting operators out of the sight of an upcoming driver. The system takes images from multiple standard CCTV cameras, which are used to calculate the ground-truth position of the object detected. Once the real positions are obtained, their velocities and relative distances are calculated in real time, thus, performing an analysis of the situation and giving the corresponding alert to the worker‘s device.

According to the article published in VentureBeat website, “Early into installation, one factory in Singapore saw a 22% drop in incidents (...) Across the board, on average, Bigmate is seeing a 80% drop in incidents in their clients‘ work environment” [7]. They ensure a network with nearly 100% accuracy and milliseconds of latency for the alerts. All the data is also collected to allow workplace analysis.

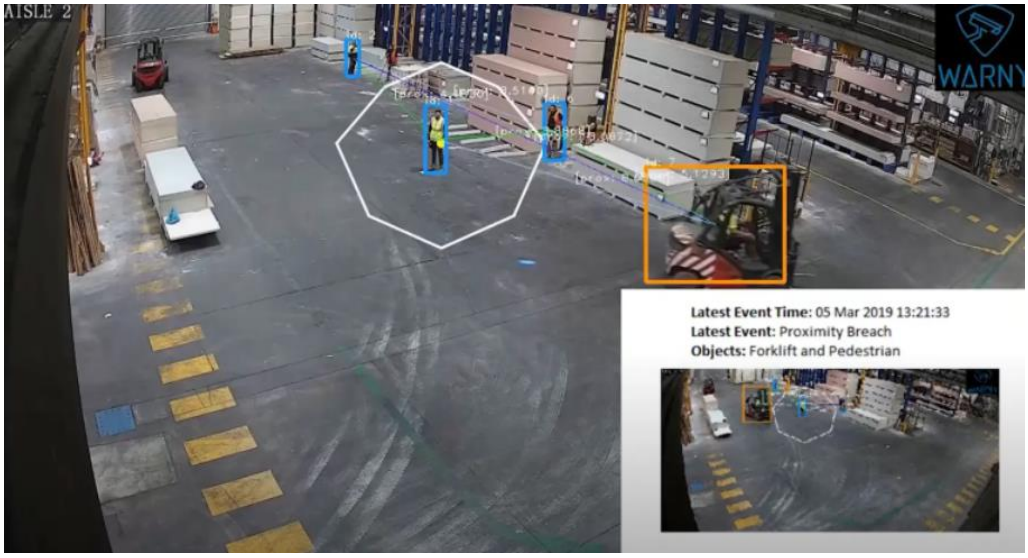


Fig. 5. Warny camera detections.

2.3. Theoretical concepts

In previous sections, two CV-based approaches to ensure work safety were presented. IBM gives the following description to this term. “Computer vision is a field of artificial intelligence (AI) that enables computers and systems to derive meaningful information from digital images, videos and

other visual inputs — and take actions or make recommendations based on that information. If AI enables computers to think, computer vision enables them to see, observe and understand" [8]. Therefore, CV is the branch of artificial intelligence that teaches computer systems how to extract and understand visual information from the environment.

2.3.1. How does CV work?

In order to extract this information, CV-based systems take advantage of a DL concept called CNN, which is used to get features from the image in a set of convolutional layers, whose level of complexity increases with the depth of the architecture. These layers are used to create a feature map with the most meaningful information of the image. Then, the model takes this feature map to understand the context of the image through a classification model.

2.3.2. Digital images

First, it is important to know what a digital image is. A digital image is a matrix of elements from 0 to 255, in which the 0 represents the minimum level of luminosity and 255 de maximum. For example, in gray scale images, the 0 is a black pixel, whereas 255 is a white pixel, see Fig. 6.

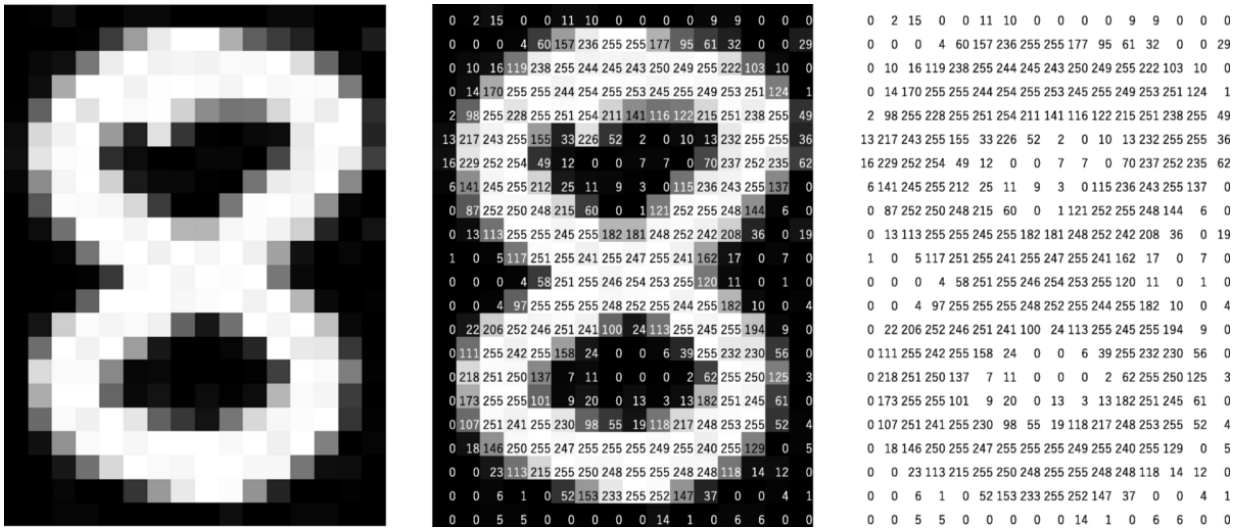


Fig. 6. Gray scale digital image.

However, digital images are usually composed by different color channels, where the scale does not necessarily mean the brightness, but some source of information. The most common color space for visualization is RGB (see Fig. 7), where each channel corresponds to the brightness of each color (red, green, and blue). Other color spaces like HSV, LAB or LUV are not suitable for visualization, but they contain useful information to increase the robustness against light changes in CV-based applications, like hue or saturation channels in HSV space.

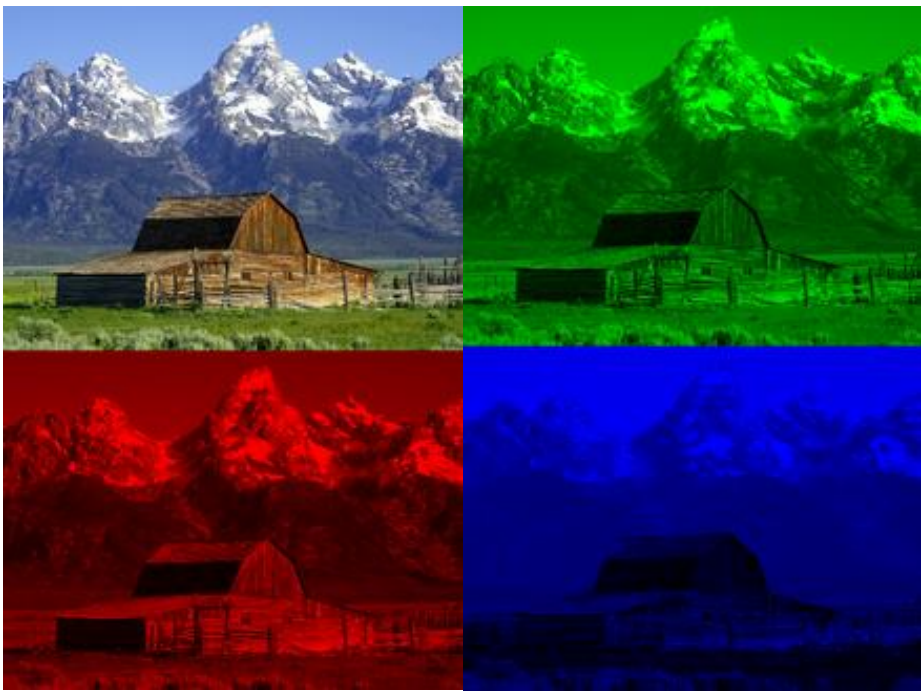


Fig. 7. RGB image.

2.3.3. The Convolution

A convolution is a sum of element-wise products between two matrixes. In computer vision, these two matrixes are the raw image and the kernel (see Fig. 8), where the kernel is an odd smaller matrix, whose elements are used to highlight some features of the raw image. The kernel is also named as filter.

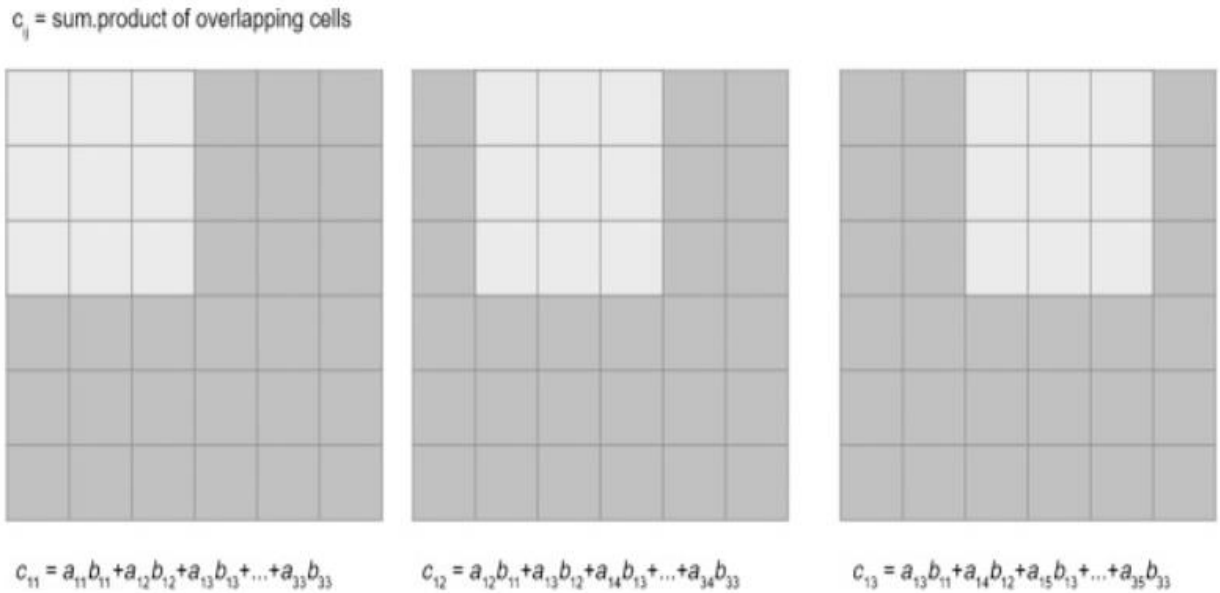


Fig. 8. Convolution [9]

Then, the kernel convolves through the different cells replacing the number that falls in the center of the overlapped elements. However, this will result in a reduction of the input size. To avoid so, a padding process is applied to the image during the convolution. This padding process consist of adding pixels to the border of an image, for example, a 3x3 kernel operation might want to use 1-unit padding, which will add one extra pixel to each one of the edges. There are different types of paddings, but the most common is the zero padding, which fills these extra cells with zeros, see Fig. 9.

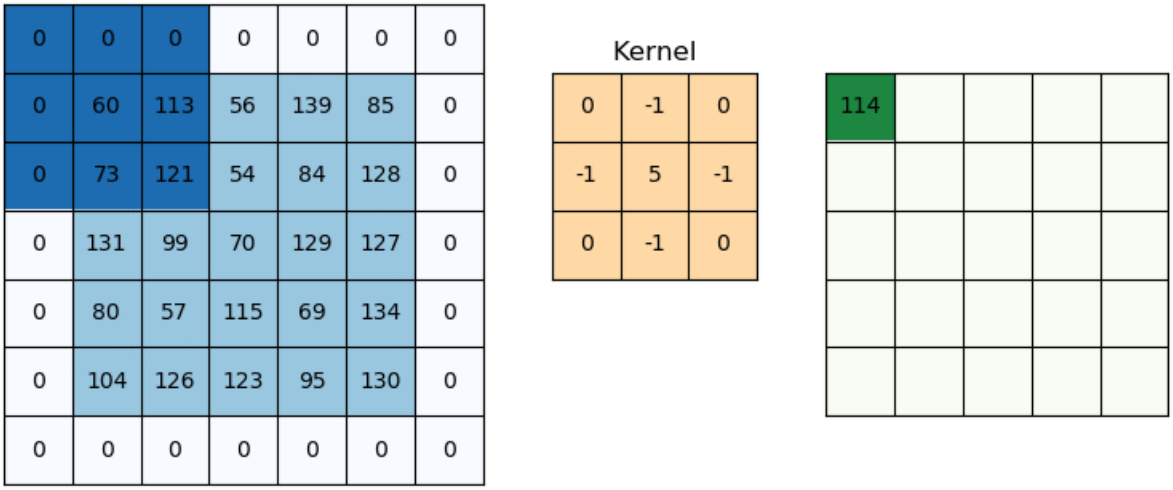


Fig. 9. Convolution with zero padding.

Another important parameter in relation to the output size is the stride, which is defined as the number of cells that the kernel moves after each iteration.

2.3.4. Pooling

Sometimes, in CV-based systems it may be desirable to get rid of non-significant information, resulting in a smaller summarized picture. This is done with the pooling operation, which fuses meaningful information across the image using a filter. Depending on how this operation is performed, one result or another will be obtained, two main types are Max Pooling and Average Pooling.

The max pooling takes the maximum value of the area covered by the filter, thus, extracting the most significant features of each region, while the average pooling takes the mean [10]. In Fig. 10, there is an example of both.

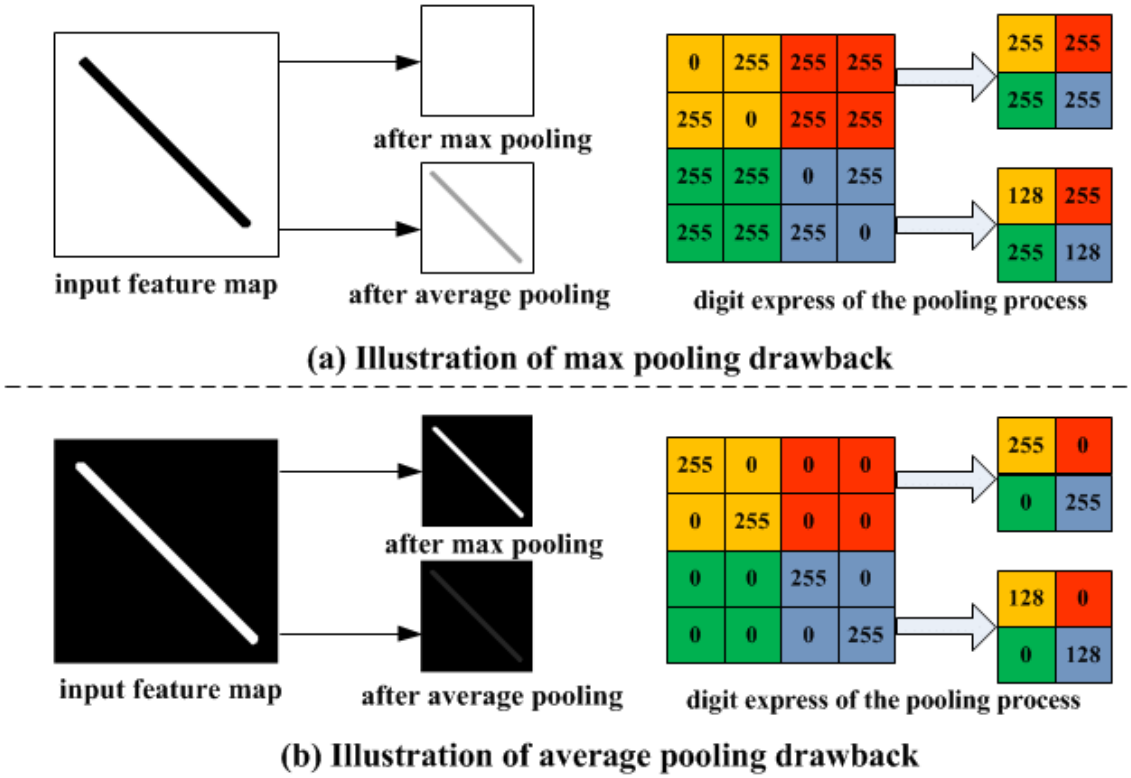


Fig. 10. Max and Average Pooling examples.

2.3.5. Linear Regression

The concepts shown above are important to understand how the features of an image can be extracted. Nevertheless, the following sections are more related to learning process in AI systems.

Linear regressions are one of the most important and basic concepts in supervised Machine Learning (ML). Basically, a linear regression is a statistic model that tries to find the line that best fits a set of supposedly related values, where the y-axis corresponds to the dependent variable, and the x-axis the independent variable. In supervised machine learning problems, the aim is to predict this y value, given a single x input, or set of inputs. Therefore, there are simple, equation 1, and multiple linear regressions, equation 2.

$$y = b_0 + w_1 x \quad (1)$$

$$y = b_0 + w_1 x_1 + w_2 x_2 + \cdots + w_n x_n \quad (2)$$

The line that best fits the model (see Fig. 11) is obtained through the slope and the intercept, which are usually referred as weight (w) and bias (b). These two parameters are calculated for a given training set as the optimal values for which the error is minimum, where the error is the distance between the predicted and the actual value. Then, the accuracy of the model is validated in a test set.

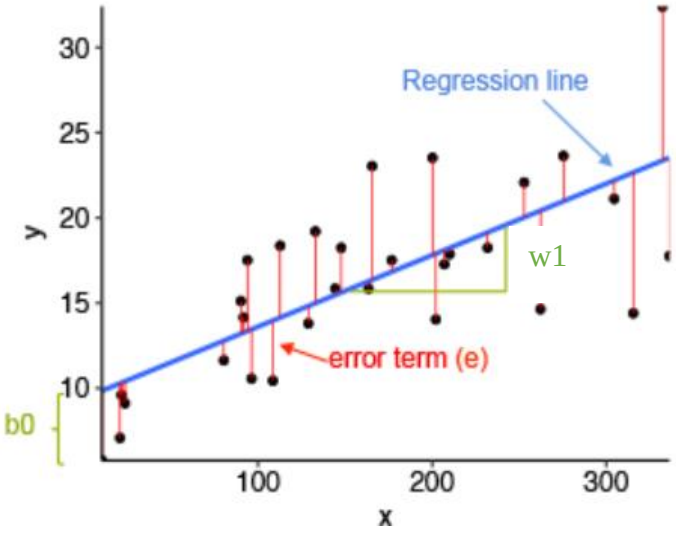


Fig. 11. Simple linear regression [11].

2.3.6. Logistic Regressions

However, in some problems it would be necessary to predict the probability of belonging to a certain class, since the dependent variable can be categorical, for example, in binary classifications. Here, a linear regression approach might cause some problems by the fact, that a linear model allows the result to be out of the boundaries of the problem, i.e. probabilities higher than one and lower than zero, see Fig. 12. It can also bring problems with the outliers, since the line that best fits the model can be shifted to decrease the distance error between the farthest outliers and the rest of the data, causing miss-classifications.

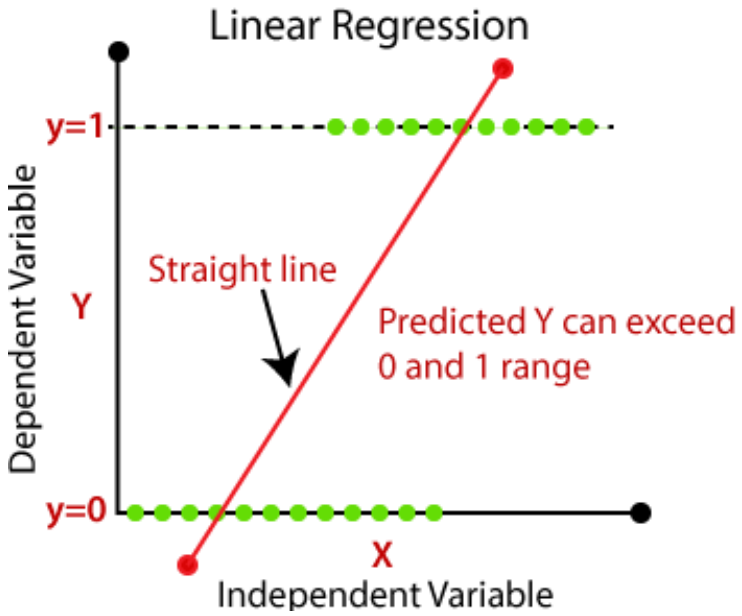


Fig. 12. Linear regression for a binary classification problem.

Therefore, a logistic regression approach is more suitable for this type of problems, where rather than a straight line it is used an S-curve, so the predictions can fall within the boundaries of the problem, and the farthest outliers do not affect much to the model [12]. To do so, a logistic function must be applied to the linear calculations.

$$\sigma(z) = \frac{1}{1+e^{-y}} \quad (3)$$

For example, equation 3, corresponds to the sigmoid function, it makes the output of the linear prediction to fall between 0 and 1, thus, resulting in a much more accurate model. A threshold value it is also set to classify the predictions, see Fig. 13.

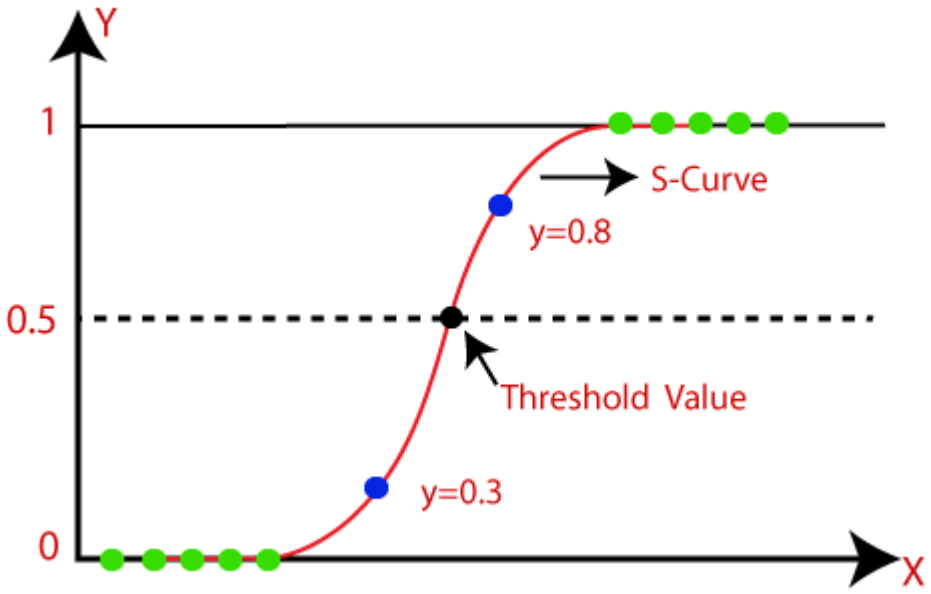


Fig. 13. Sigmoid function applied to the linear regression with a threshold of 0.5.

2.3.7. Cost functions.

To train a model in supervised learning algorithms, the output has to be evaluated iteratively until it reaches a good accuracy. This is done with a cost function, either called loss. The cost function compares the output of the model with the real output of the dataset in order to get the error of the prediction. To do so, there are many approaches depending on the type of problem, but for regression problems, the loss is a distance-based error calculation.

Based on this distance, there are two famous approaches, the MSE (equation 4), or L2 loss, and, MAE (equation 5), or L1 loss [13].

$$MSE = \frac{1}{N} \cdot \sum_{i=0}^{n} (y - y')^2 \quad (4)$$

$$MAE = \frac{1}{N} \cdot \sum_{i=0}^{n} |y - y'| \quad (5)$$

The fact that the L2 loss is squared, means that it penalizes higher the outliers of the dataset. However, the L1 loss is more robust in this aspect and also performs well with noisy data.

2.3.8. Artificial Neural Networks

An Artificial Neural Network is a deep learning model arquitecture directly inspired from the human central nervous system. The information in the human body flows in form of electrical impulses through billions of interconnected cells called neurons, see Fig. 14.

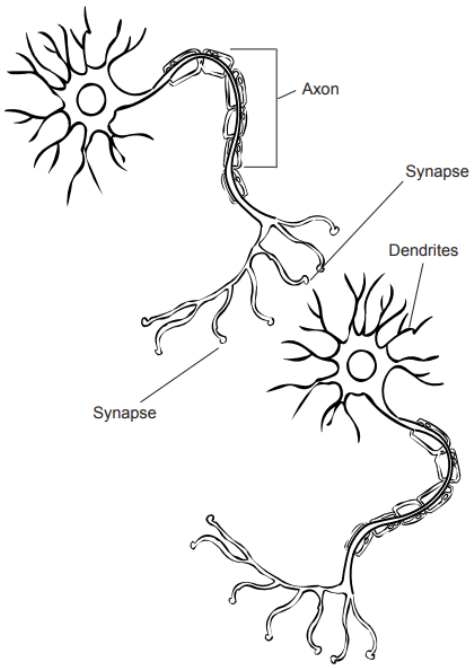


Fig. 14. Structure of a Neuron

Every single neuron has a cell body from which a set of small branches called dendrites grow, as well as a long fiber known as the axon. The information flows from the whiskers of the axon, i.e. the synapses, to the dendrites of another neuron. Then, the information from many neurons is processed in its body cell and joined together to be sent to a new neuron. Thus, constantly activating

certain neuron connections over the others, the brain learns which neurons will be more likely to use to get the expected output.

An artificial neural network works pretty much the same way, where there is a neuron that receives inputs from many different others, and send a response according to them. Its architecture is composed by an input layer, a set of hidden layers and the outputs, see Fig. 15.

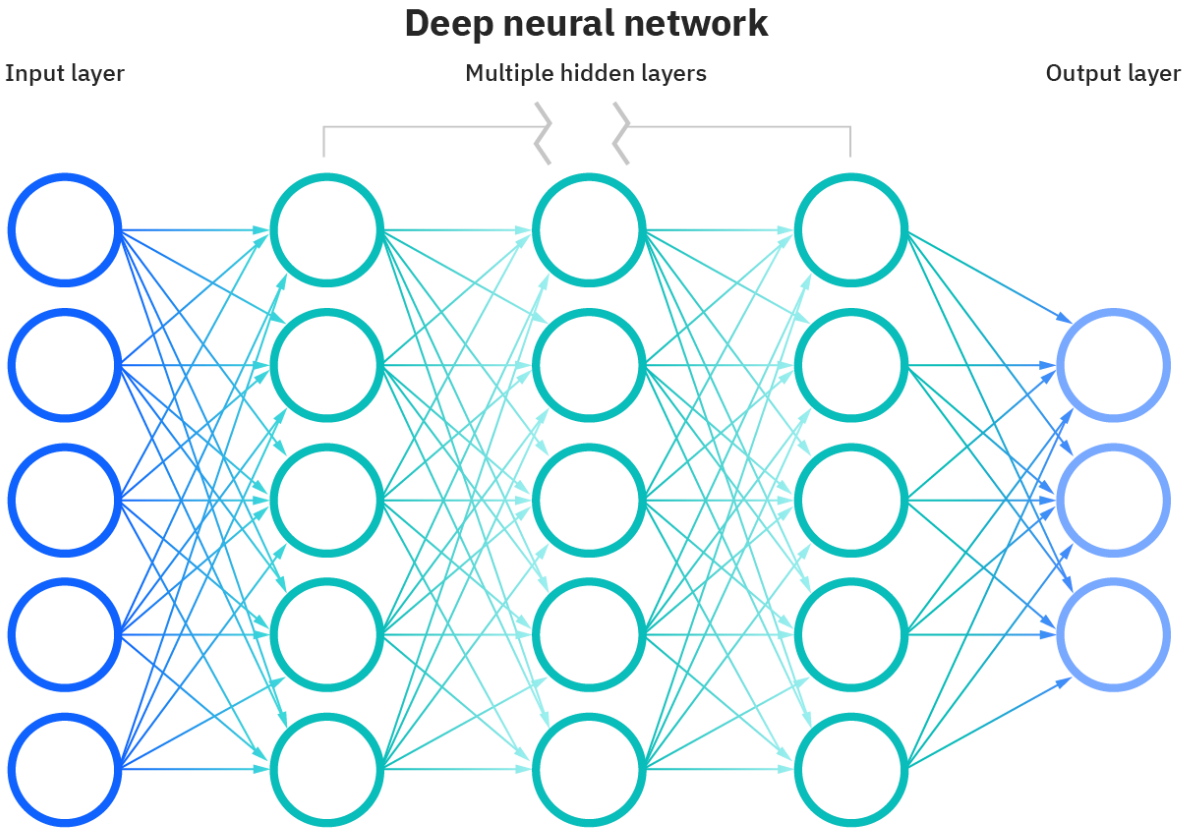


Fig. 15. Structure of a Deep Neural Network

The hidden layers can be understood as the central nervous system, where the inputs of the neuron are the dendrites and the outputs the synapses. Every neuron of an artificial neural network performs a linear regression followed by an activation function, which can be either linear, hyperbolic or logistic as seen above. On the contrary, rather than electrical impulses, the information flows in form of weighted values, which are adjusted depending on the neuron. The output of a neuron is defined in equation 6.

$$o = f(z) = f\left(\sum_i w_i x_i + b\right) \quad (6)$$

Each neuron might find different associations for the input data that can end into the expected value or not. For this reason, after reaching the output layer and calculate the loss, the error of the neurons

is back-propagated to search the path that has had the biggest implication in the result to reinforce it. This process is known as backpropagation.

The weights and bias of the neurons are randomly initialized and automatically adjusted through this backpropagation algorithm. Once the network has arrived with a result, is more efficient to search the error implications of each neuron backwards than calculating forward every change in the net. Therefore, if every neuron in the final layer has an implication in the error, it will be more likely to have a neuron that has contributed more in the result than de others. This process can be repeated for each layer discarding the neurons with less contribution in the result, thus, back propagating the error until the first layer. This way can be obtained the parameters for the calculations of the gradient descent in the training process [15], see equation 7.

$$\frac{\partial C}{\partial b^L}, \frac{\partial C}{\partial w^L} \rightarrow l = 0,1,2, \dots, L; \tag{7}$$

Here, $\frac{\partial C}{\partial b^L}$ and $\frac{\partial C}{\partial w^L}$ are the partial derivatives of the cost with respect the bias and weight respectively.

2.3.9. Optimization functions.

After the cost calculations, the parameters of the function must be optimized to find the minimum possible error. In convex functions, it can be obtained matching the cost derivative to zero, but for non-convex functions, this approach faces the problem of finding several points where the slope can be zero, like peaks or saddle points. Hence, the Stochastic Gradient Descent or ADAM approaches are betters methods for the optimization task, especially in ANNs.

The Stochastic Gradient Descent consists on a partial derivative calculation of the parameters of the function. This gradient can be subtracted on a certain percent, the learning rate, to find a minimum in the function [14].

$$\theta_{n+1} = \theta - \eta \nabla f \quad \vee \quad 0 < \eta < 1 \tag{8}$$

Where

$$\nabla f = \begin{bmatrix} \frac{\partial C}{\partial \theta_1} \\ \frac{\partial C}{\partial \theta_2} \\ \dots \\ \frac{\partial C}{\partial \theta_n} \end{bmatrix} \tag{9}$$

Here, η is the learning rate.

For small learning rates, the algorithm might never converge, while for larger ones the jump after each iteration can be such, that it turns impossible to find the minimum. The following picture, Fig 16, shows a 3-Dimentional representation of this process.

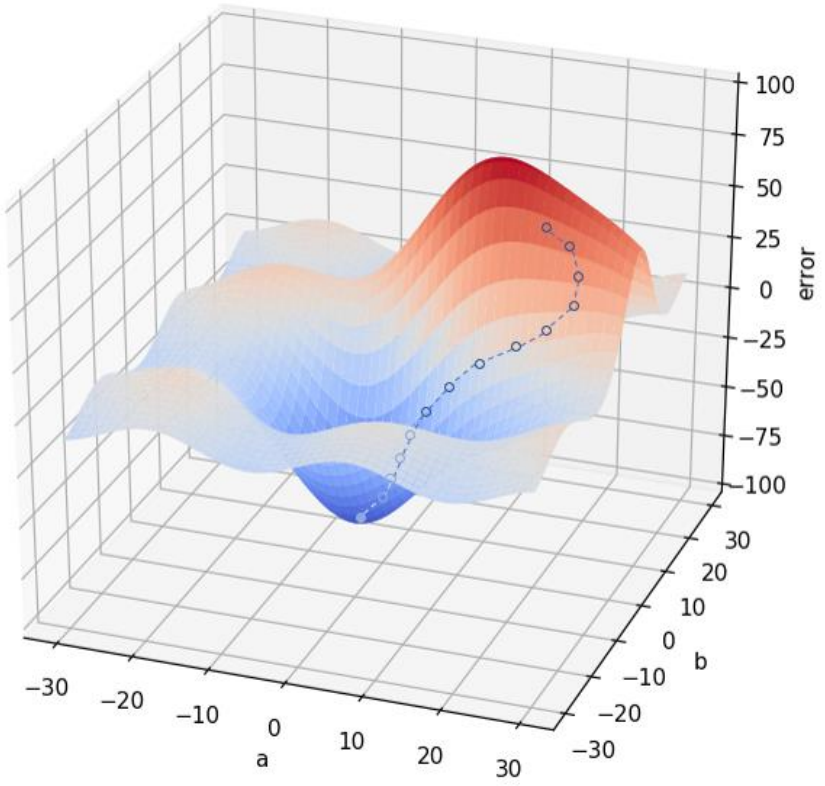


Fig. 16. Gradient Descent 3D representation.

2.3.10. Activation Functions.

As mentioned above, every linear regression in a neuron comes with an activation function. However, a common issue in deep neural networks is the vanishing gradient problem during backpropagation. Here, the chain rule is used for the gradient descent calculations, this means that after multiple concatenations, the gradients from the first layers will be inevitably smaller than the lasts, tending to vanish at a certain point if the activation output is also constrained within small boundaries. Hence, the activation function has a direct implication in the performance of the network. For this reason, there are some functions which are more likely to perform better under certain circunstances than others. Non-linear functions tend to give better results, for example, a very popular activation function in CNNs is ReLU, which maximizes positive inputs, but returns zero otherwhise, i.e. $R(z) = \max(0, z)$.

$$R(z) = \begin{cases} 0\,, & x \leq 0 \\ x, & x > 0 \end{cases} \qquad (10)$$

It performs well in most of the cases and avoids the vanishing gradient problem. Nevertheless, negative neurons are completely forgotten during the training. Leaky ReLU (see Fig. 17) solves this problem multiplying all negative inputs for a small factor, α, while keeps maximizing positive inputs [16].

$$LR(z) = \begin{cases} \alpha x\,, & x \leq 0 \\ x, & x > 0 \end{cases} \quad (11)$$

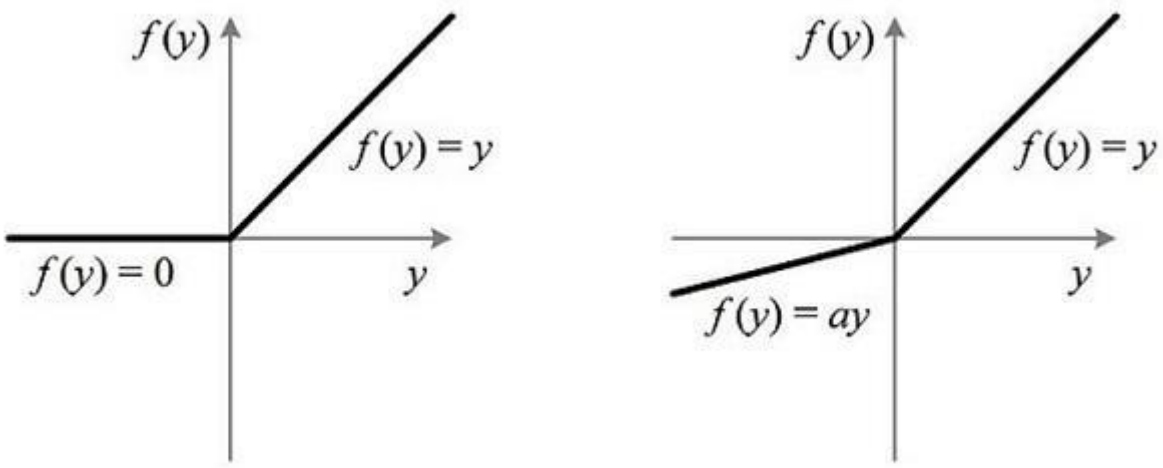


Fig. 17. ReLU and Leaky ReLU activation functions.

Another famous activation function that has been already explained is the Sigmoid function. It works well for binary classification problems, but despite of its popularity, it is computationally expensive and converges slower than, for example, the Tanh activation function (see Fig. 18), which is zero-centered between -1 and 1.

$$\tanh(z) = \frac{2}{1 + e^{-2z}} - 1 \quad (12)$$

On the contrary, for multi-classification problems, Softmax gives better results, so it is used at the end of the network. It returns a probability between 0 and 1 like the sigmoid [17].

$$Softmax(z) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (13)$$

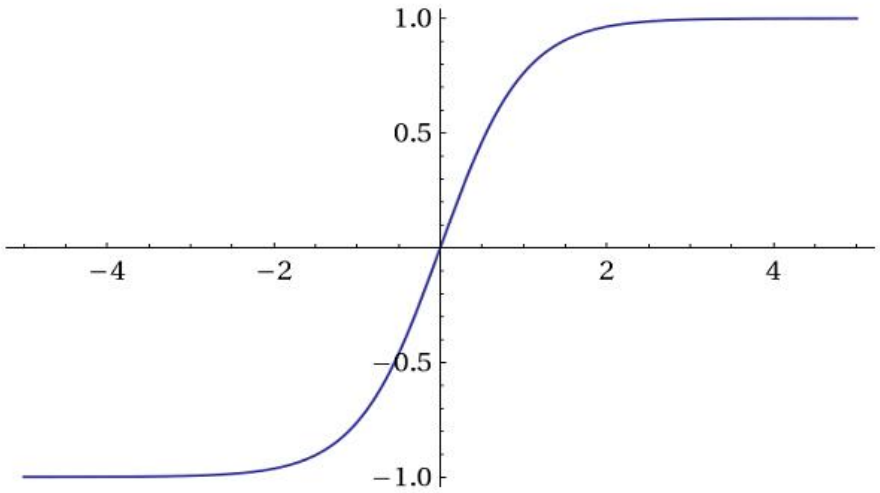


Fig. 18. Tanh activation function.

2.3.11. CNNs

All things consider, a DL model can be configured in multiples ways so that the network learns to perform different tasks based on the functions used and the connections of its layers. There are dozens of different configurations and ways of building an ANN, one of the most famous is named CNN and is fundamental for CV-based applications, as it was mentioned in previous sections.

"The first work on modern convolutional neural networks occurred in 1990, Gradient Based Learning Applied to Document Recognition" [18] . In this paper, it was found that the concatenation of filters throughout different layers ended in a progressive transformation from simple to complex feature maps. These feature maps being incremented along with the depth of the network. In this approach, the increment was from 6 to 16 after the first subsampling, but in modern CNNs the final layers are made by hundreds of them. Then, the feature map is usually flattened and each cell is used as an input for the classification model. A ReLU activation function is commonly used here as well as during the convolutional layers, but the process usually ends with a logistic function for the object classification, for example, the Softmax function if there are multiple classes. Therefore, two parts can be distinguished in a CNN, a feature learning, and a classification part. Here is a visual representation of the structure just explained, see Fig. 19.

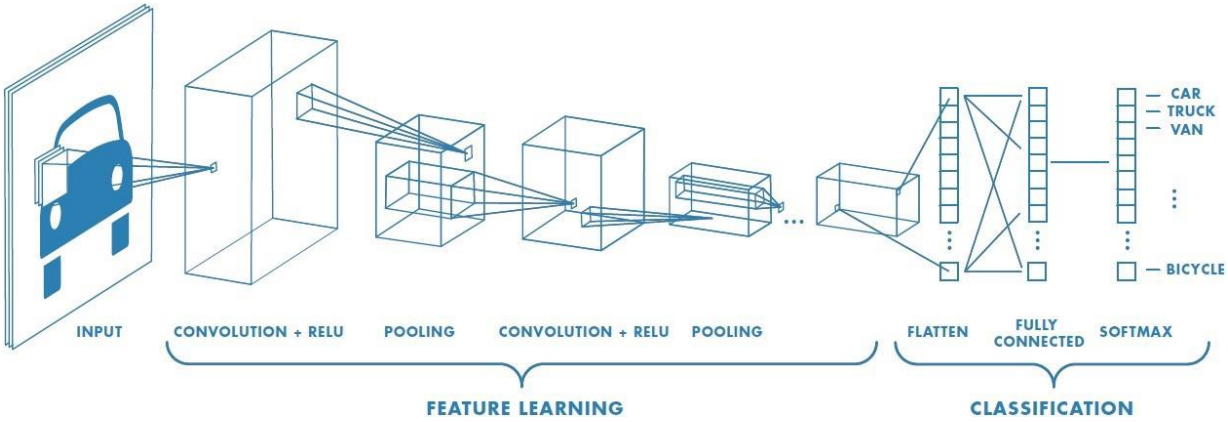


Fig. 19. Typical structure of a CNN

The learning process for the image classification requires a dataset of labeled images. These images must be different and should have different angles and different levels of luminosities, so that the network could learn to perform in different scenarios.

2.4. Object Detection

For the time being, the process of image classification has been explained, but this networks are still unable to know where the object is. To do find the object, there is something called object detection, which by making use of a proposal area or bounding box, teaches the network to also locate the object. In this section, an overview of some approaches to this problem are going to be presented, as well as the object detector used.

2.4.1. Sliding Windows

The first method ever used to find the location of an object was done by the sliding-windows technique. This technique, consists on taking a crop of the image to predict whether a particular object is on that window or not. Then, the window is moved along the image with different strides and sizes performing this predictions until the network ends finding a window that contains the object that was looked for, see Fig. 20.

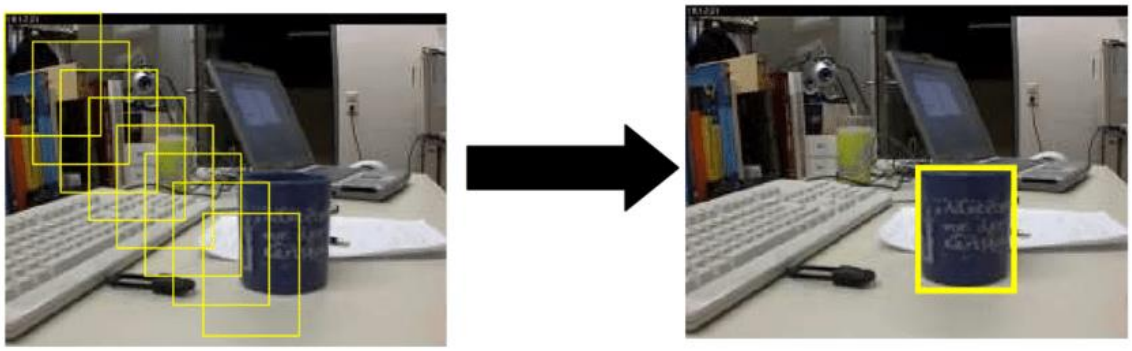


Fig. 20. Sliding Window visual example.

2.4.2. DPM

One of the classical approaches that use this technique is Deformable Parts Model (DPM). This approach takes into account that either a person or an object can have different shapes, poses and colors. In real situations, an object can be partially occluded, what might lead into an accuracy reduction. DPM, uses the sliding windows technique to find the bounding box of an object and then, doubles the size of the image to take a crop of the different parts within that bounding box from where to extract more features. Within these crops, it is later computed how far are the parts from the body of the object. The following picture, Fig. 21, shows a diagram of this process.

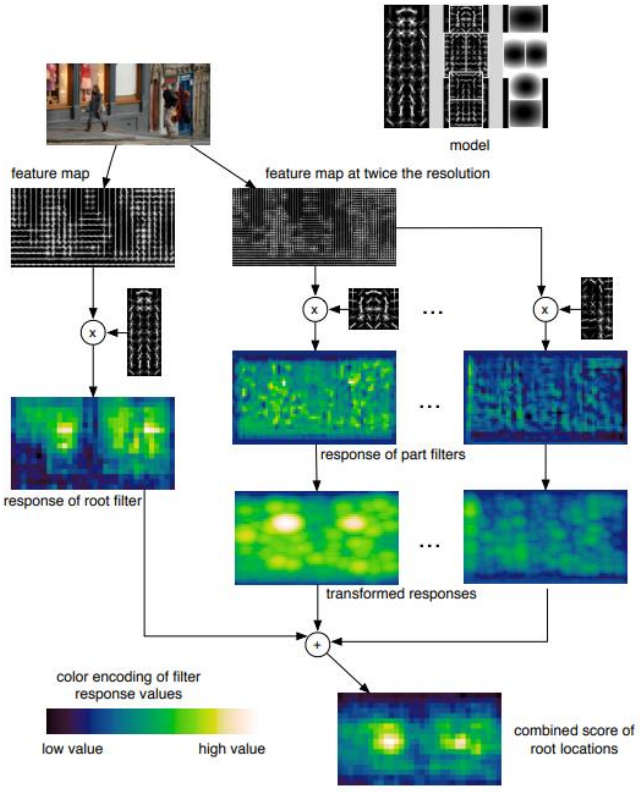


Fig. 21. DPM score process.

2.4.3. Region Proposals Network

Another famous technique for choosing possible bounding boxes within an image, is a region proposal method, which is done by a selective search of areas at different scales ratios. These areas, are found through a segmentation at different scales, resulting on a variety of several shapes for which the bounding box that fits that region is proposed. The regions are proposed by an hierarchical grouping of the most similar regions at different color spaces. Then, the color similarities are computed through their histogram intersections, as well as the textures similarities using SIFT measurements and Gaussian derivatives. The size of the region is also computed, allowing the smaller regions to merge earlier. Finally, the way in which each region fits into the

other is taken into account for the filling process. Fig. 22 shows an example of this process at different scales.

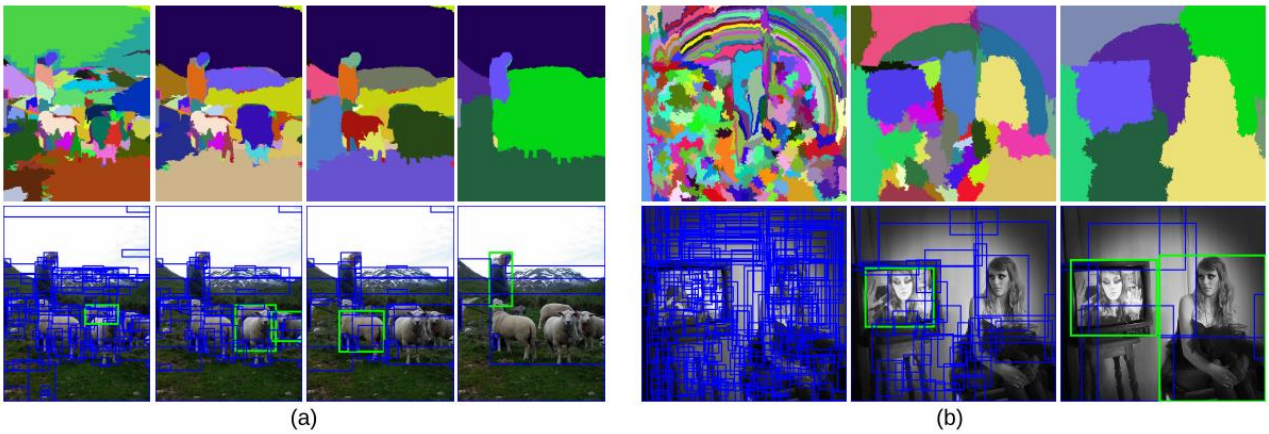


Fig. 22. Two examples of selective search at different scales. Note that (b) has detected the girl on the TV. [20]

A famous approach that implements this region proposal network is the R-CNN family, a two stages object detector where the bounding boxes for the feature extraction are got using this selective search, and a SVM algorithm is used for the classification process.

2.4.4. YOLO

The main problem with these object detection models, is the high computational cost of their methods, which makes them incredibly slow. Even the improvements done by Fast R-CNN and Faster-RCNN, were so far away from being real-time approaches. This is the purpose for which YOLO was intended. The developers of this approach, managed to solve this frame rate problem by reframing it as "a single regression problem" [21], with a lot less bounding boxes instead of the conventional region-based and sliding windows techniques.

YOLO is the choice for the object detection task in this project, but in order to comprehend how it works nowadays, it is important to first walk through its different versions.

2.4.5. YOLOv1

The first version of this algorithm, began "simultaneously predicting bounding boxes and class probabilities for those boxes" [21]. It worked over the entire image, thus, resulting on the encoding of the contextual information linked to the prediction. This was a great feature, because it allowed the model to be more generalizable in a wide range of situations while maintaining larger frame rates.

To accomplish this achievement, YOLO introduced an $S \; x \; S$ grid whose cells were responsible for providing these predictions. Every cell returned a B number of bounding boxes and a C number of class probabilities. Each bounding box contains the information of the x and y coordinates relatives

to that cell, the width and height relatives to the entire image and the IOU confidence that there was an object, ideally 1. Therefore, the prediction was an $S\ x\ S\ x\ (B * 5 + C)$ tensor limited to one object per cell. This limitation in the number of objects that can be detected was important, because it directly affected to the performance with smaller objects.
Nevertheless, what made YOLO extremely fast was not only the reduction in the number of bounding boxes proposals compared to other techniques, but its network design, which was closely based on the GoogLeNet architecture. The main difference here, remained in the fact that YOLOv1 uses just $1\ x\ 1$ reduction layers before the $3\ x\ 3$ convolutional layers instead of the inception modules. This was named Darknet. Darknet's architecture was built under "24 convolutional layers followed by 2 fully connected layers" [21] and took $448\ x\ 448$ RGB images as inputs, see Fig. 23.

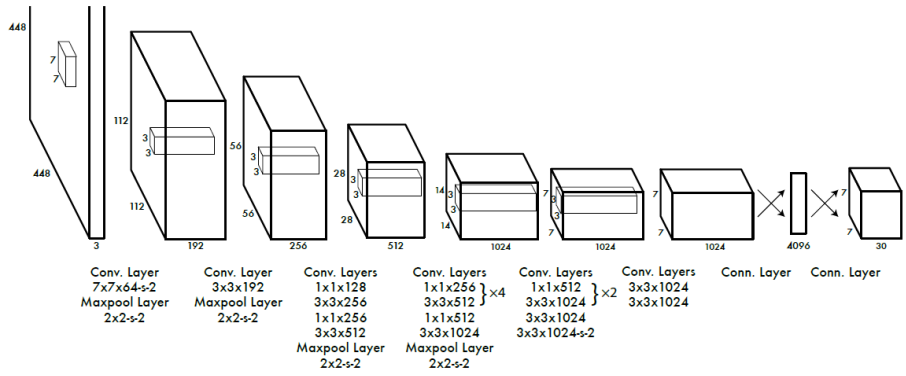


Fig. 23. Darknet [21].

Proceeding with the activation functions, a linear activation function was used for the final layer and a leaky rectified linear activation was used for the rest.

This first approach was trained with a grid size of $S = 2$, using the Pascal VOC Dataset, which contains a list of 20 different classes, each grid cell returning $B = 2$ bounding boxes, making a total of 98 proposals, much less than the thousands of proposals in previous methods. Finally, the model was optimized with the sum-squared error loss.

The results were quite impressive in terms of speed, achieving around 45 FPS, but it lacked in terms of recall and mAP, see Table 2.

Detection Frameworks	Train	mAP	FPS
Fast R-CNN	2007+2012	70.0	0.5
Fast R-CNN VGG-16	2007+2012	73.2	7
Fast R-CNN ResNet	2007+2012	76.4	5
YOLO	2007+2012	63.4	45
SSD300	2007+2012	74.3	46
SSD500	2007+2012	76.8	19

Table 2. Detection frameworks on PASCAL VOC 2007 [22]

2.4.6. YOLOv2

Later, YOLOv2 was released and with it, several changes within its architecture. One of the most significant changes made in YOLOv2 with respect to YOLOv1 to improve the location problems, was the implementation of anchor boxes (see Fig. 24) instead of predicting the coordinates directly.

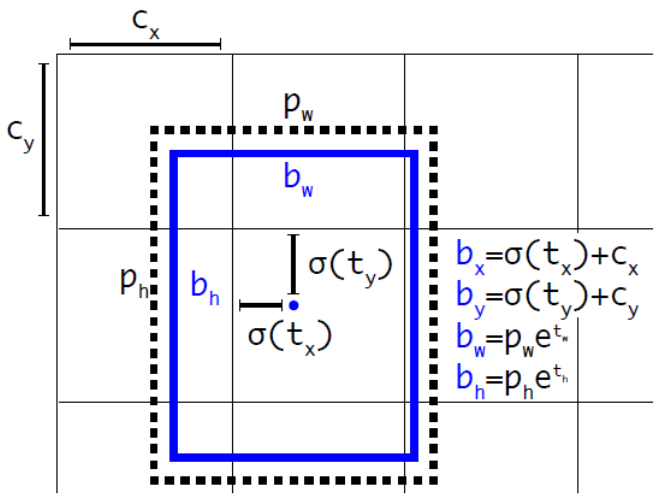


Fig. 24. Bounding boxes with dimension priors and location prediction [22]

This anchor boxes allow the network to slightly adjust their size, which is much easier than predicting bounding boxes from scratch. These anchors, are chosen running a "k-means clustering on the training set bounding boxes to automatically find good priors" [22], thus, improving the results in the average IOU compared to hand-picked priors, see Table 3.

Box Generation	#	Avg IOU
Cluster SSE	5	58.7
Cluster IOU	5	61.0
Anchor Boxes	9	60.9
Cluster IOU	9	67.2

Table 3. Average IOU of boxes to closest priors on VOC 2007 [22]

Here, it is showed how, indeed, the clusters can achieve the same results than the hand-picked priors but using almost half of them.

However, since the anchor boxes led to model instability, the approach made in YOLOv1 was kept in terms of maintaining location coordinates relative to each grid cell. Therefore, t_x, t_y, t_w, t_h and t_o were defined as the new five predictions for each bounding box, whose x and y coordinates, width, height and IOU correspond to the following terms.

$$b_x = \sigma(t_x) + c_x \quad (14)$$

$$b_y = \sigma(t_y) + c_y \quad (15)$$

$$b_w = p_w e^{t_w} \quad (16)$$

$$b_h = p_h e^{t_h} \quad (17)$$

$$\Pr(object) * IOU(b, object) = \sigma(t_o) \quad (18)$$

Where p_w and p_h are the width and height of the anchor box and $c_x$and c_y the offsets of that cell.

Another important change made in YOLOv2, was the new network design, Darknet 19 (see Fig. 25), in which the class predictions were "decouple (…) from the spatial location" [22]. This meant, that the prediction then became an $S\ x\ S\ x\ B(5 + C)$ tensor. This fact indicated that the loss would not only depend on the cell, but the index of the anchor too. On the other hand, the fully connected layers were also removed due to the use of anchor boxes for the bounding box predictions, and the input resolution was reduced to 416, downsampling the output image by a factor of 32. This way, allowing the implementation of a multi-scale training for multiples of 32 from 320 to 608. The multi-scale training, allowed YOLOv2 to learn how to perform in different scenarios, becoming faster at lower resolutions, and more accurate at higher, see Fig. 26.

Type	Filters	Size/Stride	Output
Convolutional	32	3×3	224×224
Maxpool		$2 \times 2/2$	112×112
Convolutional	64	3×3	112×112
Maxpool		$2 \times 2/2$	56×56
Convolutional	128	3×3	56×56
Convolutional	64	1×1	56×56
Convolutional	128	3×3	56×56
Maxpool		$2 \times 2/2$	28×28
Convolutional	256	3×3	28×28
Convolutional	128	1×1	28×28
Convolutional	256	3×3	28×28
Maxpool		$2 \times 2/2$	14×14
Convolutional	512	3×3	14×14
Convolutional	256	1×1	14×14
Convolutional	512	3×3	14×14
Convolutional	256	1×1	14×14
Convolutional	512	3×3	14×14
Maxpool		$2 \times 2/2$	7×7
Convolutional	1024	3×3	7×7
Convolutional	512	1×1	7×7
Convolutional	1024	3×3	7×7
Convolutional	512	1×1	7×7
Convolutional	1024	3×3	7×7
Convolutional	1000	1×1	7×7
Avgpool		Global	1000
Softmax			

Fig. 25. Darknet 19 [22]

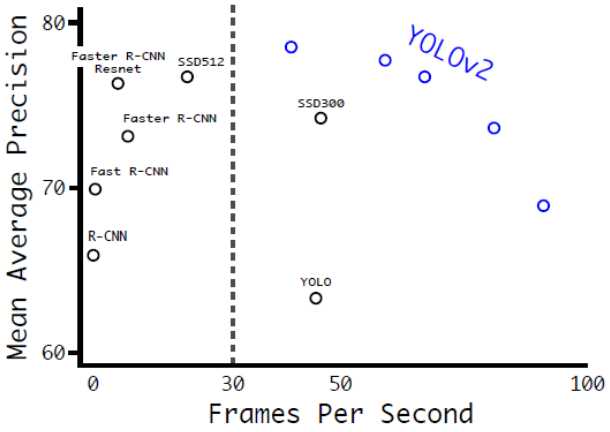


Fig. 26. Accuracy and speed on VOC 2007 [22]

2.4.7. YOLOv3

In YOLOv3 there is just one important change with respect to YOLOv2, since the implementation of the anchor boxes, the new Darknet 19 and the multi-scale training were incredibly successful on improving recall and mAP without losing speed in the process. It was a new version of Darknet, Darknet-53 (see Fig. 27), which merged the previous structure used in Darknet-19 with the residual blocks introduced in ResNet [23] within an FPN. These residual blocks, allow the network to become deeper while solving the vanishing gradient problem. This is the main reason of the new three different levels of predictions, where the feature map is upsampled after each one of them. Thus, allowing the net to perform better with smaller boxes. For the class predictions, each bounding box may now have a multilabel classification, using independent logistic classifiers, and the binary cross-entropy loss during training.
Table 4 shows how YOLOv3 reaches the same mAP than other methods, but clearly overcoming them in terms of speed.

	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			

Fig. 27. Darknet 53 [24]

Method	mAP-50	time(ms)
SSD321	45.4	61
DSSD321	46.1	85
R-FCN	51.9	85
SSD513	50.4	125
DSSD513	53.3	156
FPN FRCN	59.1	172
RetinaNet-50-100	50.9	73
RetinaNet-101-500	53.1	90
RetinaNet-101-800	57.2	198
YOLOv3-320	51.5	22
YOLOv3-416	55.3	29
YOLOv3-608	57.9	51

Table 4. Speed/mAP-50 between YOLOv3 and other methods [24]

2.4.8. YOLOv4

Previously, it was mentioned that object classifiers are composed by two main parts, in object detection, these two parts are named as backbone, which extract the features, and head, which perform predictions, but ever since most recent develops in object detection are including a way of mix together feature maps from different stages, a "neck" has started to take part in the structure. Thus, the last version of YOLO, YOLOv4, implemented several new features to Darknet-53 to improve its performance on single conventional GPUs. The following picture, Fig. 28, shows this structure.

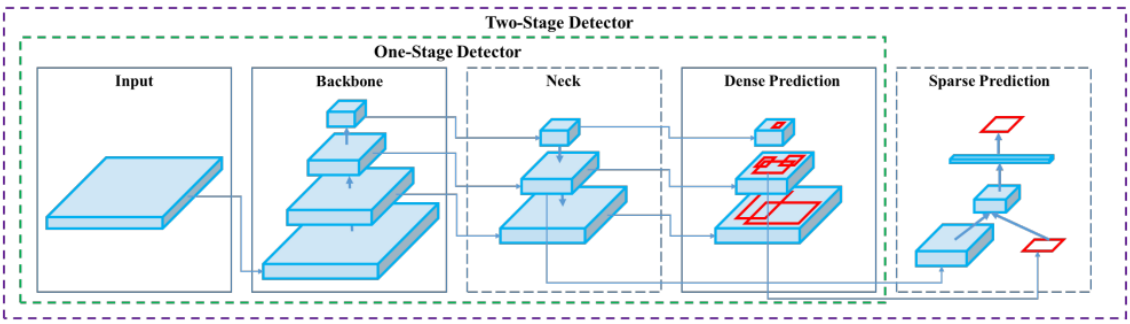


Fig. 28. Object detector [25]

The new backbone in YOLOv4 maintained Darknet-53, but merging it with a CSPNet on top of its basis. The CSPNet, takes just one portion of each output before the next convolutional layer, thus, resulting in lighters convolutional blocks. The rest, is concatenated in the transition layers, see Fig. 29.

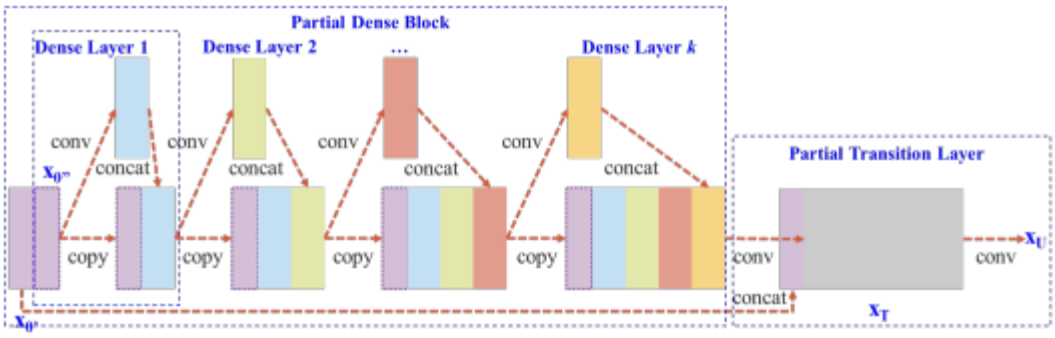


Fig. 29. CSPDenseNet example.

Usually, network lightening leads to worst performances, but on the contrary, this technique results in a reduction of the computational cost from 10% to 20% and still outperforming in terms of accuracy, also reducing memory costs and "removing computational bottlenecks" [26]
Furthermore, YOLOv4 adds a modified version of the SPP model to its model neck, setting a multi-scale max pooling with different kernel sizes but stride 1, and a subsequential concatenation of those outputs. This block not only improves the receptive field but screens the most significant context features with nearly 0 speed reduction. The neck also includes a modified PANet [27] for the aggregation of parameters, using element concatenations instead of element-wise additions. The head remains the same as in YOLOv3

Ultimately, a Mosaic data augmentation was included, next to a Self-Adversarial Training and a modified version of the CBN, it was called CmBN. Mosaic data augmentation helps to add more context information within one image, reducing the necessity of larger mini-batch. This new mosaic data augmentation works well with Cross Batch Normalization, as the tendency of higher resolution images has grown in recent years. In this case, the CmBN "collects statistics only between mini-batches with a single batch" [25].

Fig. 30 shows YOLOv4 performance.

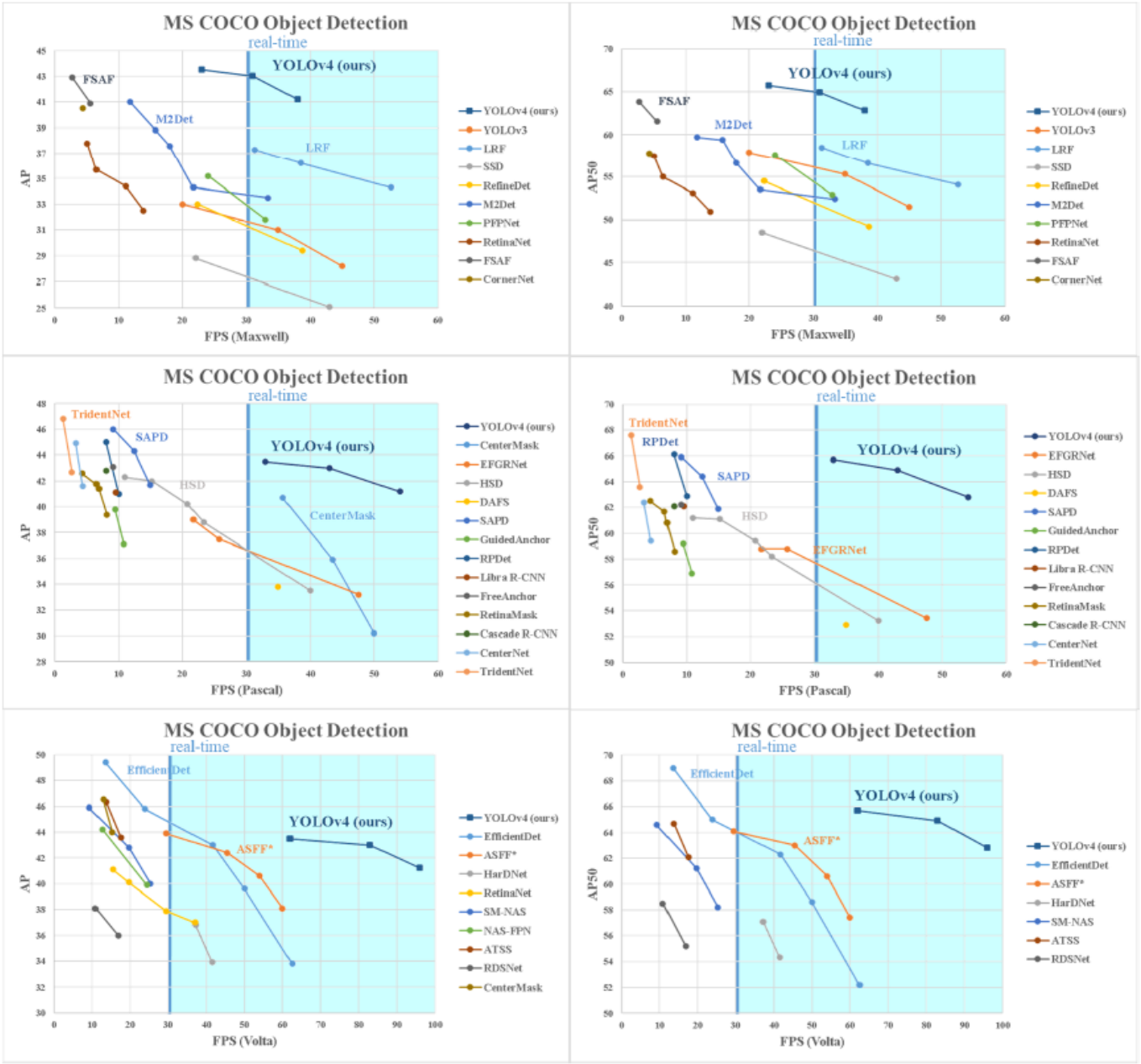


Fig. 30. Comparison of the speed and accuracy of different object detectors [25]

This figure shows how YOLOv4 outperforms different object detectors in terms of speed and works in par in terms of AP due to its previously explained model design, being a very balance and suitable option for real-time object detections.

2.5. Object Tracking

Object detection is often coupled with object tracking for many reasons, since we may not only need to know where a certain object is, but its trajectory. This has become a very important task that must be taken into consideration if we talk, for example, about autonomous vehicles or security systems for collision avoidances.

2.5.1. DeepSORT

One of these approaches often coupled with YOLO is DeepSORT, a deep learning improvement of a famous object tracker released in 2007 called SORT.
SORT

The methodology followed by SORT, takes advantage of the nice performance of another two famous methods for motion estimation and combinational optimization, the Kalman Filter [28] and Hungarian algorithm.

SORT methodology has 4 main steps:
1. Detection;
2. Estimation;
3. Association;
4. Creation and Deletion of Track identities.

The detections can be made by any object detector, the better detections, the greater performance in SORT.

2.5.2. Estimation model. Kalman Filter.

The Kalman Filter is a probabilistic state estimator that fuses information from different sources to give a final estimate for unknown states. The estimate is calculated through both the predicted motion model and measurement model distributions, taking into consideration a certain noise for each one of them.
The estimation model is done by the Kalman filter using the following state vector.

$$X = [u, v, s, r, vu, vv, vs]^T \quad (19)$$

Where u and v are the horizontal and vertical centre coordinates of the target, s is the scale area of the bounding box and r the aspect ratio of that bounding box. The rest of the parameters are their respective velocities.
For a 1-Dimentional state, the predictions are given by.

$$x_k^{pred} = F_k x_{k-1} + B_k u_k \quad (20)$$

$$P_k^{pred} = F_k P_{k-1} F_k^T + Q_k \quad (21)$$

Where

$$F_k = \begin{pmatrix} 1 & \delta t \\ 0 & 1 \end{pmatrix} \quad (22)$$

$$G_k = \begin{pmatrix} \frac{1}{2}\delta t^2 \\ \delta t \end{pmatrix} \quad (23)$$

Where x_k is the state vector, P_k the covariance, u_k a control input noise, and F_k, B_k and Q_k are the transition, control and covariance noise matrix, respectively.

Then, the measurent is used to correct the prediction based on the innovation and some gain. This kalman gain is also used to propagate the state covariance.

$$x_k^{corrected} = x_k^{pred} + K_k * Innovation \quad (24)$$

$$P_k^{corrected} = (I - K_k H_k) P_k^{pred} \quad (25)$$

Where

$$K_k = P_k^{pred} H_k^T \left(H_k P_k^{pred} H_k^T + R_k\right)^{-1} \quad (26)$$

$$Innovation = (y_k - H_k x_k^{pred}) \quad (27)$$

Here, y_k corresponds to the measurement, K_k is the Kalman Gain, H_k is the relation matrix between the predicted state and the measurements in case of having different input units, and R_k is the measurement covariance noise.

2.5.3. Data Association. Hungarian Algorithm.

For the data association, a cost matrix is calculated based on the IOU distance between all the predicted and detected objects. Later, the Hungarian algorithm matches the bounding boxes.
The Hungarian algorithm is an optimization algorithm which finds the minimum values for each not repeated row and column within a given $N\ x\ N$ matrix in assigment problems. The fundamental of this problem is that the optimal assigment for a reduced cost matrix, is also the optimal assigment for the original cost matrix.

2.5.4. Track Identities.

Finally, the new identities are created only if their IOU is greater than a fixed minimum distance and remain for a certain amount of time. Then, if the identity is lost for a T_{Lost} number of frames, it is eliminated.

Fig. 31 shows SORT performance.

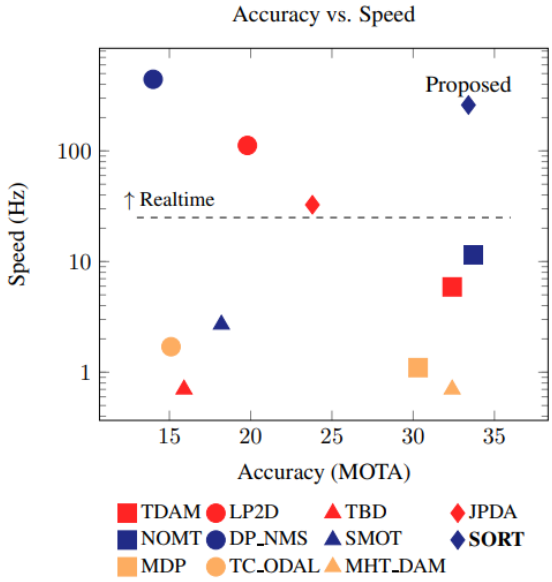


Fig. 31. SORT performance in relation to several baseline trackers. [29]

As shown, SORT had a nice performance in comparison to other object trackers. The problem in SORT was the high number of switches, since it does not perform well under high state uncertainties, for example, during occlusions.

2.5.5. Deep Association metric for SORT

To improve this behavior, in 2017 was introduced a deep association metric for SORT. They included an appearance feature descriptor to consider along with the state estimation in order outperform SORT previous results. There are also some little changes with respect the original SORT, for example, the state vector.

$$y_i = (u, v, \gamma, h, vu, vv, v\gamma, vh) \quad (28)$$

Where γ is the aspect ratio and h the height of the bounding box.
Besides, the squared Mahalanobis distance is used instead of the Hungarian algorithm due to that change.

$$d_{i,j}^{(1)} = (d_j - y_i)^T S_i^{-1} (d_j - y_i) \quad (29)$$

Here, S_i is de covariance matrix and d_j is the bounding box detection.
The problem with the Euclidean distance to perform the data association, is that it does not work well when covariances are involve. Therefore, Manhalanobis distance is a better choice for rescaling the problem, so that these covariances can vanish. In this case, it is used a threshold of 95% the Manhalanobis distance instead of the IOU minimum.

2.5.6. Feature Descriptor.

However, as used to happen in the original SORT, the Manhalanobis distance is not suitable enough under high uncertainties, since the Kalman filter estimates are not so accurate. This is where the appearance descriptor vector takes part in.
Fig. 32 shows the architecture of the obtention of the feature descriptor.

Name	Patch Size/Stride	Output Size
Conv 1	$3 \times 3/1$	$32 \times 128 \times 64$
Conv 2	$3 \times 3/1$	$32 \times 128 \times 64$
Max Pool 3	$3 \times 3/2$	$32 \times 64 \times 32$
Residual 4	$3 \times 3/1$	$32 \times 64 \times 32$
Residual 5	$3 \times 3/1$	$32 \times 64 \times 32$
Residual 6	$3 \times 3/2$	$64 \times 32 \times 16$
Residual 7	$3 \times 3/1$	$64 \times 32 \times 16$
Residual 8	$3 \times 3/2$	$128 \times 16 \times 8$
Residual 9	$3 \times 3/1$	$128 \times 16 \times 8$
Dense 10		128
Batch and ℓ_2 normalization		128

Fig. 32. CNN architecture for the feature descriptor [30]

The feature descriptor is obtained throughout the above architecture, for which the nearest neighbor queries are used to process the relation between the measurement and the existing track, using the smallest cosine distance as the metric and a binary variable for the unlikely associations.

$$d_{i,j}^{(2)} = \min\left\{1 - r_j^T r_k^{(i)} \,\middle|\, r_k^{(i)} \in R_i\right\} \quad (30)$$

Where r_j is the appearance descriptor for the bounding box and $r_k^{(i)}$ the associate appearance descriptor for the i-th track.
Then, both state and appearance metrics are combined using a weighted sum.

$$c_{i,j} = \lambda d_{i,j}^{(1)} + (1 - \lambda) d_{i,j}^{(2)} \quad (31)$$

Nevertheless, the creation and deletion of identities follows the same logic as the original SORT.
Fig. 33 shows some DeepSORT results.

		MOTA ↑	MOTP ↑	MT ↑	ML ↓	ID ↓	FM ↓	FP ↓	FN ↓	Runtime ↑
KDNT [16]*	BATCH	68.2	79.4	41.0%	19.0%	933	1093	11479	45605	0.7 Hz
LMP_p [17]*	BATCH	**71.0**	**80.2**	**46.9%**	21.9%	434	**587**	7880	**44564**	0.5 Hz
MCMOT_HDM [18]	BATCH	62.4	78.3	31.5%	24.2%	1394	1318	9855	57257	35 Hz
NOMTwSDP16 [19]	BATCH	62.2	79.6	32.5%	31.1%	**406**	642	**5119**	63352	3 Hz
EAMTT [20]	**ONLINE**	52.5	78.8	19.0%	34.9%	910	**1321**	**4407**	81223	12 Hz
POI [16]*	**ONLINE**	**66.1**	79.5	**34.0%**	20.8%	805	3093	5061	**55914**	10 Hz
SORT [12]*	**ONLINE**	59.8	**79.6**	25.4%	22.7%	1423	1835	8698	63245	**60 Hz**
Deep SORT (Ours)*	**ONLINE**	61.4	79.1	32.8%	**18.2%**	**781**	2008	12852	56668	40 Hz

Fig. 33. DeepSORT tracking results [30]

It can be seen a reduction in the lost percentage and number of identity switches with respect the original SORT, and an increase in the tracked percentage while maintaining a real-time runtime. Definitely, a more robust and accurate version than SORT, and still faster than other options. Therefore, the choice for the object tracking.

3. Project Development and Results

The images used on this project are recorded with an Asus Xtion Pro Live and the further post processing is done in Python using Google Colaboratory and Visual Studio Code. Here, there is a brief explanation of these working tools.

3.1. Asus Xtion Pro Live

The Asus Xtion Pro Live [31] is an RGB camera with a depth measurement sensor for distances in between 0.8 m and 3.5 m. It is thought to operate indoor and has a field of view of 58° H, 45° V, 70° D (Horizontal, Vertical, Diagonal). It has a power consumption below 2.5 W and uses OpenNI2 as software.
For this project, the image acquisition was done at a resolution of 640x480 and 30 FPS.

3.2. Programming Language. Python

"Python is an interpreted, object-oriented, high-level programming language" [32] with dynamic typing and programming structure. It is popular because of its portability and simple syntax, which facilitates the readability of the code and the learning process. It has one of the largest programming communities, hence, there are a lot of different libraries available for almost every scenario. It has multiple applications in artificial intelligence and computer vision problems.

3.3. Programming environments

Although the aim of this project is to develop a collision avoidance algorithm, first, an object detection and tracking must be done. For that reason, Google Colaboratory is used. However, the rest of the project has been developed using Visual Studio Code instead.
Google Colaboratory is a free Jupyter Notebook based environment for cloud programming released by Google, and enabled for everybody with an internet connection without the need of installing anything. It is given the possibility of using a random GPU or TPU from their servers for deep learning applications. Therefore, it is perfect for the object detection and tracking tasks of the individuals appeared in this project.

3.3.1. Visual Studio Code

Visual Studio Code, on the other hand, is a free code editor from Microsoft. It supports almost any programming language and allows the customization of its interface throughout an extension store. It also includes git connection, a debugging window, and a command promnt. Hence, one of the best choices for app and web developing.

Due to the fact that Google Colaboratory is run on the cloud, it has some limitations with respect other code editors, like for example some OpenCV functions. Thus, it is justified the use of Visual Studio Code during the rest of the project, i.e. camera calibration, image acquisition, error measurement and collision avoidance scripts.

3.4. Proposed Solution

In this section, the proposed solution for the collision avoidance between humans and vehicles will be explained. That said, during the introduction, it was mentioned that this solution was focused on human-human interactions. However, later it will be explained how it could be applied for human-vehicle situations.

First of all, a calibration must be done to get the intrinsic parameters of the camera. It will be done running a calibration script which returns a YAML file with the OpenCV calculations. Then, these parameters will be used to correct the distortion of the image, and calculate the error on the ground projection between the original and the undistort images.

After the camera calibration and error calculations for the ground projections, a set of frames will be recorded as inputs for the object detection and tracking scripts. The model is taken from a public github repository from Mikel Brostrom, it will be later explained in more detail.

Finally, the standing points of the individuals detected corresponding to the tracked bounding boxes will be mapped from the pixel coordinate system to the ground plane. This ground projections, will be used to set the orientation of a safety area according to the trajectory of the detection. Therefore, the collision alerts will be given depending on these safety areas and their trajectories.

3.4.1. Camera Calibration

In computer vision applications, it is important to perform a camera calibration from the operating point of the camera, since the image might have a positive or negative radial distortion, which is related to the field of view of the camera lens, see Fig. 34.

Fig. 34. Type of distortions [33]

This calibration is used to get the intrinsic parameters of the camera, as well as the distortion parameters, and rotation and translation vectors, so that any possible distortion on the image could be corrected beforehand in order to perform accurate measurements or any needed calculation.

This is possible due to the fact that the camera performs a 2D representation of the 3D world, which in fact, is directly related to their intrinsic parameters like the focal length and the location of its optical center. The pinhole camera model (see Fig. 35) mathematically describes this relationship as:

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \quad (32)$$

Where (f_x, f_y) are the focal lengths in pixels, (c_x, c_y) are the coordinates of principal point, and the r_{mn} parameters are part of the rotation-translation matrix, which is related to the scene.

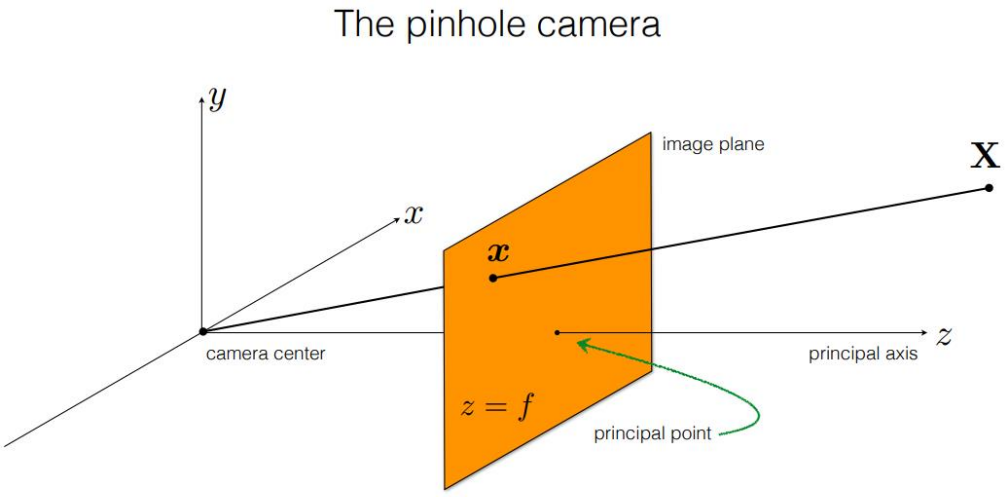


Fig. 35. Pinhole camera model.

3.4.2. Chessboard Method

OpenCV has some functions to calculate these intrinsic and extrinsic parameters throughout the corners of a chessboard and their relationship within a set of images at different positions, see Fig. 36.

Fig. 36. Two examples of the calibration images with the chessboard at different positions

Table 5 shows to get the images for the calibration process.

Table 5. Loop to get the calibration images.

```
# initialize the camera
openni2.initialize("C:\Program Files\OpenNI2\Redist")
dev = openni2.Device.open_any()

color_stream = dev.create_color_stream()
color_stream.set_video_mode(c_api.OniVideoMode(pixelFormat =
c_api.OniPixelFormat.ONI_PIXEL_FORMAT_RGB888, resolutionX = int(640),
                                                resolutionY = int(480), fps = 30))
color_stream.start()

i=0
start = time.time()
while True:

 cframe = color_stream.read_frame()
 cframe_data = cframe.get_buffer_as_uint8()
 cimg = np.ndarray((cframe.height, cframe.width, 3), dtype=np.uint8,
                       buffer=cframe_data)
 cimg = cv.cvtColor(cimg, cv.COLOR_BGR2RGB)

 end = time.time()

 #stores the frame every 5 seconds
 if int(round(end-start,2)) == 5:
  cv.imwrite("calibration_images/"+str("{}".format(i)+"chessboard") +
              ".png",cimg)
  i+=1
  start = end
 cv.imshow("color", cimg)

 #breaks the loop after 10 images
```

```
31. if len(glob.glob('calibration_images/*.png')) == 10:
32.  break
33.
34. if cv.waitKey(10) & 0xFF == ord('q'):
35.  break
36.color_stream.stop()
37.openni2.unload()
38.cv.destroyAllWindows()
```

For this process, ten chessboard images were got in loop, storing a frame every five seconds so that the chessboard could be situated at different positions. To measure the time, the function time is used. In line 23, is set the statement for which, if the difference between the end variable, line 20, and start variable, line 11, is equal to five, it would mean that five seconds were spent.

After that, some preparation for the calibration process is needed. Table 6 shows the code for this preparation.

Table 6. Chessboard preparation.

```
1. chessboardSize = (9,7)
2. frameSize = (640,480)
3.
4. # prepare object points, like (0,0,0), (1,0,0), (2,0,0) ....,(6,5,0)
5. objp = np.zeros((chessboardSize[0] * chessboardSize[1], 3), np.float32)
6. objp[:,:2] = np.mgrid[0:chessboardSize[0],
7.                       0:chessboardSize[1]].T.reshape(-1,2)
8.
9. size_of_chessboard_squares_mm = 10
10.objp = objp * size_of_chessboard_squares_mm
11.# Arrays to store object points and image points from all the images.
12.objpoints = [] # 3d point in real world space
13.imgpoints = [] # 2d points in image plane.
```

The window size and the number of x and y-axis corners of the chessboard should be defined. These corners are also used to prepare an array with the location in millimeters of each one of them. Moreover, two empty lists are defined to store the image and real world corners in case they are found, see lines 12 and 13. Now, in Table 7 is presented the code for the calibration process.

Table 7. Camera calibration.

```
1. # termination criteria
2. criteria = (cv2.TERM_CRITERIA_EPS + cv2.TERM_CRITERIA_MAX_ITER, 30, 0.001)
```

```
3. images = glob.glob('calibration_images/*.png')
4.
5. for i, image in enumerate(images):
6.  img = cv2.imread(image)
7.  gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
8.
9.   # Find the chess board corners
10.  ret, corners = cv2.findChessboardCorners(gray, chessboardSize, None)
11.
12.  # If found, add object points, image points (after refining them)
13.  if ret == True:
14.
15.   objpoints.append(objp)
16.   corners2 = cv2.cornerSubPix(gray, corners, (11,11), (-1,-1), criteria)
17.   imgpoints.append(corners)
18.   # Draw and display the corners
19.   cv2.drawChessboardCorners(img, chessboardSize, corners2, ret)
20.
21.  cv2.imwrite("calibration_images/calibrated/"+str("{}".format(i)+"calib")
22.                 + ".png",img)
23.cv2.destroyAllWindows()
24.# CALIBRATION
25. ret, cameraMatrix, Distortion_Params, Rotation_vec, Translation_vec =
   cv2.calibrateCamera(objpoints, imgpoints, frameSize, None, None)
```

The calibration process works as follows. After the chessboard is prepared, a rough estimation of the corners in the calibration image is done, line 10. If this estimation is done correctly, the corners locations are refined with another function in line 16. Then, both 3D and 2D lists of chessboard corners are stored for each calibration image. These two lists as well as the frame size, are used as inputs for the camera calibration function in line 25.
Fig. 37 shows the calibration points.

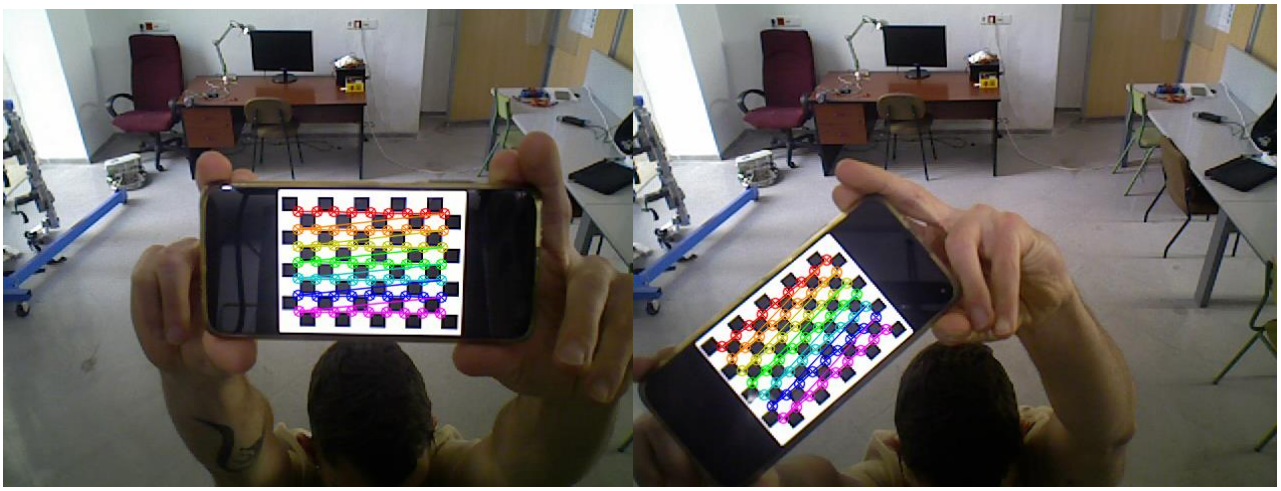


Fig. 37. Corners found within the calibration images.

The functions used to get the chessboard corners were:

cv2.findChessboardCorners(image, patternSize[, corners[, flags]]) [34]**:** It finds the positions of internal corners of the chessboard.

- Image: source chessboard view. It must be an 8-bit grayscale or color image.
- patternSize: number of inner corners per a chessboard row and column.
- corners: output array of detected corners.
- flags: various operation flags.

cv2.cornerSubPix(image, corners, winSize, zeroZone, criteria) [35]**:** It refines the corner locations.

- image: input single-channel, 8-bit or float image.
- corners: initial coordinates of the input corners.
- winSize: half of the side length of the search window.
- zeroZone: half of the size of the dead region in the middle of the search zone over which the summation in the formula below is not done.
- criteria: criteria for termination of the iterative process of corner refinement.

Finally, the optimal camera matrix is obtained and and everything is stored in a YAML file. Table 8 shows the code for this process.

Table 8. Optimal parameters.

```
# GETTING OPTIMAL PARAMETERS
h, w = img.shape[:2]
newCameraMatrix, roi = cv2.getOptimalNewCameraMatrix(cameraMatrix,
                                          Distortion_Params, (w,h), 1, (w,h))

print('Saving parameters !')
cv_file = cv2.FileStorage('cameraIntrnsic.yaml', cv2.FILE_STORAGE_WRITE)
cv_file.write('Camera_Matrix', cameraMatrix)
cv_file.write('newCamera_Matrix', newCameraMatrix)
cv_file.write('Roi',roi)
cv_file.write('Distortion_Params', Distortion_Params)
cv_file.write('Rotation_Vec', np.array(Rotation_vec))
cv_file.write('Translation_Vec', np.array(Translation_vec))
```

The functions used in the calibration process were:

cv2.calibrateCamera(objectPoints, imagePoints, imageSize, cameraMatrix, distCoeffs[, rvecs[, tvecs[, flags[, criteria]]]]) [36]**:** It finds the camera intrinsic and extrinsic parameters from several views of a calibration pattern.

- objectPoints: it is a vector of vectors of calibration pattern points in the calibration pattern coordiante space.
- imagePoints: it is a vector of vectors of the projections of calibrating pattern points.
- imageSize: size of the image used to initialize the camera intrinsic matrix.
- cameraMatrix: input/output 3x3 floating-point camera intrinsic matrix
- distCoeffs: input/output vector of distortion coefficients.
- rvecs: output vector of ration vectors.
- tvecs: output vector of translation vectors.
- flags: different flags.
- criteria: termination criteria for the iterative optimization algorithm.

cv2.getOptimalNewCameraMatrix(cameraMatrix, distCoeffs, imageSize, alpha[, newImgSize[, centerPrincipalPoint]]) [37]**:** It returns the new camera intrinsic matrix based on the free scaling parameter.

- cameraMatrix: input camera intrinsic matrix.
- distCoeffs: input vector of distortion coefficients.
- imageSize: original image size.
- alpha: free scaling parameter between 0 and 1.
- newImgSize: image size after rectification.
- centerPrincipalPoint: optional flag that indicates whether in the new camera intrinsic matrix the principal point should be at the image center or not.

In this case, I got a mean error during the calibration of 0.09005, see Table 9

Calibration Error
0.09005

Table 9. Camera calibration error.

3.4.3. Correcting distortion in images.

Now, since the camera calibration has been performed, the following task is to use the camera parameters to undistort the image, see Table 10.

Table 10. Image undistortion.

```
1. frame = cv2.imread('error_measurement/test0/1color.png')
```

```
2. frame_copy = frame.copy()
3.
4. # Undistort image
5. dst = cv2.undistort(frame_copy, cameraMatrix, Distortion_Params, None,
6.                     newCameraMatrix)
7.
8. # crop the image
9. x, y, w, h = roi
10.dst = dst[y[0]:y[0]+h[0], x[0]:x[0]+w[0]]
11.dst = cv2.resize(dst,(640,480))
```

In line 5, the image is undistorted, and right after, it is cropped to eliminate the resulting black borders. Both images are shown in Fig. 38 and Fig. 39.

The function which performs the undistortion is:

cv2.undistort(src, cameraMatrix, distCoeffs[, dst[, newCameraMatrix]]) [38]**:** It transforms an image to compensate radial and tangential lens distortion.

- src: input image..
- dst: output corrected image.
- cameraMatrix: input camera Matrix.
- distCoeffs: input vector of distortion coefficients.
- newCameraMatrix: camera matrix of the distorted image.

Fig. 38. Original image.

Fig. 39. Undistort image

3.4.4. Ground projection.

Now, to get the actual location of the individuals, it would be necessary to map the image coodinates to another reference system, there are multiple ways to so.

One of those ways, is via homography calculations, which is commonly used to relate 2D images of the same view at different angles. In this case, the idea is to use the homography matrix to project any falling point within the boundaries of a ground layout in the input image, into an upper view of the same area, so that the actual location could be accurately obtained .

Therefore, the new coordinates could be calculated as follows.

$$\begin{bmatrix} x_a \\ y_a \\ z_a \end{bmatrix} = H_{3x3} \cdot \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} \quad (33)$$

$$\begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} x_a \\ y_a \\ z_a \end{bmatrix} \cdot \frac{1}{z_a} \quad (34)$$

Where $(x_1, y_1, 1)$ are the coordinates within the boundaries of the original image and H_{3x3} is the homography matrix.

OpenCV has two functions to do so:

cv2.findHomography(srcPoints, dstPoints[, method[, ransacReprojThreshold[, mask[, maxIters[, confidence]]]]]) [39]**:** It finds a perspective transformation between two planes.

- srcPoints: coordinates of the points in the original plane
- dstPoints: coordinates of the points in the target plane
- method: method used to compute a homography matrix
- ransacReprojThreshold: maximum allowed re-projection error to treat a point pair as an inlier
- mask: optional output mask set by a robust method
- maxIters: the maximum number of RANSAC iterations
- confidence: confidence level

cv2.warpPerspective(src, M, dsize[, dst[, flags[, borderMode[, borderValue]]]]) [40]**:** It transforms the source image using the specified matrix

- src: input image
- M: 3x3 transformation matrix
- dsize: size of the output image
- dst: output image
- flags: combination of interpolation methods (INTER_LINEAR or INTER_NEAREST) and the optional flag WARP_INVERSE_MAP, that sets M as the inverse transformation (dst→src)
- borderMode: pixel extrapolation method.
- borderValue value used in case of a constant border.

3.4.5. Homography matrix functions.

Here, two homography functions are defined. The first, is set for the original image, whereas the second is for the undistort one. See Table 11.

Table 11. Homography calculation functions.

```
1. width,height = (640,480)
2. n,m = (246,320)
3.
4. def homography()
5.  #corners of the ground layout
6.  corners = np.array([[178,105], [465,105], [0,height], [width, height]])
7.  #corners of the new perspective
8.  cornersN = np.array([[0,0],[n,0],[0,m],[n,m]])
9.  corners=np.int64(corners)
10. cornersN=np.int64(cornersN)
```

```
11.
12. h,_=cv2.findHomography(corners,cornersN)
13.
14. return h, corners
15.
16.def homography_dist():
17.
18. corners = np.array([[161,95], [461,95], [0,height], [width, height]])
19. cornersN = np.array([[0,0],[n,0],[0,m],[n,m]])
20. corners=np.int64(corners)
21. cornersN=np.int64(cornersN)
22.
23. h,_=cv2.findHomography(corners,cornersN)
24.
25. return h, corners
```

In relation to the homography calculations, the real plane has a width and height measures of 246x320 cm, these measurements are used to define the window size of the new perspective, which means that the scale is 1:1 for the upper view

3.4.6. Homography error calculations.

The next step, is to measure the error in the location estimation after finding the homography between the upper view of the real plane and the original image taken from the camera point of view. To do so, both original and undistort images are loaded and reframed to the new perspective. Then, a set of 20 points with respect the measurement of the slabs in the real plane is drawn, and the deviation within the x and y-axis is measured.

Table 12 corresponds to this process.

Table 12. Homography error measurement.

```
1. #load test images
2. frame = cv2.imread('error_measurement/test0/1color.png') #distort
3. dst = cv2.imread('error_measurement/test0/0color.png')   #undistort
4. wrap_dist = frame.copy()
5. wrap_undist = dst.copy()
6.
7. #show ground corners
8. h, layout = homography()
9. cv2.circle(frame, layout[0], 5, (0,0,255), 2)
10.cv2.circle(frame, layout[1], 5, (0,255,0), 2)
11.cv2.circle(frame, layout[2], 5, (255,0,255), 2)
12.cv2.circle(frame, layout[3], 5, (255,0,0), 2)
13.
```

```
14. h1, layout2 = homography_dist()
15. cv2.circle(dst, layout2[0], 5, (0,0,255), 2)
16. cv2.circle(dst, layout2[1], 5, (0,255,0), 2)
17. cv2.circle(dst, layout2[2], 5, (255,0,255), 2)
18. cv2.circle(dst, layout2[3], 5, (255,0,0), 2)
19.
20.#ground perspective
21. ground=cv2.warpPerspective(wrap_dist,h,(n,m),flags=cv2.INTER_LINEAR)
22. ground_undist=cv2.warpPerspective(wrap_undist,h1,(n,m),
23.                                   flags=cv2.INTER_LINEAR)
24.#set 20 ground points in the intersection of the slabs
25. ground_grid(ground)
26. ground_grid(ground_undist)
```

In lines 8 and 14, the homography matrixes are obtained and used to reframe the view in lines 21 and 22. Then, the ground points for the error measurement are set in lines 25 and 26, This is done throughout the following function, see Table 13.

Table 13. Ground grid function

```
1. def ground_grid(image):
2.  pt1 = (45, 13) #offset to the first corner
3.  slab  = 56
4.
5.  for row in range(0,4):
6.   for col in range(0,5):
7.    ptx = (pt1[0]+slab *row, pt1[1]+slab *col)
8.    cv2.circle(image,(int(ptx[0]),int(ptx[1])),2,(0,255,0),2)
```

Every slab is a 56 cm square, and the first corner is situated at a distance of 45 cm in the x-axis and 13 cm in the y-axis with respect the origin point, which is the top left corner of the original image. The following Fig. 40 and Fig. 41 correspond to the original image and its ground projection, while Fig. 42 and Fig. 43 correspond to the undistort ones.

Fig. 40. Original image ground corners.

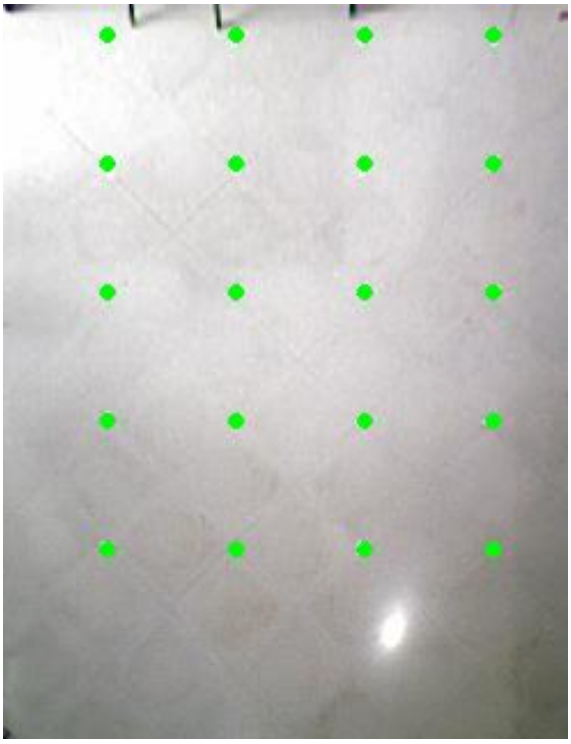


Fig. 41. Upper view of the ground after using the warpPerspective function in the original image

Fig. 42. Undistort image ground corners

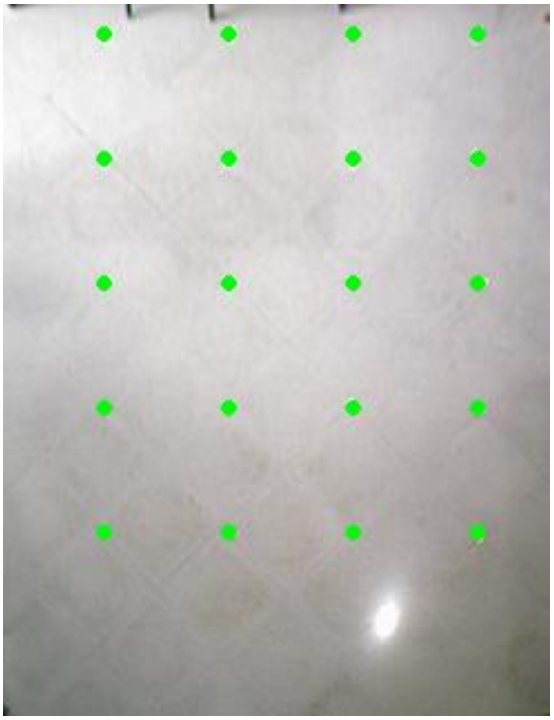


Fig. 43. Upper view of the ground after using the warpPerspective function in the undistort image

For the original image, the following x and y deviations in centimeters were obtained, see Table 14. Likewise, for the undistort image those are shown in Table 15.

Table 14. Original image error

$$X_{dev}^{original} = \begin{bmatrix} -3 & 0 & 0 & 0 \\ -3.5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2.5 \\ 0 & 0 & 2 & 3 \\ 2 & 0 & 4.5 & 5 \end{bmatrix} ; Y_{dev}^{original} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 4 & 4 & 3.5 \\ 0 & 2.5 & 1.5 & 1.5 \\ 0 & 0 & 2.5 & 3 \\ 0 & 0 & 1 & 1.5 \end{bmatrix}$$

Table 15. Undistort image error

$$X_{dev}^{undistort} = \begin{bmatrix} 0 & -2 & -2 & -2 \\ 0 & 0 & 0 & 0 \\ 2.5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 2 & 0 & 1.5 & 0 \end{bmatrix} ; Y_{dev}^{undistort} = \begin{bmatrix} -1 & -2 & -2 & -2.5 \\ -0.5 & 0 & 0 & 0 \\ -1.5 & -2.5 & -1 & -2 \\ 0 & 0 & 0 & -1.5 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

Table 16 shows the error of the ground projections.

Image	**Mean Absolute Error X axis**	**Mean Absolute Error Y axis**
Undistort	0.6	0.875
Original	1.275	1.25

Table 16. Mean absolute error of the ground projection

Since the original image had nearly zero distortion, the mean absolute error in both cases is really small. There are various points with no deviation, while the rest are deviated less than 5 centimeters in one or both axis. However, the maximum deviation reached in the original image is slightly higher. In any case, it is a good accuracy for the location estimation.

3.4.7. Object Detection and Tracking

The object detection is done with YOLOv5, whose model structure is the same as YOLOv4, but entirely built in Pytorch and using a focus CSPDarknet53 as backbone, see Table 17.

Table 17. YOLOv5m model summary

```
==========================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================
Model                                    --                        --
├─Sequential: 1                          --                        --
│    └─Detect: 2                         --                        --
│    │    └─ModuleList: 3-1              --                        343,485
│    └─Conv: 2-1                         [2, 48, 160, 160]         --
│    │    └─Conv2d: 3-2                  [2, 48, 160, 160]         5,184
│    │    └─BatchNorm2d: 3-3             [2, 48, 160, 160]         96
│    │    └─SiLU: 3-4                    [2, 48, 160, 160]         --
│    └─Conv: 2-2                         [2, 96, 80, 80]           --
│    │    └─Conv2d: 3-5                  [2, 96, 80, 80]           41,472
│    │    └─BatchNorm2d: 3-6             [2, 96, 80, 80]           192
│    │    └─SiLU: 3-7                    [2, 96, 80, 80]           --

                                              (...)                                .

│    └─Conv: 2-22                        [2, 384, 10, 10]          --
│    │    └─Conv2d: 3-59                 [2, 384, 10, 10]          1,327,104
│    │    └─BatchNorm2d: 3-60            [2, 384, 10, 10]          768
│    │    └─SiLU: 3-61                   [2, 384, 10, 10]          --
│    └─Concat: 2-23                      [2, 768, 10, 10]          --
│    └─C3: 2-24                          [2, 768, 10, 10]          --
│    │    └─Conv: 3-62                   [2, 384, 10, 10]          295,680
│    │    └─Sequential: 3-63             [2, 384, 10, 10]          2,952,192
│    │    └─Conv: 3-64                   [2, 384, 10, 10]          295,680
│    │    └─Conv: 3-65                   [2, 768, 10, 10]          591,360
│    └─Detect: 2-25                      [2, 6300, 85]             --
==========================================================================
Total params: 21,190,557
Trainable params: 21,190,557
Non-trainable params: 0
Total mult-adds (G): 12.22
==========================================================================
Input size (MB): 2.46
Forward/backward pass size (MB): 371.06
Params size (MB): 84.76
Estimated Total Size (MB): 458.28
==========================================================================
```

Fig. 44 shows a comparison of the different versions in YOLOv5.

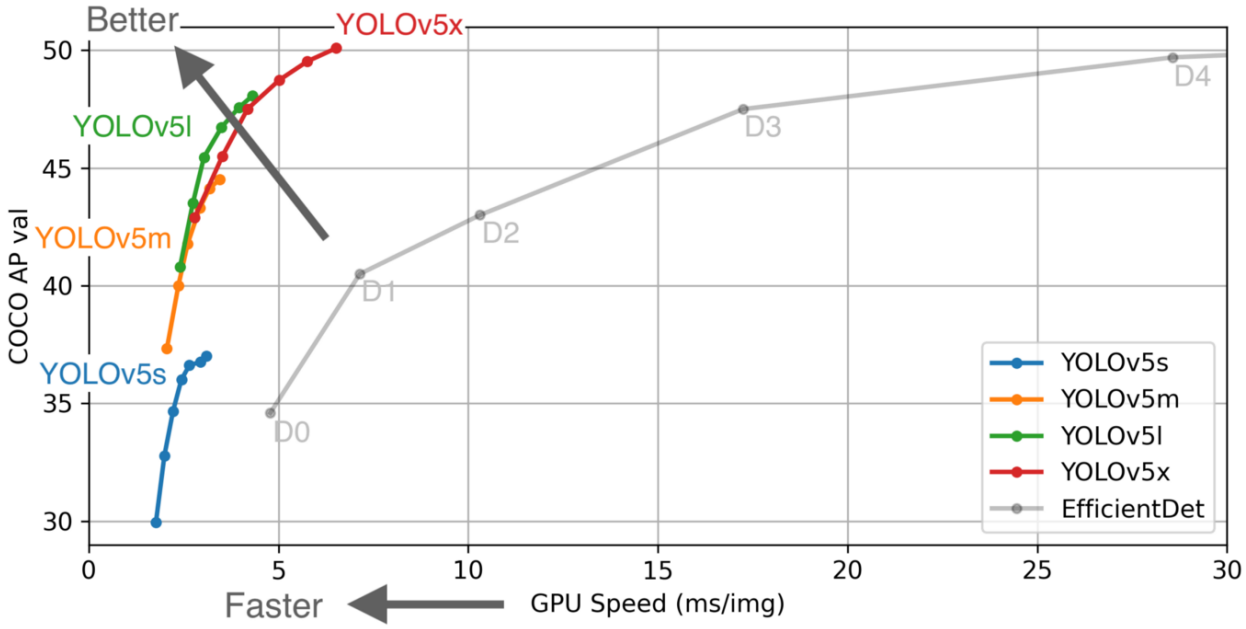


Fig. 44. YOLOv5 variants

More specifically, this project uses the weights from the variant YOLOv5m, which sets a good balance between speed and AP, as can be seen above. Its size is estimated in about 458 MB and has a total 21,190,557 trainable parameters

On the other hand, the object tracking and re-identification is done with DeepSORT in combination with OSNet, see Table 18.

Table 18. OSNet_x0_25 model summary

Layer (type:depth-idx)	Output Shape	Param #
OSNet	--	--
├─ConvLayer: 1-1	[2, 16, 160, 160]	--
│ └─Conv2d: 2-1	[2, 16, 160, 160]	2,352
│ └─BatchNorm2d: 2-2	[2, 16, 160, 160]	32
│ └─ReLU: 2-3	[2, 16, 160, 160]	--
├─MaxPool2d: 1-2	[2, 16, 80, 80]	--
├─Sequential: 1-3	[2, 64, 40, 40]	--
│ └─OSBlock: 2-4	[2, 64, 80, 80]	--
│ │ └─Conv1x1: 3-1	[2, 16, 80, 80]	288
│ │ └─LightConv3x3: 3-2	[2, 16, 80, 80]	432
│ │ └─Sequential: 3-3	[2, 16, 80, 80]	864
│ │ └─Sequential: 3-4	[2, 16, 80, 80]	1,296

```
│    │    └─Sequential: 3-5                  [2, 16, 80, 80]       1,728
│    │    └─ChannelGate: 3-6                 [2, 16, 80, 80]       49
│    │    └─ChannelGate: 3-7                 [2, 16, 80, 80]       (recursive)
│    │    └─ChannelGate: 3-8                 [2, 16, 80, 80]       (recursive)
│    │    └─ChannelGate: 3-9                 [2, 16, 80, 80]       (recursive)
│    │    └─Conv1x1Linear: 3-10              [2, 64, 80, 80]       1,152
│    │    └─Conv1x1Linear: 3-11              [2, 64, 80, 80]       1,152
│    └─OSBlock: 2-5                          [2, 64, 80, 80]       --
│    │    └─Conv1x1: 3-12                    [2, 16, 80, 80]       1,056
│    │    └─LightConv3x3: 3-13               [2, 16, 80, 80]       432
│    │    └─Sequential: 3-14                 [2, 16, 80, 80]       864
│    │    └─Sequential: 3-15                 [2, 16, 80, 80]       1,296
│    │    └─Sequential: 3-16                 [2, 16, 80, 80]       1,728
│    │    └─ChannelGate: 3-17                [2, 16, 80, 80]       49
│    │    └─ChannelGate: 3-18                [2, 16, 80, 80]       (recursive)
│    │    └─ChannelGate: 3-19                [2, 16, 80, 80]       (recursive)
│    │    └─ChannelGate: 3-20                [2, 16, 80, 80]       (recursive)
│    │    └─Conv1x1Linear: 3-21              [2, 64, 80, 80]       1,152

                                             (...)

├─Conv1x1: 1-6                               [2, 128, 20, 20]      --
│    └─Conv2d: 2-12                          [2, 128, 20, 20]      16,384
│    └─BatchNorm2d: 2-13                     [2, 128, 20, 20]      256
│    └─ReLU: 2-14                            [2, 128, 20, 20]      --
├─AdaptiveAvgPool2d: 1-7                     [2, 128, 1, 1]        --
├─Sequential: 1-8                            [2, 512]              --
│    └─Linear: 2-15                          [2, 512]              66,048
│    └─BatchNorm1d: 2-16                     [2, 512]              1,024
│    └─ReLU: 2-17                            [2, 512]              --
==========================================================================
Total params: 201,864
Trainable params: 201,864
Non-trainable params: 0
Total mult-adds (M): 514.20
==========================================================================
Input size (MB): 2.46
Forward/backward pass size (MB): 249.06
Params size (MB): 0.81
Estimated Total Size (MB): 252.32
==========================================================================
```

The OSNet model chosen for the re-identification task is its tiniest version, OSNet_x0_25. In the above table, it can be seen that it has a size of 252 MB and a total of 201.864 trainable parameters. Both detection and tracking models, are already trained in humans with the COCO VOC Dataset.

3.4.8. Google Colaboratory implementation

As mentioned previously, this object detector and tracker is taken from a public repository from Mikel Brostrom, so the first step is to clone the repository and install the dependencies. The following code from Table 19, corresponds to the first cell from Google Colaboratory.

Table 19. Cloning repository.

```
!git clone –recurse-
submodules https://github.com/mikelbrostrom/Yolov5_DeepSort_OSNet.git
# clone repo
%cd Yolov5_DeepSort_OSNet
%pip install -qr requirements.txt  # install dependencies
```

Now, to get the actual position of the detections, it is made the assumption that the middle point of the width and the highest value of the height, corresponds to the standing point of the human in the image, which is the closer location to the feets. Table 20 shows the calculation of this standing point.

Table 20. Standing point calculation.

```
# draw boxes for visualization
if len(outputs[i]) > 0:
 for j, (output) in enumerate(outputs[i]):

  bboxes = output[0:4]
  id = output[4]
  cls = output[5]
  conf = output[6]

  if save_txt:
  # to MOT format
   bbox_left = output[0]
   bbox_top = output[1]
   bbox_w = output[2] - output[0]
   bbox_h = output[3] - output[1]
   bbox_groundx = bbox_w/2 + output[0]
   bbox_groundy = output[3]
   # Write MOT compliant results to file
   with open(txt_path + '.txt', 'a') as f:
    f.write(('%g ' * 10 + '\n') % (frame_idx + 1, id,
              bbox_groundx,bbox_groundy, bbox_w, bbox_h))
```

In the following table, it can be seen a modified fragment from the track.py file from Yolov5_DeepSort_OSNet folder obtained after cloning the repository. Here, the variables from lines 12 and 13 were stored in line 21, line 206 of the original code. However, since the needed values are the ones corresponding to the standing point of the object detected, the variables calcualted in lines 16 and 17 are saved instead.

To run the model, it can be done throughout the track.py file, see Table 21.

Table 21. Running command.

```
1. !python track.py  --yolo_model yolov5m.pt
2.                   --source '/content/drive/MyDrive/TFG/prueba0/*'
3.                   --save-vid
4.                   --save-txt
5.                   --classes 0
```

By default, the weights from YOLOv5s and OSNet_x0_25 are set. Therefore, the YOLO model is changed to YOLOv5m, whereas the DeepSORT model is let by default. Likewise, there are many other default parameters that can be change by typing some commands in the running line. In this case, the detections are limited to the class 0 corresponding to humans, and the commands --save-vid and --save-txt are specified so that the video and text record could be obtained. In relation to the text record, the information is stored in rows per detection, as seen in table 18. The first two positions of each row, corresponding to the frame number and tracking id of the object detected, and the next four, to the standing x and y points, and the width and height lengths of the bounding box respectively.
To end the section, it is important to mention another set of parameters corresponding to the DeepSORT configuration file, see Table 22.

Table 22. DeepSORT configuration file.

```
1. DEEPSORT:
2. MODEL_TYPE: "osnet_x_25"
3. MAX_DIST: 0.2
4. MAX_IOU_DISTANCE: 0.7
5. MAX_AGE: 30
6. N_INIT: 3
7. NN_BUDGET: 100
```

Here, in lines 3, 4 and 5, it is set a maximum distance for the ID matching of 0.2, an IOU threshold of 0.7 and 30 frames of ID storing after losing the detection. Furthermore, the minimum number of matching frames for considering a valid ID is set to 3 and the maximum size of the appearance descriptor is fixed to 100.

3.4.9. Tracking preparation

Finally, the last step is to use these results to set the orientation of the safety zones for the collision alerting.

To do so, the tracking file is loaded, split and saved as a numpy array. Then, this array is split into another two, so that the frame numbers and detection information could be separated, see the following code from Table 23.

Table 23. Detection array preparation 1.

```
1. #import object detection info
2. f = open('detections/test3/tracks/prueba3.txt').read()
3. detections = f.split('\n')[:-1]
4.
5. record = np.zeros((len(detections),6))
6. for i, rec in enumerate(detections):
7.  rec = np.array(rec.split())
8.  record[i:] = rec
9.
10.#prepare the number tracks per frames
11.frames = np.array([np.array(list(j)).astype(int) for i, j in
12.groupby(record[:,0])], dtype=object)
13.max_detects  = max([len(frame) for frame in frames])
14.
15.ground_points = record[:,1:].astype(int)
16.tracks = np.zeros((3,frames.shape[0], max_detects), dtype = object)
```

In line 3, the tracking record is split per row, but it is also needed to split the columns, which are 6. This is done in the for loop from line 6. Then, once this process has finished, the frames, whose number is the same, are clustered together. The objective here, is to separate the detections that were done at each frame. After that, the maximum number of detections made at certain point and the number of frames, are used to define a 3-Dimentional array. This array, containing the ground location of all the human detections at each frame and their corresponding ID.
Table 24 shows the last part of the tracking array preparation.

Table 24. Detection array preparation 2.

```
1. row = 0
2. for n1, frame in enumerate(frames):
3.  ids = list(ground_points[row:row+len(frame),0])
4.  tx = list(ground_points[row:row+len(frame),1])
5.  ty = list(ground_points[row:row+len(frame),2])
6.
7.  tracks[0,n1,:len(frame)] = tx
8.  tracks[1,n1,:len(frame)] = ty
9.  tracks[2,n1,:len(frame)] = ids
```

```
10.
11. if len(frame) < max_detects:
12.  tracks[0,n1,len(frame):] = np.nan
13.  tracks[1,n1,len(frame):] = np.nan
14.  tracks[2,n1,len(frame):] = np.nan
15.  row += len(frame)
```

Depending on the length of each frame, there will be more or less detections. This information is used to separate the IDs, as well as the ground locations, as it can be seen in lines 3,4 and 5 from the above code. However, due to the fact that number of columns is fixed to a maximum value, in case of less number of detections, the last position is always set to a None value, see line 11.

3.4.10. Local plane coordinates calculation.

Now, in Table 25 the real coordinates are obtained from the ground projections.

Table 25. Real coordinates calculation in the main code.

```
1. images = glob.glob('tests/prueba3/*.png')
2. images = natsort.natsorted(images)[6:]
3. for i, image in enumerate(images):
4.
5.  if i <= tracks.shape[1]-1:
6.   img = cv2.imread(image)
7.   ground = np.zeros_like(img)
8.   ground=cv2.warpPerspective(ground, h,(n,m), flags=cv2.INTER_LINEAR)
9.
10.  for person in range(0,len(frames[i])):
11.   if np.isnan(tracks[0,i,person]) != True:
12.
13.    x = tracks[0,i,person]
14.    y = tracks[1,i,person]
15.    id = tracks[2,i,person]
16.
17.    xy_pixels = np.array([x,y],dtype=int)
18.
19.    xyreal = real_coords(xy_pixels,h)
20.    xyreal = xyreal.reshape(1,2).astype(int)[0]
21.
22.    cv2.circle(img, xy_pixels, 2, (0,0,255),2)
```

After the tracking array preparation, the ground location of each detection is got, see lines 10 to 15. This location is converted to the ground projection throughout the homography matrix, as mentioned in section 3.4.4. For that reason, the function in line 19 is defined as follows in Table 26.

Table 26. Real coordinates function definition

```
1. def real_coords(pxl_point,h):
2.  coords = np.array([[pxl_point[0]], [pxl_point[1]], [1]])
3.
4.  real_coords = np.dot(h, coords)
5.  real_coords = real_coords/real_coords[2]
6.  return real_coords[:2]
```

Notice that, as it was shown in formula 34, to get the new positions the coordinates are divided by the z value. Now, these real coordinates can be used to get direction of the human detected.

3.4.11. Safety areas calculation

Table 27 correspond to the obtention of the security areas.

Table 27. Safety area calculation in the main code

```
1.     if id not in tracks_dict.keys():
2.      tracks_dict[id] = xyreal
3.
4.     else:
5.      t1 = tracks_dict[id]
6.      t2 = xyreal
7.      tracks_dict[id] = xyreal
8.
9.      xy_edges,xy_half_edges = limits_safety_zone(t2, t1, ground)
10.     tracks_edges[id] = xy_edges, xy_half_edges
11.     cv2.circle(ground, xyreal, 2, (0,0,255),2)
```

First of all, two locations are needed, for that reason, an if-else conditional is set to check whether or not the algorithm has seen the current identity of the loop. In case of a new identity, its first location is stored, otherwise, both previous and current positions are named as t1 and t2, see lines 5 and 6. Then, a circular sector of 50 degrees is got in the same direction of the movement. This sector is obtained throughout the function defined in line 9, see Table 28.

Table 28. Safety areas function definition.

```
1. def limits_safety_zone(xyreal_t2,xyreal_t1, ground):
2.  xydiag = xyreal_t2 - xyreal_t1
3.
4.  diag = np.sqrt(xydiag[0]**2 + xydiag[1]**2)
5.  x = xydiag[0]
6.  y = xydiag[1]
7.
8.  if diag==0:
```

```
9.    return [],[]
10.
11. theta = math.acos(x/diag)
12. theta = theta*180/math.pi
13.
14. if (x >= 0 and y >= 0) or (x <= 0 and y >= 0): #1 quadrant(4), 2 quadrant(3)
15.  start2 = 335-theta
16.  end2 = start2 + 50
17.
18. else: #3 quadrant(2), #4 quadrant(1)
19.  start2 = theta - 25
20.  end2 = start2 + 50
21.
22. xy_edges = np.zeros((int(int(end2)-int(start2-1)), 2))
23. xy_half_edges = np.zeros_like(xy_edges)
24.
25. for i,angle in enumerate(range(int(start2),int(end2))):
26.  rads = angle*(math.pi/180)
27.
28.  # external edge
29.  xedge = xyreal_t2[0] + 100 *np.cos(rads)
30.  yedge = xyreal_t2[1] - 100 *np.sin(rads)
31.
32.  xy=np.array([int(xedge),int(yedge)])
33.  xy_edges[i,:] = xy
34.
35.  # middle edge
36.  xedge = xyreal_t2[0] + 50*np.cos(rads)
37.  yedge = xyreal_t2[1] - 50*np.sin(rads)
38.
39.  xy_half=np.array([int(xedge),int(yedge)])
40.  xy_half_edges[i,:] = xy_half
41.
42.  cv2.circle(ground, xy,2,(255,255,0),2)
43.  cv2.circle(ground, xy_half,2,(0,0,255),2)
44.
45. return xy_edges, xy_half_edges
```

Here, the distance from t1 to t2 is calculated, but if t1 and t2 are equals, then two empty lists are returned, see line 9. Nevertheless, when these two variables are different, the angle of displacement is obtained as the arccosine of the triangle formed between these two points. This angle is eventually used to get the starting and ending points with respect to that orientation, see lines 11 to 20.

Finally, a set points with a separation of one degree each, are situated at two different radius of distance. These two radius corresponding to the limits of the security area, one being the half of the other. In this case, since the ground area is not so big, this radius is set to one meter long. Notice

that in lines 30 and 37, the radius is substracted from the current y position instead of being added. This is due to the fact, that the y-axis of the window grows downward.

3.4.12. System of Alerts.

Finally, the alerting system is defined in Table 29.

Table 29. Alerting system in the main code.

```
1.      ids = tracks[2,i,:]
2.      for id_list in ids:
3.       if id_list in tracks_edges.keys() and id != id_list:
4.        alert = alerts(tracks_edges, alert, id, id_list)
5.        #actual id of the loop, other ids
6.
7.        if alert[2][id] >= 6:
8.         print('ALERT 2: inminent collision for object {}'.format(id) )
9.         cv2.putText(img, 'ALERT', (50, 50), cv2.FONT_HERSHEY_SIMPLEX, 1,
10.                                          (0, 0, 255), 2, cv2.LINE_AA)
11.       elif alert[1][id] >= 6:
12.        print('ALERT 1: object {}  is on the way to collide
13.                                       alert'.format(id) )
14.        cv2.putText(img, 'ALERT', (50, 50), cv2.FONT_HERSHEY_SIMPLEX, 1,
15.                                           (0, 255, 255), 2, cv2.LINE_AA)
16.       elif alert[0][id] >= 6:
17.        print('ALERT 0: object {} has someone close, take care'.format(id))
18.        cv2.putText(img, 'ALERT', (50, 50), cv2.FONT_HERSHEY_SIMPLEX, 1,
19.                                             (0, 255, 0), 2, cv2.LINE_AA)
```

For the alerting system, there are three different alerts depending on the distance between the limits of the security areas. In lines 7, 11, and 15, it is showed that they are named as ALERT 2, ALERT 1 and ALERT 0 respectively, for which the danger increases with the number of the alert.

The alerts are given throughout the alert function in line 4, see Table 30. It takes as inputs a dictionary with the arrays containing the limits of the safety areas of each individual, the previous alert dictionary, the current id, and an id from the list of identities seen in that instance. The idea is to compare the position of the current safety area with the rest of areas from the map, so that the system could know which identity is in danger with which other. Besides, it is set a minimum number of 6 consecutive alerts, to avoid fake warnings. he alert function definition.

Table 30. Alerting system function definition.

```
1. def alerts(tracks_edges, alert, id, id_list):
2.  alrt_ID0 = alert[0]
3.  alrt_ID1 = alert[1]
4.  alrt_ID2 = alert[2]
```

```
5.
6.  id_xyedges, id_xy_halfedges = tracks_edges[id]
7.  id_list_xyedges, id_list_xy_halfedges = tracks_edges[id_list]
8.
9.  if len(id_xyedges) == len(id_list_xyedges) and len(id_xyedges) != 0:
10.
11.   distance_far_edges = id_xyedges - id_list_xyedges
12.   distance_farclose_edges_1 = id_xyedges - id_list_xy_halfedges
13.   distance_farclose_edges_2 = id_xy_halfedges - id_list_xyedges
14.
15.   euclid_far_distance = np.sqrt(distance_far_edges[:,0]**2 +
16.                                 distance_far_edges[:,1]**2)
17.   euclid_farclose_distance_1 = np.sqrt(distance_farclose_edges_1[:,0]**2 +
18.                                        distance_farclose_edges_1[:,1]**2)
19.   euclid_farclose_distance_2 = np.sqrt(distance_farclose_edges_2[:,0]**2 +
20.                                        distance_farclose_edges_2[:,1]**2)
21.
22.   dist_mean_far = np.mean(euclid_far_distance)
23.   dist_mean_farclose_1 = np.mean(euclid_farclose_distance_1)
24.   dist_mean_farclose_2 = np.mean(euclid_farclose_distance_2)
25.
26.   if dist_mean_farclose_2 < 50 or dist_mean_farclose_1 <50 :
27.
28.    #ALERTS 2
29.    if id not in alrt_ID2.keys():
30.     alrt_ID2[id] = 1
31.     alert[2] = alrt_ID2
32.    else:
33.     n = alrt_ID2[id]
34.     n += 1
35.     alrt_ID2[id] += n
36.     alert[2] = alrt_ID2
37.
38.   elif dist_mean_far < 90:
39.
40.   #ALERTS 1
41.    if id not in alrt_ID1.keys():
42.     alrt_ID1[id] = 1
43.     alert[1] = alrt_ID1
44.
45.    else:
46.     n = alrt_ID1[id]
47.     n += 1
48.     alrt_ID1[id] += n
49.     alert[1] = alrt_ID1
50.
51.   elif dist_mean_far < 120:
52.   #ALERTS 0
53.    if id not in alrt_ID0.keys():
54.     alrt_ID0[id] = 1
55.     alert[0] = alrt_ID0
```

```
56.
57.    else:
58.     n = alrt_ID0[id]
59.     n += 1
60.     alrt_ID0[id] += n
61.     alert[0] = alrt_ID0
62.   else:
63.    alrt_ID0[id] = 1
64.    alrt_ID1[id] = 1
65.    alrt_ID2[id] = 1
66.
67.    alert[0] = alrt_ID0
68.    alert[1] = alrt_ID1
69.    alert[2] = alrt_ID2
70.
71. else:
72.   alrt_ID0[id] = 1
73.   alrt_ID1[id] = 1
74.   alrt_ID2[id] = 1
75.   alert[0] = alrt_ID0
76.   alert[1] = alrt_ID1
77.   alert[2] = alrt_ID2
78.
79. return alert
```

Here, the Euclidean distances between the external, and between the external and internal limits of the security areas are calculated. After that, the mean of each set of distances is obtained and the results are used to get a rough estimation of the overall distance, see lines 22, 23 and 24. Considering the distances between the external and internal boundaries as the most important, if any of those values is less than 50 cm, it would mean that the hazard of collision is higher than any other. Likewise, if the distance is not that close, but the external limits are less than 90 cm, then, a medium alert in the scale of danger is given, whereas if the distance is in between 90 and 120, the alert is just a suggestion of velocity moderation, because another human is close.

On the other hand, the count in the number of consecutive alerts is done individually at each level of danger. If the dictionary of a certain alert for the given current id has saved that id previously, its value is incremented, otherwise is set to one. Moreover, the count of the three types of alerts is reset for the given id every time that there is not a hazard, what forces a minimum continuity to avoid fake warnings, see lines 72 to 77. These three dictionaries are saved within another dictionary named as alert, which is the output of the function. Now that this function is clearer, it is better understood the alerting system from Table 30.

3.5. Experimental Investigation.

To evaluate the collision avoidance system, four tests for which the distortion has been corrected have been recorded. In these tests, the trajectories are within the boundaries of the area defined previously, i.e. a rectangle of 246 cm width and 320 cm height. The first two tests, correspond to a

single person walk and there are a total number of 465 and 617 frames, whereas for the remaining two, there are two people at the same time and a total 707 and 419 frames respectively.

The following figures, Fig. 45 and Fig. 46, are examples of the image acquisition process.

Fig. 45. Frames from test 1, on the left, and test 2, on the right.

Fig. 46. Frames from test 3, on the left, and test 4, on the right.

As mentioned previously, the detections are done in Google Colaboratory with the weights from the YOLOv5m model and OSNet_x0_25. Likewise, the DeepSORT configuration file is set as it was showed in table 20.

Some examples of human detections are presented in Fig. 47 and Fig. 48, followed by an extract of the 20 firsts detections made at each test in Tables 31, 32, 33 and 34.

Fig. 47. Detection examples from test 1, on the left, and test 2, on the right.

Fig. 48. Detection examples from test 3, on the left, and test 4, on the right.

Table 31. Test 1. Detections from the 20 firsts frames

1. 3 1 388 475 260 391
2. 4 1 384 474 256 400
3. 5 1 380 476 250 408
4. 6 1 376.5 477 233 415
5. 7 1 374 478 220 424
6. 8 1 371.5 478 205 437
7. 9 1 367.5 479 201 448
8. 10 1 363.5 477 199 451
9. 11 1 360.5 476 197 455
10. 12 1 357 464 200 455
11. 13 1 359 451 194 449
12. 14 1 361 448 194 448
13. 15 1 363 446 192 446
14. 16 1 368.5 445 191 445
15. 17 1 375 445 190 445
16. 18 1 385.5 444 189 444
17. 19 1 394.5 440 187 440
18. 20 1 401.5 429 185 429

Table 32. Test 2. Detections from the 20 first frames

1. 1 281.5 478 349 207
2. 4 1 290 478 336 221
3. 5 1 300 478 336 234
4. 6 1 307 478 334 243
5. 7 1 313 479 332 251
6. 8 1 320.5 478 325 260
7. 9 1 330 478 320 268
8. 10 1 340.5 478 317 276
9. 11 1 355 479 316 282
10. 12 1 365.5 479 313 284
11. 13 1 382 479 314 284
12. 14 1 397 479 310 286
13. 15 1 404 479 310 288
14. 16 1 406.5 479 309 289
15. 17 1 409.5 479 299 294
16. 18 1 409 479 298 300
17. 19 1 406 479 290 310
18. 20 1 398.5 479 245 343

Table 33. Test 3. Detections from the 20 first frames.

1. 3 1 167.5 478 311 302
2. 3 2 587.5 356 103 355
3. 4 1 166.5 478 311 306
4. 4 2 583 351 112 350
5. 5 1 166 479 312 308
6. 5 2 578.5 344 121 343
7. 6 1 166 479 308 307
8. 6 2 575.5 340 127 340
9. 7 1 164.5 479 301 307
10. 7 2 572.5 338 133 338
11. 8 1 164.5 479 293 306
12. 8 2 570 336 138 335
13. 9 1 164 479 280 308
14. 9 2 568 335 142 333
15. 10 1 162 479 268 312
16. 10 2 567.5 333 143 331
17. 11 1 161.5 479 253 319
18. 11 2 567.5 332 141 329
19. 12 1 160.5 479 247 327
20. 12 2 568 332 140 329
21. 13 1 158.5 478 231 336
22. 13 2 568.5 331 139 328
23. 14 1 154.5 479 207 354
24. 14 2 568.5 332 141 328
25. 15 1 152 478 204 363
26. 15 2 568 332 142 326
27. 16 1 150 478 186 375
28. 16 2 568.5 333 141 324
29. 17 1 148 478 184 388
30. 17 2 568.5 334 139 328
31. 18 1 146 479 190 396
32. 18 2 568.5 335 141 333
33. 19 1 145.5 479 267 421
34. 19 2 568 335 142 329
35. 20 1 139 479 270 432
36. 20 2 568.5 335 139 332

Table 34. Test 4. Detections from the 20 first frames.

1. 1 136 479 264 336
2. 2 540 308 144 307
3. 4 1 127.5 479 247 350
4. 4 2 544.5 304 151 303
5. 5 1 116.5 479 227 364
6. 5 2 547 303 154 301
7. 6 1 108 479 216 372
8. 6 2 548.5 302 157 300
9. 7 1 95.5 479 187 381
10. 7 2 548.5 300 157 298
11. 8 1 96 479 192 391
12. 8 2 548 298 154 297
13. 9 1 93.5 479 187 400
14. 9 2 545.5 297 147 296
15. 10 1 95 479 190 406
16. 10 2 543.5 298 145 297
17. 11 1 97 479 194 411
18. 11 2 542.5 298 145 298
19. 12 1 100.5 478 201 419
20. 12 2 542 298 144 298
21. 13 1 102.5 478 205 428
22. 13 2 542 297 142 297
23. 14 1 103.5 479 207 434
24. 14 2 541 298 140 298
25. 15 1 110.5 479 221 436
26. 15 2 541.5 299 143 299
27. 16 1 117 479 234 438
28. 16 2 542.5 301 147 301
29. 17 1 120.5 479 241 439
30. 17 2 543 303 146 303
31. 18 1 123 479 246 441
32. 18 2 543.5 304 147 304
33. 19 1 125 478 250 450
34. 19 2 545 304 152 304
35. 20 1 126 478 252 454
36. 20 2 546.5 305 153 305

Some information can be extracted from the detections made. In all the cases, the detection confidence is above 80%, even if the most distant individuals cannot be fully seen.

On the other hand, the tracking identities of test 3 and 4, remained the same during the first 20 frames. However, DeepSORT eventually ended switching these identities due to some long occlusions occurred during both tests. In test 3, these identities ended as human 3 and human 8, while in test 4, the identities ended as human 3 and human 5 respectively. Nevertheless, this was not a problem, since after each switch, that identity remained enough time.

With respect to the visualization of the standing points and safety areas, as it was mentioned previously, there are two radious of danger, one being the half of the other, where the longest radius is one-meter long. Here, there are some examples from each test, see Fig. 49, Fig. 50, and Fig. 51.

Fig. 49. Test 1 localization.

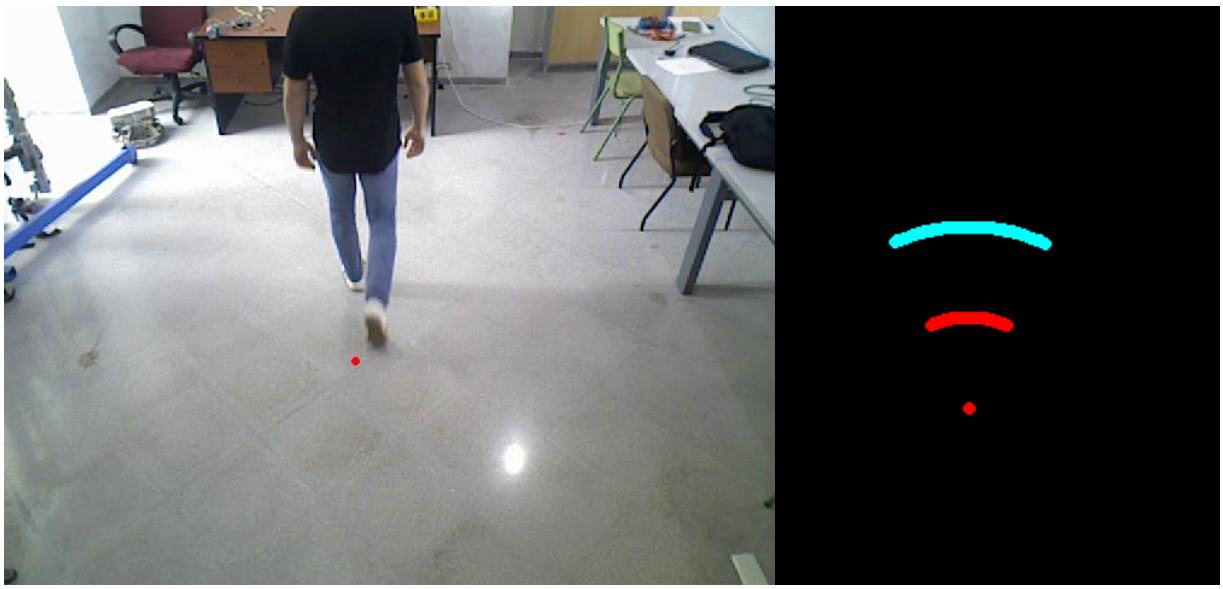


Fig. 50. Test 2 localization.

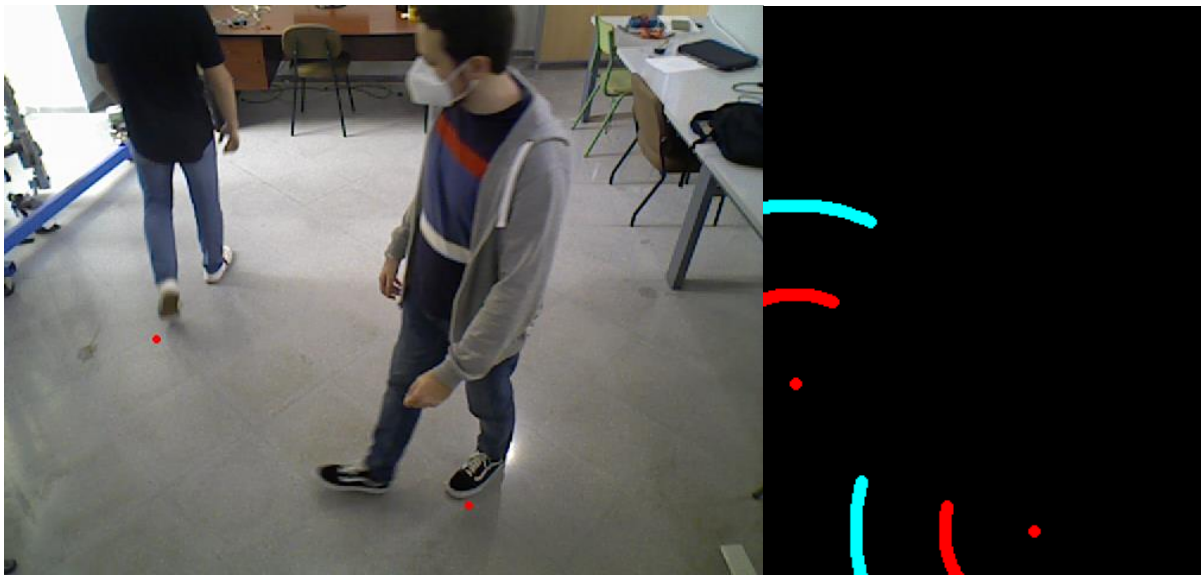
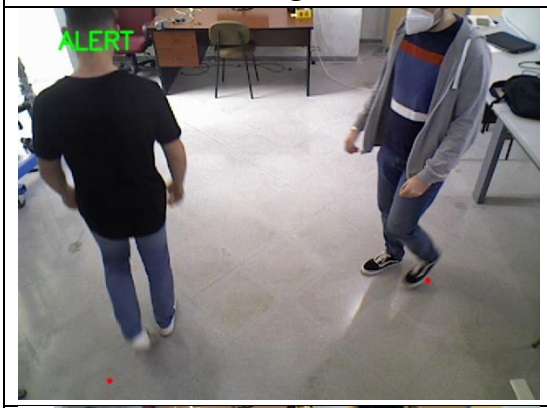


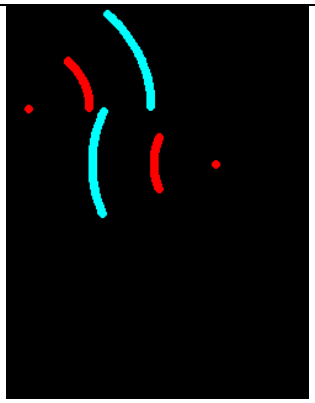
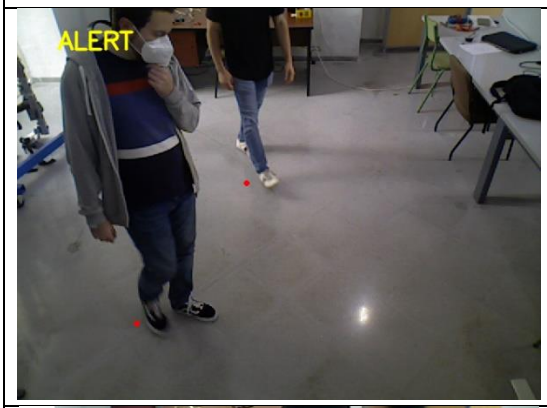
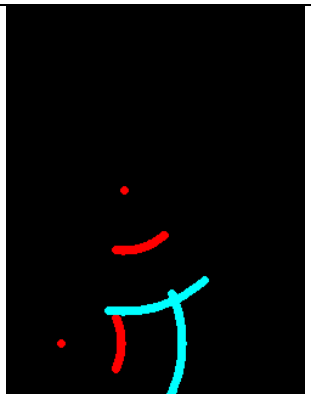
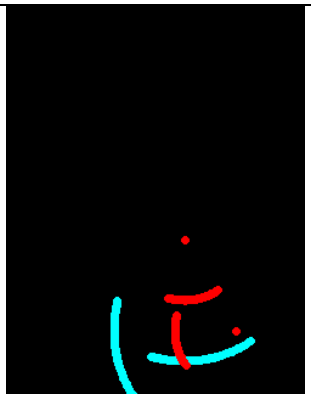
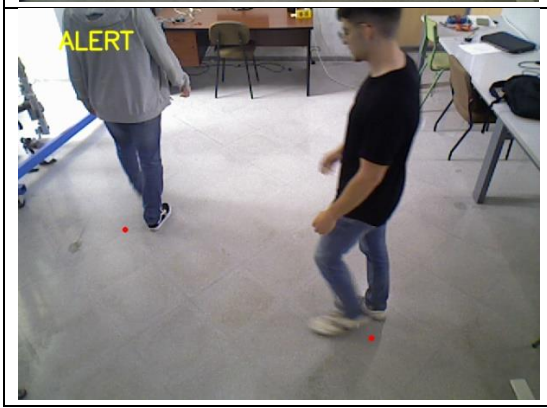
Fig. 51. Test 3 localization.

Fig. 52. Test 4 localization.

Finally, three types of warning are given depending on the distance and trajectory of the individuals, as it was explained in section 3.4.12. In Tables 35 and 36, the results obtained for the dangerous situations in both test 3 and 4 are shown, where the type-0 is drawn in green letters, type-1 in yellow and type-2 in red.

Table 35. Warnings from test 3

Image	Ground	Type and Frame
		Type-0. Frame 33.
		Type-0. Frame 118.

		Type-1. Frame 231.
		Type-1. Frame 237.
		Type-2. Frame 478.
		Type-1. Frame 533.

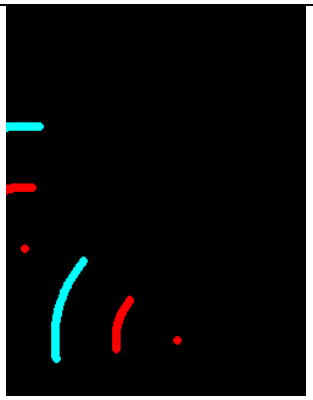
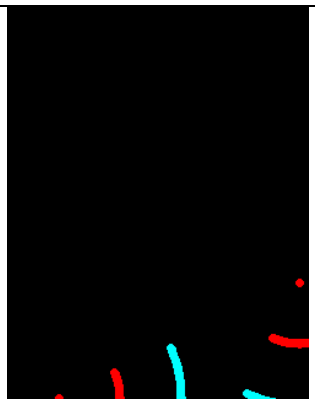
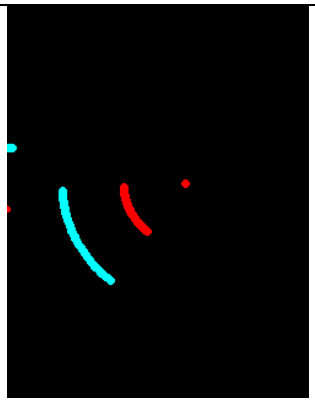
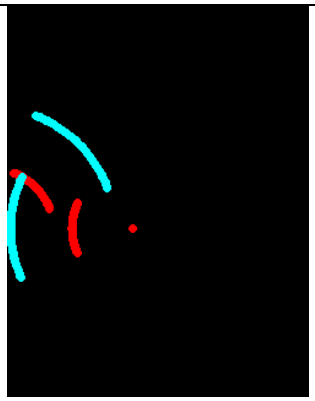
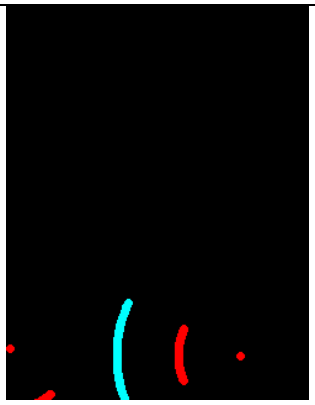
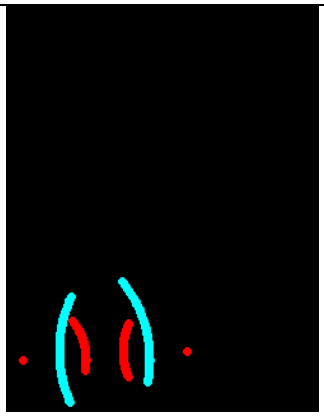
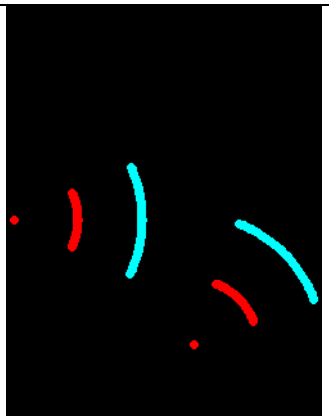
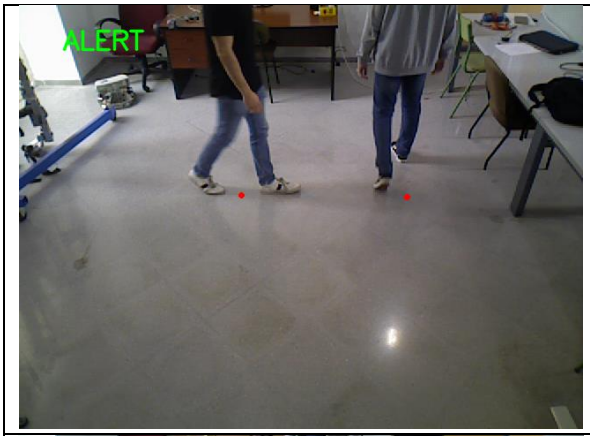
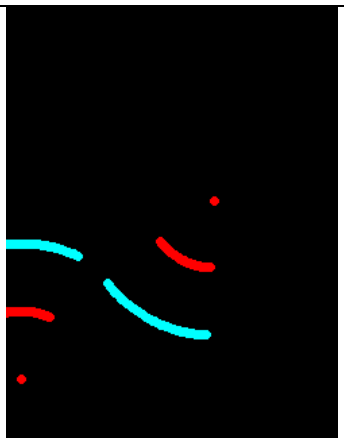
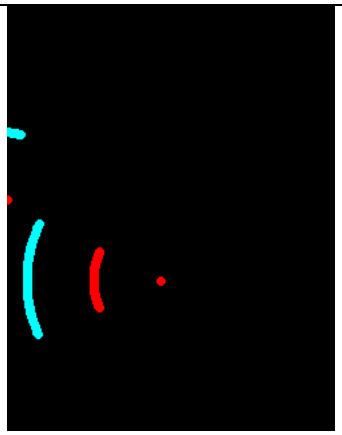
		Type-2. Frame 538.

Table 36. Warnings from test 4

		Type-0. Frame 13.
		Type-0. Frame 117.
		Type-2. Frame 124.
		Type-0. Frame 197.

		Type-2. Frame 206.
		Type-1. Frame 241.
		Type-1. Frame 249.
		Type-1 Frame 261.

		Type-0 Frame 268.
		Type-0 Frame 292.
		Type-2 Frame 310.
		Type-1 Frame 367.

		Type-0 Frame 384.

There are a total of 7 situations in which the algorithm returned an alert on test 3, and a total of 13 on test 4. In test 3, there is just one error, which is in frame 118. Here, there is a false positive from a type-0 alert. Likewise, the same error occurred in frames 241 and 292 from test 4, for which a type-1 and type-0 alerts were given respectively.

On the other hand, the situation in frame 268 from test 4 was set as a type-0 alert, when it was a type-2 situation. Something similar can be said from the frame 367, were a type-1 alert was given for a type-0 situation.

Therefore, there are a total of 20 alerts, for which 3 were not needed, and 2 returned the wrong type of alert. From these errors, the most important is the error on frame 267, which is classifying the situation as less dangerous than it is.

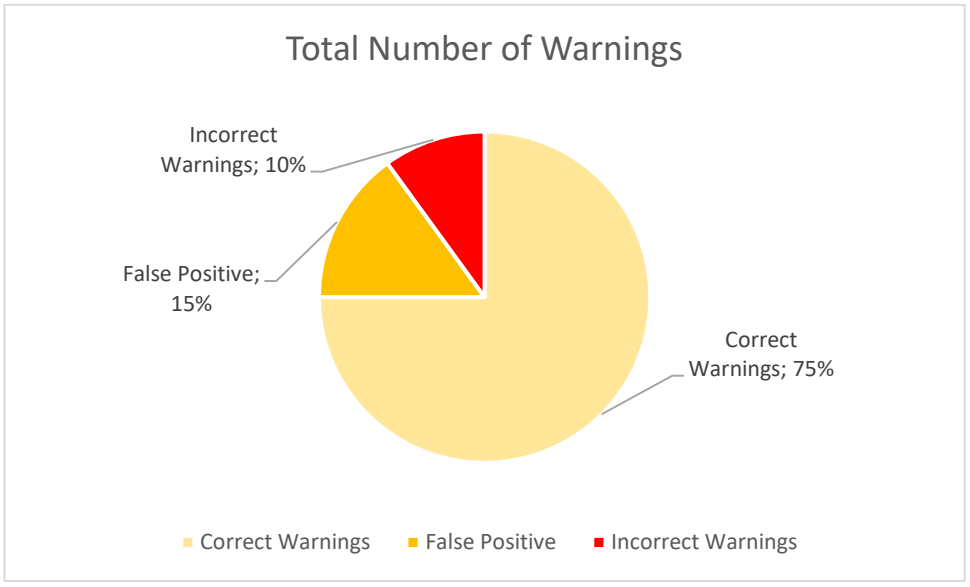


Fig. 53. Pie chart of warnings.

On the other hand, the safety areas sometimes are slightly shifted to a different sight, but in general terms, it has a good performance.

These results can be completely extrapolable for human-vehicles and vehicles-vehicles situations, if the detection model is trained in forklifts. Likewise, the security areas can be easily extended considering bigger angles and longer radius. Therefore, as a future work, I would like to improve the performance on the orientation of the security areas, as well as testing the algorithm in real-time, and train the detection model to be able of recognizing these type of vehicles, which in conclusion, is translated into a more robust collision avoidance algorithm.

Conclusions

1. The aim of the project is achieved throughout two test, on which two people have walked around a predefined area simulating possible collision situations. Here, the algorithm, has been able to effectively classify most of them with the correct type of alert, depending on the distance between the individuals appeared.
2. After reading and comparing the performances in terms of speed and accuracy of several object detection models, the usage of YOLO instead of any other was a key factor. Even though it was not test in real time, YOLOv5 is extremely fast and allow a real-time implementation, which is crucial for this problematic.
3. The researches done in chapters 3, 4 and 5, were essential to understand the basis of a CNN, as well as the fundamentals of an object detector and object tracker respectively.
4. Due to the hardware limitations, Google Colaboratory helped to obtain the detection and tracking files needed for the development of the project. Therefore, it was another key factor in this project.
5. The collision avoidance algorithm has demonstrated to perform accurately, correctly returning a warning for all the 17 situations with a real hazard of collision, although one of those was classified as less dangerous.
6. According to the goal of the project, these results can be use for future work safety developments in the manufacturing industry.

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Appendices

Appendix 1. Tracking file – Test 1.

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Appendix 2. Tracking file – Test 2.

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Appendix 3. Tracking file – Test 3.

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Appendix 4. Tracking file – Test 4.

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