Imperial College London

Using Deep Learning to Identify Cyclists Risk Factors in London

MRes Biomedical Research (Data Science)

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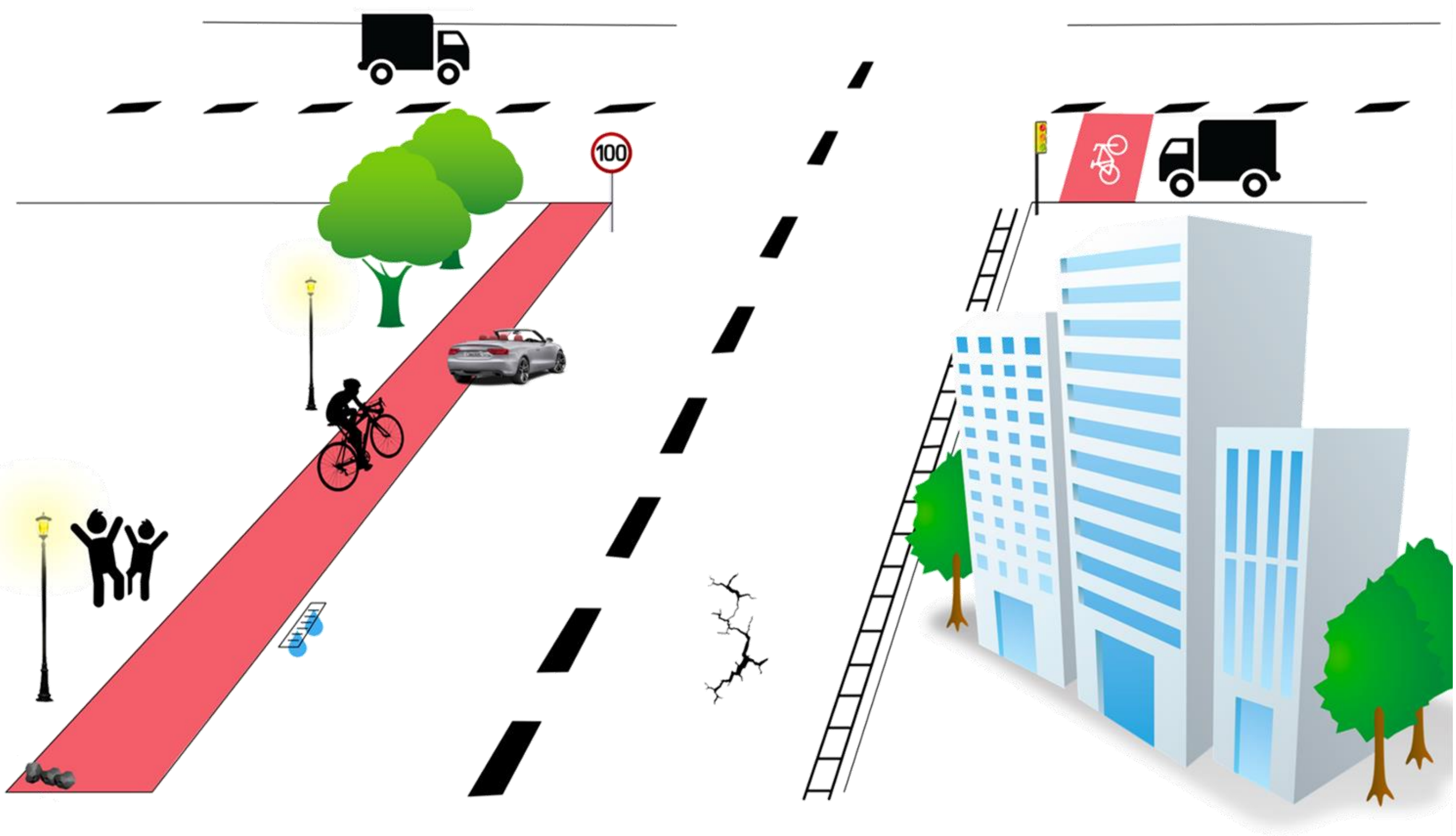

I certify that this thesis, and the research to which it refers, are the product of my own work, conducted during the current year of the MRes in Biomedical Research at Imperial College London. Any ideas or quotations from the work of other people, published or otherwise, or from my own previous work are fully acknowledged in accordance with the standard referencing practices of the discipline.

Luís Rita

Abstract

Cycling encompasses many societal benefits. It influences community safety, economy, environment, equity and health. The number of cyclists on the roads is highly influenced by their perception of safety. To determine road safety, it is fundamental to have a clear metric, so that risk factors can be ranked. Google Street View (GSV) imagery is a cost-effective approach to analyse city environments. Due to the high number of images needed to extract accurate results, models to automatically detect objects or structures are used.

The aim of this project was to use object detection and image segmentation models to extract cyclists' road risk factors from GSV images of London. This involved compiling road safety indicators and risk factors. Analysing GSV dataset, before using two state-of-the-art tools, YOLOv5 and PSPNet101, to detect objects and segment images, respectively, and further analysing results distributions. Determining the limitations of YOLOv5, PSPNet101 and suggesting ways of making cyclist's safety assessment more accurate.

Approximately 2 million objects were identified, and 200 billion pixels labelled in the half-million images available in the imagery dataset. On average, there were 108 images per LSOA. Using YOLOv5, the distribution of the following risk factors was (un)directly identified at an LSOA level: high vehicle speed, tram/train rails, truck circulation, parked cars and pedestrian presence. Using PSPNet101, road width and streetlight risk factors were retrieved. It was found a statistically significant negative correlation between buses x cars, cyclists x cars and people x cars (strongest). And positive correlations bicycles x people (strongest) and bus x people. Long-tail distributions on the number of heavy-vehicles was observed. YOLOv5 biggest limitation was the lack of additional road categories in the pre-trained model. In the case of PSPNet101, structure occlusion contributed for structure distortion. All the results and implementations were made available in the project's repository.

Future developments include increasing the availability and resolution of GSV images. Training YOLOv5 and PSPNet101 with datasets containing a higher number of categories. Define a safety metric to weight proportionally to their importance detected objects and segmented structures.

Deep Learning | Cycling | Risk Factors | London

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1. Introduction

This section starts with an overview on the most important societal benefits associated to cycling. Then, road safety indicators are introduced so that a clear ranking on the most relevant cyclist's risk factors could be established. Available datasets with relevant objects or segmented images in the context of this project are presented. One object detection and another image segmentation model are described.

1.1. Cycling Benefits

Cycling comprehends multiple benefits to society. They can be categorized in 5 main domains: Safety, Economy, Environment, Equity and Health [1].

The main cause of death in the USA in youngers was traffic accidents. Accounting for 41% of the total number of deaths in the age group 15 to 24 [CDC]. In the European Union, in the past 10 years, deaths among cyclists remained constant, while for car drivers and passengers had decreased 24%. Among pedestrians fell by 19% (Figure 1). UK was one of the only 3 EU nations which fatality rate among pedestrians increased, 1.3% a year. On average, it fell 2.6% in EU per year. For cyclists, in the UK, the number of fatalities decreased 1.3%, with the 13th-best average annual drop. Given that 99% of the pedestrians killed were struck by motor vehicles and 1% by bikes, it is evident the necessity of promoting cyclists' safety and increase their number in the streets. In parallel, this promotes safety in numbers: cyclists are safer if their number increases. The awareness drivers develop by contacting more frequently with cyclists is the root cause.

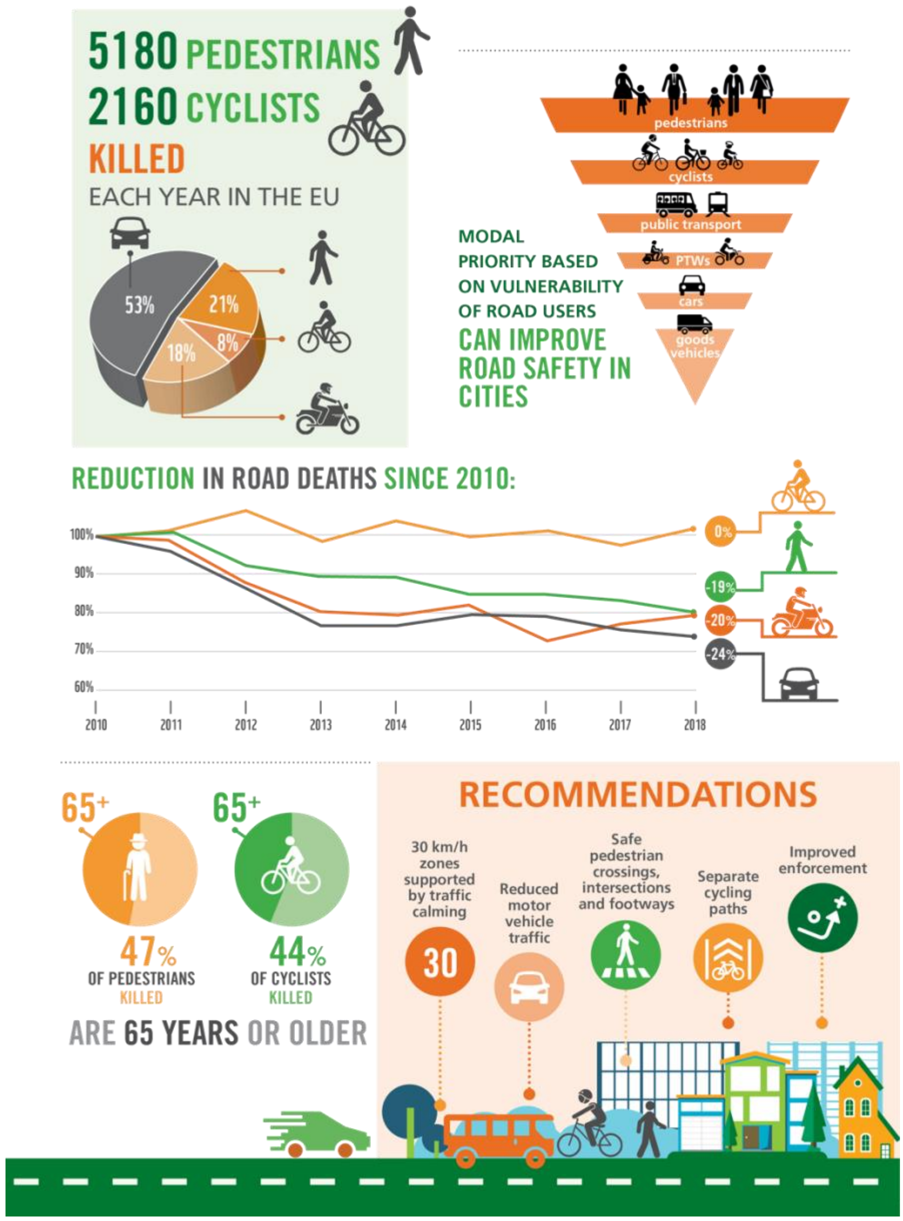


Figure 1 Road safety in EU countries. Accounting for the fact pedestrians and cyclists are the 2 most vulnerable elements on the roads (upper right corner), new safety measures should focus on them. [2]

Many economic benefits for individuals, companies and communities are known from promoting walking and cycling as alternative ways of transportation (Figure 2). According to 2015 Urban Mobility Scorecard, the cost of congestion for the US in 2014 was 160 billion dollars. For an individual was estimated to be 960 dollars each year. These values account for time and fuel expenses. While the cost of having a car in the USA in 2018 was calculated to be 8849 dollars, for a bike was 308 dollars and walking was considered free. 2018 Benchmarking Report adds that bike tourism has a positive economic impact in multiple regions worldwide. Protected Bike Lanes Mean Business Report shows the positive impact cycling may have in business.

It was found that workers doing their commutes cycling, on average, spent more time and travelled more often to their companies, then car drivers. Moreover, in a 2011 study, the Political Economy Research Institute found that 11.41 jobs were on average created when investing 1 million pounds in bicycle-only projects, comparing to 7.75 jobs while investing the same amount in road-only projects.

Figure 2 Sedentarism increases the chance of developing chronic diseases (top). There is a high burden associated with the lack of physical activity (bottom). Adapted from [3].

Reducing the dependency on non-renewable sources, it is also one of the positive aspects of cycling. It was estimated by the United States Environmental Protection Agency that the transportation sector was responsible by the largest share of greenhouse gas emissions – 28% (in the USA). From those, passenger vehicles and light-duty trucks account for most of the overall transport sector – 60%. Moreover, it is also known that structures such as roads and parking lots increase significantly the probability of urban flooding, stormwater runoff and urban heat island effect (due to the lack of shadows and exposed land in the cities, they often register higher temperatures than the surroundings, resultant from the low levels of air humidity). Promoting cycling will reduce the need of the previous infrastructures and mitigate some of the consequences.

Promoting cycling among the population of a country promotes equity. Due to the high cost of car ownership, when a city prioritizes road infrastructure for these vehicles, it puts in higher risk low-income families that cannot afford it. This is particularly important in low-income communities where a brief from Bridging the Gap estimated that only 50% of the roads have sidewalks, comparing to 90% in high-income homologous. This results in higher threat for pedestrians and cyclists. The New Majority: Pedalling Towards Equity reported that 26% of people of colour would like to cycle but do not do it due to safety concerns, comparing to 19% in white respondents.

Physical activity, such as cycling and walking, has numerous benefits to physical and mental health (Figure 3). Centre for Disease Control and Prevention reported that 1 in 10 premature deaths, 1 in 8 breast cancers, 1 in 8 cases of colorectal cancer, 1 in 12 people suffering from diabetes and 1 in 15 cases of heart disease could be prevented if citizens became more active. It can also reduce the risk for coronary heart disease, stroke and many respiratory chronic diseases, which are intimately related to air quality [3]. 2018 State of the Air report states over 133.9 million Americans live in counties with unhealthy levels of ozone and/or particle pollution. A factor that is highly influenced by the transportation patterns inside a community. Vehicles are one of the main contributors accordingly to the United States Environmental Protection Agency. Due to all these benefits, it becomes evident the importance of promoting a less sedentary lifestyle among the population.

Figure 3 Impact of physical activity in the risk of premature death (top). Benefits of maintaining an active lifestyle in different stages of life (middle). In a higher scale, communities also benefit from having physically active citizens (bottom). [3]

For this reason, by promoting cyclists' safety, the whole society will benefit. Cyclists and pedestrians will be safer. Drivers will reduce their commute times and translate that into society gains such as lower levels of pollution and economic losses.

1.2. Road Safety Indicators

Road safety indicators are essential for policy making. According to the European Road Safety Charter, they allow us to assess the current situation of the roads, observe the impact on accident rates after an intervention, monitor its progress over time and predict further evolutions.

To be useful, road safety indicators should comply with several criteria:

1. Relate to some aspect of road safety, such as the causes or consequences of a road accident.
2. Be Measurable in a reliable way.
3. Be Monitorable over time.
4. Allow road safety engineers or public health experts to set targets.
5. Be Useful for establishing comparisons and benchmarking different safety performances.

There are 6 dimensions common to all indicators: geographical scope, time span, numerical format, representation/visualization, reliability, accuracy, representativeness and a specific "level" of road safety. The first encompasses where the measurement takes place: organisation, city, region, country, Europe or global. The second relates to the time frame comprehensive to the analysis: day, week, month, quarter, year, decade or longer. The units of the measure are represented by the third feature. They can be a proportion, a percentage or some other well-defined ratio. Representation described the way in which data is presented, e.g. in the form of a map, graph or table. Reliability, accuracy and representativeness are linked to the design and implementation of the measurement system. Finally, the "level" of the indicator differs on whether it considers one of the following: impact of the crashes, post-crash response, crash outcomes, crash causes and predictors, road safety policy and measures, or safety culture and safety systems.

Crash outcomes, including indicators such as mortality, severely/slightly injured and accident rates, were the ones considered while selecting the risk factors presented in the next section.

1.3. Risk Factors

14 cyclist risk factors were identified on the roads of London. Table 1 lists them, along with an estimated score proportional to their suitability to be captured using image segmentation and object detection deep learning models. Google Street View images are used for the project. Different tiles were previously prepared to guarantee visual uniformity.

Table 1 Complete list of risk factors identified as relevant while cycling on the roads of London.

Risk Factor	Street View Imagery Suitability	References
Cycle Lane	★★★★★	[4] [5]
Streetlight	★★★★★	[6]
Pedestrians (e.g.: children near schools)	★★★★★	[7]
Water Drainers	★	[7]
Tram/Train Rails	★	[8] [9]
Number Intersections	★★★	[7]
Intersections Visibility	★	[5]
Bends Visibility	★	[5]
Vehicle Speed	★★★★	[4] [7]
Parked Cars	★★★★★	[5] [8] [7]
Lorries and other Large Vehicles	★★★	[8] [7]
Road Width	★★★★	[8]
Pavement Quality (Pits, Trenches, Tree Root Encroachments)	★	[5] [7] [9]
Advanced Stop Line	★	[8] [7]

In an attempt to list and order the most relevant risk factors while cycling in London, I considered the accident, injury and fatality rates. In London, the fatality rate for cyclists is relatively low, consequently, priority was given to the other two more discriminative ones (accident and injury rates). This way, a comparable quantity was used to order all risk factors when designing Figure 4 diagram. Note there is also a strong qualitative and experience-based component inherent to the same rankings.

The top 3 most relevant factors identified to influence cyclists' safety were the presence of a cycle lane, road speed limits and road lane width. Next, statistical data that supports the rankings defined in Figure 4 will be provided. Note that only a small number of accidents involving cyclists are reported [10], consequently, the statistics presented in the next paragraphs may not totally reflect a real-life scenario.

1.3.1. Cycle Lane and Parked Cars

Cycle lanes can be physically separated or located on the road. Depending on the situation, one can be more beneficial than the other.

Physically separated lanes reduce the probability of crash when a car tries to overtake a cyclist or, in the case of fall, to be hit. One of the main causes of injury among cyclists are falls caused by bad pavement quality [5] [7] [9]. With no cars parked in the surroundings, these lanes reduce the risk of injury among cyclists by half. [11] For all these reasons, risks specifically associated to high road speed limits, narrow bicycle lane widths, road pavement quality and parked cars were not considered.

In the case of an on-road cycle lane, vehicular speeds tend to be lower and there are less interactions between these and the cyclists, when comparing to no lane. [12] Near intersections and in roundabouts, some studies suggest these lanes can be safer than physically separated ones. Although, the former can still perform better than the latter if built following specific criteria to make clearly visible the cyclists.

This makes the first scenario the safest, followed by on-road and no cycle lane.

The presence of a cycle lane was considered the most decisive factor by preventing many of the previously identified risks. It was considered the number one in the rankings of risk factors.

1.3.2. Vehicle Speed

Speed was found to be one of the major contributing factors in around 10% of all accidents and 30% of the fatal ones. Speed of vehicles involved in a crash is the single most important factor in determining the severity of injuries. [13]

There are 2 distinct factors when considering speed. Not only higher speeds are known to be responsible for an increased rate of accidents, injuries and deaths, but also large speed differences. Roads with high speed variance are more unpredictable, once they favour the number of encounters and an increased number of overtaking manoeuvres. Consequently, reducing speed limits sometimes may only result in the decrease of the vehicles' average speed and not its variance. [14]

In the core of the danger posed by vehicles' high speeds are the increase in the braking distance and kinetic energy that is transferred from the vehicle to the cyclist. Once both increase with the square of the velocity, the possibility of avoiding or surviving a crash decreases faster than linearly. [14]

In a biological perspective, it is known the human body can only resist the transference of a limited amount of kinetic energy in a crash. [15] This amount varies for different body parts, age groups and gender. Considering the best-designed car, if the vehicle exceeds 30 km/h, this limit can be exceeded. [16] Studies also show if a car travels at a speed lower than 30 km/h, the probability for a pedestrian to survive a crash is higher than 90%. When hit by a car at 45 km/h, the chance of surviving decreases to 50%. [17] Or, as the speed of a car rises from 30 km/h to 50 km/h, the probability of surviving a crash decreases by a factor of 8. [18] In the driver's perspective, the best-designed car provides protection until 70 km/h in frontal collisions where all passengers are wearing belts. [16] For side impacts, the maximum supported velocity is 50 km/h. [16]

In a road safety scope and based on a work done by Nilsson in Sweden, a change in the average speed of 1% for a 120 km/h road would imply a 2% increase in the accident numbers. At 50 km/h, this accident rate would increase instead 4%. In the United Kingdom, in urban roads, an increase of 1 km/h in speed was shown to raise the number the number of accidents by 1 to 4%, depending on the quality of the road. [14]

This was considered the second most relevant factor. In the case of an on-road cycle lane next to a low-speed limit road, the risk factors related to parallel traffic were considered negligible, regardless of the width of the lane.

1.3.3. Lane Width

In the United Kingdom, recommended cycle lane width is 2 meters. Minimum required is 1.5 meters. All values below 1.5 m are considered too narrow, allowing little room to manoeuvre around obstacles, such as: debris, potholes and water drainers. It is frequently referred it is safer not having a bicycle lane, than one that is too narrow, once motorists tend to drive right up to the line and cyclists too close to the kerb.

After the road speed limits, cycle lane width was considered the following most important factor. Whenever it is considered wide, traffic risk factors were not considered. Regardless of the width of an on-road cycle lane, low-speed limits were enough to discard all traffic related risk factors.

1.3.4. Streetlight

After the top 3, streetlight was considered the most relevant criterion in determining road safety. It is known to affect drivers and cyclists' reaction time and make cyclists unnoticeable particularly when not using any reflective or luminous gear. Moreover, in the cyclists' perspective, they are less aware of other road risks associated for example to the quality of the pavement. It is not expected to encounter many significantly under illuminated roads in London, consequently, it was placed in fourth place of the ranking.

1.3.5. Pavement Quality, Tram/Train Rails and Water Drainers

As frequently referred in the literature, pavement quality is a crucial factor to consider when evaluating safety. [5] [7] [9] Pavement quality refers to the quality of the road when there is no cycle lane or to the cycle lane itself, when it is present. Along with the presence of water drainers and trails, these were the following most important risk factors. This was placed under streetlight once with enough luminosity and circulating at a moderate velocity, it may not pose a significant threat.

1.3.6. Number Intersections and Intersections Visibility

The majority of bike and car crashes occur in intersections. In [19], the reported percentage was 60% over the total number of crashes. Additionally, as part of the same study, intersections where streets do not meet at right angles, posed an additional danger to cyclists. Crashes at these areas were 31% more likely to cause serious injury to the cyclist. The main reason is the decreased intersection visibility.

1.3.7. Lorries and other Large Vehicles

In the last years, economic development and consumer demand have been increasing, and so as the number of trucks in the cities. [20] [21] While cycling has following the same trend, the number of encounters among them has significantly increased. As an example, in New York City, 15% of bicycle networks overlap with 11% of truck networks. [22] The increased number of encounters has contributed to a higher accident and mortality rates involving trucks. Truck-bicycle accidents have usually more severe consequences than any other type of accidents. [23] [24] [25] [26] In some EU countries, 30% of all cycling fatalities are associated to trucks. [27] Studies in the past 2 decades have identified trucks as the most common vehicle category involved in cyclist deaths, in London. [24] [28] [29]

1.3.8. Advanced Stop Line

These lines present in several European countries such as Belgium, Denmark and United Kingdom, allow a head start to certain types of vehicles (namely, bicycles) when the traffic signal changes from red to green. This has several advantages. First, drivers behind the line can clearly realize the presence of cyclists around them and take the right precautions to avoid danger manoeuvres. Second, it becomes safer for a cyclist to turn to the left avoiding a crash with the cars that are behind. In terms of statistical data on accident, injury and mortality rate, there is few available.

1.3.9. Bend Visibility

Several sources identify bends as a risk factor. Bends and intersections are often jointly considered as posing similar risks to the cyclist. Namely, low visibility in the cyclist's perspective, make several situations risky that usually are not (sudden appearance of pedestrians or intrusive vegetation). In the driver's perspective, it can be harder to notice cyclist's presence and, consequently, collide against them. [5]

Nevertheless, there is no clear statistical data showing how bends affect cyclists' accident, injury or fatality rates.

1.3.10. Pedestrians

Among all age-groups, pedestrian fatalities most often occur in children younger than 14 years old, when comparing with adults aged between 15 and 64 or 65 or more. In terms of gender, men are at a greater risk than women. [30] For these reasons, locations with higher concentration of people satisfying these criteria (e.g., school areas) are an additional risk. Nevertheless, in car-free zones, accidents between pedestrians and cyclists are extremely rare and almost never serious. [31] Thus, this was considered the least important of the risk factors.

1.3.11. General Overview

Generally, from the left to the right of the diagram the number of risk factors decreases. The most unsafe situation was considered to be no cycle lane. Secondly, high speed limits with a narrow lane in an on-road scenario. Thirdly, high-speed limits but with a wider lane. Fourthly, low-speed limits regardless of the presence of a narrow or wide on-road lane. Finally, a physically separated lane was considered the safest scenario. In red are highlighted the top 3 most relevant factors for each of the different scenarios.

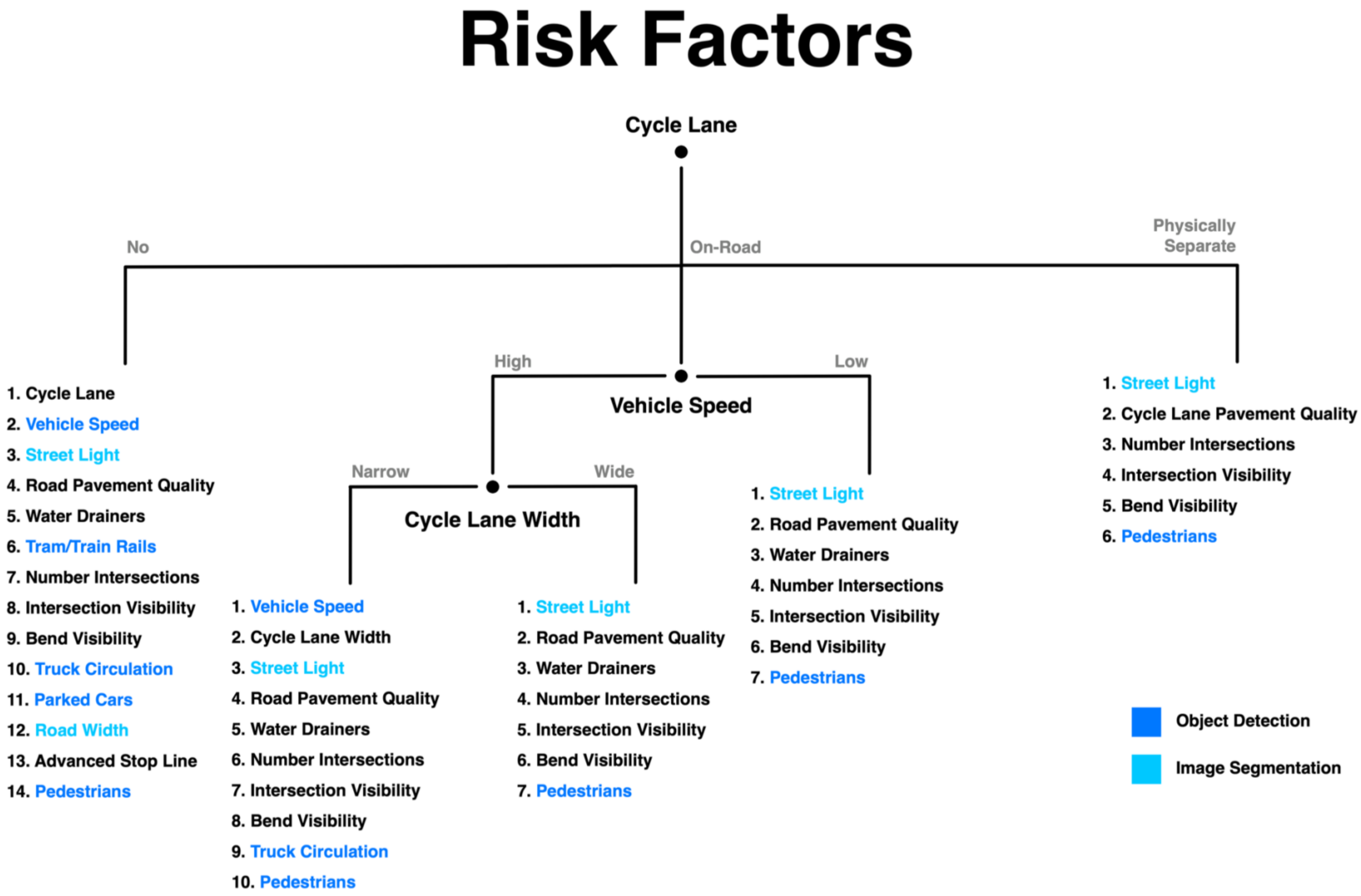


Figure 4 Identified cyclists' risk factors in 5 scenarios on the roads of London. Highlighted in red are the most relevant based on fatality and injury rates.

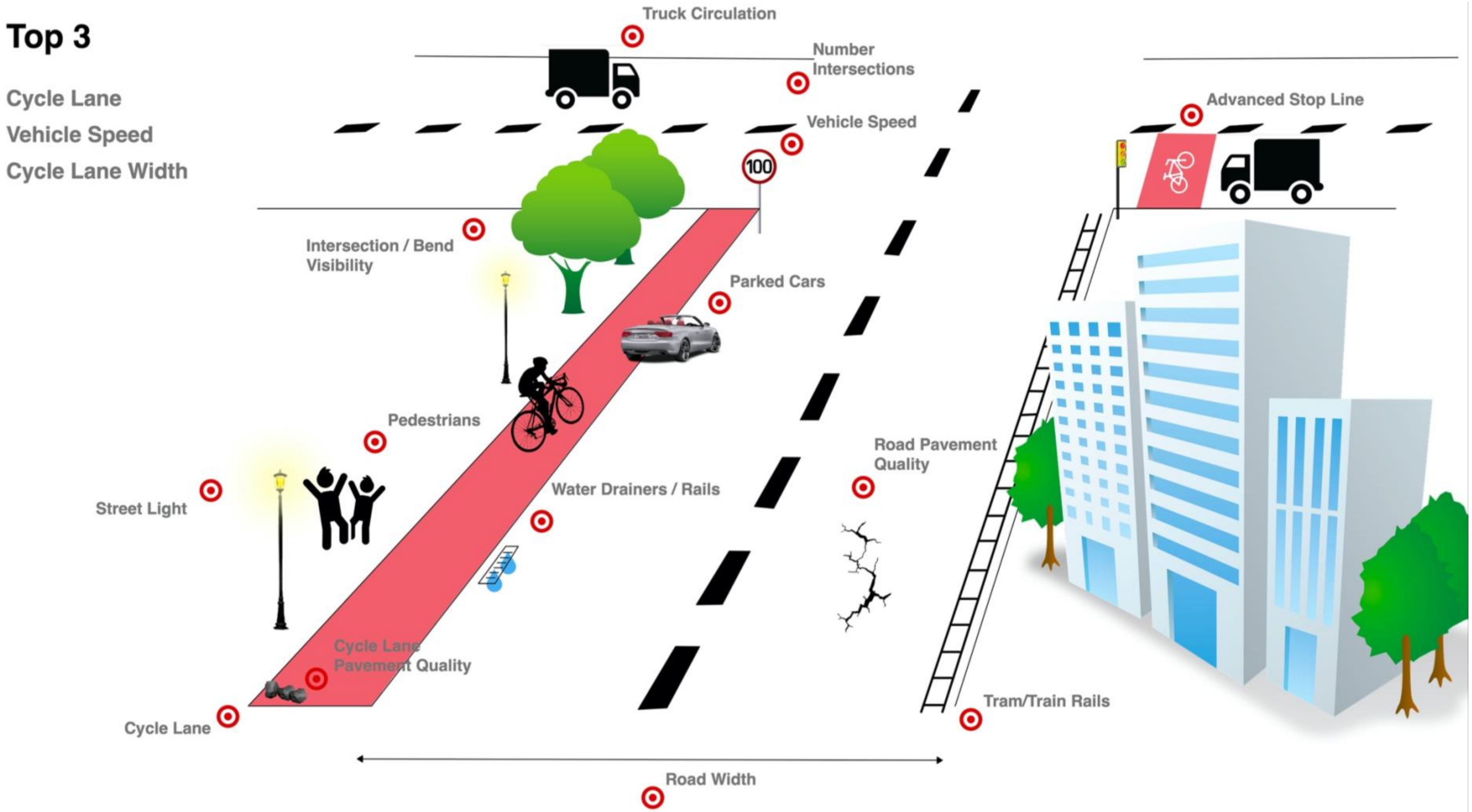


Figure 5 Cyclists' risk factors identified on the roads of London and depicted in a simulated scenario.

1.4. Training Datasets

Two object detection and two image/semantic segmentation training datasets were compared in terms of their discriminative power to identify cyclist's risk factors identified in Table _. Some were directly extracted from the Google Street View images of London, others were indirectly inferred. Features in Table _ with an asterisk are dynamic. Consequently, in the same location, they are expected to vary in number over time.

Below, four state-of-the-art datasets are compared before choosing the most suitable pre-trained deep learning models.

Table 2 Comparison between 4 of the biggest object detection and image segmentation datasets, with relevant data to assess road safety.

	Object Detection		Image Segmentation	
Risk Factor	MS Coco	Open Images V6	Cityscapes	ADE20K
Cycle Lane	-	-	Sidewalk*	-
Streetlight	-	Streetlight*	-	Streetlight* | Street Lamp*
Pedestrians (e.g.: children near schools)	People	Girl | Man | Person	Person	Person | Individual | Someone | Somebody | Mortal
Water Drainers	-	-	-	-
Tram/Train Rails	Train	Train	-	-
Number Intersections	-	-	Sidewalk* | Road	Sidewalk* | Pavement*
Intersections Visibility	-	-	Sidewalk* | Road	Sidewalk* | Pavement*
Bends Visibility	-	-	-	-
Vehicle Speed	Stop Sign* | Traffic Light*	Stop Sign* | Traffic Light* | Traffic Sign*	Traffic Light* | Traffic Sign*	Traffic Light* | Traffic Signal* | Stoplight*
Parked Cars	Car | Parking Meter*	Car | Taxi | Vehicle	Parking*	Car | Auto | Automobile | Machine | Motorcar
Lorries and other Large Vehicles	Bus | Train | Truck	Bus | Train | Van	Bus | Truck | On Rails | Caravan	Truck | Motortruck | Van
Road Width	-	-	Road*	Road* | Route*
Pavement Quality (Pits, Trenches, Tree Root Encroachments)	-	-	-	-
Advanced Stop Line	-	-	-	-

As mentioned above, some risk factors can be captured directly, while others require an indirect approach.

None of these datasets contains labelled cycle lanes. Although, Cityscapes is able to identify physically separated ones along with sidewalks, as part of the same category.

Open Images and ADE20K contain in their dataset the specific category of objects streetlight.

For the presence of pedestrians, all datasets contain various elements that let us infer about how crowded a given road might be.

None of the 4 datasets contain images with labels for features present on the ground. This include water drainers, rails, pavement quality or road lines (such as advanced stop line).

One way to indirectly capture tram rails would be to infer them by the presence of trams. Both MS Coco and Open Images datasets contain this element.

Number of intersections can be calculated by the number of interruptions in the sidewalk or the presence of perpendicular roads. Both situations can be captured using the image segmentation datasets.

Lack of visibility in intersections can be inferred by the presence of non 90 degrees road connections.

In terms of bend visibility, there are no clear elements in any of the 4 datasets that can be easily used to capture this.

Traffic calming signs are known to slowdown vehicle speed. Datasets contain labels to detect traffic lights, stop signs, stop lights and other traffic signs.

Parked cars to be detected looking for the presence of parking meters and parking areas delimited by the respective lines.

Lorries and large vehicles to be detected on the road. All datasets contain labels for these types of vehicles.

Finally, image segmentation will be used to calculate road width.

Microsoft Coco Dataset

Number of images:

Classes:

Cityscapes Dataset

Number of images:

Classes:

1.5. Object Detection

For the object detection, it will be used YOLOv5 pre-trained in the Coco dataset. This project uses static images to identify cyclist risk factors. In the future, this technique may allow us to use video sources instead and obtain more detail on the risk factor affecting cyclist's safety. This can be particularly relevant in the case of dynamic features like the ones included in Table _, with no asterisk.

1.5.1. YOLOv5

YOLOv5 is the most recent version of YOLO which was originally developed by Joseph Redmon. First version runs in framework called Darknet which was purposely built to execute YOLO.

Version 5 is the 2nd model which was not developed by Joseph Redmon (after version 4) and the first running in the state-of-the-art machine learning framework PyTorch.

This model was pre-trained using Coco dataset. Thus, it is able to identify 80 object categories. Distributed over 11 categories.

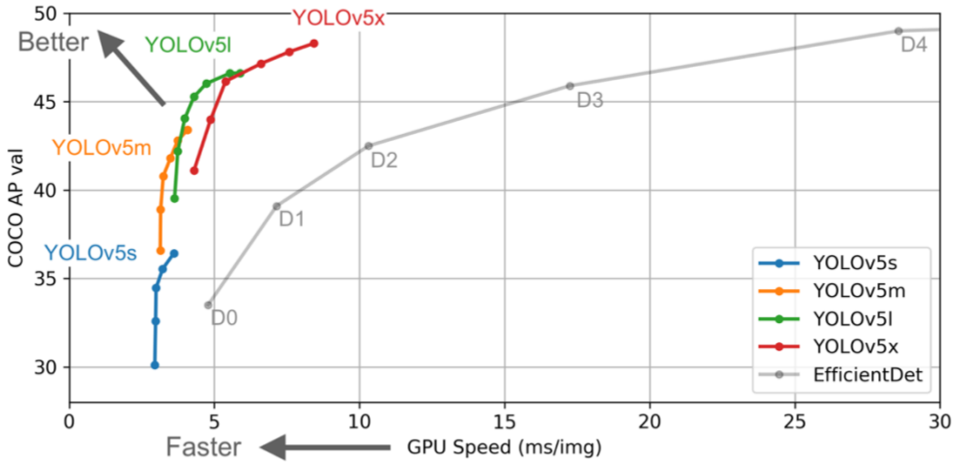


Figure 6 The most up to date YOLO model is the version 5 (July 2020). It was released with 4 different sets of weights of varying accuracy and storage requirements. All data from the project was obtained using YOLOv5x, the most accurate. The presence of EfficientDet highlights the speed of detection of YOLOv5, keeping the same high accuracy.

Table 3 Specifications for all sets of weights released with YOLOv5. Generally, as average precision increases, more processing power is required from the GPU to be executed.

Model	AP^{val}	AP^{test}	AP_{50}	$Speed_{GPU}$	FPS_{GPU}	Params	FLOPS	Weights Size (MB)
YOLOv5s	36.6	36.6	55.8	2.1	476	7.5M	13.2B	14
YOLOv5m	43.4	43.4	62.4	3.0	333	21.8M	39.4B	42
YOLOv5l	46.6	46.7	65.4	3.9	256	47.8M	88.1B	92
YOLOv5x	48.4	48.4	66.9	6.1	164	89.0M	166.4B	170
YOLOv3-SPP	45.6	45.5	65.2	4.5	222	63.0M	118.0B	241

1.6. Image Segmentation

Image segmentation will be performed using a pre-trained model with Cityscapes dataset. This method will not only allow to detect the presence of several objects in the images, but also to consider their sizes and shapes. Important factors to consider when trying to calculate road widths.

Image segmentation provides information not only on the presence of several structures (30 categories), but also their shape and location in the image. Once there are certain road safety factors that are enough to know about their absolute number of counts, such as vehicles, others importantly rely on their dimensions to tell whether they are beneficial or detrimental for cycling.

1.6.1. PSPNet101

Image segmentation models reached a precision plateau (in terms of average IoU) in the previous 2 years. Due to their long execution times, it was chosen the model executing faster and with the higher precision.

PSPNet101 was pre-trained in Cityscapes dataset. This way, it was able to label all pixels from an image across 100 categories.

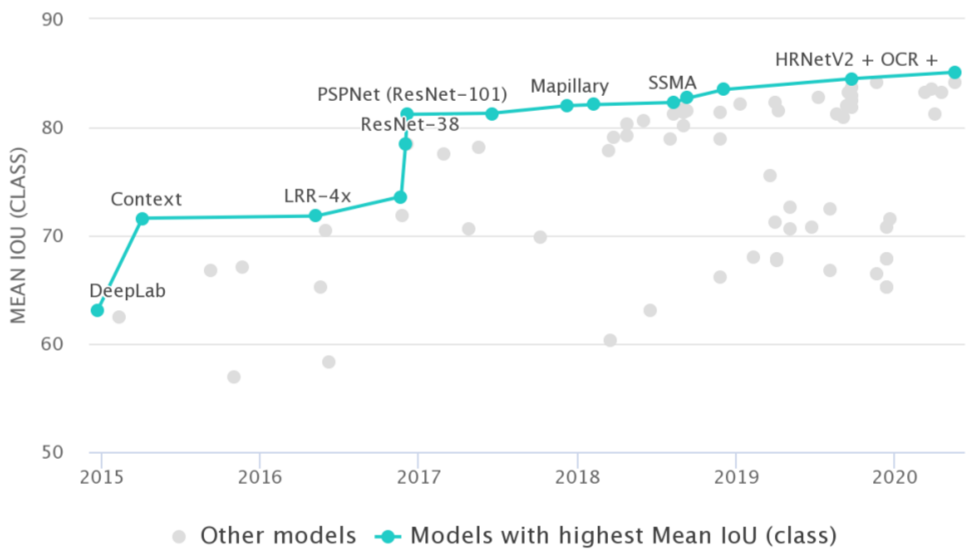


Figure 7 Evolution of image segmentation models over time. Since 2017, the increase in the mean IoU measure has been very small.

1.7. Objectives

The goal of this project was to compile a list of the most relevant risk factors for cyclists based on specific safety metrics such as accident, injury and fatality rates. Using a previously available Google StreetView imagery dataset, to extract the identified risk factors from Greater London using object detection (YOLOv5) and image segmentation (PSPNet101) models. To study, at an LSOA level, how the different safety factors are distributed across London. To identify correlations among the most detected objects. After individually analysing images from all LSOAs, to detect the most common misclassifications done by both algorithms and suggesting ways on how to mitigate them. Finally, to provide new guidelines on how object detection and image segmentation models can detect additional road safety risk factors based on the experience of this project.

2. Methodology

In this section it will be detailed how GSV imagery dataset was storage and processed using YOLOv5 and PSPNet101 models. The choice of the respective parameters. Plus, the software and hardware that were used to execute them. At the end, it is provided a roadmap of the project, since project's allocation, until the submission month.

2.1. GSV Imagery Dataset

There were multiple options to store GSV imagery dataset. Dropbox, Google Drive, Imperial RDS and locally were some of them.

GSV imagery dataset was obtained and pre-processed before the start of this project by Imperial's School of Public Health members. The full set of images is organized in datapoints. Each containing 4 perspectives covering 360 degrees angle. A separate file associates each to a given London area (OA, MSOA and LSOA).

Due to high storage requirements, all images used in this project were storage in Imperial facilities. Images in the Research Data Store were accessed using Globus platform.

They were also pre-processed to guarantee a maximum uniformity when analysing different image data points or angles.

2.2. YOLOv5

To execute YOLOv5, Imperial's High-Performance Computing cluster was used. It was accessed using the VPN connection tool – *Tunnelblick*.

Due to the speed of execution of YOLOv5, it was used one single P1000 GPU. And the set of weights handling the most accurate results was chosen- YOLOv5x. No job was submitted to HPC.

It was defined a minimum confidence of 0.5 for every detection. Higher than the standard value of 0.4. Only the text files containing the detected objects and respective locations were saved. An example is provided in Figure _. It includes numerical code for each object and the coordinate of the detection rectangle:

```
2 0.155469 0.675 0.210938 0.14375
2 0.517187 0.642969 0.1375 0.129688
2 0.774219 0.702344 0.348437 0.242188
2 0.138281 0.589063 0.126563 0.04375
2 0.25625 0.621094 0.08125 0.0703125
```

To test the efficacy of the model, it was saved and analysed one object detected image per LSOA across the full dataset. A total of 4832 images.

Using Pandas dataframe function *corr*, it was obtained the correlation matrix in Figure _.

2.3. PSPNet101

Although it was already available a pre-liminary version of the implementation executing PSPNet101 (provided by Esra Suel), the modifications were made to overcome incompatibilities with the new version of TensorFlow. Moreover, originally it was used Python *multiprocessing* tool to accelerate the execution. At the end, splitting the original dataset in multiple batches and submitting them to HPC was the chosen procedure.

State-of-the-art image segmentation methods are significantly slower than object detection. For this reason, the dataset was splitted in 13 batches and executed parallelly in 13 P100 GPUs. This way, 13 jobs were submitted to the HPC. P100 was the chosen GPU due to its higher processing power when compared to the others available (Table _).

Table 4 GPU types available on the Imperial High-Performance Computing cluster. P100 was used in this project.

GPU Type	Single Precision (TFLOPS)	Double Precision (TFLOPS)	Memory (GB)	Memory Bandwidth (GB/s)
P1000	1.8	<<1	4	80
K80	5.6	2.9	12	240
P100	8.0	4.0	16	730

RTX6000	16.3	<1	24	670

The output was the total number of images in GSV dataset segmented. Each pixel was coloured accordingly to the structure that was detected. After, two Python functions were implemented. One that generates a dictionary linking each RGB colour to a given object class. Another, that receives as input the full dataset of segmented images and outputs the total number of labelled pixels for each category.

Figure 8 NVIDIA P100. GPU used to detect objects and segment images from the GSV imagery dataset.

3. Results

In this section, the results are presented along with their discussion. First, it is provided an overview of the GSV imagery dataset across all London LSOAs. Then, object detection and image segmentation outputs are analysed.

An image after executing YOLOv5 is first shown. The most detected objects are presented in relative and absolute numbers. A correlation matrix including the most common objects is described in terms of its most significative associations. Object distribution was analysed at an LSOA level. Two extra LSOA maps were added as a step forward in generating a universal metric for assessing cyclist's road safety. Current limitations of YOLOv5 and the most common misclassifications are presented, before providing an intuition on the suggested next steps.

A segmented image is presented after running PSPNet101. Then, the relative and absolute number of pixel label counts were ranked. Misclassifications and current limitations of image segmentation are discussed. Next steps for assessing road safety using PSPNet101 are included.

3.1. GSV Dataset

GSV dataset contains 518350 images spread across Greater London. There are 512812 images identified with a London LSOA. From those, 478724 are unique (Table _).

Table 5 Not all images in the GSV dataset are LSOA identified. For this reason, a smaller set was used in the analysis – 478724.

N. Images GSV Dataset	N. LSOA Identified Images	N. Non-Repeated Identified Images	N. LSOA with Images
518350	512812	478724	24

For each datapoint there are 4 images available, ranging from 0 to 360 degrees. Consequently, there are 129588 identified points, each with four 90 degrees images.

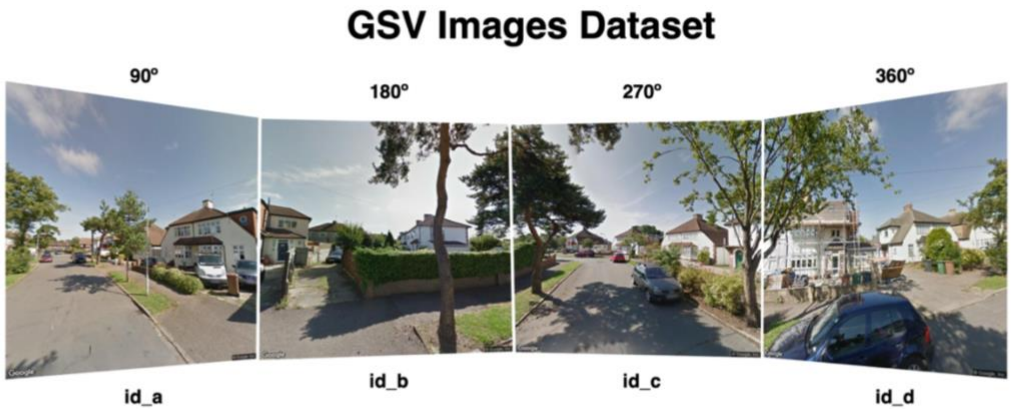


Figure 9 For each datapoint in Figure _, there are 4 images associated. Each one capturing a 90 degrees angle of the surroundings.

There is a higher density distribution near Central London, decreasing in the periphery. In Figure _, it is represented an LSOA atlas, along with the geographical distribution of all images.

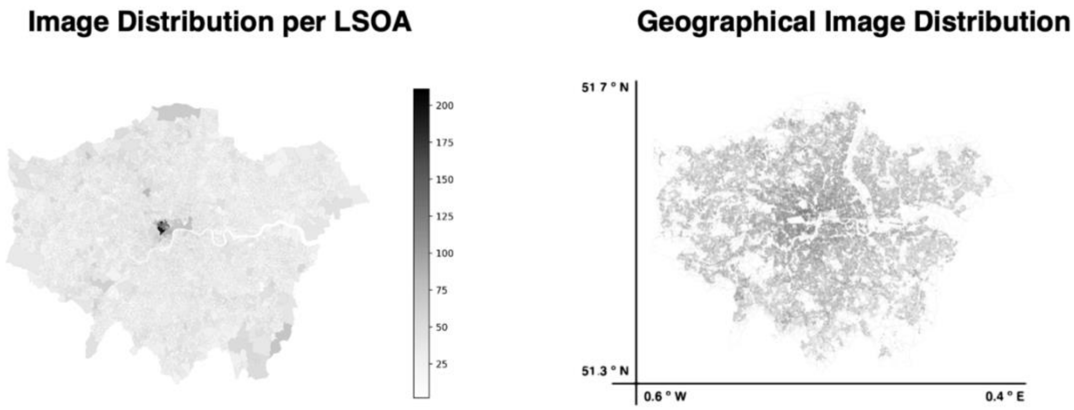


Figure 10 (Left) LSOAs coloured accordingly to the number of available images in the GSV dataset. (Right) Geographical distribution (latitude and longitude) of the same set of images.

In Table _, image distribution is analysed in absolute values. The LSOA with the highest counting of datapoints, 211, is in Central London. On average, there are 27 datapoints available per LSOA. There is one LSOA in the dataset with the minimum counting of 1. The wide distribution on the number of images compromises the accuracy of the estimation of the number of objects and segmented structures in less represented LSOAs.

Table 6 Availability of GSV points in the dataset, across all London LSOAs.

Minimum	Maximum	Mean	Standard Deviation	Mode	Median
1	211	27	24	25	11

3.2. Object Detection | YOLOv5

An example of an image after running YOLOv5 is provided in Figure _. All cars, trucks and people in the image were accurately detected. Although it is not significative analysing the accuracy of a model based on a single example, all the 10 images processed in Figure _, plus the 4832 made available across all London LSOAs show the accuracy of the most common objects in the Coco training dataset to be very high.

Figure 11 Example of a GSV image after executing YOLOv5x. Detection of a car reflection in one of the windows demonstrates the power to capture the smallest details.

Next, the relative and absolute distributions of all objects in the dataset is presented.

3.2.1. Dataset Objects Distribution

Relative distribution of the top 15 most detected categories of objects were plotted in Figure _.

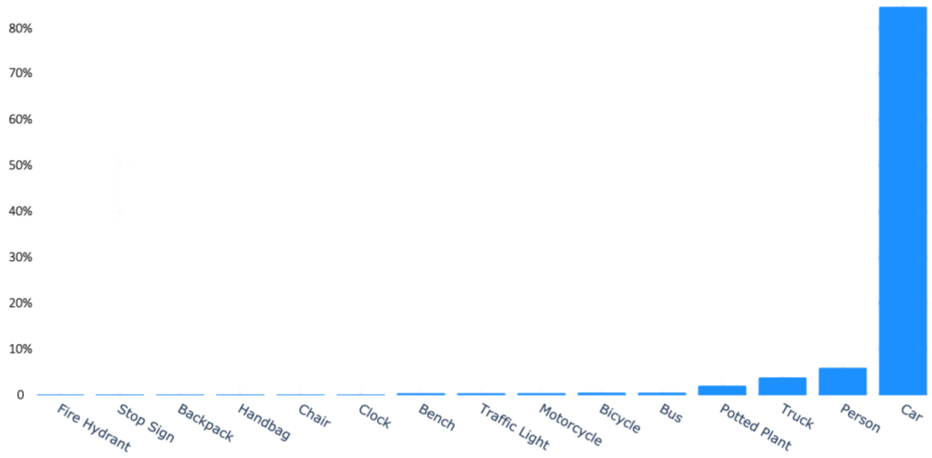


Figure 12 Relative distribution of top 15 detected objects across all London LSOAs.

Once the dataset exclusively contains street view images, it was not expected to detect a big fraction of cars. London is a city with a high populational density. For this reason, detecting people

Table 7 Absolute counting for top 15 most common detected objects.

Object	Number Detections	Object	Number Detections	Object	Number Detections
Car	1.51M	Bicycle	10.9K	Chair	2.19K
Person	107K	Motorcycle	8.97K	Handbag	2.09K
Truck	70.1K	Traffic Light	6.31K	Backpack	1.94K
Potted Plant	37.9K	Bench	5.01K	Stop Sign	1.28K
Bus	11.5K	Clock	2.75K	Fire Hydrant	1.17K

3.2.2. Correlation Matrix

After determining the most detected objects in the GSV dataset, it was studied the frequency they appear in the same images.

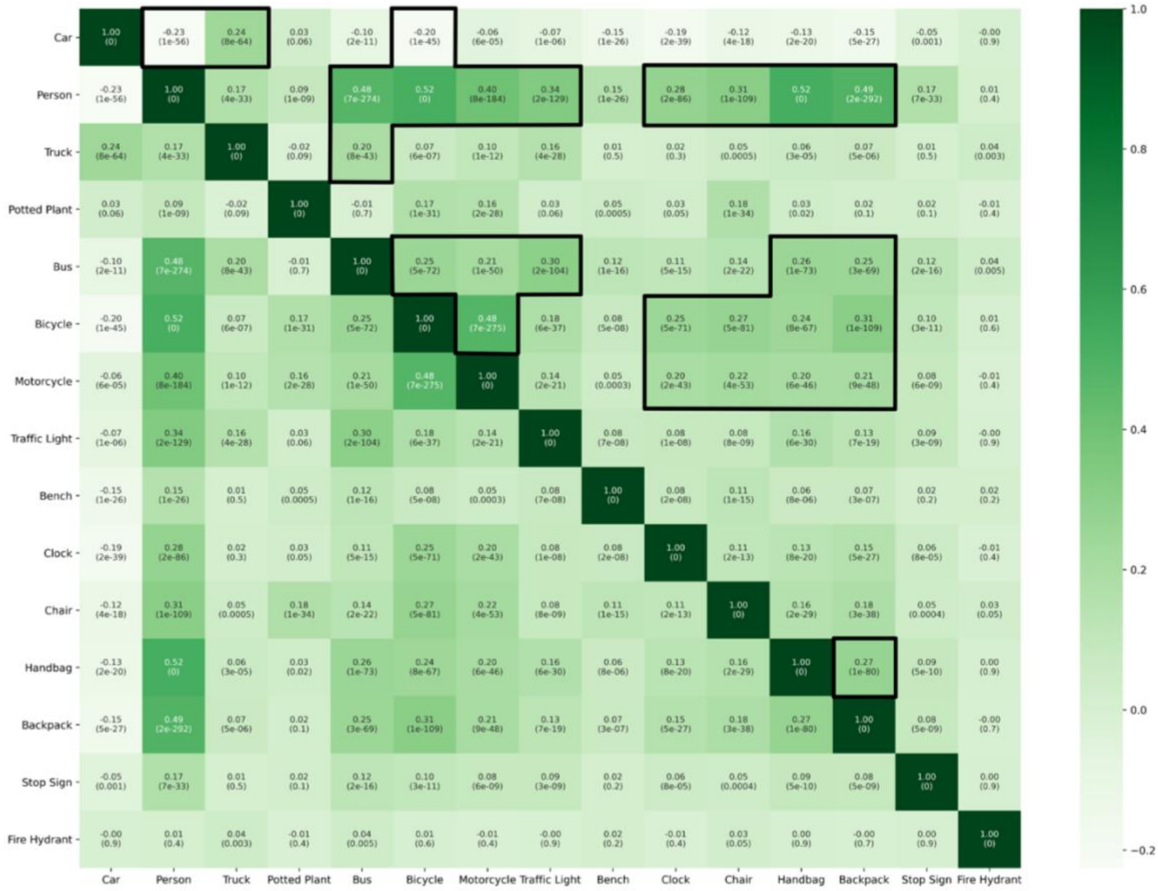


Figure 13 Top 15 detected objects correlation matrix. Inside each cell, on the top, it is Pearson correlation coefficient. On the bottom, the associated p-value.

After thresholding our analysis to correlations higher or lower than 0.2 or-0.2, respectively, and to the top 15 more common objects, it was verified the object with the highest number was *Person*. It strongly correlates with Bicycle and Handbags. Intuitively, this agrees with the expectations.

Inversely correlated in the matrix are *Car* with *Person* and *Bicycle*. This suggests areas with high concentration of cars are dissuasive for cycling and walking.

3.2.3. LSOA Maps

Compiled in Figure _ were all the LSOA distributions determined important after reviewing cyclists' road safety literature and accounting for the available dataset categories.

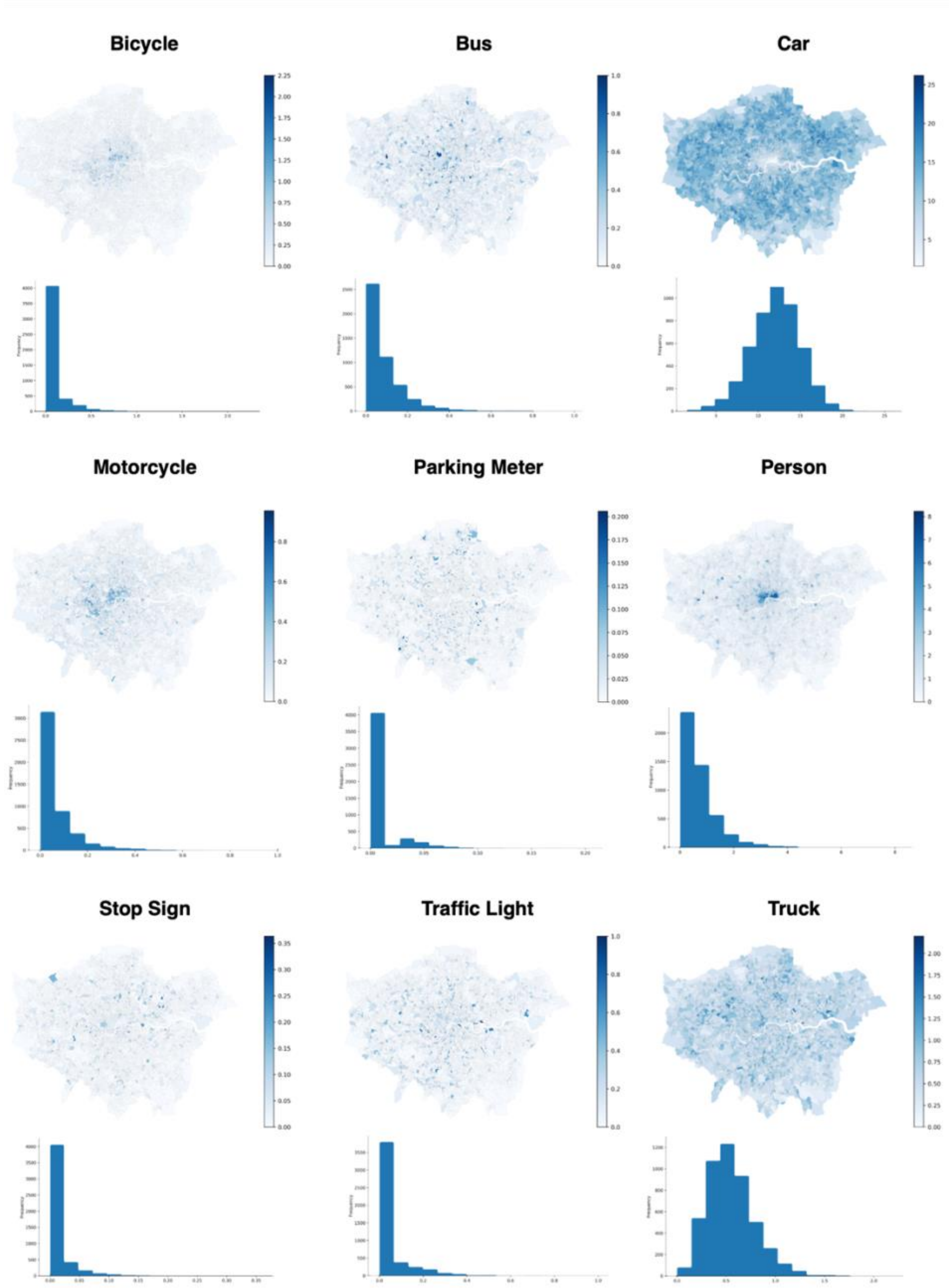


Figure 14 Detected objects' distribution across all London LSOAs. Plus, respective distribution histograms on the bottom of each atlas.

While reviewing the literature in cyclists' road safety, heavy vehicles were accounted responsible for high fatality rates. For this reason, the distribution of buses and trucks was included in the list. Crashes with cars are responsible by most cyclists' injuries and deaths. Traffic calming factors such as stop signs and traffic lights slow down road speed. Being speed one of the most important risk factors, the distribution of these objects was also studied. The presence of parking meters is known to be linked with parked cars, another factor contributing negatively for cycling safety. Presence of cyclists is known to raise awareness of other drivers, thus positively influences safety. Presence of people is inversely correlated with the presence of cars. Consequently, this is an additional positive factor. Although it is not clear the impact of motorcycles in cycling safety, they were included so that a plot of the traffic in London could be generated next.

Most bicycles were detected in Central London. Once this is a type of transport for short distances, they were essentially found in this area.

3.2.4. Traffic

It was not found a precise metric for cyclist's road safety based on the detected objects on the streets of London. Although, based on the set of LSOAs in Figure _, it was generated two extra ones that can represent a step forward in assessing road safety, not at a road level, but at an LSOA level.

One of the features that influences cyclist's safety is the number of other cyclists in the proximity. This happens because drivers are more aware on their presence. Moreover, the vast majority of serious injurious are caused by crashed between vehicles and cyclists. It was found there is a statistically significant negative correlation between the presence of cars and people. This way, the higher the presence of pedestrians, the lower the number of cars. Consequently, less risky for cyclist to get severely injured. *Bicycle* and *Person* LSOAs were combined in a single one, after summing the average number of each of these objects per image.

If cars are the main contributors for serious injuries, the counting of heavy vehicles is particularly relevant when assessing the fatality rates of a certain area. A second LSOA map was created joining the average counting per image of the following objects: *Bus*, *Car* and *Truck*.

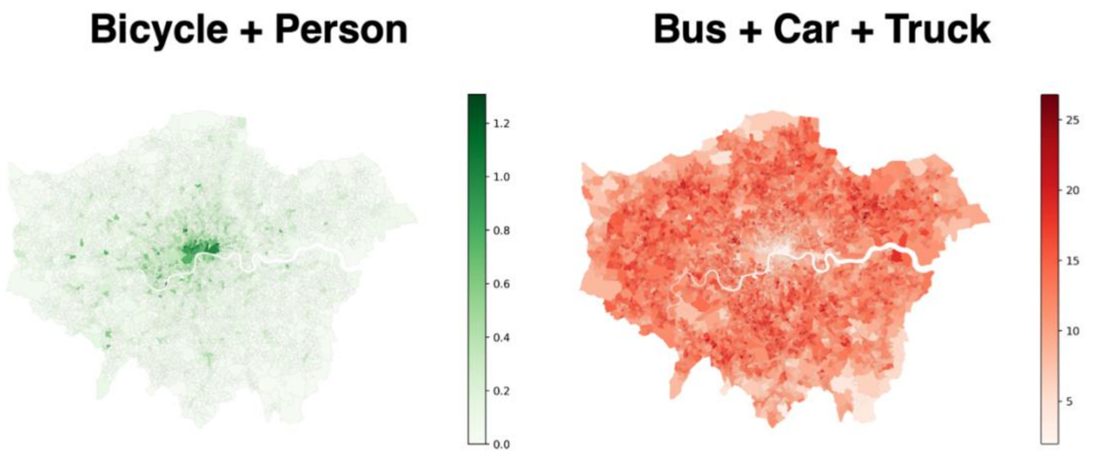


Figure 15 (Left) *Bicycle* and *Person* LSOA distributions were combined into a metric reflecting a positive score for cyclists' safety. (Right) *Bus*, *Car* and *Truck* distributions combined into a final atlas showing the traffic in London. This is inversely correlated with cyclists' safety.

3.2.5. Limitations and Misclassifications

Misclassification analysis focuses on the objects identified as relevant for cyclists' road safety. Moreover, the observations below are a result of individually assessing 1 image for each one of the 4832 London LSOAs.

It was found high levels of confidence to the top 15 most common objects (Table _). The only exception is clock detections. Moreover, YOLOv5 appears to be able to detect accurately any size of the most common objects in MS Coco training dataset. Even when partially occluded, the algorithm performs well. Despite being rare, the most unexpected observation was when the algorithm detected glass reflections of objects present on the roads of London. This demonstrates that even objects with very poor contrast were detected.

It was compiled below a set of ten object detected images (from), so that the reader can verify by itself the accuracy of the algorithm. A link to the online folder containing the full set of 4832 object annotated images is available in Table _.

After analysing images from all London LSOAs

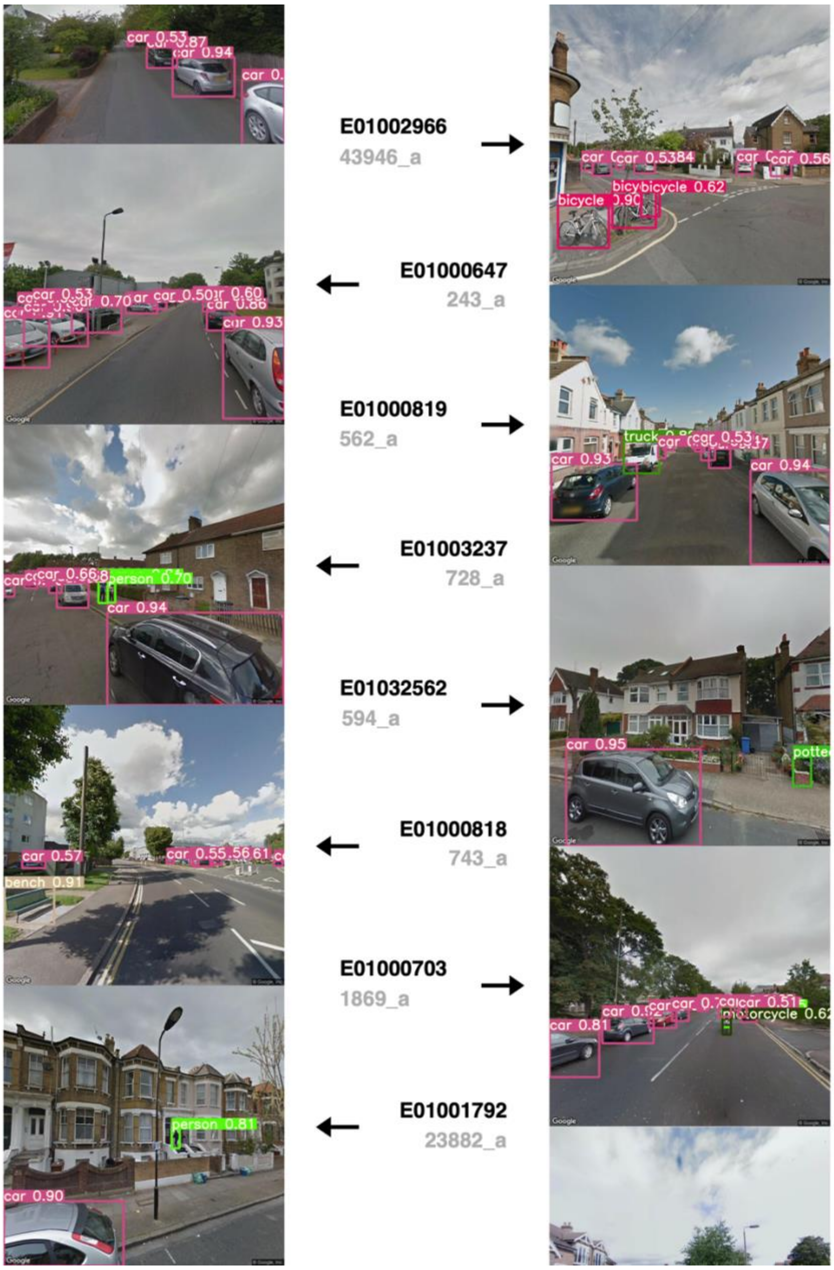


Figure 16 Ten randomly randomly picked object detected images from different LSOAs show very few objects in MS Coco dataset categories were not detected.

3.2.6. Future Directions

Similarly, all the following analysis was a result of individually assessing 1 image for each one of the 4832 London LSOAs (10 of the 4832 images in Figure _). Focus was once again in the most relevant objects for road safety.

Main difficulty of assessing cyclist's road safety using object detection was finding an accurate metric weighting object detection. For this reason, instead of presenting a final imprecise road safety score distribution, two

LSOA atlas were generated as a middle step closer to a final metric. One step forward in assessing cyclist's road safety would be to find a common metric allowing us to compare, for example, in terms of injury or death rate, how the presence of an object influences safety.

A second step forward would be to pre-train YOLOv5 in a more targeted and complete dataset for road objects than MS Coco. This would involve annotating a new big set of images, plus training it in YOLOv5. Documentation on how to train is very precise and easy to follow in the following link.

In terms of image resolution, apart from the objects located very far from the place images were taken, this does not seem to have posed a problem in the object detection analysis.

Finally, there are several features that static images do not capture. One of the reasons of choosing YOLOv5 to execute GSV imagery dataset was that it is also able to process video. In the future, using city recordings with pedestrian, cyclist and vehicle movement, it will allow to capture variables that are highly influenced by the time of the day images were obtained.

3.3. Image Segmentation | PSPNet101

All images from GSV imagery dataset were segmented. An example of a segmented image is provided in Figure _. It was identified with the respective label all the detected structures.

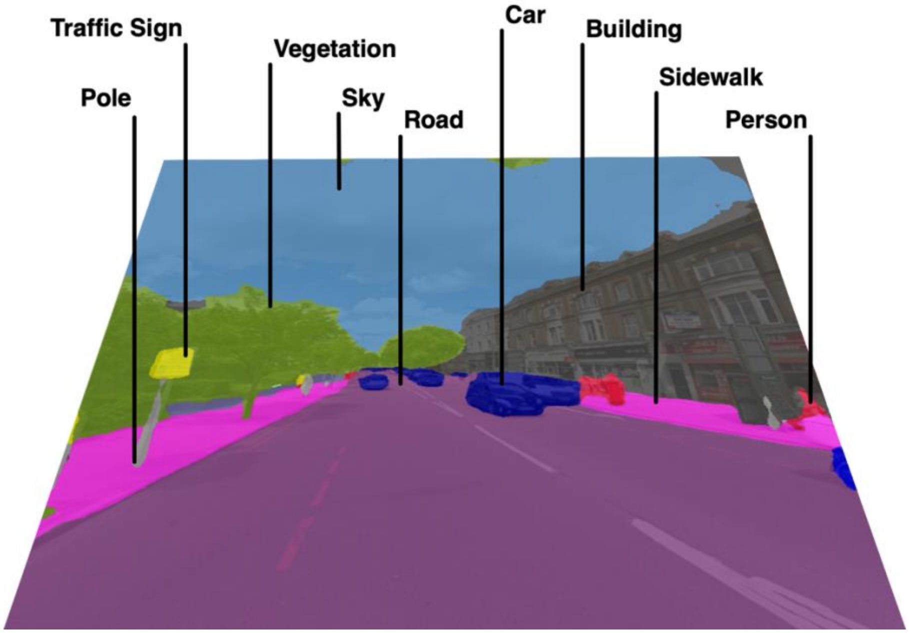


Figure 17 GSV image after segmentation using PSPNet101. All pixel labels present were identified.

It was obtained the relative and absolute distribution of pixels for all images in the GSV dataset. Buildings, sky, road, vegetation and cars cover more than 90% of the total area of complete GSV imagery dataset. In the case of the first 4 structures, this is explained by their intrinsic dimensions. Once this dataset exclusively contains images obtained from the roads of London, it was not unexpected finding a much higher number of cars than other objects. Finding a high number of car pixels is associated not with their size, but the frequency they appear in the images. This way, both object detection and image segmentation seem to be in accordance.

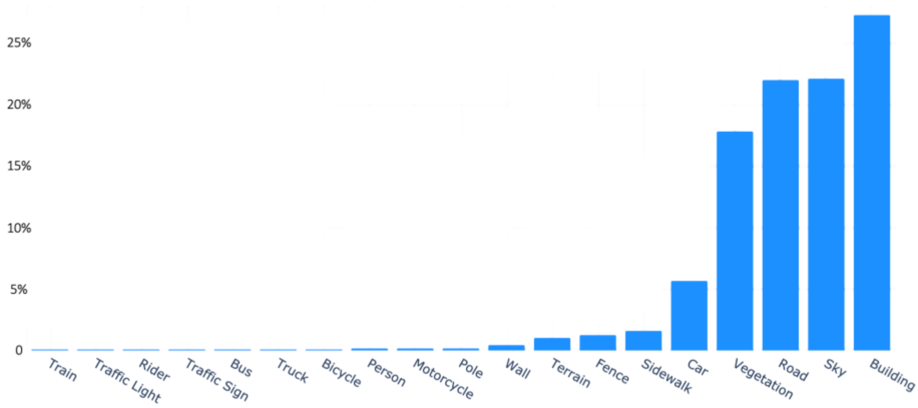


Figure 18 Relative distribution of labelled pixels after executing PSPNet101 in GSV imagery dataset.

Table 8 Absolute number of labelled pixels detected across all imagery dataset.

Label	Number Pixels	Label	Number Pixels	Label	Number Pixels	Label	Number Pixels
Building	47.4B	Sidewalk	2.77B	Motorcycle	299M	Traffic Sign	58.1M
Sky	38.4B	Fence	2.18B	Person	232M	Rider	13.9M
Road	38.2B	Terrain	1.79B	Bicycle	95.5M	Traffic Light	12.5M
Vegetation	31.0B	Wall	766M	Truck	91.3M	Train	6.84M
Car	9.83B	Pole	303M	Bus	81.5M		

The relative distribution of segmented pixels across the different categories also suggests that not only objects present on the roads were detected, but also in the surroundings, namely, in buildings and in the sky. Embedded on the buildings landscape, 2750 clocks were wrongly detected instead of satellite dishes. In the same area, 37917 potted plants were identified. In the sky, 234 airplanes were detected. Having detected a significant number of pixels labelled as sidewalk suggests objects regularly present are likely to be captured (107266 people were found, along with 5013 benches and 1168 fire hydrants).

Again, from an image segmentation point of view, GSV imagery dataset appears to be useful to estimate the area of roads and sidewalks due to the relative high number of pixels detected. The same applies to streetlights. In spite only 303M pixels were identified, the dimensions of this object suggest that a significant number of those should have been detected.

After individually analysing 1 segmented image per LSOA for the complete dataset, it appears that both the area and shape of the roads and sidewalks can be accurately retrieved.

As it was identified in the Introduction, these last properties are relevant in a road safety context because they allow to calculate road and sidewalk width. And the presence of streetlights or poles as they are called in Cityscapes, it is a proxy to assess road visibility.

In Figure _, these concepts are exemplified along with an illustrative image on the side.

3.3.1. Limitations and Misclassifications

This misclassification analysis will focus on the structures identified before as relevant for road safety. Moreover, the observations below are a result of individually assessing 1 image for each one of the 4832 London LSOAs (10 of the 4832 images in Figure _).

Due to the dimensions of certain structures, PSPNet101 was not able to accurately capture their shape. One example are the poles or pole groups which are very thin and, consequently, their detection is highly influenced by the resolution of the images in the dataset. This is not particularly problematic once the most important about these structures are their detection and not capturing their shape.

In terms of the roads and sidewalks, sometimes occlusion appears to be an issue. Nevertheless, by accounting for the objects that are usually present in any of these areas, considering their overlapped areas simultaneously seems to be an effective workaround. Specifically, this was observed for cars on the roads and people on the sidewalks. This way, it should still be possible to extract information on the shape and size of these structures.

Extracting absolute dimensions of these structures on the roads of London can be a hard task. Criteria can widely vary accordingly to the angle the images were taken. One way to overcome this would be to focus on the relative dimensions across the objects.

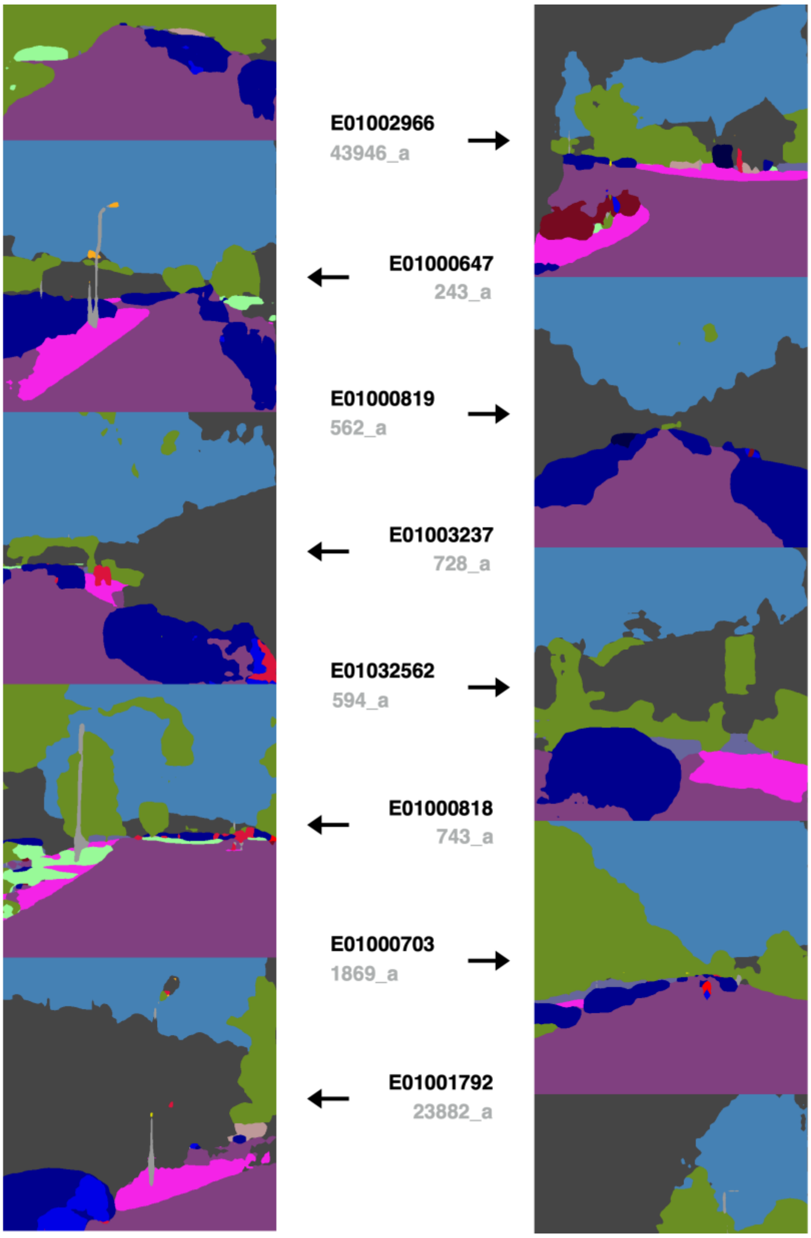


Figure 19 A glimpse on a short set of randomly segmented images from different LSOAs shows how important is to account for structure occlusion while capturing sizes and shapes.

3.3.2. Future Directions

Similarly, all the following analysis was a result of individually assessing 1 image for each one of the 4832 London LSOAs (10 of the 4832 images in Figure _). Focus was once again in the most relevant structures for road safety.

Due to time constraints, it was not possible to present a detailed image segmentation analysis, similarly to the previous object detection section. Nevertheless, below are some approaches we considered during this project.

There are objects in the streets of London that were not identified using YOLOv5 due to limitations of the dataset (MS Coco) that was used to train the model. Moreover, for some, it might be also useful to account to their shapes.

It is possible to extract the number of streetlight lamps and their locations for the GSV imagery dataset. Although there is not a specific category, most of the identified *Pole* and *Polegroup* were light sources. This was concluded after analysing one image for all London LSOAs. In terms of image resolution, it may not be enough to capture streetlights poles, depending on the distance the image was captured. This appears to be a problem only in the case one pretends to retrieve their shape.

Another structure that was identified as determinant for cyclist's road safety was the presence of cycle lanes. It was not possible to identify a one dataset with segmented images with specific labels for these lanes. Consequently, there were no pre-trained models. Cityscapes considers them part of the road when those are shared with other vehicles. Or, sidewalk, when they are physically separate. Although we did not find evidence whether sidewalks correlate with cyclist's safety, in the future, proven there is an important association, PSPNet101 pre-trained in Cityscapes will allow us to extract this information. Two of the main drawbacks of detecting sidewalks are the angle of the analysed image and obstructing structures such as *Vegetation*, *Person* or other common objects.

Road width was identified to be crucial for cyclist's safety, mainly when there is no physical separation between vehicles and the cycle lane, and in high speed roads. Estimating road width is not a straightforward task due to the angle the image was captured and presence of obstructive objects.

Due to time constraints,

Figure _ summarizes all information extractable by PSPNet101 using GSV imagery dataset that was found to be determinant to asses road safety in a cyclist's perspective.

Image Segmentation

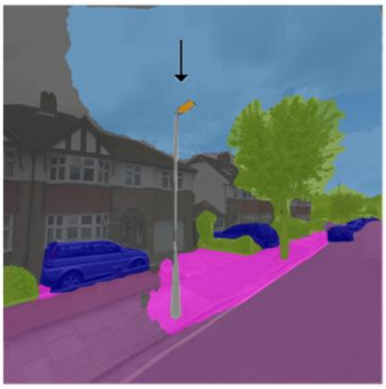
PSPNet101

Road

Road width is determinant for cyclists' safety.
In the presence of a shared cycling lane, this is crucial. Keeping a safe lateral distance between vehicles and cyclists (generally, legally enforced >1.5 m) decreases fatality rate of the latter.

Pole

Light conditions influence drivers and cyclists reaction time. In high speed roads, it tends to be very short. Cyclists are more aware on the presence of pedestrians during the night when there are streetlights.



Sidewalk

Cityscapes incudes in this same category walking paths and physically separate cycling lanes.
The width of cycling lanes is one main factor contributing to cyclists safety. Allowing them to keep their distance from other vehicles and avoiding holes or other obstacles on the floor.

4. Conclusion

The goal of this project was to use object detection and image segmentation to extract cyclists' road risk factors from a dataset of GSV images of Greater London. This included the study of image distribution across all LSOAs. Identifying relevant road safety indicators to rank cyclists risk factors. Using YOLOv5 and PSPNet101, pretrained in MS Coco and Cityscapes datasets, respectively, to detect all objects and segment images. Analysing object distribution and correlations among the different categories. Finally, identifying common misclassifications and limitations of both methods, and propose new ways of advancing road safety assessment based on object detection and image segmentation.

Approximately 2 million objects were identified, and 200 billion pixels labelled in the half-million images available in the imagery dataset. On average, there were 108 images per LSOA. Using YOLOv5, the distribution of the following risk factors was (un)directly identified at an LSOA level: high vehicle speed, tram/train rails, truck circulation, parked cars and pedestrians. *Car* (84.5% of all objects), *person* (6.01%), *truck* (3.92%), *bus* (0.60%), *traffic light* (0.4%), *stop sign* (0.07%), parking meter (0.05%) and train (0.04%) counting were used to identify previous risk factors. Using PSPNet101, road width and streetlight risk factors were identified. *Road* (22.0% of all pixels) and *pole* (0.17%) were the structures used to identify them. London road traffic captured by imagery was found to be higher outside of Central London. In contrast, the presence of cyclists and pedestrians is higher inside this area. Former was defined as a general negative measure of safety and, the second, positive. It was found a statistically significant negative correlation between buses x cars, cyclists x cars and people x cars (strongest). The strongest positive correlation was bicycles x people. Long-tail distributions on the number of heavy-vehicles (buses and trucks) was observed. Most important limitations to YOLOv5 were found to be the lack of relevant categories for road safety in the pre-trained model. In the case of PSPNet101, structure occlusion and respective sizes contributed for structure distortion. All the results and implementations were made available in the project's repository.

Future directions include increasing the availability (particularly, in the areas surrounding Central London) and resolution of GSV images. Train YOLOv5 and PSPNet101 with datasets containing a higher number of categories relevant for road safety. Define a safety metric to weight proportionally to their importance detected objects or segmented structures. Combine both object detection and image segmentation results at a road level. Finally, being able to process street view images or video as close as possible to real-time would allow to better account for the dynamics of road safety (example).

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Appendices

Detected Objects

One of the main goals of this project was to show the potential of Street View imagery. Given a dataset big enough, there are plenty of information that can be extracted.

While analysing all the processed LSOAs atlas, it was found two that illustrate the potential of this technique: *Airplane* and *Potted Plant* categories.

In the case of the first, it was detected a higher density of planes per image in the areas next to the airports of Heathrow and City of London. Moreover, all detected planes are on the right of each of these structures. This phenomenon is explained by the wind direction West-> East, which makes the planes preferably landing from East-> West. Thus, only images taken on the right contain them. Finally, it is also clear the difference on the number of detections next to each of these airports. Due to the increased air traffic of Heathrow, most of them are in its proximities.

Potted plants were also frequently detected. These were mainly present in images closer to the biggest parks of London. This category includes all vegetation inserted in any type of pot. Given vegetation was the second most labelled type of pixels across the GSV dataset after executing PSPNet101, it is not surprising the high levels of captured potted plants (fourth most detected object).

Figure 20 (Left) Density of planes present in images taken next to the closest London airports is in agreement with what was expected to observe. (Right) Identically, the biggest density of potted plants was observed closer to the biggest parks.

Misclassifications

For the objects we defined as relevant to cyclist's road safety, the number of misclassifications was very small. This was achieved because it was defined a high threshold of 0.5 to count as a detection and in MS Coco training dataset the most common objects are the ones we are interested.

Although, there were objects consistently misclassified. The most common were satellite dishes being detected as clocks. Depending on the angle, arm dishes can easily resemble a clock pointer. It was detected 2750 clocks in the complete GSV imagery dataset (Figure _). Other less represented objects were also wrongly identified. Sometimes due to their shape, others because of their texture. Another example of the former was the detection of boats instead of construction containers or, for the latter, benches instead of fences.

Figure 21 The most common misclassification identified after executing YOLOv5 was the detection of clocks instead of satellite dishes.

Project Timeline

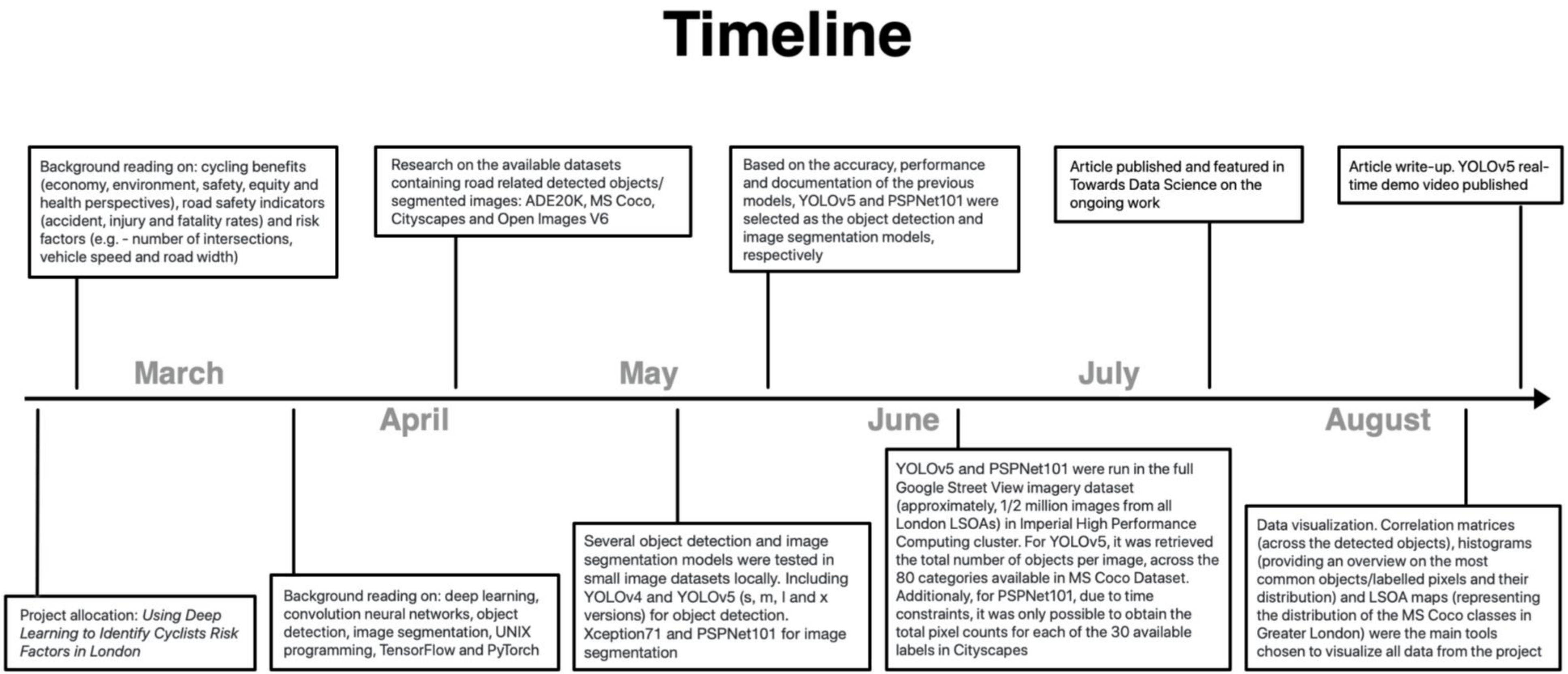

Figure 22 Project's roadmap since it started in March, until the submission month, August.