Cyclist Route Assessment Using Machine Learning

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Abstract

Increasing the number of bike commutes can provide numerous benefits for individuals and communities. However, several factors including the availability of cycle paths, traffic characteristics, and pavement quality, can either encourage or discourage the use of bicycles. To promote cycling and understand how cyclists interact with the urban environment, it is crucial to assess the quality of cyclist routes. This paper proposes a pipeline that calculates the level of safety and comfort for cyclists by examining route segments using computer vision models trained on YOLOv5 to classify pavement types, detect pavement defects and detect the presence of cycle paths. The models for pavement type and cyclist paths had good results but the pavement defect model will demand more training to be used. The first experiment with the pipeline did not achieve high accuracy but helped to identify the next steps.

Keywords: cyclist safety assessment; computer vision; deep learning; yolov5.

1. Introduction

Individuals and communities can greatly benefit from using bicycles for commuting instead of cars. This mode of transportation offers environmental and health benefits. However, several factors can influence the preference for using the bicycle as a transportation mode. One of the primary factors is safety perception, which is closely linked to the availability of infrastructure that separates cyclists from motorized traffic. In cases where such infrastructure is absent, other factors like road width, the presence of parked motorized vehicles, speed, and overall traffic safety can also influence the preference for cycling [1, 2].

In addition to safety, the comfort of the route and the level of effort required for the commute are also crucial. Studies have shown that cyclists prefer paved surfaces over unpaved paths, whether on or off-street, while rural roads are the least preferred option [2]. Moreover, routes with detours, slopes, and other obstacles that make the ride longer and more challenging tend to be seen as less desirable [1]. In addition to studying the factors that impact the decision to commute by bicycle and their relative importance, it is also crucial to develop methods for mapping and evaluating cycling routes. There are several studies exploring different approaches to use these findings to calculate indexes, such as the bikeability index, to provide users with easy-to-understand information.

Most existing studies on evaluating cycling routes do not employ automated approaches. For example [3] compared safety perception levels on routes with actual infrastructure preference and safety data in Galway City, Ireland, using mental mapping and a stated-preference survey. [2] conducted a population-based survey in Metro Vancouver, Canada, using pictures of routes to ask about preferred and actual route types. In Catania, Italy, [4] combined object risk data captured by monitoring equipment (e.g., GPS, cameras and GNSS-video system) and analyzed by experts, with perceived risk from a web survey to score the same components. These studies provide valuable insights into the factors that influence bikeability perception. However, the assessment and identification of traffic objects in images were made manually, limiting their scalability. Therefore, further research is needed to explore the potential of artificial intelligence (AI) for the automatic detection of events and improve the scalability of route evaluations [4].

The objective of this research is to develop a novel approach for automatic identification of safe and comfortable bicycle routes using a parameterized weighted system, computer vision techniques, and road network data. By integrating computer vision algorithms that can detect features relevant to bicycle commuting and leveraging road network data, this approach has the potential to provide a tool for mapping the safest and most comfortable routes for cyclists. Such a tool can be used to encourage the use of bicycles and support decision-making for infrastructure improvement. The remainder of this paper is organised as follows. In Section 2, we review the related work and describe how our approach differs from previous studies. Section 3 presents the proposed methodology in detail. Section 4 describes the training and performances of the models and details our experiment. Finally, Section 5 discusses the result of the experiment, summarizes the conclusions of this research and outlines possible directions for future work.

2. Related work

Recent studies have shown an increasing interest in automating the assessment of urban spaces for various transportation modes. One such example is iWalk [5], which was developed to measure the quality of urban infrastructure from the perspective of pedestrians without the need for personal inspections. The authors compiled relevant factors for calculating the walkability index and used public geospatial databases to retrieve and analyze data about the environment. The solution has been tested in Lisbon, Portugal, and was found to be efficient, scalable, and capable of calculating the walkability index for different segments.

Although [5] were able to assess most aspects of urban environment quality using only geospatial data, it may still lack some relevant information that is generally not present in public geospatial databases, such as the quality of pavement and unmapped obstacles. To address this issue, recent studies have supplemented geospatial data with features detected using computer vision. For example, [6] proposes a video processing pipeline with a safety scoring mechanism for evaluating cycling resourses. The pipeline uses factors related to the format of the route obtained from OpenStreetMap (OSM), such as the shape of turns, road types, declines, and roundabouts. To detect unmapped details like manholes, signalization poles, and cracks on the asphalt, a computer vision model is applied to the frames of a geotagged video. The authors validated this automated approach against an analysis performed manually by experts. Although the results showed the need for some fine-tuning, the tool demonstrated potential for real-world scenarios. To assess commuting routes, an object detection model is needed to identify key features such as pavement type, cracks, asphalt defects, and cycle paths, which are essential to address the issues mentioned in this document.

The study presented in [7] aimed to develop a camera-based surface detection model using Deep CNN to determine road-tire friction coefficients and parameterize vehicle control algorithms. To create the training data, the researchers built a mixed dataset using multiple publicly available datasets with pictures of different surfaces representing both wet and dry conditions. To balance the dataset, the researchers added pictures of less representative surfaces from Google Image search. Two architectures were used for classification performance comparison, using ResNet50 and InceptionNetV3, applying batch normalization and data augmentation mirroring, scaling and rotating the pictures. The ResNet50 architecture outperformed InceptionNetV3, demonstrating a slightly higher average classification accuracy. In the experiments, InceptionV3 architecture had a test accuracy of 90% with the basic dataset but started overfitting more easily with the additional images from Google image search, ending with an accuracy of 84%. The ResNet50 architecture reached an average accuracy of 92% trained with the extended dataset. While the average accuracy of the ResNet50 architecture outperforms the results of other referenced studies, there are still some misclassifications of "wet asphalt" and "dirt" as "asphalt," which represents a critical obstacle to assessing the road in real time. However, this may not be a problem for a static assessment of a city. Although the primary application of this study is supporting vehicle control algorithms in real time, it has demonstrated the possibility of adaptation to identify pavement characteristics related to cycle safety.

Pavement defects, such as cracks and potholes, are important risk factors that are often not captured in geospatial databases of cities. In [9], the author proposes a novel framework called DASNet to detect pavement diseases from images, which is based on the Faster RCNN architecture and uses a deep convolutional neural network. The framework consists of three modules: a deformable convolution module for feature extraction, which allows the convolutional layer to adapt to irregular shapes, a feature pyramid network using AugFPN, and a sample weighted loss function. When the feature detected has a large curvature the detection bounding box can have an imbalance between the foreground and background, and the sample weighted loss function can help to solve that. The DASNet approach outperformed other state-of-the-art detection methods with a mean average precision (mAP) of 41.1%, according to the author's comparative analysis.

Detecting cycle lanes from images is crucial, especially since the available data sources can be outdated or incomplete. In [15], a deep learning model was developed using the TensorFlow 2 Object Detection API to identify cycle lanes. The study was conducted in Victoria, Australia, where cycle lanes are indicated by bicycle markings on the ground. To recognize this symbol, the author created a custom dataset of cycle lane images using Google Street View and fine-tuned a pre-trained model called "CenterNet HourGlass104 512x512" from the TensorFlow 2 Model Garden, which is based on the COCO 17 dataset. According to the authors, the model performed well, achieving 100% recall and 92% precision on the validation images. In addition, when applied to map an area, the model was able to identify segments of cycle lanes that were not documented in the official dataset or OpenStreetMap.

These research works demonstrate how to build computer vision models that could be used to detect different traffic features that are cited in urbanism surveys and studies as factors that influence cyclists' perceptions. Although some of the authors presented automated assessment tools, none of them are for commuters. Adapting these models and combining them with the knowledge about the commuters' behaviour can result in tools to automate the assessment of the routes in a city, helping the cyclists to find the safest and most comfortable routes and finding opportunities for improvements in the city infrastructure.

3. Methodology

This research work introduces an assessment tool implemented in Python, aimed at calculating a safety and comfort perception score for route segments based on a range of traffic features. The tool integrates multiple sources of information, including the presence of cycle lanes or paths, pavement type, pavement defects, and the classification of the road as major or local. To evaluate a segment, the tool relies on a picture of the road and the corresponding coordinates at the time the picture was taken, which are used to retrieve the road network dataset. The pipeline follows a specific sequence of steps outlined in Figure 1 and described in detail in the list below.

Parameters The assessment of a segment requires a picture of the road and corresponding coordinates. For practical purposes, the Google Street View Static API was chosen to retrieve images, as it allows control over camera angle and resolution.

Cycle infrastructure model The pipeline first detects the presence of cycle paths or lanes in the image. If any detection is made, a score is attributed accordingly.

Pavement type model Next, the picture is classified as asphalt, cobblestone, or unpaved. If the pavement is classified as unpaved or cobblestone, the score is attributed directly without searching for pavement defects.

Pavement defects model This model utilizes object detection to identify pavement defects such as cracks or potholes. Only pictures classified as asphalt are processed in this step.

Road type retrieval The final feature is the road type, which can be classified as either a major or local road. The road network dataset is fetched using the provided coordinates, and the road hierarchy is used to determine the road type.

Output Finally, the pipeline utilizes the feature values and parameterized weights to calculate a score for the route segment. The output consists of the calculated score and a list of the identified features.

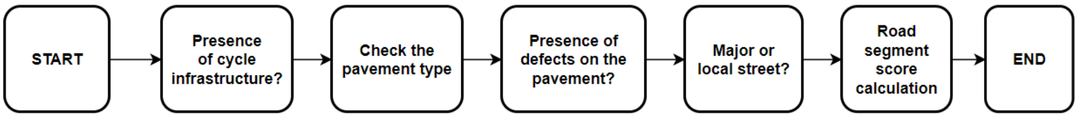

Fig. 1. Diagram showing the steps of the automatic assessment.

Three computer vision models were trained using Yolov5 to extract the route segment features. YOLO (You Only Look Once) is a recent and famous algorithm that uses neural networks for image classification and object detection [13]. The main advantages of using YOLO are the model's small size, strong generalization and fast calculation speed [14]. Yolov5 was built to have customization on the model's size to control the trade-off between inference speed and performance. The model size options are yolov5n (nano), yolov5s (small), yolov5m (medium), yolov5l (large) and yolov5x (extra large). Larger models mean a bigger network with more parameters and, consequently, a better inference performance, but also demand more processing resources to train, a longer time to infer and more disk space on the device. yolov5n, yolov5s and yolov5m models are recommended for situations when inference speed and disk space are important, like mobile applications and real-time inference [13]. In this research, the capabilities of image classification and object detection were both needed to extract the desired features.

Although it is not in the scope of this work to define the weights for each feature, it is going to be necessary an initial set of weights that represent the cyclist's perception in order to test the automatic assessment tool. Ideally, there should exist a definition of the weight of the safety and comfort perception for each feature present on the pipeline in the target city, but unfortunately, there is no research work like that for Lisbon. Adding to that, a part of the research work on cyclists' perception uses subjective features to measure it and was hardly found papers that had objective values for all the features needed in this assessment tool. Due to this reason, it was decided to use the values present in [16] as a source of parameterization for the reason of having the variables most aligned with our assessment tool.

In [16], the authors use a stated preference survey to analyze the importance of the factors that affect the cyclists' route choice. Two types of factors were used, route-level and link-level factors, being "link" a segment between two intersections. The survey showed a list of preferences, the following are the most useful examples for the context of the assessment tool: the presence of bicycle infrastructure, paved streets over unpaved, smooth pavement over rough pavement, and residential streets over streets with more traffic. The authors use logistic regression to obtain the coefficients that represent the magnitude of the influence of each variable on the cyclists' preferences.

To be able to use these coefficients to calculate a score and rank, it is necessary to translate these weights proportionally to the same scale of the survey (1 - 10) and correlate the features between [16] and our assessment tools. Certainly, "smooth pavement" refers to asphalt without defects, the same way "coarse sand" is the same as unpaved for the assessment tool. It did not specify exactly "rough pavement", but it is a less comfortable pavement between smooth pavement and coarse sand. Ideally, it should be a study to address asphalt with defects and cobblestone with different values, but in this correlation, they both were put inside the concept of "rough pavement". The only bicycle facility type selected to be used is "separate path" because all the cycle infrastructures identified by the assessment tool are separated paths from traffic. Regarding the roadway class, the paper describes three classes: major arterial, minor arterial and residential. Without question, the residential correlates to the local street, but the assessment tool does not differentiate between major arterial or minor arterial, being necessary to join the two arterials into the category of "major" using an average of the two as the corresponding coefficient. Table 1 shows the correlations made and the coefficient from [16]. The negative values represent detractor factors and the positive are factors that incentivize the route choice.

Table 1. Correlations between the values obtained in [16] and the assessment tool.

Reference paper variable	Paper coefficient	Corresponding feature
Roadway class - residential street	0	Type of road - Local
Roadway class - Major and minor arterial	-1.265	Type of road - Major
Bicycle facility type - separate path	1.780	Presence of cycle infrastructure
Bicycle facility type - no bicycle facility	0	No presence of cycle infrastructure
Pavement type - smooth pavement	0.33	Pavement type - asphalt without defects
Pavement type - rough pavement	0	Pavement type - asphalt with defects and cobblestone
Pavement type - coarse sand	-0.980	Pavement type - unpaved

Once the correlation between the features was made, the next step was to transform these coefficients into the same scale as the assessing tool. The distance between the two extremes of the coefficients was interpreted as the magnitude of the factor's influence on the route choice. Based on the literature review, the perfect route choice (score 10) for the assessment tool have to be asphalt with no defects, in a local street and with the presence of cycle infrastructure. With that definition, it was calculated the proportion of a 10 score for each one of the features based on the coefficients. After that, it was defined the multipliers for each value of the features. For example, the proportion of the feature pavement type to the perfect score of 10 is 2.9, and the extremes "asphalt without defects" and "unpaved" are going to be multiplied by 1 and 0 respectively according to their contribution to route choice. Following the same rule was defined a multiplier of 0.75 for the value "asphalt with defects or cobblestone" because its coefficient is positioned at 75% of the higher value for this feature. Table 2 demonstrates how each coefficient is used to define a proportional part of the score. The final score is the value used to parameterize the assessment tool.

4. Experiments

In order to train a model to identify if a pavement type is asphalt, cobblestone or unpaved, the Yolov5 were used in classification mode, since the pavement is the bigger part of the image. The first experiments were made with a pre-built dataset used for pavement detection for autonomous cars with bumper cams [8]. Although this dataset had the classes needed for this experiment, the resulting model was not capable of producing any generalization to the GSV images, probably because of different resolutions and zoom and pictures being taken in movement with some blur.

Table 2. Coefficients being transformed to the same scale as the assessing tool.

Feature	Coefficient	Magnitude	Proportion to score	Value multiplier	Final score
Type of road - Local	0	1.265	2.9	1	2.9
Type of road - Major	-1.265			0	0
Presence of cycle infrastructure	1.780	1.78	4.09	1	4.09
No presence of cycle infrastructure	0			0	0
Pavement type - asphalt without defects	0.33			1	3.01
Pav. type - asphalt w/ defects and cobblestone	0	1.31	3.01	0.75	2.26
Pavement type - unpaved	-0.980			0	0

For this reason, a script was implemented to extract the images in a pattern of angle and image size using the Google Street View Static API.

The Google Street View Static API allows retrieving a panorama image from Google Street View(GSV) with a specific angle and size and without the user interface elements occluding the image. The request to this API can be made via URL or programmatically and the parameters include size, location(in coordinates), heading(horizontal angle) and pitch(vertical angle) [11]. There are other parameters but they were not explored in this research.

This implementation was useful to extract images to build the cycle path and pavement type datasets and was used to extract the image from GSV with the same pattern to be assessed by the pipeline. The parameters used are size 640x640 and pitch -50 to achieve a dashcam-like angle, being able to capture the pavement and cycle infrastructure.

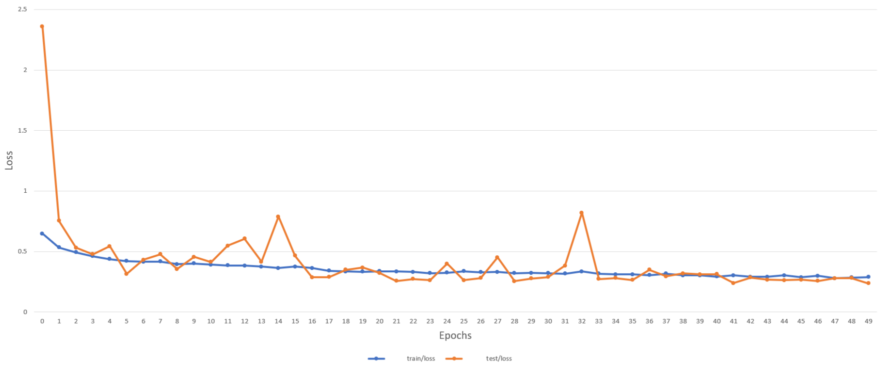

Fig. 2. Pavement type model learning curve with yolov5x configuration during 50 epochs.

1552 pictures of pavement were extracted from the main cities of Portugal, being equally balanced between the three classes. The split train/validation/test was made with the proportion of 75% of the images for the training, 20% for validation and 5% to test the model. As it is not required to use the entire picture to classify the pavement only a small portion of the pavement texture, was applied a pre-processing to zoom the image 150% and crop in the centre to a fragment of 224x224. This way, most of the resulting images were not occluded samples of the pavement and the training can be more efficient, quicker and accurate than training with 640x640 images with buildings, sidewalks and other elements around. Figure 3 shows the results of the preprocessing. Yolov5 has the option to use pre-trained weights on the training and there are default weights available for each model size [13]. It was decided to take advantage of this feature to compensate for the smaller pavement type dataset. The training parameters used for this dataset were 50 epochs, image size 224, batch size 64 (automatically selected for the environment) and three pre-trained weights to compare the results: yolov5s, yolov5x and ResNet50.

The pavement type model training reached excellent results, as can be seen in table 3. The pre-processing strategy probably played the main role in reaching this result, because limiting the image to a part of the pavement area removes other textures on the border of the road,

Table 3. Pavement type classification models performance with 50 epochs.

Architecture	Accuracy
YOLOv5 model S	0.975
YOLOv5 model X	0.963
ResNet50	0.963

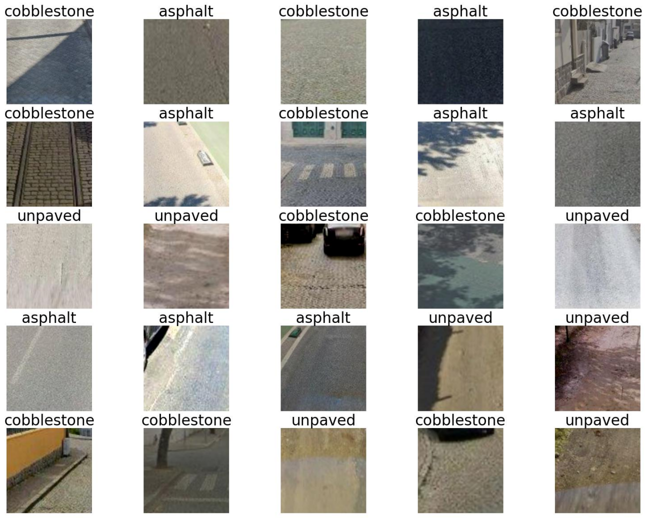

Fig. 3. Pavement type dataset preprocessed images.

such as vegetation, sidewalk, dirt and constructions, that could influence the model without having a relationship with the pavement type classes. The yolov5s was the training configuration with better performance, even though it is the model configuration with the lower complexity. Presumably, the other configurations had been able to reach even higher performance with more epochs, as figure 2 demonstrates that the model was still learning at the end of the 50 epochs. But since the small model had the same level of performance, it will be preferred because it is quicker to infer and demand less disk space. The decision of using pictures from Google Street View not only helped with maintaining the pattern of angle, resolution and saturation but also made the model flexible to different lighting and shadows on the pavement.

To train the model to detect pavement defects, the Road Damage Dataset (RDD2022) was used, which is a dataset of road images built for the Damage Detection Challenge. This dataset has 47,420 road images from six countries (Japan, India, the Czech Republic, Norway, United States and China) and is labelled mainly with four types of road damage: longitudinal cracks, transverse cracks, alligator cracks and potholes [12]. For this task, it was chosen to use Yolov5 in the object detection mode, as the dataset is already prepared with the bounding box annotations. This dataset had a considerable size to process during the training, which limited the training strategy options in the available infrastructure for this research work. For this reason, only the model size S was explored during the training. In addition to that, the pre-trained weight yolov5s was also used to reduce the training time. The selected image size was set to 640 and the batch size was automatically set to 16. It was run two experiments with and without label smoothing as a regularization technique to delay overfitting.

The training with the default settings for 50 epochs resulted in an mAP of 0.549 and setting the label smoothing parameter to 0.1 the mAP slightly improved to 0.556. Unfortunately, the results of this model are not satisfactory for real use, as the F1 Curve in figure 4 shows that the model was not able to reach a significant confidence level. The training results in figure 5

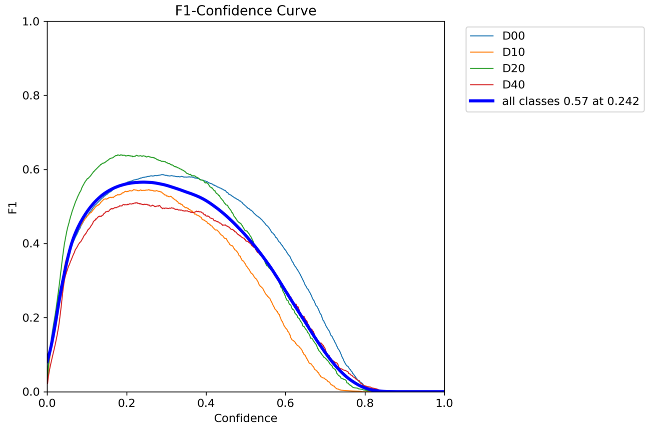

Fig. 4. Pavement defects detection model F1 curve with 50 epochs and pre-trained model yolov5s.

indicate that the model can be trained for more epochs before starting overfitting, and doubtless will be able to reach higher mAP and confidence. Due to the immense size of this dataset, the first experiments were done with fewer epochs, to test the different configurations more quickly and because the runtime used for these experiments does not allow longer training. The next step is to set up a suitable environment to run this training until it reaches the best performance.

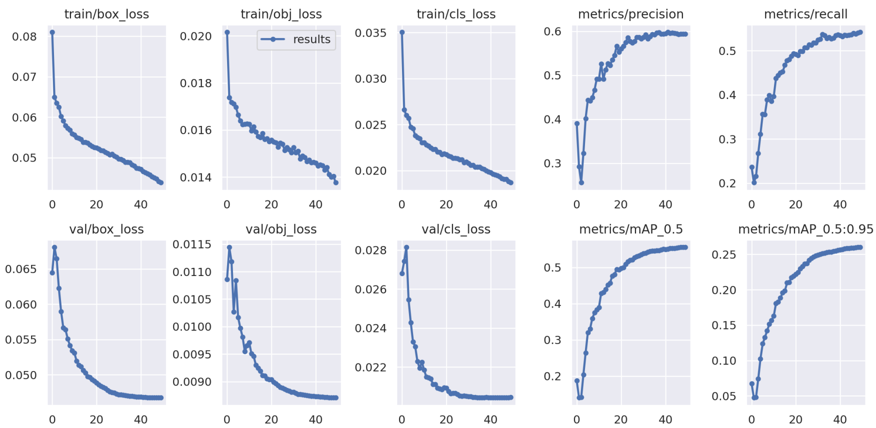

Fig. 5. Pavement defects detection model training results with label smoothing 0.1 for 50 epochs and pre-trained model yolov5s.

For the cycle infrastructure identification task, a similar strategy present in [15] was followed. As each location has a pattern of colour or symbol for cycle infrastructure, it is impossible to use cycle lane datasets from other locations, thus, for this research, was required to collect and label the cycle lane images for the target location. The Google Street View Static API also helped in this case, allowing to collect cycle infrastructure pictures from Lisbon with the same pattern. The object detection mode was also preferred for this task because the cycle infrastructures being marked with bounding boxes can help the model train with a small dataset.

1136 images were collected, in which there are images of asphalt and cobblestone roads with and without cycle infrastructure and unpaved roads with and without vegetation around. The size of the images is 640x640. In the 1136 images, there are 560 object annotations in most cases 1 annotation per image. 634 images do not have any object annotated. For this model, the split was 89% for training, 8% for validation and 2% for testing. Examples of cycle infrastructure annotations can be seen in figure 6. The yolov5s pre-trained weight was also used

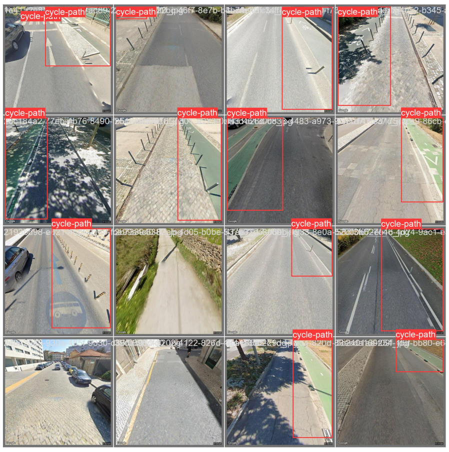

Fig. 6. Cycle infrastructure dataset annotated images.

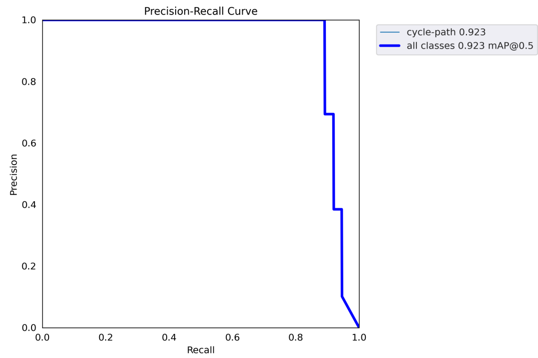

Fig. 7. Cycle infrastructure detection model PR curve with 100 epochs and pre-trained model yolov5s.

here due to the limited size of the cycle infrastructure dataset. The chosen image size was 640 and the batch size was automatically defined as 16. The remaining configurations were used as default and the first experiment ran for 100 epochs.

The cycle infrastructure detection model also had very good results with the default configurations and the pre-trained model yolov5s. In the last experiment, the training was able to reach an mAP of 0.923 at the end of 100 epochs, shown in figure 7. Besides that, it can be seen in figure 8 by the obj_loss curve that the model is still decreasing the loss value, indicating that the model is not overfitting yet and can be improved training with more epochs. Despite Lisbon having at least 4 different patterns of cycle infrastructure, the model apparently was able to adapt to the different colours and aspects.

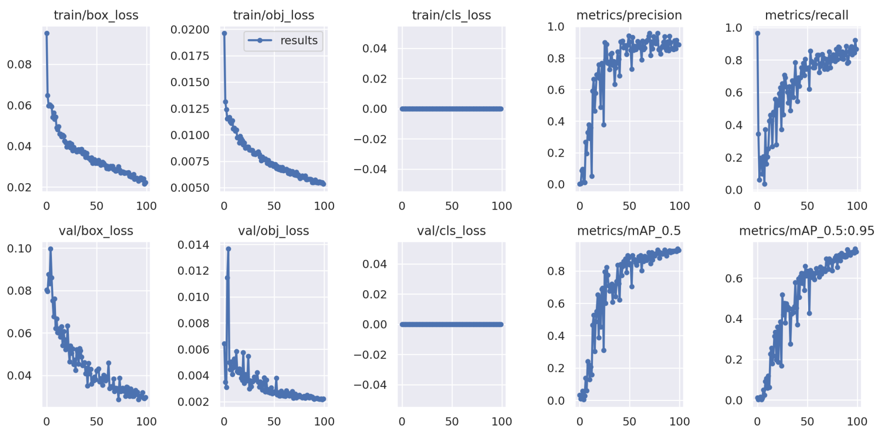

Fig. 8. Cycle infrastructure detection model training with 100 epochs and pre-trained model yolov5s.

This section described partial results of the experiments. The training options for the models were not completely explored, there is still room for improvement in using more epochs or manipulating hyperparameters, for example.

After the evaluation of each model separately, an experiment was made to evaluate if this automatic assessment tool can predict the cyclists' perceptions of each route. This was evaluated by comparing the cyclists' perceptions on a survey with an automatic assessment software built for the experiment. Figure 9 shows the steps of the experiment evaluation.

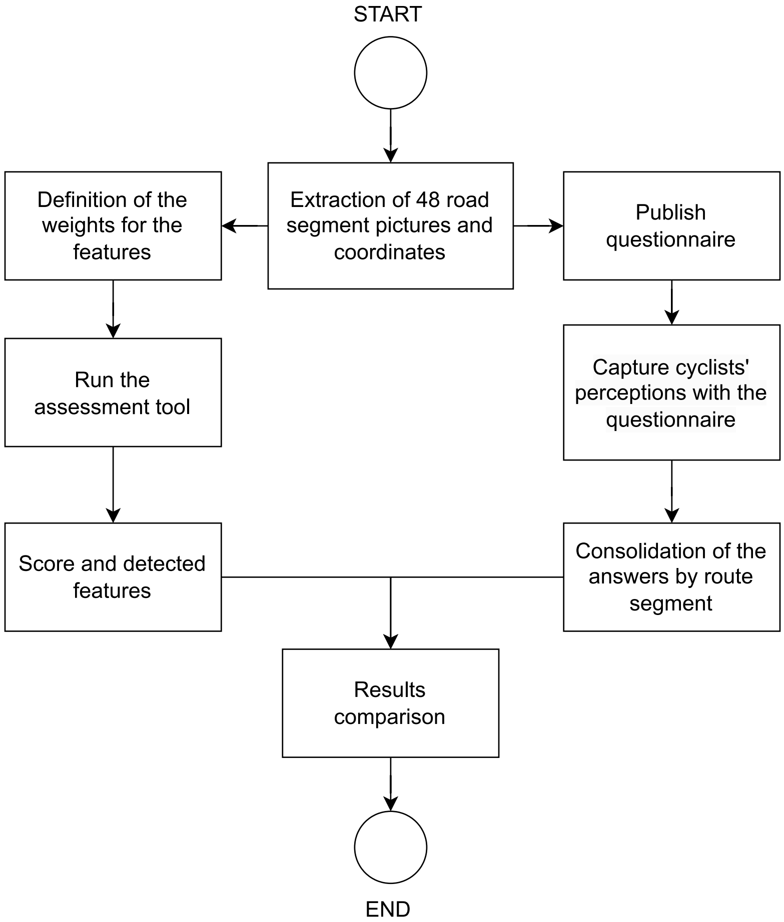

Fig. 9. Steps to evaluate the assessment tool's performance.

Fifty road segments with different combinations of these factors were selected for the experiment. The same picture of the road segment will be included in the survey and processed by the pipeline to be assessed. A specific questionnaire was created to assess the road segment pictures. Each page has a picture of a road segment and questions about the respondent's perception. There are two types of questions: close-ended questions asking which traffic features the respondent identifies on the picture and a Likert scale question for rating the level of comfort and safety perceived. For practical purposes, this questionnaire was applied as a web survey and shared via cycling-related groups and communities on the internet. A total of 48 pictures of route segments were selected to be assessed by the cyclists. The route segments were randomly ordered to be shown by the survey, so the first were not answered more than the last ones.

5. Results and discussion

The survey received 500 answers for the 48 route segments. The 48 route segments were processed by the automatic assessment tool. The results of the survey were aligned with the literature, as the cyclists submitted higher scores for smoothes pavements and the presence of cycle infrastructure. The table 4 compares the average score given by the cyclists on the survey with the score calculated automatically. The average difference between all the segments' scores was 2.03 and 28 of the segments had a difference of 2 or less between the tool and the cyclists. Although this is not a result that validates the tool to be used in real situations, it showed a tendency to rank the segments in a similar order that the cyclists in most cases. The scores calculated as zero by the tool are naturally incorrect, as this score can not exist in real-life segments using this

Table 4. Automatic assessment scores compared to survey results.

Route	Cyclists score	Automatic score	Route	Cyclists score	Automatic score
1	7.15	7.1	25	5.56	3.01
2	3.67	5.91	26	3.73	7.1
3	7.38	6.99	27	4.09	0
4	4.86	5.91	28	6.73	2.9
5	4.75	0	29	4.75	2.9
6	4.64	5.16	30	5.62	0
7	4.25	7.1	31	7.73	9.25
8	5.38	7.1	32	6.36	5.91
9	2.57	9.25	33	4.5	5.16
10	4.91	5.16	34	3.78	2.9
11	4.3	2.26	35	5	5.91
12	4.14	3.01	36	4.63	5.91
13	6.25	2.9	37	4.4	2.26
14	3.71	10	38	5.2	3.01
15	4	2.9	39	4.2	2.26
16	2.92	7.1	40	8.14	7.1
17	6.11	5.91	41	4.67	3.01
18	8.75	7.1	42	8.4	5.91
19	7.91	9.25	43	8	9.25
20	2.5	3.01	44	6.8	7.1
21	5.77	7.1	45	8	7.1
22	6	10	46	5.75	2.9
23	4.09	5.16	47	5	2.9
24	5.17	5.16	48	5.67	2.9

methodology and was caused by incorrect predictions of the pavement type, as some asphalt pictures with too much brightness were classified as unpaved.

These are preliminary results and will be analyzed further, but some clues are already clear on what is causing these differences and how to improve the tool. Some segments had a too lower score from the cyclists because they have factors that are not identified yet by the tool, for example, tram rails that are naturally dangerous for cyclists and lines on the right exclusively for buses, forcing the cyclists to be between the cars and the buses. Another impact was the poor performance of the pavement defects detection model, which was not able to make predictions with good confidence to be added to the score. It is expected that new experiments with a better version of this model will increase the entire tool's accuracy. Probably the next features to be included in the pipeline to be identified are tram rails and exclusive bus lines.

In addition to that, it was expected some unbalance between the weights used and the ones attributed by the cyclists, for the reason that the weights were adapted from a survey made in a city with different characteristics. In the future, the application of this tool after a specific study suggesting weights for the city would certainly bring better results.

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