IMAGE SEGMENTATION APPLIED TO URBAN SURFACE AND AERIAL CONSTRAINTS ANALYSIS

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ABSTRACT: *The rapid progress of artificial intelligence (AI) has prompted the exploration of its potential applications in the construction industry, although at a slower rate. Since the starting point of a design is the analysis of the site's constraints, the purpose of the ongoing research is the application of artificial intelligence in risk assessment for site areas. The primary objective of this research project is to develop an interactive map that employs AI to identify potential surface and aerial interferences. This map aims to support planners, engineers, and architects during the site context analysis phase by providing real-time visualization of obstacles. The interactive map allows users to explore and analyze identified obstacles, enabling cluster markers and filtering of features. The results obtained from applying this approach in Milan, Italy, demonstrate its functionality and usability, highlighting the tool's ability to provide valuable information in both localized and citywide scenarios. Potential improvements such as size assessment and advanced marker generation are also being examined to enhance the management of surface and air interferences. The goal is to enhance the tool's functionality, accuracy, and planning efficiency in construction projects.*

KEYWORDS: *Image Segmentation, Risk Assessment, Construction Site, Clustering Techniques.*

1. INTRODUCTION

During the project execution phase, a multiplicity number of agents and situations may affect the organization and the functioning of a construction site in terms of time and costs of the project. Indeed, these elements of 'disorder' can cause activities outside the program with negative effects on the quality, work, and safety of workers. The presence of the yard can be also a potential operational problem as continuity, health, and safety must be ensured both within the yard and outside. Thus, both perspectives must therefore be studied bidirectionally, at the interface between the site and environment. In addition, potential problems that may arise in terms of the size and duration of the project must be carefully analyzed for the construction of the network and mobile infrastructure and mobile construction site.

The *operational criticalities* represent the construction process variables, not necessarily known a priori, which may cause difficulties or inability to perform planned works. The analysis of potential criticalities in construction projects helps to identify operational issues and anticipate additional costs or time needed to avoid surprises during the work. For this reason, developing a specific design analysis is fundamental to arriving at the execution phase with an informed attitude toward possible problem solving. Operational criticalities can be organized into five criticality classes related to different areas, adopted as:

- Surrounding situation: analysis of the several characteristics related to the construction site and its surrounding.
- Production: analysis of the relationship and the organization between functional-spatial design elements, technological-productive design elements, and the utilization of human/techniques/materials/resources which are crucial for efficient and cost-effective execution.
- Specific design elements: analysis of programming aspects of a project which may be left incomplete for a conscious choice caused by specific difficulties in obtaining useful data to improve the design.
- Health and safety of the site: evaluation of how preventive and protective equipment, organizational measures, and training can affect the time and cost.
- Contingencies: analysis of those situations outside the construction site which may occur without generating surprise.

The risk assessment is a crucial step in evaluating and comparing design options, as any identified issues can be addressed during both the design and execution phases. It is important to investigate criticalities beforehand to address and solve them during the execution phase. This helps to quantify any increased costs and construction times. Writing an operational criticality report can support the validation of the design and contribute to client and designer awareness of any unresolved criticalities. It is important to update the document regularly throughout each design phase. This ensures that any critical issues that are identified during the first phase are addressed, and

Referee List (DOI: 10.36253/fup_referee_list)
FUP Best Practice in Scholarly Publishing (DOI 10.36253/fup_best_practice)
Marco Lorenzo Trani, Federica Madaschi, *Image Segmentation Applied to Urban Surface and Aerial Constraints Analysis,* pp. 907-916, DOI 10.36253/979-12-215-0289-3.90

any new critical issues that arise in subsequent phases can be resolved with an improved level of detail. The question then arises of how to exploit existing models of artificial intelligence related to the analysis of images to create a support tool aimed at drafting the document on the identification and analysis of critical issues and its constant updating. Indeed, it may be applied during the different project phases: for example, when the site inspection has not yet been carried out, the analysis of images from Google Street View (GSV) of the area can help the designer to have a clearer idea of the context in which it will operate. Instead, if the analysis is carried out on the photographic survey of the site, also carried out at different times of the duration of the yard, it can help to keep the surrounding criticalities monitored. Some critical issues that may arise during the development of the work can be detected with greater precision and detail. Hence, this paper focuses on the operating criticalities relative to the surrounding situation of a yard. The project presented aims to create an interactive map through simple and easy-access implements. It wants to demonstrate how using an artificial intelligence model for image segmentation applied to input images from GSV, is possible to create an interactive map that accurately provides the position of possible criticalities. A tool of this type, although of simple structure, can be very useful to designers, architects, or engineers during an inspection. It can become a support from which to draw a list of elements to be evaluated once they arrive at the site, because obviously, it is not possible to avoid this activity.

2. LITERATURE REVIEW

The development of an interactive tool supported by artificial intelligence, that provides a constantly updated view of the critical issues due to the context can be a basis for the implementation of further improvements to better support designers and engineers. The dynamic nature of the map must be able to allow the continuous updating of the input data, ensuring a greater precision than the static maps provided by the geographic information systems (GIS) (D. Farkas et al., 2016) which may contain inaccuracies or outdated information, regarding the positioning of services and sub-services.

The contextualization of the intervention plays a crucial role in construction projects. It involves a thorough study of the site, its surroundings, and the internal factors that directly impact the time, cost, and feasibility of individual operations. In today's construction industry, where companies often face significant pressure to meet strict time and budget targets, insufficient evaluation and consideration of surrounding constraints can result in an unsafe and accident-prone workplace (E. Rahnemay et al., 2017). Addressing these challenges, the integration of artificial intelligence with Building Information Modeling (BIM) has gained prominence in recent years (Y. Pan et al., 2022). This integration offers the potential to handle the vast amounts of complex and uncertain data present in construction projects more reliably and efficiently.

2.1 The Dense Prediction Transformers Model

Fully convolutional networks are the prototypical architecture for dense prediction (Long et al., n.d.; Sermanet et al., 2013). Dense prediction, a foundational challenge in computer vision, entails leveraging input images to generate intricate output structures such as semantic segmentation, depth estimation, and object detection through learning (Liu, 2021).

Convolutions are linear operators with a restricted receptive field, which requires sequential stacking in deep architectures to attain a comprehensive context and substantial representational capacity due to the limited receptive field and expressivity of individual convolutions. The image segmentation model used for the development of the tool in this paper was developed by Ranftl et al., who introduced Dense Prediction Transformer (DPT). DPT is an architecture for dense prediction tasks that adopts an encoder-decoder design, where the encoder utilizes a transformer as its fundamental computational building block. Notably, the authors employed the vision transformer (ViT) proposed by Dosovitskiy et al..

Thus, this model introduces a distinct architecture that replaces the conventional convolutional neural network. The main advantage of the vision transformer lies in its ability to generate a consistent and high-resolution global receptive field at each stage. Unlike the traditional convolutional approach, which examines individual windows gradually, transformers possess a unique mathematical architecture that establishes relationships between each neuron or zone in an image and each other. As a result, transformers show a relational nature, considering the entire image simultaneously in each position. This attribute facilitates the generation of predictions that are more refined and globally consistent than fully convolutional networks.

3. SURROUNDING SITUATIONS

The surrounding situations class is crucial as thoroughly examines the variety of factors that are closely related to the construction site and its surroundings. These factors can have a significant impact on work time and cost, influence the construction site's layout, and how materials are stored, handled, and manufactured (Marco Lorenzo Trani, 2012).

Speaking of yard contextualization, are numerous categories of operating criticalities to analyze and report in the analysis of criticalities document. Indeed, within it, problems deriving from site location in an urban fabric, hydrogeological characteristics of the site, subsurface constraints and due to the sub-services, aerial and surface constraints, also analysis of the environmental impact of the yard and the interference it may have with other nearby activities, are reported. Therefore, based on the categories of objects that the DPT model can recognize, seven elements have been identified on which to base the realization of the model (buildings, trees, plants, signboards, streetlights, skyscrapers, and poles), representative of certain categories just mentioned, going to focus the attention on localization in the territorial context, surface features, surface features, aerial restriction, and interferences with other activities.

The first mentioned controls the general access conditions to the construction site which may represent a potential operation criticality. For example, where the primary road is restricted, uneven, or overcrowded, it may be imperative to carry out extra measures to enhance the current road infrastructure or build new infrastructure to satisfy requirements. In case of temporary unavailability of the usual routes, the absence of alternative routes can further think hard about the planning of certain supplies to reduce the risk of a failed delivery or of lack of construction site-free spaces. The presence of road constraints for example represents a potential operational criticality in relation to the need to acquire dispensations or permissions from the public body. If the usual routes are temporarily unavailable and there is no alternative, it's important to carefully consider the planning of supplies to minimize the risk of failed deliveries or lack of space at a construction site. Road constraints, such as the need for dispensations or permissions from public bodies, can also create operational challenges. In the project developed this translates into the realization of the street network for the area under examination based on driveways, to provide an analysis of the critical issues concerning the main roads.

The technological-architectural, urban, and naturalistic preexistences represent a source of potential criticality, for example, the presence of a cantilever roof that, because of its height, doesn't allow the site access. As part of the project, the surface features were considered in the analyzed area by identifying the nearby buildings. Evaluation of neighboring buildings, in addition to influencing the height development of the yard, may also determine the choice of specific workings to avoid damage to elements not belonging to the site.

The presence of plants, trees, or poles in the area can pose a significant challenge to the safe and efficient operation of construction activities. This includes both aerial and mechanized handling, as well as the installation of temporary structures like scaffolds. Therefore, the aerial restriction analysis is important to ensure that these obstructions do not hinder the proper functioning of the construction site and that cranes can rotate freely at night without interfering with nearby buildings.

Lastly, the construction site's proximity to other productive activities can be a potential operational issue since the continuity, healthiness, and safety of both subjects must be ensured. If the site involves public services, the protection of service users is also considered in the critical analysis. Both perspectives need to be investigated in the interface between the construction site and the environment. The healthiness or hazardous elements generated from the environment to the site must be evaluated concerning the anthropic use of the environmental system. Additionally, potential issues that may arise in terms of the project's size and duration must be carefully analyzed for the construction of network infrastructure and mobile yards.

4. THE PROJECT

The purpose of the presented project is to identify potential surface and aerial interferences that may affect the area where a construction or civil yard is expected to open. To achieve this, an interactive map was created using the Python library "*folium*" to pinpoint the exact location of these obstacles. Python code was used to generate a street network for an interactive map using Google's OpenStreetMap. Users could choose to create the network for an entire city or a portion by entering coordinates or neighborhood names. The Lambrate and Città Studi neighborhoods in Milan were analyzed for this paper project. By incorporating the street network into the code, geographic coordinates were established that allowed downloading images from Google Street View. To ensure that ample data was gathered for identifying constraints, the network points were settled to be downloaded at a consistent distance of 25 meters.

In Figure 1, the road network generated is shown. Figure 2, with the orange points, shows the 2625 points identified for the analysis: each of them is characterized by an ID which is associated with the longitude and latitude of the position where it is located. After which, the corresponding images through GSV were downloaded. It’s important to note that there isn't a direct correspondence between points and images, as GSV provides multiple frames from different angles. This feature worked to benefit the project, as it allowed to detect possible interferences with greater accuracy.

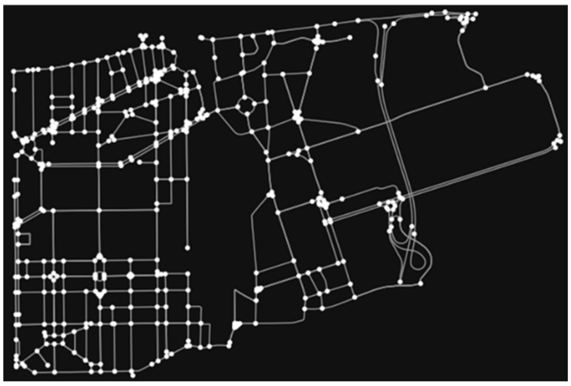

Fig. 1: Milan neighborhoods street network

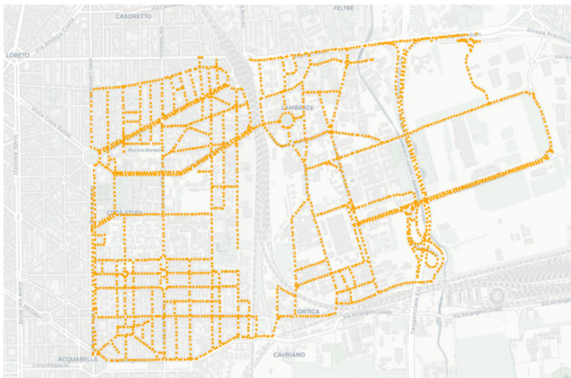

Fig. 2: 2625 street network points arrangement

Once the images were downloaded the DPT Model was utilized to analyze them. Rather than using object detection, image segmentation was chosen in the tool for obstacle identification due to its approach. It processes of classifying each pixel of the image into a class or label that identifies the occupied area of the object that can be recognized by the algorithm. This model proved to be highly effective in recognizing a wide range of possible obstacles, even in urban environments with numerous overlapping elements, limited image quality, or small obstacle sizes. In Figure three, how the process works it shown. The first row displays the input data in the form of images from GSV. Meanwhile, the second row showcases the model's image segmentation results. By utilizing pixel classification based on the labels integrated into the model, the reconverted objects like machines, poles, and bicycles can be identified in the images.

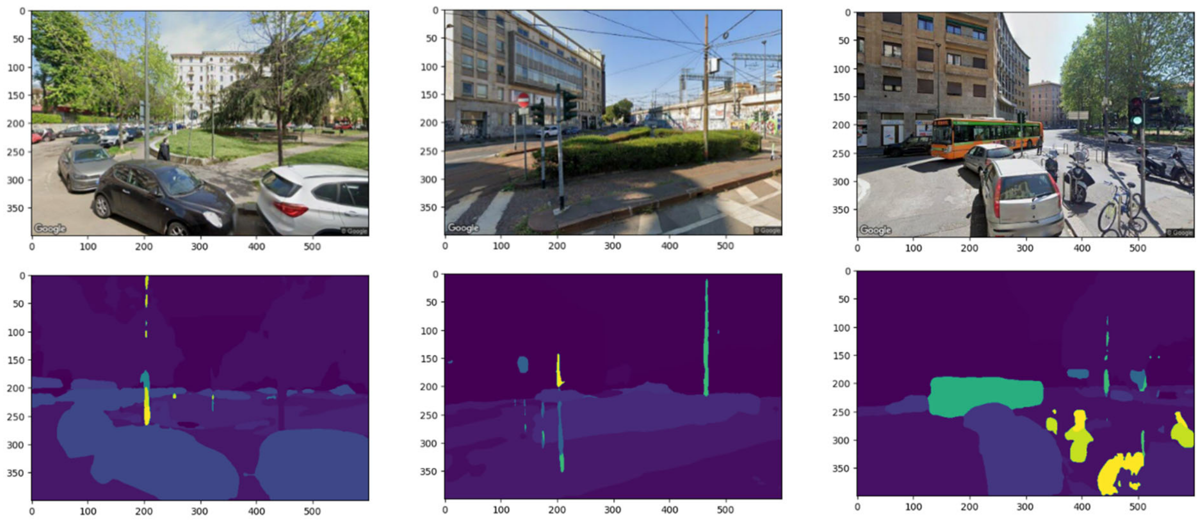

Fig. 3: Example of images segmented by the model

The model was trained to recognize over a hundred objects and use a filtering command to store outcomes for the most relevant constraint elements, including buildings, trees, plants, signboards, streetlights, skyscrapers, and poles a new CSV file with results was created.

After conducting Image Segmentation, the focus shifted toward visualizing the identified constraints. Upon counting the objects, it was observed that there were over 10,000 potential constraints that were recognized. The table below categorizes and counts these constraints.

Table 1: Number of elements recognized from 10500 images analyzed by Image Segmentation Model

Element	Building.	Tree	Plant	Signboard	Streetlight	Skyscraper	Pole	Total
Total	1882	1868	1563	1749	1655	4	1499	10220

Using the Folium library, constraint indicators have been configured with precise geographical coordinates from the road network generated previously: the code iterates each element of the CSV file containing the data related to the project. For each obstacle a marker has been generated that has been assigned a color based on a color dictionary for quick and easy identification. Included is the option to select markers, which displays a popup with specific information such as object name, image segmentation result, latitude and longitude coordinates, and reference image. Additionally, is possible to have multiple markers linked to the same image input. This is due to the fact that the image segmentation was done on the same input, resulting in different outcomes for the two objects. The reason for this is that during analysis, the model searches for all the elements it was trained for, as shown in Figure 3. Therefore, having the same references within the popup is not an indication of an error.

Let's examine the output tools in detail, focusing on their key features and assessing the advantages and disadvantages of the chosen representatives. The main difference between them lies in the type of marker used. The first tool employs *CircleMarkers* to indicate obstacles, while the second uses *ClusterMarker*.

To identify the position of obstacles in the studied area, the first tool created uses CircleMarkers for each element. These markers are color-coded based on the results obtained, allowing for a visual representation of the data. All the obstacles identified in Table 1 are displayed on the final map, thanks to the code implementation. Figure 4 depicts how the output appears to a user who has zoomed in on a specific area.

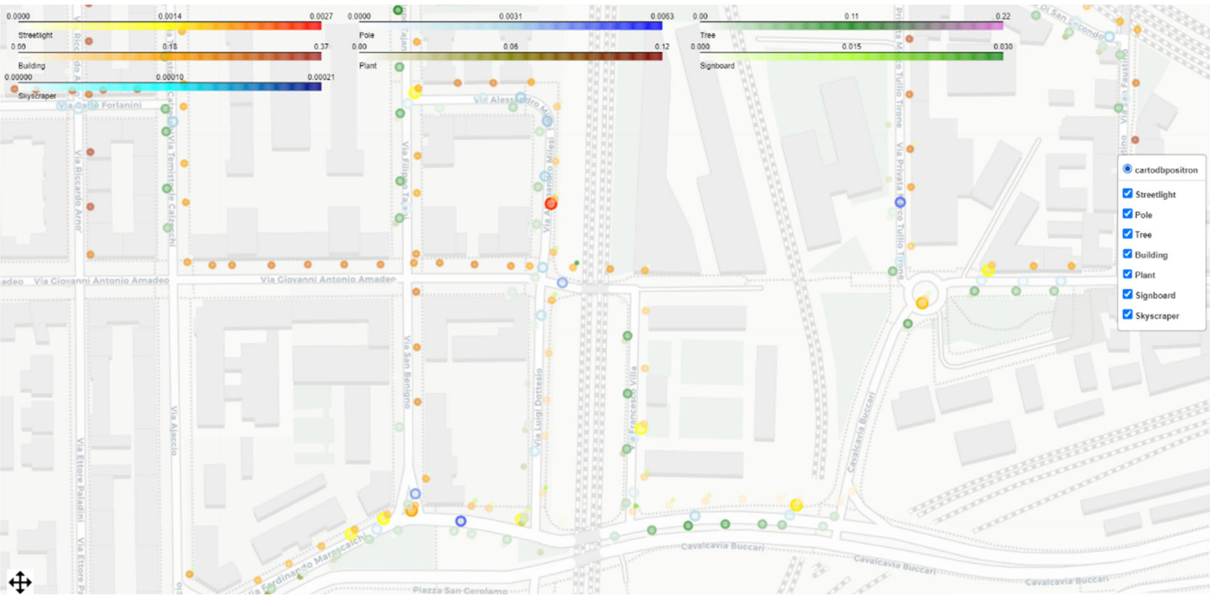

Fig. 4: *CircleMarkers* output map, zoom in is applied

To facilitate the reading of the position of markers, two solutions have been adopted. The first is general, inserted inside the code as a constraint for the positioning of the various indicators according to the reference category. In fact, an offset in the generation conditions within the map was made so that there was not a total overlap that prevented the display. Instead, the second solution concerns the possibility of managing the layers on which the markers have been inserted. Figure 4 shows that points with the same coordinates are slightly separated from each other. However, the exact location can be determined by selecting the marker of interest for the popup display. Different size radii were used to distinguish between the various markers, with their size gradually decreasing. To display or hide a marker, simply select it from the drop-down menu located on the left side of the map.

The second map proposed shows surface and air constraints via *ClusterMarker*. These markers are sued to clearly showcase clusters of data that are focused on a specific point while also indicating the number of elements in a micro zone. This is achieved by displaying circular markers that contain a numerical value within the area it covers.

By adjusting the map zoom, the markers can be enlarged or reduced. The groupings are distinguished by their color: green indicates a few markers, while red indicates a large number. In Figure 5 a visual representation of the second type of output is reported.

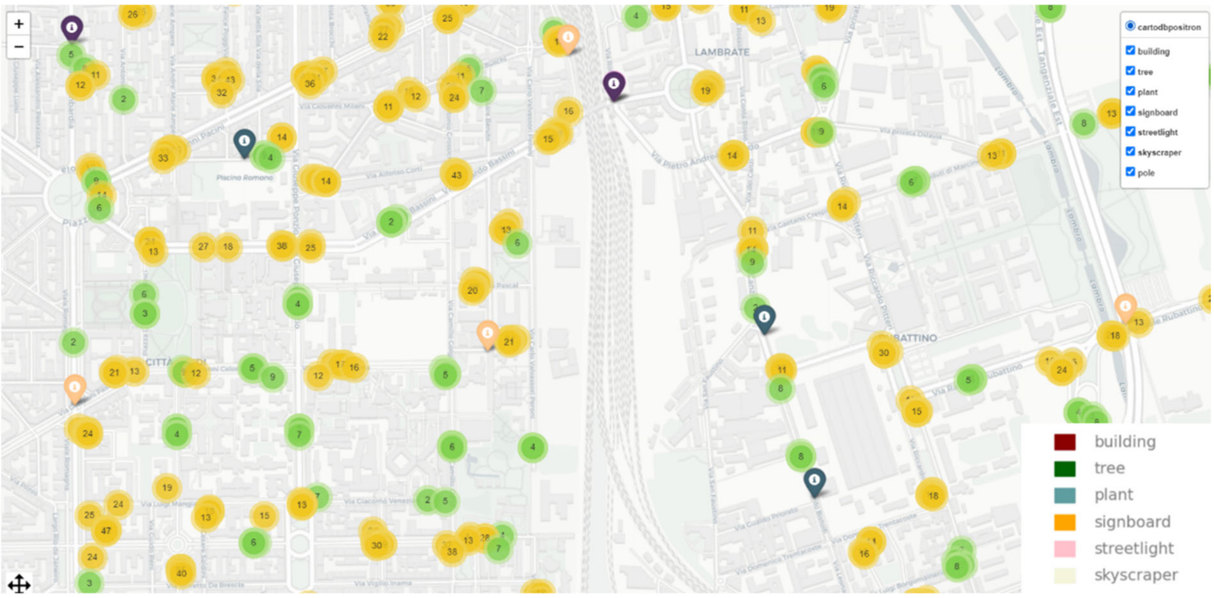

Fig. 5: *ClusterMarker* output map

This second output exhibits the same characteristics as the *CircleMarker version* but with distinct functions and interpretations. For instance, the filter option is always incorporated to allow for data selection, but instead of concealing layers, it directly hides the obstacle category. Moreover, the legend, located at the bottom right, no longer changes color scale based on outcomes, but rather on the classification of constraints, assigning a specific color to each. Figure 6 illustrates a zoom-in on the map to see more clearly the markers. However, when multiple groups appear at the same location, it can be challenging to get in an immediate overview of constraint positions. It is necessary to click on the specific interest group to view it. Moreover, there may be overlaps between groups associated with different categories and various *ClusterMarkers*, which can make the results less clear and immediate. Figure 6 demonstrates also how a popup appears when a marker is selected.

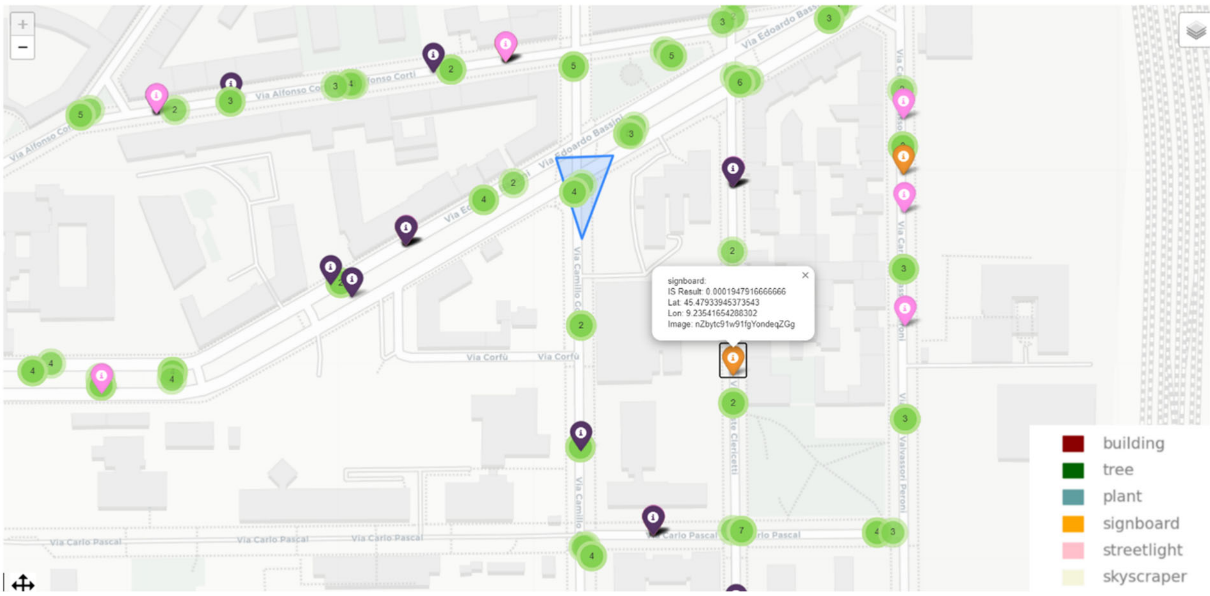

Fig. 6: *ClusterMarker* output map, zoom in and popup are applied

5. TOOLS APPLICATION AND VALIDATION

An application case was used to perform a thorough analysis of the tools' operation. In this case, the focus was on analyzing the criticality of the intervention that needs to be carried out at the junction of via Carlo Pascal and via Celeste Clericetti. Figure 6 depicts the map of the area before results from the analysis were included. The blue rectangle represents the intervention's position, while the red circle marks the specific area to be analyzed.

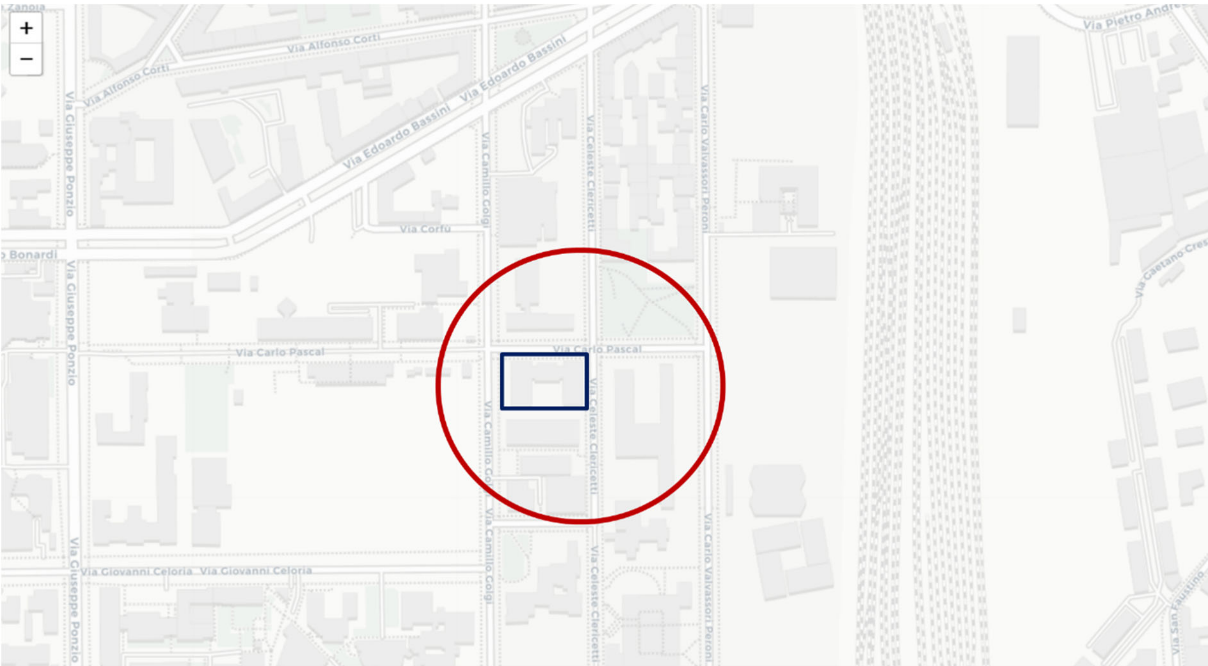

Fig. 7: Identification of the location of the assumed construction site and the area to be analyzed

To identify critical points, Figures 8 and 9 were analyzed, which report the output results obtained using the developed tools.

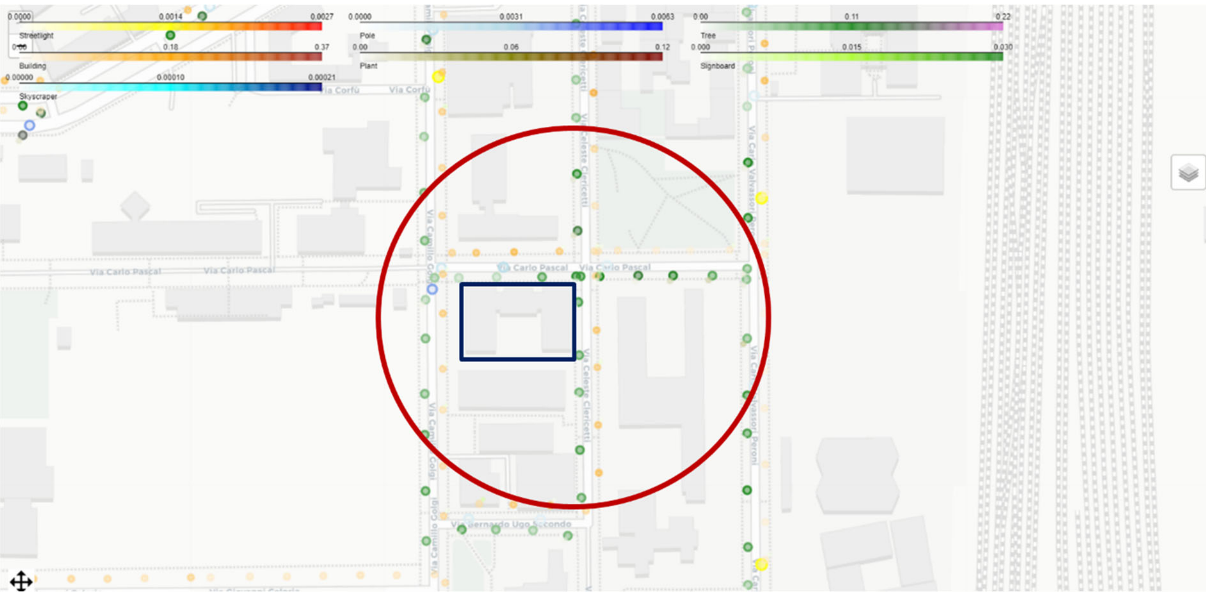

Fig. 8: Operational criticalities from tool Output 1

In Figure 8, there is a depiction of the constraints located near the intersection that has been identified as the area of analysis. The main issues that may arise are related to the presence of trees and buildings, which could potentially cause problems during future air handling procedures. Despite this, the arrangement of markers appears to be tidy and easily discernible, although this could be due to the high zoom used on the area and the existence of only two primary categories of elements.

In contrast, Figure 9 displays the outcomes obtained by utilizing tool number 2. Upon comparing these results with the previous image, it becomes apparent that reading the results, in this case, is neither rapid nor straightforward. The presence of numerous *ClusterMarkers* in one location hinders readability as one must open them to view specific locations. Additionally, this grouping only applies to Markers that belong to the same category. As shown in the figure, when multiple elements that belong to different categories overlap, their groupings also overlap. This can make it difficult to read the results when using the map at a higher zoom level than what is shown in the figure.

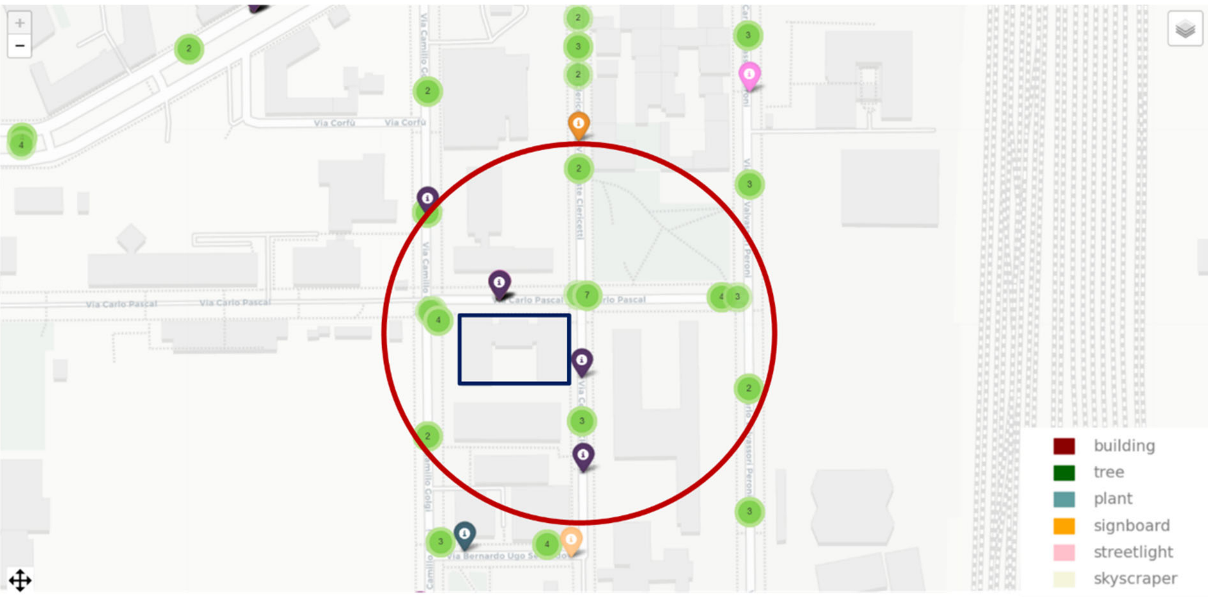

Fig. 9: Operational criticalities from tool output2

Although with the respective problems, identifying critical points in the area was relatively easy. Table 2 clearly shows the number of obstacles that could potentially cause issues during the operational phases of the future construction site. It is evident that the main obstacles are the buildings and trees adjacent to the area being analyzed, as previously mentioned.

Table 2: Number of elements recognized in the analyzed area

Element	Building.	Tree	Plant	Signboard	Streetlight	Skyscraper	Pole	Total
Total	23	32	6	0	3	0	8	69

Therefore, the proposed project has achieved its objective of reliably identifying objects and their positioning on the map with good results while acknowledging operational limits. However, it is important to note that the clear display of obstacle placement seen previously may not always be guaranteed. The first tool requires the application of a filter to provide a clear view of individual obstacles, although improvements have been planned for the overall view. On the other hand, the instrument with *ClusterMarkers* may have poor readability due to the overlap of different object groupings at the same point.

Typically, to assess potential risks in a particular environment, images are analyzed to identify any potential obstacles. Hence, it's crucial to study how the model segmented the images and locate these obstacles on output maps. The proposed code provides visual support for this analysis. Two of the images extracted by GSV for the analysis of Via Carlo Pascal (Figure 10) are shown below. Normally the designer would identify and manually report the possible obstacles, such as the presence of trees for air handling, or car parking in case the occupation of public land was necessary. Analyzing images through the image segmentation model, this procedure becomes assisted and facilitated. Comparing the original with the results obtained and shown in Figure 10, it is possible to see how elements such as cars, trees, sidewalks, and poles are recognized and marked distinctly. The classification of image pixels according to the elements for which the model has been trained can therefore be of fundamental help where the overlapping of objects makes it difficult to recognize them.

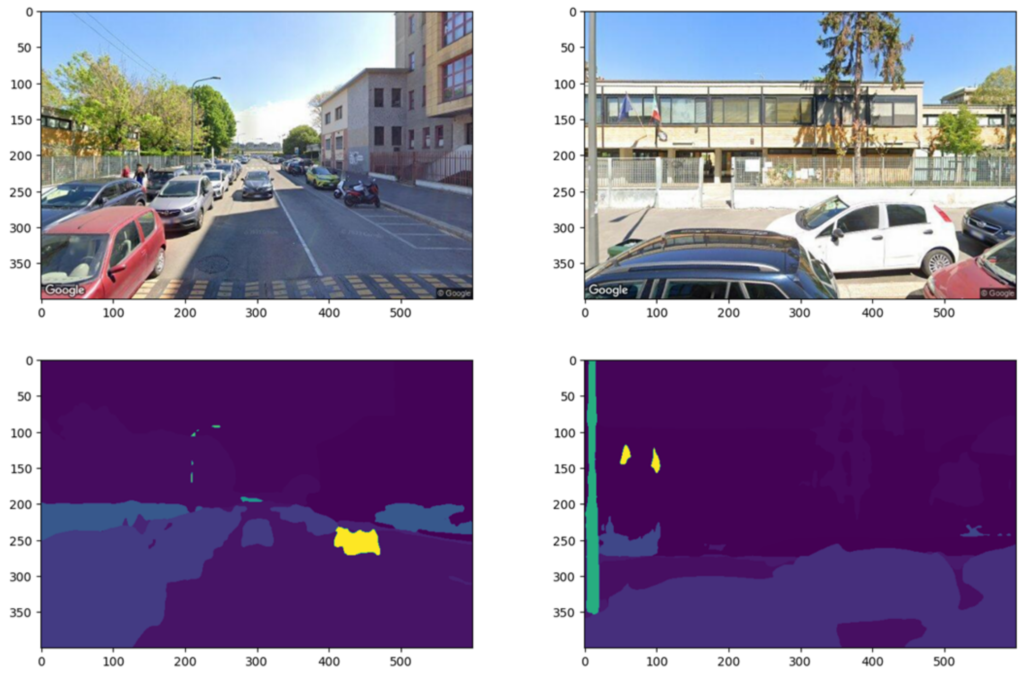

Fig. 10: Image segmentation results for the street analyzed in the example

However, by exploiting this type of approach for the analysis of criticalities, two fundamental limits can be identified, one technical and one "operational". The technical limit concerns the elements for which the model used has been trained. Indeed, there are about 150 objects that it can recognize, and not all of them are useful results for the purpose of this research. The solution to this limitation could be solved by developing a model trained to recognize a list of specific objects, related to the sector. Clearly, the realization is not immediate because in-depth knowledge of this type is beyond our competence.

The "operational" limit consists in not being able to rely entirely on the instrument. The validity of the results in terms of object recognition and positioning according to geographical coordinates has been obtained and demonstrated with excellent results. However, it should be remembered that an analysis carried out by this tool does not completely replace an analysis conducted directly by the designer. As stated above, the tool wants to be a support to ensure greater accuracy in the assessment of criticalities, but it is good to remember the existence of a margin of imprecision that only human experience can fill.

6. POSSIBLE IMPLEMENTATIONS AND CONCLUSIONS

The improvement and further development of the tool could lead to higher output quality and the implementation of additional functionalities. One of these functionalities could involve classifying objects based on their height and identifying them within the map as either aerial or surface constraints.

By adopting this classification approach and changing the output type, it would be possible to develop a tool that neglects the classification of objects according to their category of belonging. The recognized elements would still be positioned on the map based on their geographic coordinates; however, the color scale representing them would be based on the evaluation of their heights. Assuming to give the possibility to the user enters the reference value beyond which a constraint is considered aerial, the chromatic scale could then be defined based on this input that would represent the central value.

Nevertheless, regardless of the approach adopted for the development of such a tool, the utilization of artificial intelligence models, like the one employed in this study, has proven to be a proactive way to identify potential difficulties related to construction site organization and planning operations. However, it is essential to recognize that the images used as input, sourced from Google Street View (GSV), may have limitations in terms of quality and detail. Therefore, it is plausible to consider that the effectiveness and accuracy of the tool could be optimized by employing photographic surveys executed with appropriate instrumentation. This integration would enable the tool to provide more detailed and precise results concerning the construction site context, facilitating better analysis and identification of critical areas. In addition to the possibility of employing specific and higher-quality photographic surveys, considering the development of a dedicated AI model for this purpose could further enhance the capability to identify and address challenges inherent in construction site organization, offering a tailored solution for this domain.

In conclusion, adopting these measures would provide designers with a more sophisticated and efficient tool to navigate the complexities of construction sites, reducing the risk of errors or unforeseen complications, and enhancing overall decision-making in construction planning and management.

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