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OpenTrack: a Sensor for Monitoring the Usage of Territory

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Abstract

Understanding how people and vehicles move through public spaces is essential for designing inclusive, safe, and efficient urban spaces. In the Mendrisio district (Switzerland), we deployed a low-cost, AI-powered sensor to monitor pedestrian and vehicle flows in different seasons. The sensor uses camera-based image recognition to detect and classify objects in real time while preserving privacy by avoiding biometric or identity-related data capture, in full compliance with GDPR. The system was developed using open source hardware and software. Processes video frames on edge using a lightweight machine learning model optimized for embedded devices and periodically transmits summary data (object type, direction, timestamp) via NB-IoT to a centralized data platform. The collected data was used to generate temporal analyses and heatmaps of space usage and to validate the classification accuracy in different weather and lighting conditions. Field tests demonstrated the sensor's capability to operate autonomously for extended periods with low power consumption, while highlighting limitations in NB-IoT connectivity in specific locations. Despite these constraints, the system provided valuable information on public space utilization, identifying peak hours and spatial patterns relevant for mobility planning and urban design. This approach offers a replicable and cost-effective solution for municipalities seeking data-driven support for decision-making. By combining privacy-sensitive AI, open technologies, and standard data models (such as SensorThings API), the project contributes to a more transparent and inclusive digital urban ecosystem.

1. Introduction

Monitoring the movement of people, animals, and vehicles in daily territorial use can improve spatial development, enhancing safety, sustainability, and inclusiveness (Papageorgiou et al., 2024, Handcock et al., 2009). Across Ticino canton, many stakeholders, such as regional natural parks, are eager for a system that can provide valuable data on space usage to better manage costs, justify new investments, and handle maintenance activities (Yan et al., 2023). During the INSUBRIPARKS Interreg project, a cost-effective prototype was developed to track and count the passage of tourists in specific park areas (Cannata et al., 2022). The system consists of a device with a camera that, through image recognition and machine learning techniques, collects data that are then sent to a data warehouse based on istSOS (Cannata et al., 2015), an open-source implementation of the Sensor Observation Service (SOS) standard of the Open Geospatial Consortium (OGC). The system fully complies with European GDPR regulations, as it only stores anonymous metadata such as the type of object (person, car, bicycle, etc.) and the object's movement path. No video or images captured by the camera are saved. Because of these features, the device has also been adopted in the Adaptive Space project, funded by the Federal Office for Spatial Development (ARE). This project aims to develop a protocol with guidelines for inclusive last-mile mobility planning. To this end, two sites were selected as study areas (SA) to analyze the behavior of citizens who frequently use these spaces. The choice of the areas takes into consideration the increasing attention to transportation platforms and is framed within the projects promoted at the municipal and cantonal levels. One area is located outside the Mendrisio train station (SA1), is occupied by four parking lots, and is subject to movements that prioritize the passage of pedestrians and the flow of vehicles to and from the station and the city center. The second site is located in Mendrisio S. Martino, also outside the railway station (SA2). This area is of particular interest because in the last year a parcel characterized by a functional mix has been completed, generating a new inducement with important consequences in pedestrian flows. The methodology involved an automatic detection approach by installing sensors to collect continuous data. Three main data collection campaigns were conducted at each site: one in summer, one in autumn, and one in winter. Since the device has high power consumption, it had to be installed with a battery, as no viable solution was found to connect the sensor to a continuous power source. During the campaigns, the device collected data on the number of detected objects, their classification, and their movements across the monitored areas, using tracking capabilities that gather coordinates frame by frame to monitor the movement of each object. Such data have been validated through manual sampling and, on the other hand, have been provided a broader overview of the usage of the selected areas across different periods of the year. The analysis developed during this project focused on tracking data coordinates, which proved to be essential for understanding how the objects are distributed across the area and determining where activities are most concentrated, based on the different categories to which each object belongs. This approach results in the generation of heatmaps for pedestrians and vehicles using data from the entire day, as well as filtering for evening and morning peak-hour traffic. The dataset has also been evaluated in terms of data accuracy, as for each object present in the frame, the percent of confidence is archived. By plotting this data through a histogram, it was possible to understand the accuracy assessments of the detected objects from the chosen classification model. In this context, the challenges encountered during the project will be reported, primarily those related to data transmission. Due to the large amount of data collected, it was difficult to transmit everything using only an NB-IoT connection via the MQTT standard, which, due to its low bandwidth, cannot handle the transmission of large amounts of data.

2. Methods

2.1 Study area

The project involves two main areas of study where the device was used to collect data for analysis. After discussions with representatives of the City of Mendrisio and consultations with other stakeholders, such as the Canton and PubliBike, the company operating the local bike-sharing service, two areas were selected for this study (see figure 1 and 2):

- SA1 is the area located in front of the Mendrisio railway station. It is characterized by a one-way street running through the center and four parking zones, three on the right side and one on the left. This area is typically used for short-term stops. A pedestrian walkway separates the parking area from the main road, and on the left side of the image, a pedestrian crossing is visible, allowing safe access to the station;

- SA2 is located at the San Martino railway station, near the FoxTown shopping center. This area is frequently used by people arriving by train and heading either to work or to the shopping center. On the left side of the image, there is a main road, and below the concrete barriers runs a side street, which is primarily used by customers looking to park their cars or by trucks delivering goods to the shopping center.

The goal of the project was to identify two representative places that could benefit from improvements through the use of flexible urban planning tools such as tactical urbanism (Lydon and Garcia, 2015). In recent times, this tool has had great momentum in initiating reflection on the quality of public spaces and, in general, to initiate reflection on inclusive urban spaces. These are often temporary solutions, with minimal impact in terms of time and finances, that precede structural and lasting interventions. The Adaptive Space project intends to verify the flows affecting the two study areas in order to implement preferable interventions and evaluate their effects on pedestrian flows and usage practices.

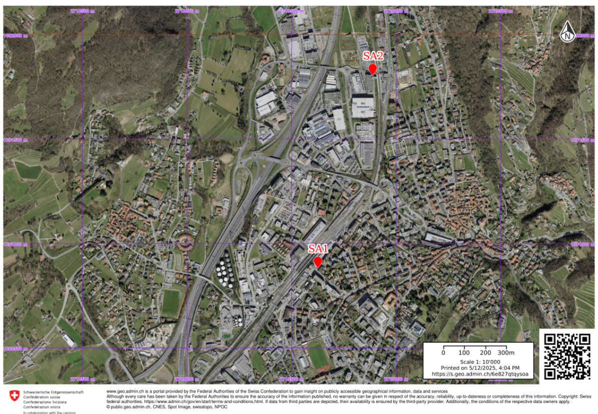
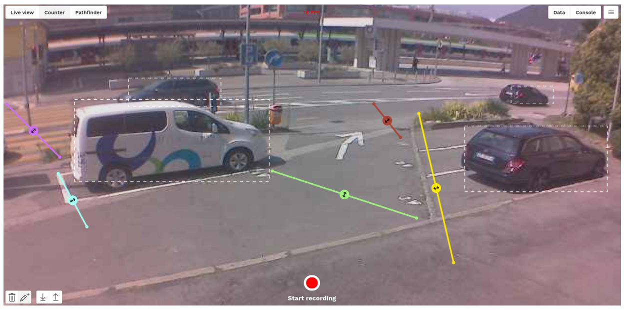
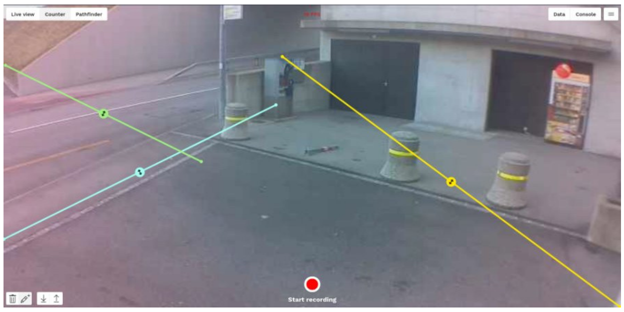


Figure 1. Map of the selected areas.



(a)



(b)

Figure 2. Views of the two areas: a) SA1; b) SA2.

2.2 The OpenTrack device

The device is based on OpenDataCam, an open-source implementation for detecting and quantifying moving objects, released under the MIT license (https://opendata.cam). It is widely used, especially for traffic monitoring and analysis (Broekman et al., 2021, Valladares et al., 2021). We previously employed this technology in a project aimed at monitoring the passage of tourists in order to quantify park usage by pedestrians, cyclists, and others. Thanks to the good results obtained in that project, we chose to adopt this technology again, not only to count objects, but also to analyze the use of specific urban areas through post-processed tracking data. This allows us to understand how the space monitored by the camera is being used.

The device consists of the three main components:

- Jetson Nano (Kurniawan, 2021), which serves as the main processing unit running the OpenDataCam application;

- Sony IMX219 camera, responsible for capturing video input;

- DC-DC converter, used to step down from 12V to 5V for powering the Jetson Nano.

The system consumes approximately 15-20 watts per hour. Since we were unable to guarantee a stable and continuous power supply from external sources, we planned to add a 12V 22Ah battery to power the device for approximately 12-14 hours. Thanks to the OpenDataCam software, it is possible to collect data about detected objects, including their category and tracking information, by recording their coordinates. Figure 3 shows an example of how these coordinates are collected. Essentially, for each frame in which an object is detected, it is continuously tracked. This makes it possible to reconstruct the object's direction of movement using its coordinates. These coordinates refer

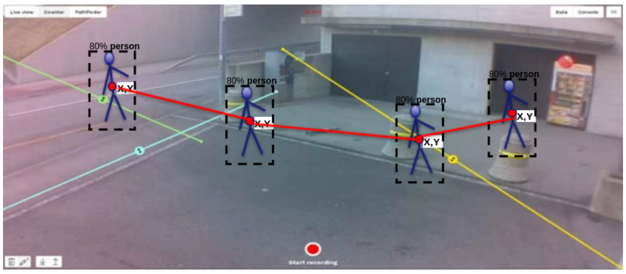


Figure 3. Object tracking schema.

to the center of the bounding box surrounding the detected object.

Thanks to the collaboration with the TecInvent company in Ticino (https://tecinvent.ch), the device has been significantly improved, particularly in terms of heat dissipation.In fact, during the prototype testing phase, the device encountered issues related to heat dissipation, as the real-time streaming analysis is particularly energy-intensive, causing both the CPU and GPU to generate significant heat. Figure 4 shows the device represented as a 3D model. The heat sink, which is partially exposed outside the enclosure, is equipped with an insulating edge cover to enhance safety and environmental protection.

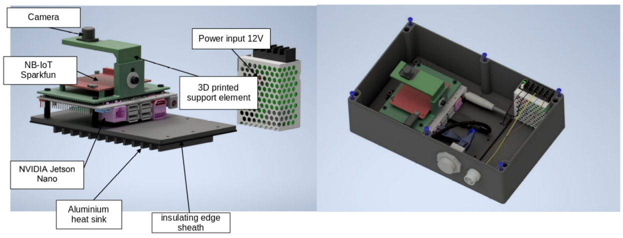


Figure 4. OpenTrack device 3d representation.

2.3 Surveys and data validation

According to the project's needs, three surveys were planned for each area: one in summer, one in autumn, and one in winter. On each survey day, the device was installed in the morning to collect data from approximately 7-8 a.m. until 6-7 p.m., in order to capture the daily peaks in area usage. In addition to automatic surveys, manual observations were also made. These served both to validate the data collected by the devices and to gather additional information, such as gender, direction of movement, and other behavioral patterns, that the automated system could not detect. Table 1 presents the details of the surveys.

Date	Place	Season
30.07.2024	Mendrisio	summer
6.08.2024	S. Martino	summer
8.08.2024	Mendrisio	summer
21.10.2024	Mendrisio	autumn
7.11.2024	S. Martino	autumn
15.01.2025	Mendrisio	winter
16.01.2025	S. Martino	winter

Table 1. Table of dates, places, and seasons of the surveys

2.4 Data processing

The data collected by the OpenTrack device are stored into a local instance of MongoDB. In this database there are two main collections:

1. *tracking collection*: this data represents the real-time or recorded list of all detected and tracked objects. This includes details such as the object class, confidence, position, and unique tracking ID;
2. *counter collection*: this data contains the count of objects that have crossed a predefined virtual line (or zone) in the video feed, based on tracking paths.

During the INTERREG project INSUBRIPARKS, only counting data was analyzed and an automatic data transmission was scheduled every 15 minutes to report how many objects passed through specific points in the monitored area. However, in the current study, we attempted to automatically transmit tracking data as well. Unfortunately, the volume of data proved to be too large, and the NB-IoT connection combined with the MQTT transmission protocol was insufficient, resulting in data transmission bottlenecks. This issue is particularly relevant in this case study, as the monitoring took place in urban areas, not only detecting people and animals, but also capturing large amounts of data from vehicles, especially during rush hours when the streets were frequently congested. Therefore, the data was analyzed in post-processing using a Python Notebook developed to replicate the processing workflow for each survey. The analysis relied on Python libraries such as Shapely (https://shapely.readthedocs.io), for manipulating and analyzing geometric objects, and GeoPandas (https://geopandas.org), which extends the popular Pandas library by adding support for geospatial data within dataframes. In Table **??**, the description of the dataset columns is presented. The main columns used during the analysis are mthe x and y coordinates to identify the position of the object, the frameId, the object ID and finylly the timestamp.

Furthermore, two different analytical methods were applied to the two study areas. In SA1, along with heatmap generation and accuracy evaluation, the analysis focused on parking areas by calculating the stationary time of detected objects, helping to assess how citizens use these parking areas. In contrast, in SA2, a different approach was taken, custom-defined zones were created to analyze object counts and determine the percentage of people or vehicles using specific parts of the area compared to the rest.

3. Results and discussion

Hereinafter, the preliminary results of the analysis are presented. The Python notebook used to generate the data is available online at the following repository:
https://github.com/danistrigaro/OpenTrack . Figure 5 shows the heat map of the survey conducted on October 21, 2024, for SA1 displaying data for both filtered categories: people and vehicles. The vehicle category includes objects such as cars, buses, trucks, and motorcycles. In panel (a), it can be observed that vehicles are mainly concentrated along accessible streets, as expected. In addition, some hotspots appear near parking areas. This data is useful not only for identifying movement patterns, but also for estimating how long a specific object, such

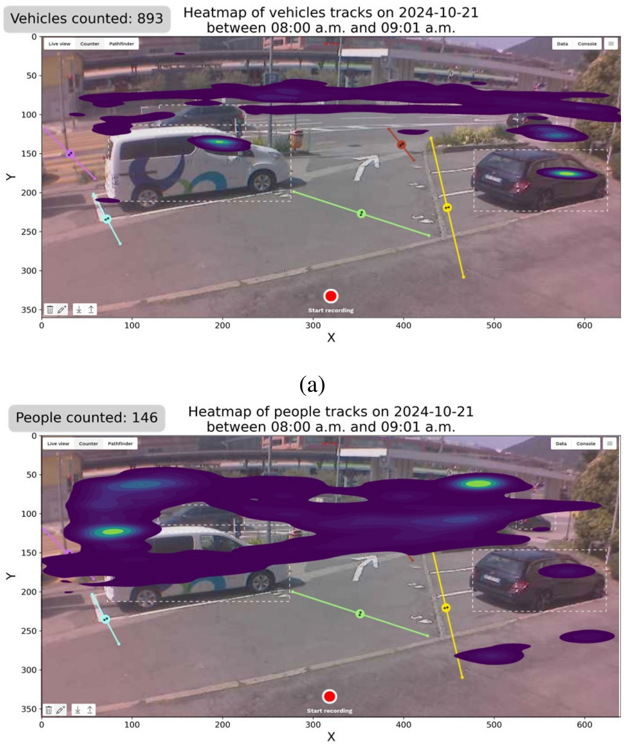
Column	Description
`id`	Unique identifier for the detected object.
`x, y`	Coordinates of the object's position in the frame.
`w, h`	Width and height of the bounding box around the object.
`bearing`	Direction of movement (in degrees), indicating the object's heading.
`confidence`	Confidence score of the detection, typically between 0 and 100 percent.
`name`	Class of the detected object (e.g., person, car, bicycle).
`_id`	Internal identifier assigned to each detection entry.
`recordingId`	Identifier of the specific recording session.
`frameId`	Identifier of the video frame in which the object was detected.
`timestamp`	Time (in milliseconds) since the start of the recording when the frame was captured.

Table 2. Description of the columns in the tracking dataset collected using OpenDataCam.

as a vehicle, remains in a particular area. This is especially relevant because the area in question is limited to 30-minute stops. To better understand this behavior, Figure 6 presents the stationary time calculated for each object. The analysis shows that in most cases the vehicles remain in the area for no more than 10-15 minutes. Only a few vehicles exceeded the allowed time. A total of 893 vehicles were detected. However, this figure could not be fully validated by manual sampling, as it is difficult for an operator to count both people and vehicles simultaneously. For this reason, the manual counts during the survey were primarily focused on people. In panel (b), the same data is shown, but for people. A total of 146 individuals were detected, which can be compared to the manual count of 118, resulting in a difference of 28 people. By analyzing people's behavior, it can be observed that pedestrian crossings are primarily used. However, there are also instances of street crossings in areas not covered by designated crossings. In particular, a significant flow is observed from the railway station toward the opposite side of the street. In addition, a hotspot is visible in the upper right area of the map. This is likely because people are commonly waiting there for the bus to arrive. Finally, Figure 9 shows the data related to the maximum confidence level for each detected object. We focus on this metric because we assume that, during the streaming process, the moment an object reaches its maximum confidence represents the most reliable identification, providing the best indication of whether the object has been correctly classified.

From the data, it is evident that vehicles are detected with higher confidence than people. In most cases, people are detected with relatively low confidence, around 30%, whereas vehicles typically reach a maximum confidence of over 90%.

It is important to note that these confidence levels can be affected by several factors, especially when using a system like OpenDataCam. The hardware components are capable of processing a stream of images at 11-18 FPS, which results in a low-smoothness video, which potentially introduces bias when the scene is complex. Other key aspects include the distance of the object from the camera, its speed, the lighting conditions, and the presence of visual obstacles such as trees, poles, or other vehicles. In particular, smaller people and moving more unpredictably are more susceptible to partial occlusion and blurred outlines, which can significantly lower the detection confidence. Of course, by improving the hardware, these biases can be reduced. For example, the Jetson Nano originally used by the device has been replaced by the newer Jetson Nano Orin or even the Jetson Nano Super, both of which are significantly more powerful than the original version. Future developments will certainly explore the adoption of more advanced computing hardware, along with higher-resolution cameras, which can be supported by the enhanced capabilities of the upgraded processing units.

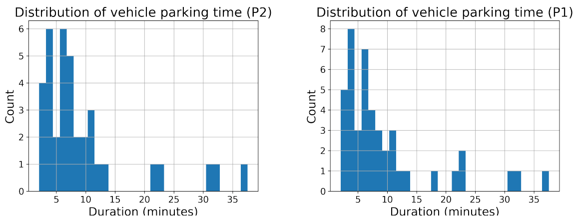


(a)

(b)

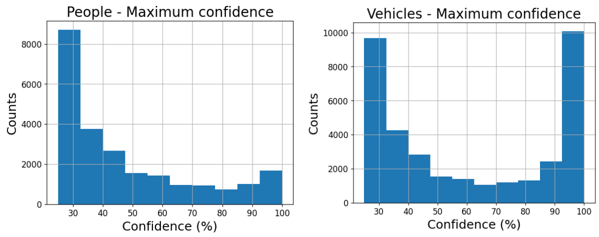
Figure 5. Heatmaps of vehicle (a) and people (b) tracks between 8:00 and 9:00 a.m. on October 21st, 2024, in SA1, showing the number of counted objects.

In Figure 8, the heat maps generated from the tracking data between 8:00 am and 9:00 am are presented, showing the movement of vehicles (a) and people (b). The system recorded a total of 355 vehicles and 121 people. In comparison, manual sampling counted 115 people, resulting in a discrepancy of 6 additional individuals detected by the tracking system. The vehicle heat map (Figure 8 a) shows that traffic is generally concentrated along the main street, with some hotspots near the station entrance, where cars usually stop to drop off or pick up passengers. An interesting pattern emerges in the heat map of people (Figure 8b). Two main flows are clearly visible: one that heads from the station toward the bottom left corner, leading to the pedestrian street, and another that stops near the main



(a) (b)

Figure 6. Histograms about the calculated parking time for the two areas detected: P1 in the middle of the monitored area (a) and P2 composed by three parking areas on the right part of the monitored area (b).



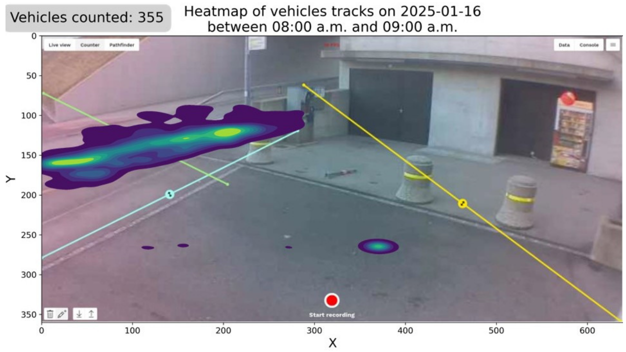
(a) (b)

Figure 7. Histograms about the maximum confidence of the objects detected: people (a) and vehicles (b).

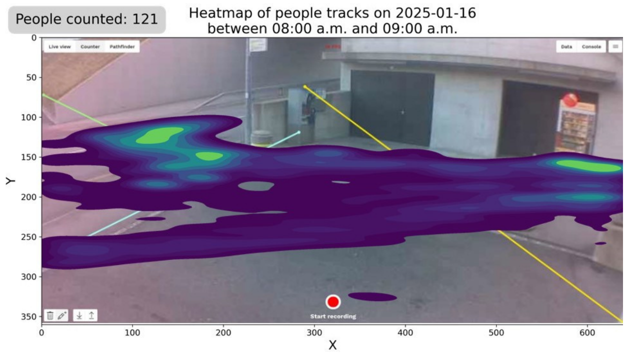
road before crossing at a location without a marked pedestrian crossing. According to the tracking data, this latter behavior appears to be the most frequent. This information has been highly valuable for stakeholders and decision-makers in understanding how the space is used and in identifying mitigation measures, such as reorganizing the area to improve safety, given that the street is often very crowded.

4. Conclusions

Thanks to this research during the Adaptive Space project, new advancements have been made using this device firstly developed during the INSUBRIPARKS project, such as analysis based on object tracking coordinates rather than solely relying on object counts. However, further developments are needed, including the possibility of georeferencing the data, since the current system uses an absolute reference system based on image coordinates, and improving the overall performance of the device. One of the critical aspects in this regard is the video streaming frame rate, which currently ranges from 11 to 18 FPS. A more powerful device, combined with a higher-resolution camera, could achieve 30-40 FPS, which would enhance both detection accuracy and the ability to track object positions more precisely during video capture. In conclusion, this paper presents and analyses the collected data, along with the preliminary results derived from the implemented methodology, where tracking data served as the raw input for all analyses. This approach is highly promising in providing valuable insights for urban planners to improve the studied areas, enhancing security, and supporting sustainable and inclusive urban development.

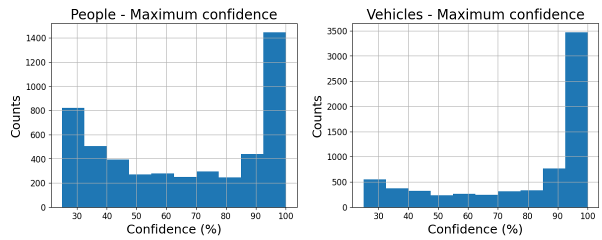


(a)



(b)

Figure 8. Heatmaps of vehicle (a) and people (b) tracks between 8:00 and 9:00 a.m. on January 16th, 2025, in SA2, showing the number of counted objects.



(a) (b)

Figure 9. Histograms about the maximum confidence of the objects detected in SA2: people (a) and vehicles (b).

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