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Open webcam data for traffic monitoring: YOLOv8 detection of road users before and during COVID-19

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ABSTRACT

Traffic volumes are rising globally, creating a growing need for accurate and scalable data collection to address mobility challenges and enhance transport systems. Yet, traditional methods remain costly and time-consuming despite advances in automated monitoring. This study explores the feasibility of using open webcam data in combination with the state-of-the-art object detection model YOLOv8 out-of-the-box for road user monitoring. Publicly accessible webcam imagery presents challenges such as high variability in image quality, road user occlusion, and environmental factors like poor visibility due to weather conditions. To assess their potential for traffic monitoring, we utilize open webcam data from Germany to evaluate the performance of YOLOv8's model variants, testing 110 parameter combinations with a manually labeled reference dataset. Among the tested out-of-the-box model variants, YOLOv8x achieved the highest performance, with an F1-score of 0.75. This optimized model was applied to about 500,000 open webcam scenes to monitor the change of road users before and during the COVID-19 pandemic. The analysis revealed a 9.5% overall reduction in road users volume, with motorized road users declining significantly while bicycles increased by 25.2%. This reflects mobility patterns observed during the COVID-19 pandemic, where restrictions led to a significant shift towards cycling as an alternative mode of transport. The results are plausible as they mirror broader trends in active mobility observed in various urban contexts. Our findings demonstrate the potential of leveraging open webcam data and pre-trained object detection models for scalable, cost-effective transport monitoring.

1. Introduction

Traffic volumes have been increasing globally, driven by growing mobility demands, a rise in cars and trucks, and a growth in vehicle kilometers traveled (VKT) (Cameron et al., 2004). Accurate traffic data collection and analysis are vital for addressing various mobility challenges, such as detecting, classifying, and counting road users to better analyze, plan, and evaluate transport systems (Azimjonov and Özmen, 2021; Zhang et al., 2022). Traditional traffic data collection methods, including manual monitoring or costly sensor installations, are often time-consuming and expensive. While camera-based traffic monitoring is now widespread, manual analysis persists in practical applications (Zhang et al., 2024) despite significant advancements in automated approaches within the scientific community (Dubska et al., 2015; Hoxha et al., 2023; Staab et al., 2021).

Automatic approaches have shown significant promise in analyzing traffic scenes efficiently, reducing the need for extensive infrastructure and manual data processing. In addition to "traditional" computer vision techniques (Al-qaness et al., 2021; Azimjonov and Özmen, 2021; Zhang et al., 2022), Convolutional Neural Networks (CNNs) offer a cost-effective solution for transport monitoring. In the field of CNN-based object detection, the YOLO ("You Only Look Once") models are widely used due to their minimal hardware requirements (Al-qaness et al., 2021; Azimjonov and Özmen, 2021). As single-stage detectors, YOLO models simultaneously identify candidate boxes and classify objects, enhancing speed and accuracy. They achieve high accuracy while being computationally lightweight, which allow them to operate in real-time even on devices with limited hardware resources (Kumar et al., 2024). Since its introduction in 2015 with YOLOv1 (Redmon et al., 2015), YOLO has undergone continuous development, with subsequent versions incorporating significant advancements.

In this study, we use YOLOv8 (Ultralytics, 2025), which offers

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notable improvements over earlier versions of YOLO (Huang et al., 2024). Various YOLO versions have been applied in recognizing road users. Al-qaness et al. (2021) and Azimjonov and Özmen (2021) applied YOLOv3 to highway and other road videos to detect, classify, track, and count vehicles. Cao et al. (2019), Zhang et al. (2022) and Zhu et al. (2021) optimized YOLO models using various techniques and applied them to different traffic scenarios in China. Chakraborty et al, (2018) detected traffic congestion on highways in the U.S. using YOLOv1, Dewi et al. (2021) performed traffic sign recognition in Taiwan with YOLOv4, and Khazukov et al. (2020) analyzed intersection videos from two Russian cities to count traffic and identify driving direction and speed using an approach based on YOLOv3. Khalili and Smyth (2024) refined YOLOv8 for small object detection using a traffic scene dataset. Safaldin et al. (2024) proposed a refined YOLOv8 to detect moving objects on videos from benchmark datasets. Along the ongoing development of YOLO models, there are no studies to date that used recent versions in combination with open webcam data to count road users. Furthermore, YOLO has not been used on open webcam data from Germany to identify traffic patterns and changes over several months. This aspect is particularly relevant because object detection models do not perform uniformly across geographical contexts, as vehicle fleets, road user characteristics, and traffic environments differ significantly between regions. Evaluating YOLOv8 in the German context therefore provides essential insights into its applicability and robustness under region-specific conditions.

Open webcam data has emerged as a valuable resource for traffic analysis. For instance, Hipp et al. (2015) analyzed active transportation (e.g., walking and cycling) using two webcams in Washington D.C. They captured 24 images daily over approximately 20 months, which were annotated through a crowdsourced approach. Zhang et al. (2017) utilized video webcam imagery to estimate vehicle density and counts by applying two methods: an optimization-based rank-constrained regression and a deep learning-based FCN approach. Tung et al. (2019) investigated the impact of weather and lighting on YOLOv1′s accuracy in detecting cars and humans via public video cameras, while Aung and Lwin (2024) used YOLOv8 for distance estimation between webcams and vehicles. A large-scale study highlighted the potential of webcams for vehicular networks by using data from existing public webcams installed at intersections and roadways, focusing on video feeds for analyzing vehicular density and spatial patterns in urban environments (Thakur et al., 2012). Open webcam data offer several advantages: they are cost-effective, already installed, and widely available, providing a vast pool of potential data sources for traffic observation. However, these data also pose significant challenges, including non-standardized image formats, variability in image quality, low temporal resolution with inconsistent capture frequencies (ranging from continuous video to intervals of several minutes), and data outages. Additionally, environmental factors like rain, diverse camera perspectives with wide angles, potential occlusions of objects, and object size variability further complicate analysis (Zhang et al., 2017). Moreover, the use of open webcam data raises concerns about personal data security and privacy, particularly when analyzing footage that may unintentionally capture identifiable individuals or sensitive locations (Du et al., 2019).

This research work is conducted in Germany with a special focus on Berlin. Usually, Berlin is at the top position in the ranking of German cities with the most severe congestion consequences. In 2022, drivers spent 71 h in traffic jams (INRIX, 2023). Our test period, however, covers two specific situations over time. The COVID-19 situation as well as a normal situation (pre-COVID-19), allowing to analyze changes in mobility across different societal situations. The COVID-19 pandemic emerged in late 2019 and escalated into a pandemic by March 2020. This period provides a unique context for this research. Mobility patterns were significantly affected by lockdowns, travel restrictions, and other measures. Studies have highlighted changes in mobility behavior during the pandemic, including reduced overall movement due to lockdowns, increased use of sustainable and solitary modes of active transport (like biking and walking), and shifts in commuting patterns influenced by remote work (Ghosh et al., 2020; Liu, 2020; Molloy et al., 2021; Xin et al., 2022). During the case study period, high infection rates and consequently, restrictive measures influenced mobility. Studies conducted in Germany found a general reduction in mobility, a shift from public transport to car use, walking, and cycling, and changes in travel patterns due to lockdowns and restrictions (Anke et al., 2021; Kolarova et al., 2021; König and Dreßler, 2021).

The local authority operates several official and automatic traffic counting stations across Berlin, primarily using passive infrared technology or induction loops. These stations generally do not provide precise differentiation between road user classes, typically distinguishing only between car and truck sizes or relying on separate counting stations for cyclists. Notably, no permanent traffic counting stations are installed at or near the selected webcam locations (Verkehrsinformationszentrale (VIZ) Berlin, 2023a). In this context, webcam-based monitoring could provide a valuable complementary data source. Unlike conventional counting stations, automated analysis of webcam imagery enables detailed information on the full road user composition (e.g., pedestrians, cyclists, motorcyclists, cars, trucks, buses) and thus allows for a more accurate estimation of the modal split at specific locations. Such information would be particularly beneficial for traffic management and mobility planning in Berlin, where congestion and capacity constraints are persistent challenges.

In this study, freely available webcam data from sixteen webcams located in three German cities, comprising 4.63 million images, are analyzed with YOLOv8 to observe road users in urban environments. Moreover, for ten selected webcams in Berlin, approximately 493,000 open webcam images, spanning pre- and during-COVID-19 periods, are analyzed to assess the pandemic's impact on urban mobility. Specifically, the study pursues two main objectives: (1) to assess the feasibility and performance of applying YOLOv8 to open webcam imagery for automated detection and counting of road users in diverse urban settings, and (2) to demonstrate the applicability of this approach through a Berlin case study, comparing mobility patterns between pre-COVID-19 (2018) and during COVID-19 (2020) periods.

This paper is structured as follows: Section 2 outlines the concept and potential of using open webcams for mobility analysis. Section 3 describes the data used, followed by the methodology in Section 4. Results are presented in Section 5, discussed in Section 6, and conclusions are drawn in Section 7.

2. Concept and potential of using open webcams for urban transportation research

Webcams are often maintained by public authorities or private entities for purposes like traffic monitoring, safety, or tourism, which means they require no additional setup costs. Additionally, the diverse geographical distribution of webcams enables the collection of data from various urban and rural areas, allowing for large-scale, multi-location analyses. Open webcam data also enables longitudinal studies, as many webcams have been operational for years, offering historical data for trend analysis. This accessibility and scalability make open webcam data a valuable resource for studying transportation systems with minimal financial and logistical barriers.

Open webcam data originates from a variety of sources installed for different purposes (Fig. 1a). Traffic-specific webcams, installed explicitly for transport monitoring, provide imagery with a clear focus on roads, intersections, and other transport-relevant areas. This ensures that the relevant target objects like vehicles, bicycles, and pedestrians are well-captured with (more) appropriate object sizes and clear visibility. While the majority of such cameras are not publicly broadcasted, some are made openly available by authorities, such as city and highway administrations. These webcams often cover central urban roads, intersections, highways, or country roads, offering critical data for traffic analysis.

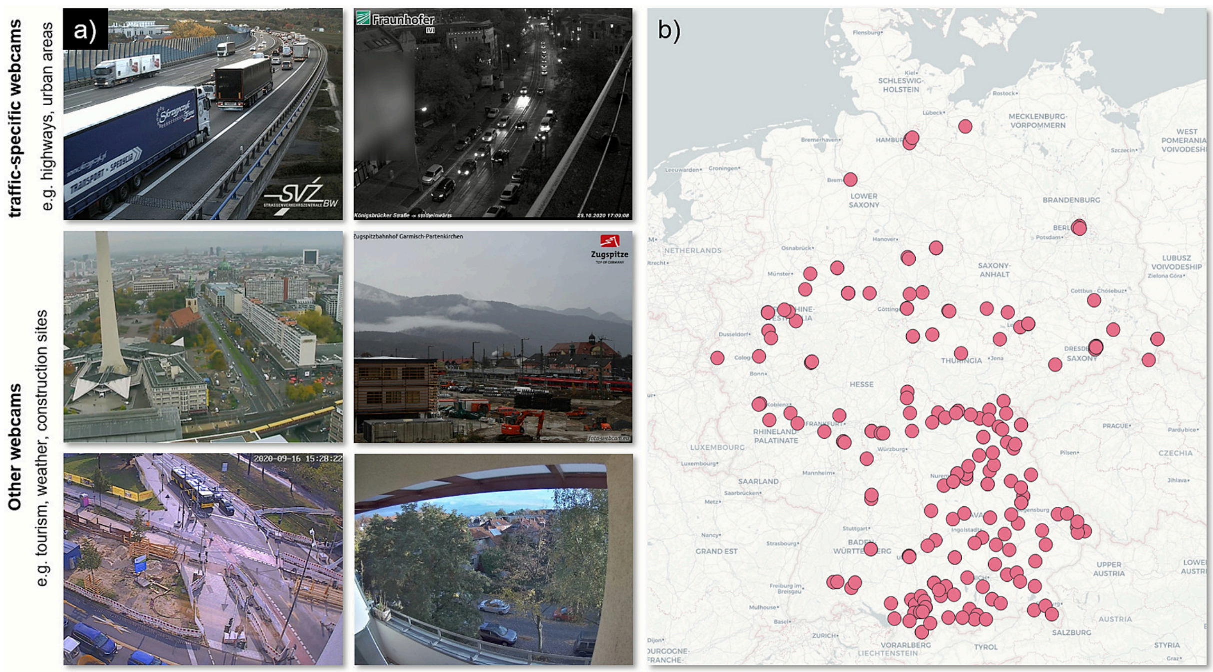

Fig. 1. (a) Examples of open webcams capturing transport-relevant scenes. (b) Map of selected webcam sites in Germany featuring transport-relevant imagery.

In contrast, webcams installed for purposes other than traffic monitoring – such as weather observation, tourism, or documenting construction progress – can also contribute valuable insights for mobility research. These cameras often capture essential mobility-related features like roads, bike lanes, pedestrian pathways, rail lines, or transportation hubs (e.g., airports and ports). For example, webcams showcasing landmarks, natural reserves, central plazas, beaches, ski areas, or hiking trails may unintentionally include transport-relevant elements within their frames. Similarly, cameras monitoring construction sites for bridges, roads, or significant infrastructure projects can capture traffic and mobility patterns around those locations. However, these types of webcams present unique challenges for transportation research. Since their primary focus is often unrelated to mobility, only small portions of the image may include transport-relevant areas, such as a segment of a road or bike path. This often results in objects of interest appearing disproportionately small or located in less prominent parts of the frame. Consequently, while such imagery shows potential for transport analysis, its usability may be limited, particularly when high-resolution details are necessary for accurate object detection and classification.

Despite its potential, open webcam data is accompanied by significant challenges. Zhang et al. (2017) identified four key issues with webcam imagery: low frame rate, low resolution, high occlusion, and large perspective variability. Building on these observations, we identify key technical and environmental limitations that complicate data collection and analysis:

- Data Quality and Consistency: The lack of standardization in image formats and resolutions across different cameras complicates the integration of data from multiple sources and leads to inconsistencies in the data pipeline. Some webcams produce high-resolution, clear images, while others deliver grainy, low-quality outputs, especially older or poorly maintained ones. Temporal inconsistencies, such as sporadic frame rates or irregular capture intervals ranging from continuous video to snapshots taken minutes or even hours apart, hinder the ability to perform continuous time-series analyses.
- Operational Reliability: Webcams are prone to various reliability issues that impact data collection, such as outages due to technical failures, internet connectivity problems, or shutdowns by operators. These interruptions can result in data loss or the collection of "frozen" frames, which are repeated images captured when the webcam feed is not refreshed. Such outages can vary in duration, ranging from minutes to several weeks, or even become permanent in some cases. This variability complicates the continuity and consistency of data required for detailed analysis.
- Environmental Factors: Weather conditions, such as rain, fog, snow, or poor nighttime lighting, can obscure visibility and reduce the reliability of object detection algorithms (Tung et al., 2019). Similarly, artificial lighting, wet road surfaces, or glare can further degrade image quality.
- Camera Placement and Perspective: Diverse camera angles and perspectives pose additional challenges for object detection. Cameras mounted at significant heights or distances may make smaller road users, like pedestrians or cyclists, difficult to identify. Conversely, close-range cameras in crowded urban areas or busy intersections may struggle with object overlap and occlusion.
- Ethical and Legal Concerns: The use of webcam data for research introduces significant ethical and privacy considerations. Webcams may inadvertently capture sensitive locations or identifiable individuals, raising questions about informed consent and data anonymization (Benton et al., 2023). To address these concerns, researchers must adhere to general ethical principles (Kochupillai et al., 2022), such as minimizing harm, ensuring data security, and processing only the data necessary to achieve research objectives (Mok et al., 2014). Compliance with broader legal frameworks, like the European General Data Protection Regulation (GDPR), is essential to safeguard privacy and ensure responsible data use (Benton et al., 2023).

In Germany, approximately 250 publicly available webcams relevant to mobility were identified by the end of 2023 (Fig. 1b). These include cameras capturing urban centers, roads, and intersections. However, this collection is neither exhaustive nor unbiased, serving instead as an illustration of the coverage and potential of webcams for transportation research. The majority of these webcams capture still images rather than video footage, limiting their temporal resolution. Highway webcams are notably excluded from this dataset. Since March 2022, the public broadcasting of highway cameras in Germany has been discontinued due to security concerns linked to the current geopolitical situation (Balser, 2022). This example highlights how geopolitical factors can influence the availability and application of webcam data in specific contexts. In Germany, the legal landscape for webcam data usage is shaped by strict privacy and data protection regulations, including the GDPR, the Federal Data Protection Act (BDSG), and the Artistic and Copyright Act (KUG). These frameworks establish clear boundaries for the lawful processing of personal data, requiring measures such as anonymization and pixelation to protect individuals' rights.

3. Data

For this study, webcam images of real-world urban traffic scenes were used. To mitigate privacy concerns and to ensure compliance with GDPR and related regulations, only data necessary for the research objectives were collected. Moreover, sensitive information was anonymized by the operators: license plates cannot be decrypted, and larger sensitive areas, such as residential buildings, are pixelated.

Table 1 summarizes the four datasets prepared. In total, 16 webcams were used for the 110 parameter experiments, and a subset of 10 webcams was used for the COVID-19 case study. Each webcam captures one image per minute with a resolution of 640x480 pixels.

The **raw dataset** comprises 4.63 million images collected from 16 webcams across three cities in Germany: 12 cameras in Berlin, 2 in Nuremberg, and 2 in Ulm (Fig. 2).

The **base dataset** was derived from these data through filtering and cropping, resulting in 1.96 million images. Filtering retained only daytime scenes, based on precise sunrise and sunset times per location (sunrise-and-sunset.com., 2023) and removed corrupt image files such as still frames, empty files, and black frames. Cropping excluded areas such as parking lots and distant road sections, where road users could not be reliably identified.

The **reference dataset** was created to optimize YOLOv8 parameters (Confidence and Intersection over Union (IoU), see Section 5.1). It consists of 48 images, with three randomly selected images from each of the 16 webcams from the base dataset. Road users were manually labeled following the COCO object categories (Lin et al., 2014), specifically: car, truck, motorbike, bus, bicycle, and person. In total, 662 road users were annotated, though the dataset is imbalanced, with the class 'car' (n = 507) dominating the annotations, followed by 'truck' (n = 80) and 'person' (n = 45), while categories like 'bus' (n = 12), 'bicycle' (n = 11), and 'motorbike' (n = 7) appear rarely.

The **case study dataset**, used to examine the impact of COVID-19 on traffic, consists of 493,000 images drawn from the base dataset. It focuses on the Berlin webcams, the only sites with pre-COVID-19 observations from 2018. Of the 12 Berlin webcams, 10 were included in the case study analysis, as two had major outages in 2018. The imagery spans from October 31 to December 18, for both 2018 (pre-COVID) and 2020 (during COVID), covering an identical seven-week period (49 days, 35 working days). The 2020 period was marked by a surge in COVID-19 infections in Berlin, with record-high infection rates (Fig. 3). In response, stricter public health measures were implemented. Gastronomic and cultural establishments were ordered to close starting November 2. From November 26, gatherings were limited to a maximum of five people from two households, and mask mandates were expanded. Retail stores and schools were also required to close starting December 16 (Betschka et al., 2021).

The selected Berlin webcams are positioned along the following streets: five webcams are located on Heerstrasse, four on Messedamm, and one webcam is located in the district Alt-Moabit with different levels of road network classification and speed limits (see Table 2). However, the selection is limited to road network classification levels 1, 2, and 3, as no publicly accessible webcams were available for level 0 (highways) or level 4 (local roads).

Table 1
Overview of the used datasets.

Name of dataset	description	number of selected webcams	(approx.) number of images
Raw dataset	The complete collection of image data acquired from all webcams without any filtering or preprocessing	16	4.63 mio.
Base dataset	A refined version of the raw dataset, containing only daytime scenes. Corrupt image files were removed, and areas such as parking lots and distant road sections were masked through cropping	16	1.96 mio.
Reference dataset	A subset of images (three randomly selected images per webcam) from the base dataset. Road users in these images were manually labeled to serve as a reference for analysis	16	48
Case study dataset	A focused subset of the base dataset, consisting exclusively of images from Berlin webcams. It covers the period from October 31 to December 18 in the years 2018 (pre-COVID-19) and 2020 (during COVID-19).	10	493,000

4. Methods

YOLOv8 was released in January 2023, offers state-of-the-art accuracy and speed, with improvements in real-time inference (Ultralytics, 2025). YOLOv8 is available in five variants of increasing complexity, n, s, m, l, and x, where higher complexity yields greater accuracy at the cost of higher computational requirements and longer processing times.

In this study, YOLOv8 is used out-of-the-box, as YOLO models without fine-tuning have already demonstrated promising results (Jan-Hendrik Witte, 2022). The goal is twofold:

1) to evaluate YOLO's out-of-the-box performance on the reference dataset, including the assessment of Confidence and IoU parameters to determine the optimal combination for best performance, and
2) to assess its ability to track relative changes between two time periods: pre-COVID-19 and during COVID-19.

Using YOLOv8′s pre-trained models significantly reduces the time and complexity typically required for model fine-tuning with domain-specific data. Trained on the COCO 2017 dataset, which includes over 120,000 labeled images (Lin et al., 2014), YOLOv8 can be readily integrated into workflows and applied without large, custom datasets. Its efficiency in processing large image collections makes it well-suited for extensive webcam imagery.

For this study, the IoU threshold and Confidence level parameters were tuned to optimize road user detection in webcam images. Confidence [0;1] expresses the model's certainty for a class bounding box, while IoU [0;1] represents the overlap between predicted and ground-truth bounding boxes. YOLO usually suggests multiple bounding boxes for the same detected object. Non-max suppression was applied using the IoU threshold, retaining only the most likely prediction for each detected object. In a grid search, both parameters were varied in steps of 0.1, resulting in 110 experiments for each YOLO model variant (n, s, m, l, x).

Predictions were evaluated with an IoU threshold of 0.5, a common choice in prior work (Al-qaness et al., 2021; Wu et al., 2020; Zhu et al., 2021). The F1-score is a standard metric in object detection (Guney et al., 2022) and was therefore used as the accuracy metric to obtain the

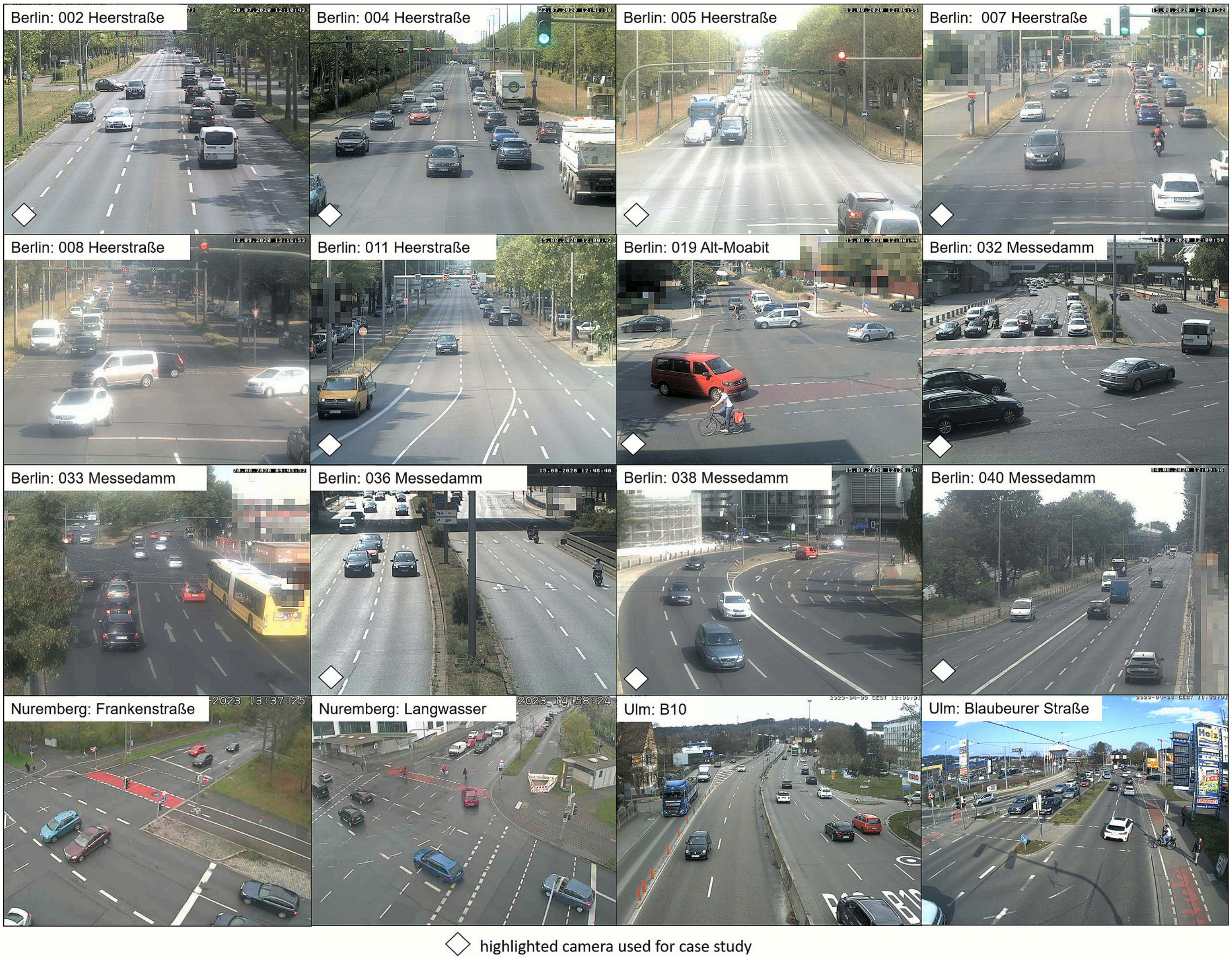

Fig. 2. Sample images from the sixteen webcams used in the study illustrating variations in viewing angle, number of lanes, and road user object size for the cities of Berlin, Nuremberg, and Ulm. Cameras highlighted in the figure indicate those used for the Berlin COVID-19 case study.

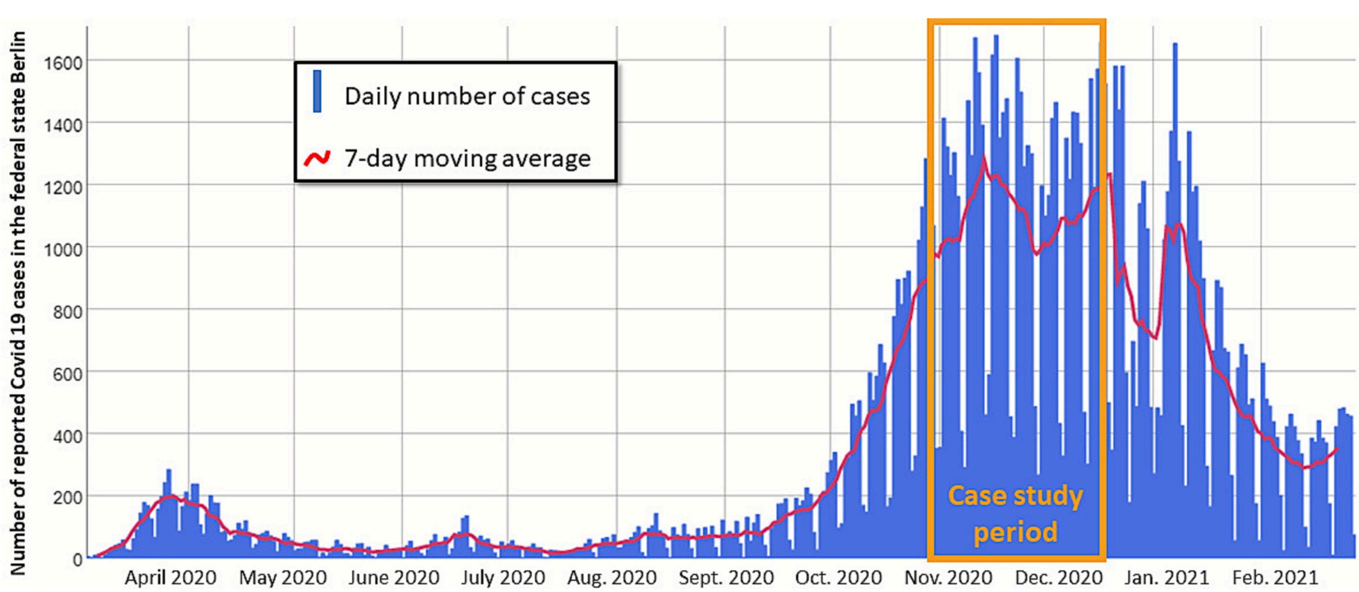

Fig. 3. Progression of reported COVID-19 cases in Berlin from March 2020 to February 2021, with the case study period highlighted (adapted from LAGeSo Berlin (Landesamt für Gesundheit und Soziales Berlin, 2021)).

Table 2
Overview of the selected Berlin webcams along the streets Heerstrasse, Messedamm, and Alt-Moabit with RIN road network classification (Richtlinien für integrierte Netzgestaltung) according to Senatsverwaltung (2023).

Street, number of webcams	RIN road network classification with levels 0 to 4	Description	Speed limit (km/h)
Heerstrasse, 5 webcams	level 1 "large-scale road connection"	Part of federal road B2, major commuter and arterial route (Bezirksamt Charlottenburg-Wilmersdorf, 2023)	50
Messedamm, 4 webcams	level 2 "higher-level road connection"	Proximity to highways 100 and 115, the expansive trade fairgrounds (Messe Berlin, 2021), and the Central Bus Station (Berlin.de, 2023)	50
Alt-Moabit, 1 webcam	level 2 "higher-level road connection", and level 3 "local road connection"	The Moabit district is closer to the city center and is described as central, young, and international, with an average income lower than other parts of the city and comparatively affordable rents (Berlin.de, 2023)	50 and 30

best Confidence and IoU combination.

For bicycle and motorcycle, YOLO often detects both, the vehicle and its rider. Therefore, the number of detected persons was substracted from the bicycle and motorcycle counts (negative values were set to zero). Following this adjustment, the three classes will be referred to as pedestrians, bicyclists, and motorcyclists in the following.

5. Results

5.1. YOLOv8 parameter testing

For finding optimal IoU and Confidence parameters for open traffic webcam data, we conducted 110 experiments for testing various IoU and Confidence value combinations. The parameter combinations were evaluated based on the F1-score and an overview of the results for YOLOv8x can be seen in Table 3.

The highest F1-score of 0.75 was achieved with a confidence value of 0.1 and an IoU of 0.4, indicating that this parameter combination performed best for the reference dataset of the sixteen selected webcams. As the confidence value increases, a decline in F1-scores is observed. Additionally, a balanced selection of confidence values between 0.1 and 0.3, combined with IoU values ranging from 0.1 to 0.9, consistently yields F1-scores around 0.7. In addition to YOLOv8x, the F1-score was also calculated for the four less complex variants of YOLOv8 (n, s, m, l) for all parameter combinations. As expected, the highest F1-score increases or stays the same as the model complexity increases (F1-scores for model variants of YOLOv8: n = 0.63, s = 0.70, m = 0.72, l = 0.75). Since the computing time of YOLOv8x is acceptable, even for very large image sets, YOLOv8x was chosen for the COVID-19 case study.

5.2. COVID-19 case study

The relative numbers of detections highlight the dominance of the class 'car' and the imbalance across different classes of 'road users' (Table 4). However, distinct differences emerge between webcams and across streets.

On Heerstrasse, the share of car detections among all road users ranges from 81.3 % to 85.2 % across all cameras and years. At Messedamm, this value is slightly lower, ranging from 71.9 % to 79.0 %. For the Alt-Moabit camera, the car share is significantly smaller, ranging from 60.6 % to 61.8 %. Notably, Camera "038 Heerstrasse" records a relatively high share of pedestrians, accounting for 12.6 % of detections in 2018 and 12.7 % in 2020. At Alt-Moabit, there is a significant increase in the share of bicyclists between pre-COVID-19 and during COVID-19 periods, rising from 5.9 % in 2018 to 8.5 % in 2020, a 2.6 % increase.

YOLO detections for **all motorized road users during** the 2018 and 2020 study periods are illustrated in Fig. 4a, displaying both absolute and relative changes for each webcam. The total number of motorized road users detected ranges from just under 150,000 to just over 400,000 across the ten webcams and two time periods. With approximately 25,000 images per camera (temporal resolution: one minute), this corresponds to an average of 6 to 16 motorized road users per image. Among the four Heerstrasse webcams, camera "*Heerstraße 011*" stands out with a notably lower number of motorized road users. At Messedamm, 038 and 032 recorded the highest counts, followed by 036, while 040 showed significantly lower numbers. The Alt-Moabit webcam recorded relatively low levels of motorized road users overall. A comparison of the 2018 and 2020 data reveals a decrease in motorized road user counts for nine of the ten cameras. The only exception is webcam "*007 Heerstrasse*", which showed a slight increase. The decreases observed on Heerstrasse are relatively minor, remaining below 5 %. In contrast, the other webcams exhibited more pronounced reductions, ranging between 14 % and 32 %.

The detection results for **non-motorized road users**, combining pedestrians and bicyclists, indicate that these classes are particularly frequent at webcams "*038 Messedamm*" and "*019 Alt-Moabit*" (Fig. 4 b). At these locations, **pedestrians** make up approximately 13 % (038) and 17 % (019) of all detected road users. In comparison, the proportion of pedestrians at other webcams ranges between 1.8 % and 4.4 %. The observed decline in non-motorized road users is entirely driven by a decrease in pedestrian counts. In contrast, **bicycle**s increased across all webcam locations in 2020 (Fig. 4c). The most significant rise was recorded at the "*032 Messedamm*" webcam, which captures a bike lane (Fig. 2), showing a 45.4 % increase.

Fig. 4d summarizes the changes in road user counts in 2020 compared to 2018 **across all webcams and user classes**. Significant

Table 3
Summary of F1-scores for all 110 Confidence and IoU YOLOv8x prediction parameter combinations for YOLOv8x, highest F1-score of 0.7512 at Conf = 0.1 and IoU = 0.4 is highlighted in bold.

IoU	Conf	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.0		0.0718	0.6464	0.6364	0.6161	0.5973	0.5620	0.5039	0.4444	0.3667	0.1401
0.1		0.0663	0.7069	0.6981	0.6710	0.6485	0.6146	0.5559	0.4928	0.4128	0.1478
0.2		0.0718	0.7377	0.7288	0.6983	0.6730	0.6341	0.5750	0.5121	0.4179	0.1478
0.3		0.0744	0.7506	0.7402	0.7071	0.6799	0.6416	0.5795	0.5137	0.4179	0.1478
0.4		0.0760	**0.7512**	0.7411	0.7087	0.6824	0.6443	0.5825	0.5137	0.4179	0.1478
0.5		0.0770	0.7494	0.7398	0.7081	0.6817	0.6443	0.5825	0.5137	0.4179	0.1478
0.6		0.0779	0.7445	0.7385	0.7081	0.6817	0.6443	0.5825	0.5137	0.4179	0.1478
0.7		0.0775	0.7405	0.7365	0.7075	0.6811	0.6443	0.5825	0.5137	0.4179	0.1478
0.8		0.0782	0.7269	0.7331	0.7055	0.6811	0.6443	0.5825	0.5137	0.4179	0.1478
0.9		0.0781	0.6704	0.7041	0.6924	0.6798	0.6436	0.5825	0.5137	0.4179	0.1478
1.0		0.0749	0.1754	0.1806	0.1803	0.1790	0.1784	0.1692	0.1638	0.1613	0.1058

Table 4
Class shares of total road user detections in the Berlin COVID-19 case study dataset, shown per webcam and year, for all ten webcams. The table illustrates the relative proportions of each road user class in 2018 (pre-pandemic) and 2020 (pandemic) observations.

	Heerstrasse					**Messedamm**				**Alt-Moabit**
detections, year	**002**	**004**	**005**	**007**	**011**	**032**	**036**	**038**	**040**	**019**
car, 2018	85.2 %	82.2 %	82.6 %	84.3 %	83.6 %	79.0 %	76.3 %	71.9 %	78.0 %	61.8 %
car, 2020	83.7 %	81.3 %	81.4 %	83.6 %	82.4 %	78.8 %	77.4 %	73.2 %	78.5 %	60.6 %
truck, 2018	11.4 %	12.6 %	13.0 %	9.9 %	10.7 %	15.1 %	14.8 %	12.2 %	16.4 %	12.6 %
truck, 2020	12.5 %	13.6 %	13.7 %	10.5 %	11.7 %	15.7 %	15.4 %	11.1 %	16.4 %	11.7 %
bus, 2018	1.3 %	2.0 %	1.8 %	2.0 %	1.5 %	2.1 %	5.8 %	2.0 %	0.7 %	1.5 %
bus, 2020	1.5 %	2.2 %	2.2 %	2.2 %	1.8 %	1.3 %	4.6 %	1.3 %	0.8 %	1.0 %
motorcyclist, 2018	0.3 %	0.3 %	0.3 %	0.6 %	0.3 %	0.4 %	0.4 %	0.6 %	0.3 %	1.1 %
motorcyclist, 2020	0.4 %	0.4 %	0.3 %	0.5 %	0.3 %	0.5 %	0.4 %	0.6 %	0.4 %	1.4 %
pedestrian, 2018	1.8 %	2.7 %	2.2 %	2.4 %	3.5 %	2.6 %	2.6 %	12.6 %	4.4 %	17.1 %
pedestrian, 2020	1.9 %	2.3 %	2.2 %	2.3 %	3.4 %	2.4 %	2.0 %	12.7 %	3.4 %	16.9 %
bicyclist, 2018	0.1 %	0.2 %	0.2 %	0.9 %	0.4 %	0.8 %	0.1 %	0.7 %	0.2 %	5.9 %
bicyclist, 2020	0.1 %	0.3 %	0.2 %	0.9 %	0.5 %	1.3 %	0.2 %	1.1 %	0.4 %	8.5 %

decreases are evident for nearly all road user categories. However, bicyclists stand out with a substantial increase of over 25 % in 2020, marking a notable exception. Additionally, a modest rise of 2.5 % is observed for motorcyclists.

6. Discussion

In this study, we combined open-access webcam images with YOLOv8 pretrained object detection models to count and analyze road users in urban environments. Sixteen webcams with one-minute temporal resolution were selected, and their images underwent preprocessing and filtering to ensure data quality and consistency. A manually labeled reference dataset was used to evaluate 110 parameter combinations for YOLOv8′s Confidence and IoU thresholds, with the highest F1-score of 0.75 achieved with YOLOv8x at a Confidence threshold of 0.1 and an IoU threshold of 0.4. This optimized model was then applied to almost 500,000 images captured by ten Berlin webcams during fall 2018 (pre-COVID-19) and fall 2020 (during COVID-19). The resulting analysis offered valuable insights into local traffic patterns, revealing significant decreases in road user counts between pre- and during COVID-19 times across most classes, with variations depending on streets and user types. Notably, bicyclist counts showed a marked increase, highlighting potential shifts in mobility behavior during the pandemic.

6.1. Webcam data for counting road users

A defining feature of this study was the exclusive use of open webcam data combined with open-source software. This approach significantly reduced the cost and effort associated with data acquisition while enabling the analysis of road user counts over extended periods. The use of webcam data allowed for trend and change analyses, such as comparing road user counts during pre-COVID-19 and during COVID-19 periods, providing valuable insights into local mobility behavior.

The use of open webcam data, however, comes with inherent challenges. Researchers lack control over the cameras' exact location, field of view, image quality, and maintenance. For optimal road user detection using YOLO, cameras should ideally capture the entire cross-section of the street, show objects of interest in detectible size (Aung and Lwin, 2024), minimize distracting non-traffic elements, reduce occlusions, and maintain adequate illumination throughout the day and night. The webcams used in this study exhibited varying degrees of deviation from these ideal conditions (Fig. 2), which may limit the comparability of detection results across different locations (Zhang et al., 2022).

To address challenges in detecting road users under poor lighting conditions (Al-qaness et al., 2021; Zhu et al., 2021), images captured during low-light periods, such as early mornings and late evenings, were filtered out during preprocessing. This filtering reduced the number of images available for analysis each day, with variations in daylight hours considered in the subsequent analyses. However, this step also represents a limitation, as nighttime traffic patterns were excluded, potentially impacting the overall comprehensiveness of the findings.

Despite these limitations, the webcams' temporal resolution of one image per minute enabled a comparative analysis of road user counts. This highlights the potential of webcams with similar temporal resolution to serve as valuable data sources for long-term trend analysis. While related studies often employ video footage for YOLO-based traffic detection (Al-qaness et al., 2021; Azimjonov and Özmen, 2021; Tung et al., 2019), videos offer higher temporal resolution but dramatically increase the data storage, processing, and analysis requirements, particularly for extended observation periods like those in this case study.

6.2. Detection of road users with YOLOv8

This study employed a YOLOv8x model pretrained on the COCO 2017 dataset. To determine the optimal parameter combination for Confidence and IoU thresholds, 110 configurations were tested, achieving a robust F1-score of 0.75 (Section 5.1). The focus was on evaluating YOLOv8 out-of-the-box performance, avoiding the labor- and time-intensive process of fine-tuning that requires manual labeling, domain expertise, and computing resources often unavailable to practitioners, e.g. GPUs. While fine-tuning has proven effective in related studies (e.g.,Azimjonov and Özmen, 2021; Cao et al., 2019; Stark et al., 2023), it involves substantial workloads, when assuming one minute per image, with labeling efforts of estimated 447 h for 26,820 images (Cao et al., 2019) or estimated 120 h for 7,216 images (Azimjonov and Özmen, 2021). Techniques such as data augmentation (Stiller et al., 2019) or synthetic oversampling for imbalanced datasets (Jain et al., 2020) could mitigate labeling demands and enhance future performance.

A reference dataset of 48 images (3 per webcam) was randomly selected for evaluation. Given the exploratory nature of this study, this relatively small sample size should be considered when interpreting the results, as it may limit the robustness of class-level performance estimates. The dataset revealed significant class imbalance, with 507 cars, 80 trucks, and 45 persons among 662 labeled objects. Such imbalance can disproportionately impact the model's detection performance for underrepresented classes, particularly smaller or less frequent ones. Underrepresented classes included buses (12), bicycles (11), and motorbikes (7), reflecting both webcam locations (e.g., major traffic roads like Heerstrasse and Messedamm) and mirrors patterns already observed in literature (Liu et al., 2017). Class-specific sampling could address this imbalance more effectively than random selection.

Although YOLOv8x performed robustly out-of-the-box, misdetections occurred in specific scenarios (Fig. 5). In particular, poor

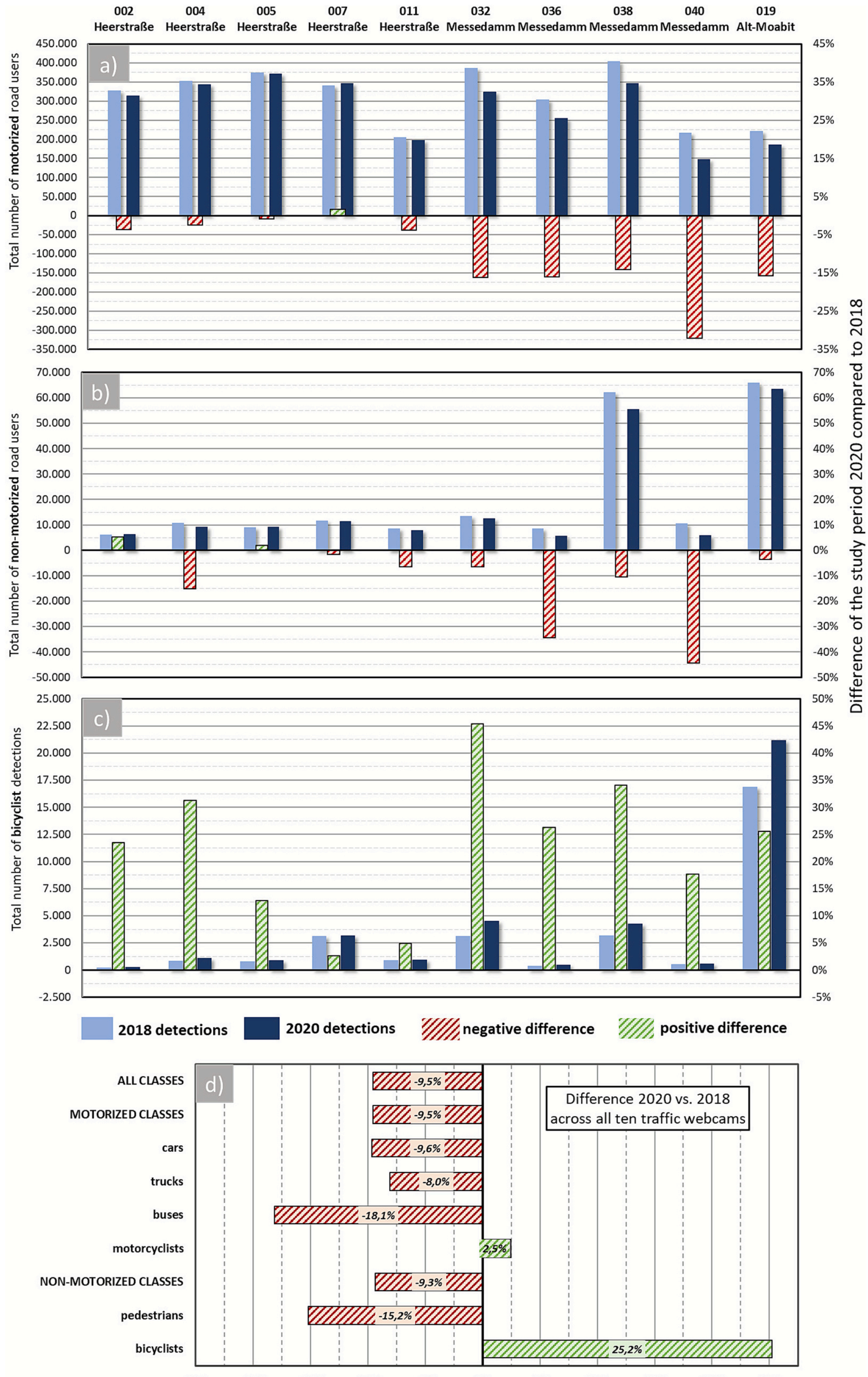

Fig. 4. Detections from the 2018 and 2020 study periods in the Berlin COVID-19 case study dataset across all ten webcams, along with differences between the two years for (a) motorized road users, (b) non-motorized road users, (c) bicyclists, and (d) all road users. These comparisons highlight changes in traffic composition and volume between the pre-pandemic (2018) and pandemic (2020) periods.

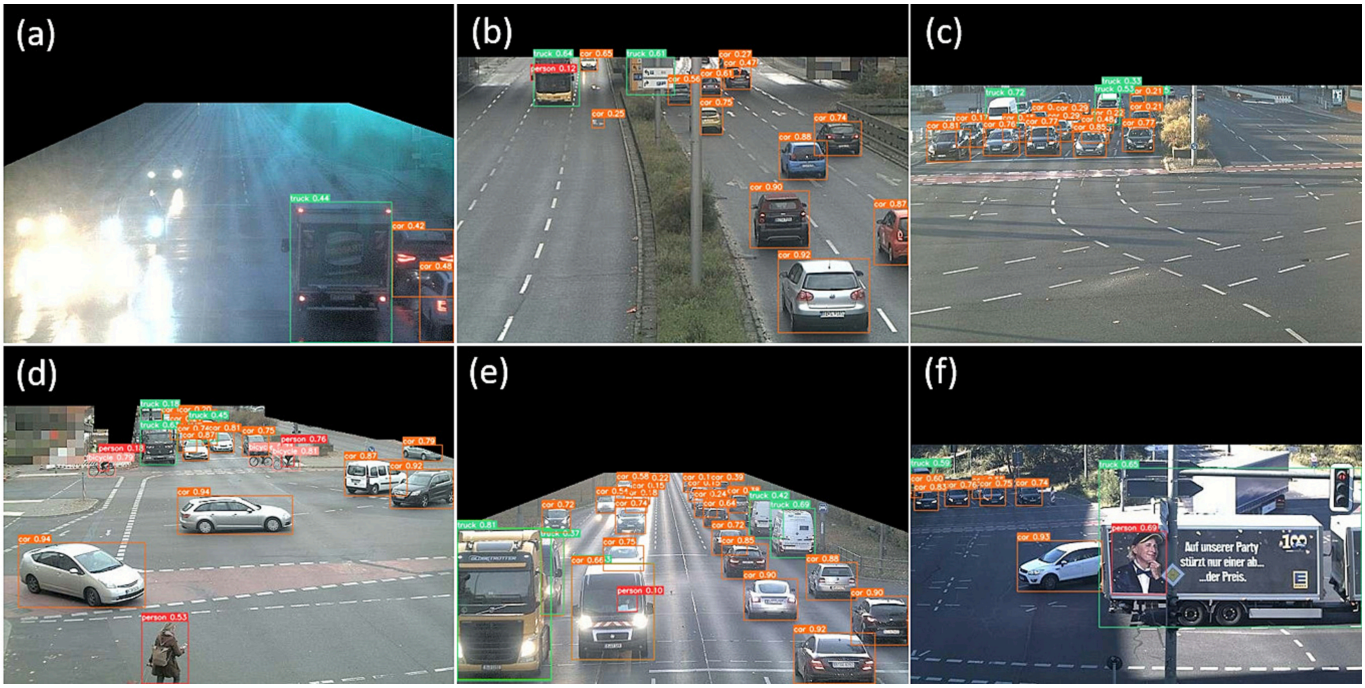

Fig. 5. Examples of detection errors produced by YOLO on the Berlin COVID-19 case study dataset, illustrating both systematic and random error types observed during analysis. (a) Random detection error caused by overexposure of headlights on a wet road surface; (b) Systematic detection error identifying a road marking as a car; (c) Systematic detection error due to road user occlusion in front of traffic lights; (d) Random detection error resulting in a false negative for a person on a bike; (e) Systematic semantic error classifying (sprinter) vans as either "car" or "truck"; (f) Random semantic error caused by a detected person on a truck advertisement.

lighting and weather conditions led to missed detections, as illustrated in Fig. 5a (Cao et al., 2019; Zhang et al., 2022). Occlusions and closely spaced road users, as in Fig. 5c, resulted in missed detections for background objects, an issue also reported in related studies (Cao et al., 2019; Jiang et al., 2022; Zhang et al., 2022). Increasing the IoU threshold can exacerbate multiple detections for a single object (Al-qaness et al., 2021).

Errors also included misclassification (e.g., street signs as trucks), multiple overlapping detections (e.g., Sprinter vans classified simultaneously as cars and trucks), and inaccuracies in pedestrian counts due to undetected pedestrians, detected drivers, or advertisement images, in Figs. 5b, d, e, and f. While individual errors are negligible in large datasets, systematic errors (e.g., static misclassifications) could distort results. Enhanced preprocessing, such as image cropping, could help mitigate these issues.

Overall, YOLOv8's detection performance is satisfactory, given its out-of-the-box use. While a related study achieved an F1-score above 0.9 (Azimjonov and Özmen, 2021) through large-scale retraining, the achieved F1-score of 0.75 is a promising result, particularly without additional fine-tuning. Table 5 summarizes the identified error types, distinguishing between systematic, random, detection, and semantic errors.

Table 5
Illustration of different types of errors that occurred using open webcam images and the pre-trained YOLOv8x on the Berlin COVID-19 case study dataset.

	Systematic errors	Random errors
Detection errors	False positives (FP) for static objects, such as street signs, road markings, etc.	Occasional false positives (FP) and false negatives (FN) for road users.
	False negatives (FN) in camera fields of view with frequent road user occlusions.	Poor visibility caused by weather conditions, darkness, or vehicle headlights.
Semantic errors	For bicyclists/motorcyclists: separate detection of bicycles/motorcycles and their riders.	Isolated detections of irrelevant elements, e.g., drivers or printed persons on vehicle advertisements.
	For (sprinter) vans and similarly sized vehicles: misclassification as either "car" or "truck".	

6.3. *Detecting road users in pre-COVID-19 and during COVID-19 webcam scenes*

The case study focused on relative road user changes in 2020 compared to 2018, under the assumption that YOLO detection errors were consistent across both periods. Consequently, the percentage changes are considered robust within the almost 500,000 analyzed webcam scenes, despite potential distortions in absolute values.

Factors beyond the COVID-19 pandemic may have influenced the observed road user differences. Two potential confounders were examined: First, construction works, restrictions, and disruptions were assessed via online searches, visual analysis of webcam images, and a request to the local traffic authority. No significant construction projects or disruptions were found for the study periods (Verkehrsinformationszentrale (VIZ) Berlin, 2023b). Second, weather and lighting conditions, which impact both YOLO's detection performance (Al-qaness et al., 2021; Zhu et al., 2021) and citizens' transport choices, were compared using data from the Berlin-Tegel station (Deutscher Wetterdienst (DWD), 2023a). Both periods had 17 precipitation days (Deutscher Wetterdienst (DWD), 2023b), with minor differences in total precipitation (39.3 mm in 2018 vs. 22.0 mm in 2020), sunshine duration (79.2 h in 2018 vs. 84.0 h in 2020), and average daily cloud cover (6.2 eighths in 2018 vs. 6.1 eighths in 2020). These similarities suggest that weather did not strongly distort the overall results.

While the selected webcams provide valuable insights into urban traffic dynamics, according to the RIN classification, they are limited to road network levels 1 (major and arterial roads), 2 (secondary and collector roads), and 3 (local roads). No suitable publicly accessible webcam data were available for level 0 (highways) or level 4 (minor roads), restricting the dataset's representativeness across the full range of road types. As a result, the findings may not fully capture traffic patterns on major highways or smaller minor roads in rural or residential areas, where mobility behaviors and road user compositions could differ.

The absolute motorized road user detections aligned well with road classifications (Section 3). Cameras at Heerstrasse and Messedamm generally matched expectations, with intersections like "032 Messedamm" showing higher detections due to their proximity to highways and trade fair grounds. Notably, the intersection locations at Alt-Moabit and Messedamm appear to influence detection counts.

Motorized road users decreased by 9.5 % in 2020 compared to 2018, closely mirroring Germany's nationwide decline of −9.2 % (Umweltbundesamt (UBA), 2023). However, location-specific trends varied. Messedamm showed larger decreases, likely due to reduced trade fair activity, where only 28 of 120 planned events occurred (Messe Berlin, 2021) and a 70 % drop in long-distance bus passengers at the central bus station (Statistisches Bundesamt StBA, 2021). In contrast, Heerstrasse showed mixed trends, with some declines but stable or increasing road user detection closer to the city center. Truck traffic declined less than car traffic, reflecting the growing importance of urban delivery services (Bundesministerium für Digitales und Verkehr (BMDV), 2020; Umweltbundesamt (UBA), 2023). YOLO's tendency to detect delivery vehicles as trucks may explain some of the results (cp. Figs. 5c and e). Traffic data from official Berlin sources show similar trends (Verkehrsinformationszentrale Berlin, 2022), with substantial decreases during the first lockdown, followed by partial recovery. This aligns with our webcam-based findings. Authorities reported the largest traffic reductions on Leipziger Strasse, while areas like Zehlendorf recovered more quickly (Verkehrsinformationszentrale Berlin, 2022). These patterns confirm that COVID-19 impacted motorized road users in Berlin, with local variations depending on road usage and nearby services.

Bicycle detections increased significantly (+25.2 %) across all cameras, driven by key locations such as Alt-Moabit, Messedamm, and Heerstrasse (Fig. 4c). At Messedamm, the introduction of a 7.2 km pop-up bike lane on Neue Kantstrasse/Kantstrasse in 2020 likely contributed to this increase (Senatsverwaltung für Umwelt, Verkehr und Klimaschutz Berlin (SenMVKU), 2021) adding to the plausibility of the detected trends. Similar trends were observed at city scale, with bicycle traffic increasing even in areas without infrastructure improvements (Becker et al., 2022; Buehler and Pucher, 2022; infraVelo, 2023b). For all of Berlin, bicycle traffic in 2020 increased by + 22 % compared to 2019 (Buehler and Pucher, 2022), closely matching the + 25.2 % found within this study.

Pedestrian detections decreased by over 15 % in 2020, but YOLO's performance for pedestrian detection can be assumed as the least reliable due to their small and less distinct appearance in webcam images (Fig. 4b). The German Federal Environmental Agency reported a nationwide 1.4 % increase in pedestrian passenger kilometers in 2020 compared to 2017 (Umweltbundesamt (UBA), 2023).

In summary, the results reveal significant road user changes during the 2020 study period compared to 2018, with the COVID-19 pandemic and its associated restrictions and canceled cultural events being plausible primary drivers (Betschka et al., 2021). Interestingly, upcoming changes are planned for the three case study streets. Heerstrasse is set to host a 15 km bicycle express lane heading west (infraVelo, 2023b). A protected bike lane was initiated for Messedamm in 2024 (infraVelo, 2023a), while Alt-Moabit is proposed for a redesign favoring non-motorized road users (Stadtteilvertretung Turmstrasse, 2021). The YOLO-based approach used here could be a cost-effective tool for monitoring and evaluating these projects.

7. Conclusions

This study aimed to evaluate the performance of YOLOv8, a pre-trained object detection CNN, in the context of road user analysis using open webcam data from Germany. Additionally, it explored both the potential and challenges of using open webcam imagery for road user analysis and examined the impact of the COVID-19 pandemic and related restrictions on traffic at ten webcam locations in Berlin. The results demonstrate that YOLOv8, even when used out-of-the-box, provides satisfactory detection performance, achieving an F1-score of 0.75. This outcome is notable, given the challenges posed by open webcam imagery, such as varying camera perspectives, weather conditions, object occlusions, and a lack of domain-specific fine-tuning. This indicates that the model, even without fine-tuning, can be a valuable tool for road user detection and counting, which may be particularly important for practitioners.

However, future improvements could be made through further optimization of parameters, conducting class-specific tests, and perform fine-tuning using larger labeled datasets. A more detailed pre-processing stage, including image cropping and error analysis, showed improvements to the results. Further tailoring the model by using a custom dataset could refine the classification of road users, for example, by distinguishing between different vehicle types (e.g., "compact car," "SUV," "van"). This would require the creation of substantial amounts of high-quality annotated data.

The Berlin case study revealed significant shifts in road user patterns between the two analyzed periods – pre- and during the COVID-19 pandemic. Overall, a notable decrease in road users was observed in 2020 compared to 2018, with cars and trucks decreasing by −9.6 % and −8.0 %, respectively. These changes, however, varied by street and road user type. An increase in the detection of cyclists was seen across all ten webcams, with a collective increase of + 25.2 %. These findings align with existing literature on the impact of COVID-19 and restrictive measures on traffic volumes, reinforcing the broader trends identified in similar studies.

In conclusion, this study underscores the feasibility and potential of using open webcam data and pre-trained object detection models for urban road user analysis. Despite the challenges of open webcam data and limitations of using an out-of-the-box model, the findings demonstrate that YOLOv8 can serve as a powerful tool for understanding and managing urban mobility. The ability to apply this model in real-world traffic contexts could significantly contribute to intelligent traffic management systems and promote more sustainable, safer, and efficient transport solutions in the future.

CRediT authorship contribution statement

Dorothee Stiller: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Michael Wurm:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization. **Jeroen Staab:** Writing – review & editing, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Thomas Stark:** Writing – review & editing, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Georg Starz:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jürgen Rauh:** Writing – review & editing, Supervision. **Stefan Dech:** Supervision, Resources. **Hannes Taubenböck:** Writing – review & editing, Supervision, Resources, Conceptualization.

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Declaration of competing interest

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Statement

During the preparation of this work, the authors used ChatGPT in order to refine wording, improve clarity, and enhance readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Data availability

The webcam image data used in this study cannot be publicly shared due to the inclusion of potentially identifiable personal information, which raises privacy and data protection concerns. Consequently, access to the raw data is restricted in order to comply with ethical guidelines and legal regulations regarding the handling of sensitive visual data. Researchers interested in accessing the data for legitimate research purposes may contact the corresponding author, subject to approval and compliance with data privacy regulations.

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