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Modelling the influence of traffic infrastructure characteristics on e-scooter accidents in the city of Zurich

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Abstract. The rapid emergence of shared electric scooter (e-scooter) services has posed new challenges to road safety over the last few years as a serious worldwide public concern. Previous studies have investigated e-scooter accidents from multiple perspectives. However, research gaps still exist in understanding the role of infrastructure-related factors in e-scooter accidents. This study aims to investigate and model the relationship between the characteristics of traffic infrastructure and the presence of e-scooter accidents, especially the presence of curbs and the complexity of street views. Curb extraction was first achieved by applying the Segment Anything Model to Google Street View images as a supplement to existing traffic infrastructure data. Variables related to curbs, the complexity of street views, and traffic transport were then constructed. With pseudo-absence points being generated, the influence of traffic infrastructure on the presence of accidents was analysed by applying logistic regression and Random Forest classification. Results show that bicycle traffic count, distance to road, and object complexity of the whole scene are the most important variables in the classification model, while besides these three, the presence of curbs, distance to pedestrian crossing, speed limit value, urban district, and road width are significantly correlated with the presence of e-scooter accidents.

Submission Type. Model, Analysis

BoK Concepts. [DM4] Vector data model, Feature based modelling, Applications, [IP3] Image understanding

Keywords. e-scooter accidents, traffic infrastructure, Segment Anything Model, Google Street View

1 Introduction

Road safety issues cause massive casualties and considerable economic losses globally. The growing presence of micro-mobility is identified as an emerging challenge to road safety based on the WHO's Global Plan for the Decade of Road Action 2021-2030 (World Health Organization, 2021). Among these, shared electric scooters (e-scooters) have emerged rapidly in recent years, and increasing road accidents involving e-scooters are reported, which attracts public concerns.

Previous studies indicate that adverse environmental conditions, risky behavior of riders, hazardous surface features, reduced visibility during nighttime, and infrastructure-related factors all contribute to e-scooter accidents (Stigson et al., 2021; Azimian and Jiao, 2022; Karpinski et al., 2022; Pobudzei et al., 2023; White et al., 2023). Nonetheless, the understanding of how specific road infrastructure characteristics affect e-scooter accidents is insufficient. Moreover, e-scooter users experience more severe vibration impact compared to other road users such as cyclists while riding on the same infrastructure facilities (Ma et al., 2021). Small infrastructure characteristics such as curbs are likely to cause a higher risk for road accidents involving e-scooters. However, the lack of curb data collection methods with lower cost and less complexity remains a problem.

Street view imagery (SVI) has become an important and prevalent data source for urban analysis and geographic information science across a wide range of fields (Biljecki and Ito, 2021). Numerous studies have attempted to detect, identify or extract objects on road infrastructure from SVI, incl. traffic signs (Balali et al., 2015; Campbell et al., 2019), road lanes (Mamidala et al., 2019), side walks (Ning et al., 2022), road safety barriers (Rahman et al., 2021), signalized intersections (Li et al., 2022), pavement marking (Kong et al., 2022) and pavement damage (Ren et al., 2023). Despite this, no studies have investigated curb extraction from SVI, which is worthwhile to complement current data collection methods. Furthermore, SVI offers an opportunity to analyse the influence of infrastructure from the perspective of its role in a visual environment.

Image segmentation, which can be defined as classifying pixels with semantic labels or partitioning individual objects or both, plays an important role in computer vision and image processing (Minaee et al., 2022). Many image segmentation techniques and algorithms have been applied in feature extraction, among which Segment Anything Model (SAM) stands out as a promptable zero-shot image segmentation model trained with over 1 billion masks on 11 million images (Kirillov et al., 2023). Studies have indicated that SAM has made significant progress in segmentation (Zhang et al., 2023) and offered promising solutions for extensive object detection. Considering the task of extracting curb information from SVI, SAM has the potential to address this challenge.

This study aims to understand how traffic infrastructure characteristics affect e-scooter accidents. We are specifically interested in the influence of curbs and the scene complexity from street views that e-scooter drivers might see. We propose to extract detailed information about curbs from SVI, to use entropy for modelling view complexity by applying SAM, and to generate variables comprehensively representing the influence of traffic infrastructure in both physical and visual environments. Moreover, with the creation of pseudo-absence points, which represent a broader consideration of different environments, we apply both logistic regression and Random Forest (RF) classification for the presence of e-scooter accidents.

2 Methodology

2.1 Study Area and Data

The study area is the city of Zurich, which has an extensive, modern public street network covering a traffic area of 12.8 square kilometres (Präsidialdepartement, 2022). Since 2019, several shared micro-mobility providers have started operating dockless e-scooters in the city of Zurich, such as Lime, Bird, Tier, and Voi (Reck and Axhausen, 2021).

Three main data sources were used in this study. Firstly, the e-scooter accident dataset was provided by the transportation department in the city of Zurich. This dataset includes a total of 350 road accidents involving e-scooters that occurred in the city of Zurich between 2019 and 2022, from which the coordinates of each e-scooter accident were extracted. Secondly, for each location SVI were obtained from the Google Maps Platform. Request for each GSV image was set with customized parameters, as listed in Table 1. An example of four-direction GSV images for each location point is given in Figure 1. Images with invalid content, including null, indoor, rooftop, and sky, were further filtered out. Lastly, to generate traffic transport-related variables, we collected road infrastructure and transport network data from Zurich's open government data service along with Open Street Map (OSM). Considering the usage pattern and travel characteristics of e-scooters and the concentrated distribution of dockless e-scooters in urban areas, a road network for e-scooter driving was built by merging the street network, footpaths, and bicycle paths but filtering out natural areas such as forests.

Table 1: Parameters setting for GSV API

Parameter	Description	Setting value
Location	Latitude and longitude	Coordinates
Heading	Heading of camera	0,90,180,270
FOV	Horizontal field of view	120
Pitch	Up or down angle of camera	0
Size	Output image size in pixels	640 x 640

Figure 1: Example of four GSV images in one location

2.2 Generation of Pseudo-Absence Points

As accident-absent data is non-existent, we created pseudo-absence points to include a wider coverage of different environment, specifically different traffic infrastructure characteristics, in our study area. Considering the common areas of shared e-mobility trips, pseudo-absence points were generated along the e-scooter network, which we assumed to be randomly distributed accident-absent locations. The generation procedure was similar to Biland (2023). 16,922 points on the e-scooter network were first produced, and out of them, 1,015 points were then extracted randomly. Then, by filtering points that were located within a 10-meter distance to accident points and to boundary lines of the study area, 995 pseudo-absence points were created, of which the amount was suggested by a previous study (Barbet-Massin et al., 2012). The distributions of accident locations and pseudo-absence points are shown in Figure 2.

2.3 Curb Extraction

We designed a process of four steps to extract curbs from GSV images, including image segmentation with

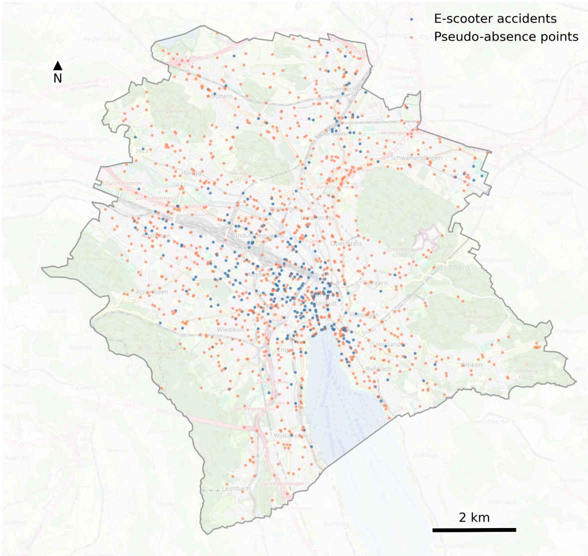
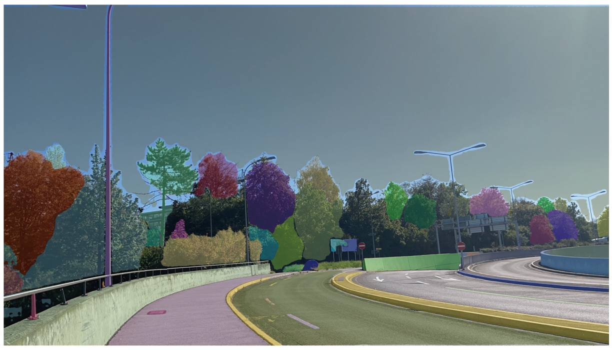


Figure 2: Distribution of e-scooter accidents and pseudo-absence points

(a) Input original image



(b) Segmentation output masks

Figure 3: Output masks example of SAM. Each colour represents one single mask segmentation

SAM, visual interpretation, calculating properties of output masks, and building a RF classification model.

First, we applied SAM automatic mask generation to images of four directions in each e-scooter accident location and pseudo point, such is the case in Figure 3. After extracting binary masks from the output, contours were identified and then filtered according to their sizes and overlaps. Second, to prepare for classifying detected contours into object groups, a total of 80 images from 20 randomly selected locations were visually interpreted and labelled, their mask output was later split to serve as training and validation data. Label groups include *sky*, *vegetation*, *curb*, *building*, *infrastructure*, and *other*. For curb extraction, object groups were further merged into four labels: *curb*, *infrastructure*, *vegetation*, and *other*. Third, to better distinguish mask contours, properties including 17 spectral features and 18 geometric attributes were calculated. Among spectral features, we computed the statistic values such as median, mean, standard deviation, and the 25th and 75th percentiles of three Red Green Blue (RGB) colour channels. Additionally, considering the commonly grey colour of curbs, we created a function to measure the similarity between pixel colours and standard grey. Regarding geometric attributes, we considered the contour properties such as aspect ratio, extent and solidity, and locations of extreme points. Fourth, we employed a RF classification model with the input of all above-mentioned mask properties. Hyperparameters such as the number of trees were selected after checking prediction accuracy within a wide range of setting values.

2.4 Modelling the Complexity of Scene

In the field of image processing, entropy is regarded as one of the metrics for describing the complexity of a given image (Hayashi et al., 2023). In this paper, we considered entropy to reflect the complexity of surrounding infrastructures in e-scooter drivers' visual environments. Three entropy-based variables were calculated from GSV images for both accident locations and pseudo-absence points.

We first calculated *image entropy*, which represents the randomness of colours. An image with a higher image entropy value denotes its complexity in pixel colour values. Secondly, we generated entropy of objects in the whole image. By training another RF classification model using mask properties and visually interpreted labels with a similar process to section 2.3, masks were classified into seven object groups: *building*, *curb*, *infrastructure*, *means of transportation*, *sky*, *vegetation* and *other*. For each image, *whole scene entropy* was then attained by computing the histogram of these seven object groups and calculating the entropy of its distribution. Furthermore, we generated *ground scene entropy* with a focus of curb and other infrastructure characteristics located at ground level. Masks identified as curb and infrastructure based on the classification result of section 2.3 with positions in the lower part of images were then classified into seven object groups: *curb*, *bike lane*, *ground sign*, *manhole*, *pavement*, *road* and *other*. Based on their distribution, we obtained the value of *ground scene entropy*.

2.5 Modelling the Influence of Infrastructure

Variables of three aspects were generated for both e-scooter accident locations and pseudo-absence points: curb variables, entropy variables, and traffic transport variables. Following curb extraction, the presence or absence of curbs, along with the number of curbs, were obtained from each image. Overall curb variables per location point were summarized into one binary variable (present or absent) and three numeric variables, including mean, maximum, and minimum curb counts. For entropy variables, image entropy, whole scene entropy as well as ground scene entropy were all included with their mean, maximum and minimum values for each location. Regarding other infrastructure variables, we calculated the distance from location points to the nearest infrastructure characteristics, including public transport stops, public traffic lines (bus, tram, train), pedestrian crossings, public lighting, and parking places (parking garages, street parking spaces, two-wheeler parking spaces). As for traffic transport variables for each location point, we derived traffic counts of both bicycles and vehicles based on occurring time and nearest counting stations, extracted traffic density and demand from the public passenger traffic model, and allocated properties of statistical zones and traffic areas. Missing values were replaced by an average number of other records that were measured in the same time period or nearby areas.

After merging the aforementioned three variable sets, two different processes of variable transformation were carried out. For numeric variables, normalization was achieved by applying a Yeo-Johnson power transformation function (Yeo and Johnson, 2000), after which standardization was completed by computing the z-score of each variable (Huck et al., 1986). Concerning categorical variables, one hot encoding was conducted. Furthermore, we detected and removed the variables with high pairwise correlation values with others and high multicollinearity values.

By regarding accident points as locations with the presence of accidents and pseudo points as locations with the absence of accidents, we applied a logistic regression model to determine the correlation between features from the three variable sets and the presence of accidents. Additionally, we built, trained, and tested a RF classification model to understand the influence of traffic transport infrastructure on the presence of e-scooter accidents.

2.6 Data and Software Availability

The workflow was implemented in Python. QGIS was used for processing traffic transport datasets. Codes of this work are available on request. The e-scooter accident dataset used in this paper is not publicly published, while traffic, transport and infrastructure datasets could be found and accessed from the website of Open Data Zurich (https://data.stadt-zuerich.ch/). GSV images used in this paper are free to access through the static Application Programming Interface (API) provided by the Google Maps Platform (https://developers.google.com/maps/documentation/streetview/overview).

Regarding the application of SAM in this work, its installation could be found from this GitHub repository (https://github.com/facebookresearch/segment-anything). The checkpoint was set to be sam_vit_h_4b8939.pth, model type was set vit_h. Moreover, Pytorch 2.0.1 and Torchvision 0.15.2 with CUDA support were utilized.

3 Results

With the application of SAM to GSV images in e-scooter accident locations, 103,373 segmentation masks were produced from 1,180 images in total. Subsequently, by identification of contours and filtering out overlaps or repetitions, 57,035 mask contours were generated. Regarding visual interpretation, 3,934 masks were defined and labelled. RF classification model was built using 35 different properties, including geometric attributes and spectral features, of each mask. Masks were then categorised into four object groups. The performance of the RF classification model was evaluated and quantified with metrics of different assessment methods, as presented in Table 2.

Table 2: Evaluation metrics of RF classification for curb extraction

Metrics	0	1	2	3	Overall
Accuracy					0.838
Precision	0.778	0.846	0.838	0.826	0.838
Recall	0.636	0.752	0.927	0.585	0.838
F1	0.700	0.796	0.880	0.685	0.833
MCC					0.693
Kappa					0.688

Note: 0, 1, 2, 3 represent classes of curb, infrastructure, other, and vegetation, respectively.

We then extracted curbs from all GSV images of both e-scooter accident locations and pseudo-absence point locations by applying this RF classification model. Figure 4 below illustrates an example of curb extraction result at one location.

After merging generation results from three different variable sets, variables were then filtered according to correlation and multicollinearity values. Table 3 below presents the selected variables which were used for modelling.

The logistic regression model built for the presence of accidents has a pseudo R-squared value of 0.695. Eight variables were recognized as significantly correlated to the presence of accidents (Table 4). For numeric variables, while 'bicyclecount' (bicycle traffic count value),

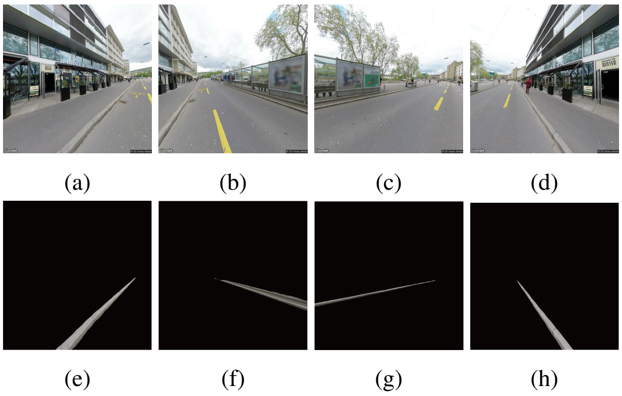


Figure 4: Example of curb extraction

Table 3: Variable sets used for modelling

Category	Variable	Description
Curb-related	cp	Presence of curb
	cmin	Minimum number of curb count
Entropy	ie	Average value of image entropy
	mew	Average value of whole scene entropy
	meg	Average value of ground scene entropy
	megmax	Maximum value of ground scene entropy
Traffic Transport Infrastructure	dbusl	Distance to bus line
	dtraml	Distance to tram rail
	dtrainl	Distance to train rail
	dplight	Distance to public light
	dstation	Distance to public transport station
	dparkcar	Distance to car parking space
	dparktw	Distance to two-wheeler parking space
	dpedcro	Distance to pedestrian crossing
	dstopsign	Distance to stop sign
	dtrafficarea	Distance to traffic area
	droad	Distance to road
	gvm_dwv	Average daily traffic
	speedlimit	Speed limit value
	bicyclecount	Bicycle traffic count value
	carcount	Vehicle traffic count value
	z_qnr*	Statistical city district
	z_knr*	Urban district
	trafficarea*	Traffic zone
	r_width*	Road width group
	speedlimit_g*	Speed limit group

Note: * marks categorical variables.

’mew’ (average value of whole scene entropy), and ’droad’ (distance to road) have positive coefficients, ’cp’ (presence of curb), ’dpedcro’ (distance to pedestrian crossing) and ’speedlimit’ (speed limit value) have negative coefficients. For categorical variables, ’z_knr’ (urban district) and ’r_width’ (road width group) are found significant.

Table 4: Logistic regression for accident presence - Significant variables

Variables	P-value	Coefficient	Significance
bicyclecount	0.000	6.991	***
mew	0.000	3.632	***
droad	0.000	2.878	***
cp	0.006	-0.541	**
dpedcro	0.010	-1.655	*
speedlimit	0.041	-1.092	*
z_knr_10	0.034	-1.968	*
r_width_1	0.033	1.312	*

Note: ***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$.

The performance of the RF classification model for the presence or absence of accidents based on these variable sets was then evaluated, as presented below in Table 5. Overall, the classification model has both an accuracy and a precision of around 0.95 and a recall of around 0.92. Furthermore, according to the top 20 important variables ranked by Gini importance values illustrated in Figure 5, the three most influential variables are ’bicyclecount’ (bicycle traffic count value), ’droad’ (distance to road) and ’mew’ (average value of whole scene entropy).

Table 5: Evaluation metrics of RF classification for the presence of accident

Metrics	0	1	Overall
Accuracy			0.951
Precision	0.948	0.961	0.954
Recall	0.988	0.849	0.918
F1	0.968	0.901	0.934
MCC			0.872
Kappa			0.869

Note: 0 and 1 represent the absence of accident and the presence of an accident, respectively.

4 Conclusion and Future Research

Extraction of curbs was achieved by applying SAM to GSV, generating variables based on properties of image segmentation, and training a RF classification model with labels from manual vision interpretation. According to the evaluation metrics results, the feasibility of this innovative method for curb extraction was confirmed.

Results from the logistic regression model indicate that traffic infrastructure characteristics are significantly related to presence of e-scooter accidents. The performance assessment of the RF classification model further confirmed their importance. Traffic characteristics, such as ’bicyclecount’ (bicycle traffic count value) and ’speedlimit’ (speed limit value), play a vital role.

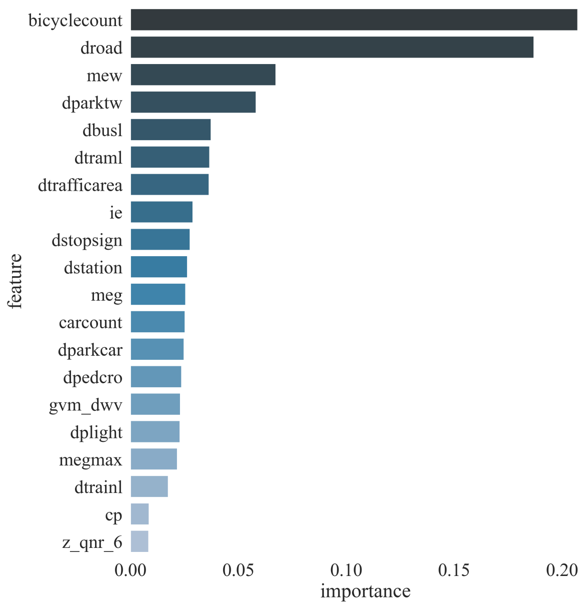


Figure 5: Variables with 20 top-ranked Gini importance values

Infrastructure characteristics also contribute to understanding the presence of e-scooter accidents from both physical and visual perspectives. For instance, 'droad' (distance to road) and 'dparktw' (distance to two-wheeler parking space) were found important in the built RF model, and 'dpedcro' (distance to pedestrian crossing) and 'cp' (presence of curb) were determined significant in the logistic regression model, which represents the influence of traffic infrastructure in the physical environment. Further, 'mew' (average value of whole scene entropy) was also recognized as influential, which illustrates the importance of infrastructure in the visual environment. Compared to previous studies, results in this paper are also consistent with the finding that riding location, such as shared-use path, road shoulder, side walk and roadway (White et al., 2023), is among the most crucial infrastructure factors for e-scooter accidents.

Several limitations of this study are acknowledged from two perspectives as follows: data availability, coverage, and quality, as well as the methodology. Fundamentally, the e-scooter accident dataset has a limited data size and potential bias. The relatively small amount of data (350 accidents over 4 years) might lead to an inadequate understanding of e-scooter accidents. Besides, the e-scooter accidents were only recorded when the police noticed or were informed by the persons involved in an e-scooter accident. It is possible that more e-scooter accidents took place without being registered in this dataset, which could cause the analysis to be biased. Regarding usage of GSV images, locations without coverage or with invalid content are not included. Also, it is noteworthy that distortion of objects, sunlight overexposure and shadows in images are likely to result in a misunderstanding of the colours and shapes of objects. Moreover, as for the application of SAM, the filtering functions applied to remove overlapping masks and small-size contours could reduce the number of repetitive and less important masks on the one hand but also possibly filter out masks containing existing curbs. This might cause inadequate extraction of curbs and a smaller number of curbs in comparison to the true number of curbs in the real world.

For future work, modelling the influence using a larger size of accident data as well as better SVI with a higher coverage is important to gain a more adequate and unbiased understanding of this problem. Also, there is abundant room for further progress in image segmentation. Including more detailed information extracted from street view images, such as feature measurement, is worth investigating. Moreover, subsequent research could aim to expand this study to understand influence of traffic infrastructure characteristics on more perspectives of e-scooter accidents, such as accident severity, and to build prediction models for understanding potential vulnerable locations to e-scooter accidents.

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