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Computer vision-based helmet use registration for e-scooter riders – The impact of the mandatory helmet law in Copenhagen

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A B S T R A C T

Problem: E-scooters are a new form of mobility used more frequently in urban environments worldwide. As there is evidence of an increased risk of head injuries, helmets are recommended and (less frequently) legislated. Denmark has enacted mandatory e-scooter helmet use legislation from January 1, 2022. So far, it is unclear how this newly implemented law influenced helmet use of e-scooter riders in Denmark immediately after its implementation. *Method:* In this observational study, we register and compare e-scooter helmet use before the mandatory helmet use legislation (December 2021) and after (February 2022). As observational survey data collection in the field can be highly time-consuming, we conducted a video-based observation survey. We trained and applied a computer vision algorithm to automatically register e-scooter helmet use in the video data. *Results:* The trained algorithm produces accurate helmet use data, which does not differ significantly from human-registered helmet use. In applying the algorithm to video data collected in December 2021 and February 2022, we register an overall e-scooter helmet use of 4.4% in n = 1054 riders. Splitting the observation between the time before and after the implementation of the helmet use law reveals a significant increase in helmet use from 1.80% to 5.56%. *Discussion:* In this study, we successfully train and apply an object detection algorithm to register accurate helmet use data in videos collected in Copenhagen, Denmark. Using this algorithm, we find a significant impact of a new mandatory e-scooter helmet use law on e-scooter riders' helmet use behavior. Limitations of the study as well as future research needs, are discussed. *Practical Applications:* Computer vision algorithms can be used for accurate e-scooter helmet assessments. Implementing a mandatory helmet use law can increase helmet use of e-scooters at specific observation sites.

1. Introduction

Electric kick scooters (e-scooters) have become an increasingly popular mode of transportation in recent years. However, research indicates that e-scooter riders have an elevated risk of experiencing crashes compared to cyclists (Gebhardt et al., 2021). Hospital data also indicates that an increasing number of e-scooter riders are being admitted, with head injuries being one of the most frequently reported injury types (Aizpuru et al., 2019; Trivedi et al., 2019; Toofany, Mohsenian, Shum, Chan, & Brubacher, 2021; Serra, Fernandes, Noronha, & de Sousa, 2021). To mitigate the high prevalence of head injuries among e-scooter riders, helmets are considered a potential and viable countermeasure (Mitchell, Tsao, Randell, Marks, & Mackay, 2019). Despite this, studies show relatively low helmet use rates in regions where e-scooter helmets are not mandatory (Trivedi et al., 2019; Petzoldt, Ringhand, Anke, & Schekatz, 2021; Siebert et al., 2021b; Siebert et al., 2021a), whereas, in regions with mandatory helmet use laws, higher helmet use rates are observed (Haworth, Schramm, & Twisk, 2021b). However, it is unclear how the introduction of mandatory helmet use laws relates to actual e-scooter rider helmet use in the immediate aftermath of the implementation of the legislation.

The helmet use rate among e-scooter riders is a critical factor affecting their safety in the event of a crash. It is one of the key performance indicators within the European Commission's Road Safety Policy Framework 2021–2030 (European Commission, 2019). Regular monitoring of e-scooter helmet use can help road safety actors better understand usage patterns, including differences in helmet use across cities, seasons, weather conditions, and commuter vs. non-commuter populations. By continuously monitoring helmet use, it is possible to quickly identify trends, such as a decline in helmet use, that may need to be addressed with increased road safety education, information, or enforcement

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campaigns. Currently, human observers are employed to register e-scooter helmet use through direct roadside observations or video-based methods, which can be time-consuming and expensive. This hinders the quick identification of changes in helmet use. While automated methods for the detection of helmet use among other road user types, such as motorcycles, have been developed (e.g., (Siebert & Lin, 2020; Lin, Deng, Albers, & Siebert, 2020)), there are currently no accurate methods available for the automated registration of e-scooter helmet use. This is because helmet detection algorithms do not solely detect helmets, as no distinction between, e.g., motorcycle and e-scooter helmets would be possible with general helmet detection. Instead, algorithms are trained to detect the combination of the vehicle (e.g., motorcycle), road users (motorcycle rider), and the rider's head as one object, which has either the attribute "helmet" or "no helmet". Hence, for each road user class, dedicated algorithm training is required. Any algorithm trained for one road user class will also need to be evaluated anew, to assess whether the specific road user class detection is prone to e.g., confusing the specific class with another.

This study addresses these challenges of evaluating e-scooter helmet use and assessing the impact of mandatory e-scooter helmet laws by accomplishing two goals. First, to develop a computer vision-based automated detection method for e-scooter helmet use. Second, to use this method to examine the impact of a mandatory e-scooter helmet law enacted in Denmark on January 1st, 2022 (Sørensen, Thomsen, Pedersen, & Jensen, 2022). The study focuses on developing and testing a computer vision-based method for the automated detection of e-scooter helmet use in video data. The aim is to provide an efficient data collection tool for road safety researchers and practitioners. Finally, the study uses video data from Copenhagen, Denmark, to assess the impact of the mandatory helmet use law for e-scooters enacted in Denmark at the beginning of 2022.

2. Background

Shared e-scooters were introduced in Copenhagen, Denmark, in January 2019. Despite the relatively long time since their introduction, there are only a few studies on e-scooter helmet use in Denmark. In the most comprehensive analysis of hospital-based e-scooter crash data in Denmark, Blomberg, Rosenkrantz, Lippert, and Collatz Christensen (2019) investigated crashes registered through emergency medical services (EMS) in the Copenhagen area, covering the first six months of the shared e-scooter introduction (January-July 2019). They found that of the 112 e-scooter riders in the EMS data, only 3.6% ($n = 4$) were registered as having used a helmet (no helmet = 55.4%; unknown helmet use = 41.1%). This is in line with most findings from other European countries, which frequently show low e-scooter helmet use in hospital-based studies (Harbrecht et al., 2022; Vasara et al., 2022) and roadside observations (Siebert et al., 2021a; Siebert et al., 2021b) (although some studies found higher helmet use (Huemer et al., 2022)). Among e-scooter riders in the EMS data, approximately one in five (20.5%) was registered with a head injury, which is in line with Nielsen, Nielsen, and Rasmussen (2021) finding of a relatively large share of head injuries in hospitalized Copenhagen area e-scooter riders. Similar findings have been reported in other hospital-based studies, where considerable shares of head injuries are found (Aizpuru et al., 2019; Trivedi et al., 2019; Toofany et al., 2021; Serra et al., 2021).

The majority of countries in the world do not have mandatory e-scooter helmet use laws (Serra et al., 2021). A main exception to this is Australia, where e-scooter riders have to use a helmet (Haworth et al., 2021b). In countries where helmet use is not legally required, it is often recommended, e.g., by shared e-scooter providers directly on the e-scooter and in related apps (Siebert et al., 2021a). Researchers have frequently highlighted the injury mitigation potential of e-scooter helmets (Uluk et al., 2022; Kazemzadeh, Haghani, & Sprei, 2023; Serra et al., 2021; Mitchell et al., 2019; Vasara et al., 2022; Kleinertz et al., 2021; Goh, Beech, & and Johnson, 2022), especially in light of the high share of head injuries in hospital-based e-scooter studies (see above). In Denmark, the mandatory e-scooter helmet use law came into effect on January 1, 2022, mainly as a reaction to requests from healthcare workers and traffic planners Sørensen et al. (2022); Jenvall and Lindegaard (2022).

Computer vision, i.e., automated image data analysis, has been successfully applied to registering safety-related road user behavior in recent years. For vulnerable road users, i.e., those road users who are relatively unprotected in case of a crash (Otte, Jänsch, & Haasper, 2012), computer vision has been applied to register the behavior of motorcyclists (Siebert & Lin, 2020; Lin et al., 2020; Lin, Chen, & Siebert, 2021; Nandhini & Brindha, 2022), pedestrians (Zaki, Sayed, Tageldin, & Hussein, 2013b; Jakobowsky, Siebert, Schiessl, Junghans, & Dotzauer, 2022), and bicyclists (Zaki, Sayed, & Cheung, 2013a; Li, Hajimirsadeghi, Zaki, Mori, & Sayed, 2014). For e-scooters, comparatively little research has been conducted on automated detection approaches. Existing studies focus on the general detection of e-scooter riders but not on the detection of safety-related behavior (Apurv, Tian, & and Sherony, 2021; Gilroy, Mullins, Jones, Parsi, & Glavin, 2022).

In computer vision applications, there are two commonly used approaches in constructing the computer vision pipelines for registering safety-related road user behavior: the two-step procedure (Chairat, Dailey, Limsoonthrakul, Ekpanyapong, & Dharma Raj, 2020) and the end-to-end algorithm (Siebert & Lin, 2020). In the two-step procedure, two separate algorithms are used, one for detecting road users, and a subsequent one for classifying safety-related behavior of the detected road users. In contrast, the end-to-end algorithm performs both steps simultaneously, and, e.g., two separate classes are detected (motorcyclist with a helmet vs. motorcyclist without a helmet) in one step. While the independence between detection and classification in the two-step procedure allows for reusing the detection algorithm with a different classification algorithm, in practice, a new classification algorithm is often trained from scratch, resulting in no computational advantage over the end-to-end algorithm. The newer end-to-end computer vision models have gained popularity as they require the training of only one model, reducing computational resources by half.

3. Methods

Since no image dataset exists on e-scooter helmet use, we set out to establish a diverse image dataset containing active e-scooters riders (i.e., persons actively using e-scooters). For this, we collected video data collection in Copenhagen, Denmark. The following details the steps taken to create a dataset of e-scooters and their helmet use. We then present how this dataset can be used to train an object detection algorithm to identify the helmet use of e-scooters.

3.1. Data creation

Due to the lack of publicly available annotated image datasets for e-scooter helmet use, a new dataset was created for developing the proposed helmet use detection algorithm. Three key requirements guided the data collection process: (1) adherence to ethical standards for data collection in public spaces, (2) representation of a diverse spectrum of e-scooters, and (3) inclusion of visually and temporally diverse images captured under various lighting and weather conditions. **Requirement 1:** To meet the first requirement of complying with laws regarding data privacy, we collaborated with the Municipality of Copenhagen to select observation sites where there is already ongoing video data collection by the city. At these sites, prominent information signs are already installed, which inform all road users of the ongoing video data collection. Hence, two locations with ongoing existing video data collection were chosen for our study. **Requirement 2** & **3:** To ensure diversity in the e-scooters and riders in our dataset, we collected data over a prolonged period to avoid solely capturing data from, e.g., commuters in the morning and evening or leisure riders on weekends. This approach also allowed us to gather images under various lighting and weather conditions. The two selected observation sites were located in high-traffic-density areas, i.e., roads connecting the city center to the suburbs, which increased the likelihood of capturing many diverse e-scooters and riders.

In accordance with the requirements established, the two observation sites selected were located in the northern and south-western parts of Copenhagen in the district of Østerbro and Valby (Fig. 1). Only one direction of e-scooter traffic was recorded at each site: northbound outwards, i.e., away from the city center in Østerbro, and eastbound inwards, i.e., towards the city center in Valby. To further diversify the data, the camera in Østerbro was positioned facing both the bicycle lane and pedestrian sidewalk. In contrast, the camera at the Valby location faced the main road with the bicycle lane in the foreground. The video data collection at both observation sites occurred in December 2021 (Valby: December 13th to 19th, 2021; Østerbro: December 7th to 12th, 2021) and February 2022 (Valby: February 12th to 18th, 2022; Østerbro: February 4th to 10th, 2022). In other words, at both sites, data was recorded *before* and *after* the implementation of the mandatory e-scooter helmet use law on the 1st of January 2022. The total video duration was 280 h, with 145 h recorded at the Østerbro location and 135 h recorded at the Valby location.

To enhance the robustness of the object detection algorithm, we obtained additional data from two supplementary sources. This so-called *robustness dataset* was composed of 78 creative commons images (with CC0 license) containing 115 active e-scooters retrieved through Google image search and 262 images with 290 active e-scooters from an existing dataset (Apurv et al., 2021). Since some images had multiple active e-scooters, this added a total of 405 e-scooters to the robustness dataset, with images varying in resolution from 220×350 to 2716×1714 pixels.

3.1.1. From raw data to annotated images

To train the object detection algorithm, image data must be annotated. For this, a human must inspect images and mark the object to be detected within images. In our case, images needed to be inspected for active e-scooters, so, e.g., parked e-scooters without a rider or e-scooters that a pedestrian was only pushing while walking were not annotated. During annotation, active e-scooters were marked with a *bounding box* (visualized in Fig. 1), a rectangular frame around the active e-scooter. This bounding

Fig. 1. Three datasets were used to train the algorithm: recordings from two cameras in Copenhagen, Denmark, as well as e-scooter images from creative commons sources and an existing e-scooter dataset (Apurv et al., 2021) (© OpenStreetMap contributors).

box later serves as a reference to the algorithm detection, as the overlap between the human-annotated bounding box coordinates of an active e-scooter within an image and the algorithm-predicted location of the active e-scooter is compared. For each bounding box, the rider's helmet use is annotated (as helmet vs. no helmet). In total, there were 963 active e-scooters in the dataset (361 with a helmet and 602 without a helmet).

Active e-scooters that were very blurry or where more than 50% of the active e-scooter was obscured were not annotated. Images for annotation were initially extracted from the video data collected at the two observation sites in Copenhagen (see Fig. 1). This way, a total of 558 instances of active e-scooters from the video data were annotated (244 with helmets and 314 without helmets, as shown in Table 1). It is important to note that this distribution does not reflect the actual helmet usage in the observed cycle lanes, as efforts were made to balance the number of helmet users and non-users in the dataset. In addition, this data partly contains the same individual e-scooters multiple times, filmed from different angles as they approach the video camera. For the robustness dataset, 117 instances of active e-scooters with a helmet and 288 without a helmet were annotated. A summary of the class distribution of active e-scooter instances in the dataset is presented in Table 1.

3.2. Object detection algorithm

Using the annotated dataset, we can train a computer-vision object detection algorithm to detect the helmet use of e-scooter riders. Once trained, the algorithm uses an image as input and will return the coordinates of any e-scooters detected within the image, if any are present. I.e., we do not train a detection algorithm that just detects the general presence of an active e-scooter in an image (yes vs. no) but train an algorithm that locates active e-scooters within an image. In addition, the detected e-scooter will have one of two attributes, either *helmet* or *no helmet*.

In this study, we selected the YOLOR (You Only Learn One Representation) object detection model (Wang, Yeh, & and Liao, 2021) to identify the presence of active e-scooter riders and determine their helmet use. YOLOR is a single-shot multi-box detector that can detect multiple objects within an image. The model uses a convolutional neural network to perform object detection, taking the entire image as the input and outputting the bounding boxes and class probabilities for each object in the image. To adapt YOLOR for our specific task, we fine-tuned a YOLOR model with the pre-trained weights on the COCO dataset (Lin et al., 2014) on our annotated e-scooter dataset. We train the model to detect the two classes: e-scooter riders with helmets and e-scooter riders without helmets. Each detection from the model consists of a probability for whether it is detecting an object, i.e., a confidence score, and the probability of the detected object being an active e-scooter rider with or without a helmet. Therefore, we can reuse the same model to detect active e-scooter riders (without considering their helmet use) by focusing only on the confidence score. After training, we evaluated the model's performance on the test set, investigating the performance for detecting both active e-scooter riders and their helmet use, using the mean average precision (explained in Section 4.2).

4. Experimental setup

This section presents the experimental methodology used to train and evaluate the computer vision-based object detection model. Our approach aligns with the established computer vision practices, which involve initial training of the model and an evaluation on a separate, unseen dataset (so-called test-set). To quantify the model's performance, we employ standard metrics commonly used to evaluate computer vision algorithms. In the following subsections, we describe the steps taken to ensure that the model is robust and accurate and highlight the methods used to assess the model's performance.

4.1. Datasets and splits

We divided the collected data into three subsets to train and evaluate the object detection algorithm. The first subset, the training set, consisted of 61.3% of the total annotated data and contained 590 active e-scooter images. The second subset, known as the validation set, contained 10.4% of the data (100 active e-scooters). Finally, the test set contained 28.3% of the data (273 active e-scooters), as summarized in Table 2.The robust dataset is excluded from the test set, so the test set only contains images that reflect the algorithm's performance on real observations. Additionally, the images in the test set also include 36 bicycles and 61 pedestrians.

We use the training set to train the YOLOR object detection algorithm and use the validation set during the training to prevent overfitting. I.e., for testing, we evaluate the performance of the trained model on the validation dataset images after each training iteration (also known as an epoch) and then select the model with the best performance on the validation test, as this is the best proxy for good performance on the test set. To assess the performance and validity of the model, we evaluated it on the independent test set, which consisted of images that were not part of the training or validation sets.

In the test set, 46.0% of the riders were using helmets, with 125 riders wearing helmets and 147 without. As mentioned before, it is important to note that the distribution of helmet use in the test set does not represent the actual helmet use distribution in the observed cycle lanes, as an effort was made to balance the number of helmet users and non-users in the dataset, to increase the robustness and generalizability of the model.

4.2. Evaluation metric

Two variables form the basis for all evaluations of the algorithm. First, we assess whether the algorithm-predicted location of the active e-scooter overlaps with the human-annotated location of the active e-scooter. This variable is called Intersection over Union (IoU). We calculate the IoU between the bounding box of the algorithm prediction and the bounding box of the annotated label. If the IoU is above 0.5, meaning the predicted object position and actual object position in the image overlap by at least 50%, we register a correct detection of an active e-scooter. We denote the mean average precision (mAP) based on a minimum IoU of 0.5 as mAP@.5. In addition, we check whether the algorithm-predicted

Table 1
Class distribution of active e-scooter instances in the dataset.

Class	Total Objects	Valby	Østerbro	Robustness Set
E-scooters without helmet	602	123	191	288
E-scooters with helmet	361	140	104	117
Total	963	263	295	405

Table 2
Distribution of active e-scooters between training, validation, and test set of the dataset.

Class	Total Objects	Training set	Validation set	Test set
E-scooters without helmet	602	383	71	148
E-scooters with helmet	361	207	29	125
Total	963	590	100	273

active e-scooter class (helmet vs. no helmet) matches the human-annotated class. To evaluate the performance of our YOLOR model, we calculate several descriptive statistics such as true positive (TP), false positive (FP), and false negative (FN) to determine the precision, recall, and mean average precision (mAP) of the detection. Note that we do not use the statistic true negative since the concept is undefined within object detection tasks. Precision is defined as TP divided by the sum of TP and FP, i.e., precision = (TP/ (TP + FP)). It describes the model's accuracy in predicting objects belonging to a specific class. On the other hand, recall is defined as TP divided by the sum of TP and FN, i.e., recall = (TP/ (TP + FN)), and describes the proportion of objects detected by the model out of all objects in the dataset for a specific class. These two metrics, precision and recall, present a trade-off between accurately classifying each object and capturing all objects. For example, maximizing precision will result in only correct detections but fewer objects detected, while maximizing recall will result in detecting all instances along with many irrelevant objects. Hence, object detection evaluation uses the so-called mean Average Precision (mAP) metric to overcome the trade-off between precision and recall. The average precision (AP) is calculated as the area under the curve of the Precision-Recall curve, and the mAP is the mean of the APs for different classes. For the algorithm evaluation, it is important to note that the detection is not made on a whole frame level, as we are not solely detecting whether there is an active e-scooter in the image or not. Instead, the algorithm predicts active e-scooter locations within an image, and these are checked against human-annotated location data.

Finally, we evaluate all these for the model by calculating the mAP for detecting active e-scooters and helmet use detection. As part of the evaluation, we also compare the annotated helmet use percentage with the algorithm-registered helmet use rate and calculate the χ^2 statistic to check for statistically significant differences between the actual and algorithm-registered helmet use percentage. The same test statistic is used to calculate whether the e-scooter helmet use rate in 2021 differs significantly from the helmet use rate registered in 2022.

5. Results

Here, we first present the results for the performance of the trained object detection algorithm on the test dataset. Then, we apply the trained algorithm to multi-day data from the two observation sites in Copenhagen to assess the impact of the mandatory helmet use law.

5.1. Algorithm accuracy

Firstly, we evaluate the model's performance in detecting active e-scooters in general, i.e., without detecting helmet use. The results show that the model achieved a mean average precision (mAP@.5) of 0.99, indicating high accuracy in detecting active e-scooters with tight bounding boxes around the objects (Table 3). The precision of the model was 98%, and the recall was 98%, indicating that the model has high accuracy when it detects an active e-scooter (precision), and detects almost all of the e-scooters in the images (recall). Regarding true positives and false positives, we detected 267 out of the 272 e-scooters and incorrectly detected 5 other objects as e-scooters. The 5 objects detected as e-scooters were bounding boxes around bicycles and a mix of an e-scooter and a bicycle (see examples in Fig. 2). However, we emphasize that the trade-offs in the numbers of true positives, false positives, and true negatives, and thereby also the precision and recall, can be adapted to the specific application, i.e., if the precision is more important than the recall, one could have chosen a precision-recall trade-off, where the precision would be 1.0, but the recall would be only 0.6. Consequently, the metric mAP@.5 describes the model's performance more precisely since it is independent of the modeler's choice on the precision-recall trade-off.

In addition, we also evaluated the model's ability to detect helmet use. The overall helmet use classification assessment shows that the model achieves a mAP@.5 of 0.96, with a precision of 82% and a recall of 95% (last line of Table 3). Looking at the two classes separately, it can be observed that the precision for detecting e-scooters with a helmet was 73%, which is lower than the precision of 91% for detecting e-scooters without a helmet. Nevertheless, the recall for both classes was high, with 94% and 99%, respectively, indicating that the model can detect the majority of active e-scooters with or without helmets.

In applying the algorithm for real-life helmet use assessment, it is important to consider the accuracy of the algorithm-generated helmet use percentage compared to the actual helmet use in the data. Our test dataset consists of 125 riders with helmets and 147 without, which is equal to a helmet use rate of 46.0%. The algorithm detected 117 of the 125 e-scooters with helmets, missing 8 and wrongly detecting 43 objects as e-scooters with helmets. For the riders without helmets, the algorithm identified 143 out of 147, missing 4 and wrongly detecting 15 objects. Hence, the algorithm detected helmet use is slightly higher with 50.3% $((117+43)/(117+43+143+15))$ compared to the actual helmet use in the test dataset with 46.0% $(125/(125+147))$. The χ^2 test reveals that this difference is not significant ($\chi^2(1)$=1.12, p=.29), i.e., the algorithm registered helmet use rate does not differ significantly from the human-annotated helmet use rate. This result indicates that the trained algorithm can register the helmet use rate in unseen image data with a relatively high degree of accuracy, which is a prerequisite for the application on longer-term real-life data.

5.2. Visualization of results and investigative analysis

Despite the good accuracy in e-scooter helmet use percentage registration, it can be beneficial to visually inspect instances of false detections of the algorithm to learn common errors. In Fig. 2, we present some sample results of the YOLOR algorithm's performance on the test set. Each image displays a bounding box around the detected object, the predicted class, and a score indicating the model's confidence level in its classification. The bottom row images in Fig. 2 visualize correct detections of active e-scooters and riders' helmet use. The instances show that the model can accurately classify the e-scooters and their helmet use, with bounding boxes closely confining the objects in all images. However, the images in the top row of Fig. 2 demonstrate instances with incorrect or missing detections. In the top left image, rain-

Table 3
Model performance on the test set.

Class	Total Objects	Precision	Recall	mAP@.5	Helmet use rate	
					Prediction	Test set
Active E-scooter	272	0.98	0.98	0.99	-	-
E-scooter with Helmet	125	0.73	0.94	0.94	-	-
E-scooter with no helmet	147	0.91	0.97	0.99	-	-
Average over the classes	272	0.82	0.95	0.96	50.3%	46.0%

Fig. 2. Visualization of the (anonymized) detection results of the YOLOR Model for active e-scooter and helmet use in the test set, including confidence score. The top row shows incorrect detections (missed detection marked with a white, dotted rectangle). The middle row shows correct detections. The bottom row shows objects incorrectly detected as e-scooters.

drops obscure the camera's view, leading to a missed detection (false negative) of an active e-scooter. Similarly, on the top right, an active e-scooter is not detected. This e-scooter rider is dressed in black clothes and uses a black e-scooter, giving little contrast between the active e-scooter and the dark cycle lane. In the top middle image, an e-scooter rider wearing a base cap is incorrectly registered as using a helmet. Our analysis of the results further reveals that the model encounters difficulties in estimating helmet use when images contain motion blur are recorded in low-light conditions, or when riders are only partially visible at the edges of the image. These challenging scenarios, such as those found in night-time or early morning settings, present difficulties for the model to make accurate classifications.

5.3. Assessing the impact of the mandatory helmet use law

The advantage of our automatic approach lies in its ability to facilitate long-term observational studies, which can identify potential changes in helmet use more efficiently than human observers. To demonstrate this, we applied the trained algorithm to all recorded videos from the two observation sites collected in 2021 and 2022. To not register the same individual e-scooters multiple times, we applied the algorithm to one image every 10 s, resulting in 182,959 images over the four weeks of recording. We applied the algorithm to all these images and register the number of e-scooters with and without helmets. In total, we identified 1054 e-scooter riders, of which $n = 1008$ did not use a helmet and $n = 46$ used a helmet. This corresponds to an overall helmet use rate for our complete observation of 4.4%. The number of hourly active e-scooters registered in 2021 and 2022 is presented in Fig. 3. The results indicate that there is little to no detection of e-scooters in the early morning hours (before 6) and a subsequent increase in detections as the day progresses, reaching peaks in the early to late afternoon. It can also be observed that more e-scooters were observed in February 2022 than in December 2021.

The helmet use of e-scooter riders at different times of day is presented in Fig. 4. It can be observed that helmet use stays under 5% for all observation times in December 2021, while an increased

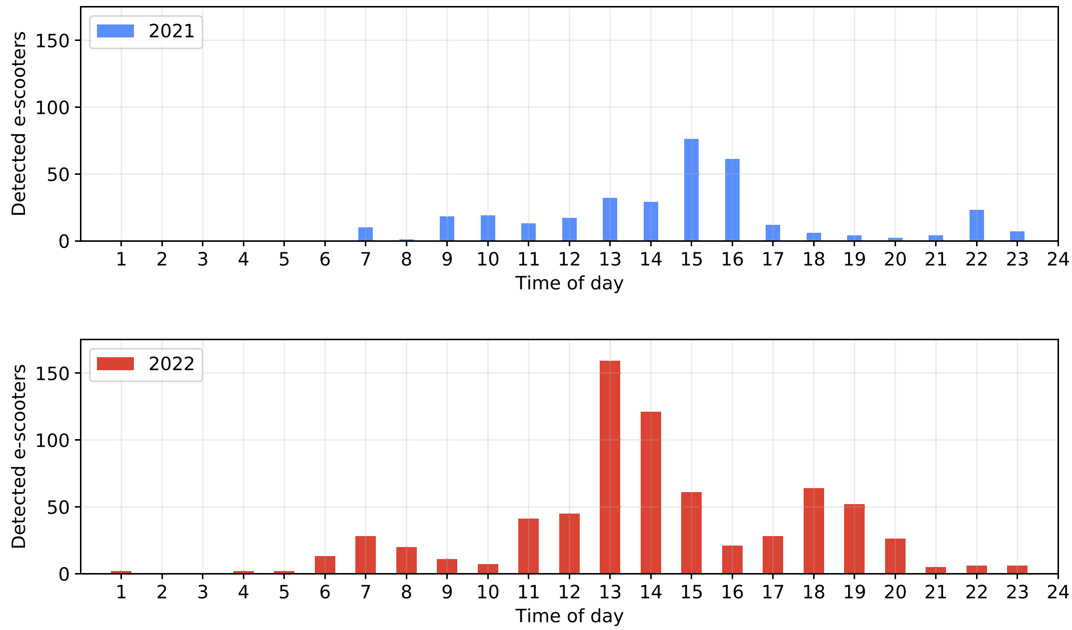

Fig. 3. Active e-scooters registered in Copenhagen at different times of day in December 2021 (top) and February 2022 (bottom).

helmet use can be observed in 2022 for the morning (6–10) and afternoon (14–18) hours. In Fig. 5, the average e-scooter helmet use for 2021 and 2022 is presented. It can be observed that the average registered helmet use is higher in 2022 (m = 5.56%) than in 2021 (m = 1.80%). The χ^2 test reveals that this difference is significant ($\chi^2(1)$=7.73, p<.01), i.e., e-scooter helmet use has increased significantly at the two Copenhagen observation sites after the enactment of the mandatory helmet use law.

6. Discussion

In this paper, we investigated the feasibility of a computer vision-based object detection algorithm for registering e-scooter riders' helmet use in video data. In addition, we analyzed the impact of the mandatory e-scooter helmet use law enacted in Denmark. The results of this study are discussed in two parts, first for the methodology used and then for the findings on e-scooter helmet use in Copenhagen.

6.1. Detection algorithm

The trained algorithm for detecting active e-scooter riders achieved a good accuracy of mAP = 0.99. This indicates that computer vision-based e-scooter detection can be a valuable tool to detect and extract occurrences of e-scooter riders in video data. For road safety researchers, this simple detection can be used as an initial step to screen long-term video data collections for occurrences of e-scooters, followed by more in-depth human analyses. The high active e-scooter detection accuracy also highlights that the algorithm does not typically misclassify other road user types as e-scooters. For e-scooter riders' helmet use, the trained algorithm achieved a high accuracy of an average mAP = 0.96. The assessment of the comparison of e-scooter helmet use percentages in the test dataset with the algorithm-registered helmet use indicates that the computer vision approach registers helmet use that is not significantly different from human-registered helmet use and only deviates by 4.3%. Our qualitative analysis of detection results on the test dataset revealed potential means to improve detection accuracy. It seems beneficial to use a higher contrast camera for data collection in the future, which should also be better protected from inclement weather conditions such as rain. The recall and precision results on the test dataset reveal a relatively low performance in the precision of the registration of active e-scooters with a helmet. A potential reason for this could be the comparatively small share of e-scooter riders with helmets (37.5%) compared to riders without a helmet (62.5%) in the overall dataset. Although we aimed to balance helmet use rates in the dataset, the inclusion of the external data shifted this balance towards a higher number of riders without a helmet.

In our application of the trained algorithm to video data facilitated the registration of n = 1054 active e-scooter riders, which

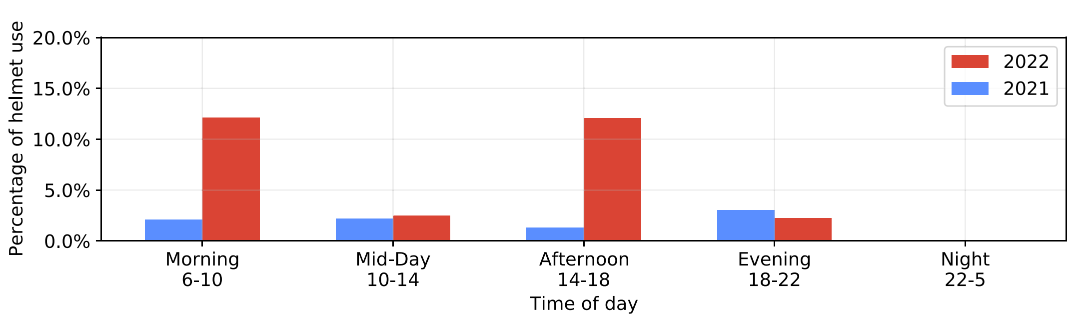

Fig. 4. Average e-scooter helmet use in 2021 and 2022 at different times of the day.

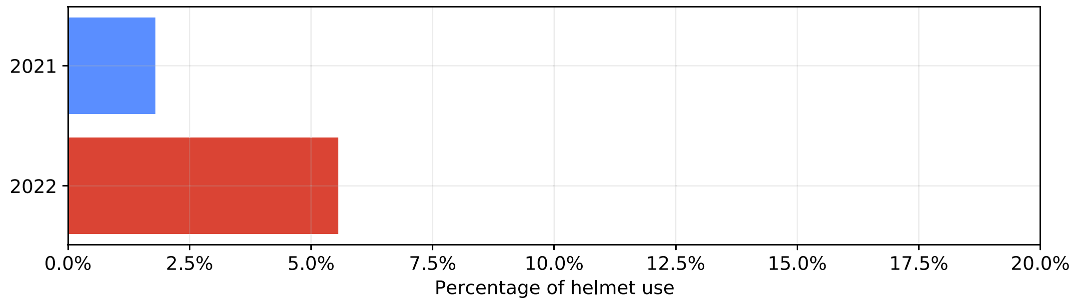

Fig. 5. Average e-scooter use at the Copenhagen observation sites registered in December 2021 and February 2022 (please note the shortened x-axis).

was lower than expected, especially in light of the aim to select high-cycle lane traffic density sites. This small number of observed e-scooter riders could relate to the relatively cold time of the year when the video data was collected and when road users might prefer public transportation. Also, e-scooters are unstable compared to, e.g., bicycles (Löcken, Brunner, & Kates, 2020; Dozza, Li, Billstein, Svernlöv, & Rasch, 2022), and hence might be used less in times of the year when bad weather such as rain or snow could further impede riding stability and comfort. Most e-scooters were registered in the early afternoon hours, indicating that they are not mainly used as a commuting modality around the observation sites. This is in line with a recent literature analysis, which found that e-scooter temporal distributions do not exhibit distinct early morning and late afternoon peaks that indicate commuting (Badia & Jenelius, 2023).

6.2. Helmet use in Copenhagen

At the two Copenhagen sites, the algorithm revealed an overall low helmet use rate of 4.4%. When separating helmet use for 2021 and 2022, we found significantly higher helmet use in 2022. This is in line with higher helmet use results in countries with mandatory helmet use laws (Haworth et al., 2021b) compared to countries without such laws (Siebert et al., 2021b; Siebert et al., 2021a). However, even after the law's passing, helmet use did not increase to levels comparable to numbers from, e.g., Australia, where helmet use is observed to be above 90% (Haworth et al., 2021b) with a mandatory helmet use law in place. There are multiple potential explanations for this. The mandatory helmet use law was enacted relatively recently before our 2022 observation (February 2022). Helmet use could be relatively low since e-scooter riders might not yet be fully aware of the new law. In addition, we did not investigate the law's enforcement level. If the traffic police did not enforce the law immediately after its enactment, e-scooter riders might have anticipated a lax implementation and not changed their behavior. Also, the comparison of the implementation of the mandatory e-scooter law in Australia with the law in Denmark is skewed, as Australia had a mandatory helmet use law for bicycles in place when e-scooters were introduced in the road system, potentially leading to carry-over effects from bicycle to e-scooter use. In addition, the established bicycle helmet use law bolsters the availability of helmets in homes, lowering a potential barrier for helmet use on e-scooters. As there is no mandatory helmet use law for bicyclists in Denmark, these possible effects could not influence the e-scooter helmet use rates observed in this study. In addition to the increase in helmet use between 2021 and 2022, we also found fluctuations in e-scooter helmet use at different times of day in the 2022 data, with higher helmet use observed in the morning (6–10) and afternoon (14–18) hours. This difference could be explained by different groups of e-scooter riders being observed at different times of day. Haworth, Schramm, and Twisk (2021a) found that there is a higher share of private e-scooters in morning and afternoon commuting hours, while the highest share of shared e-scooters was observed around noon. Since private e-scooter riders have been found to have higher helmet use than shared e-scooters Haworth et al. (2021b); Haworth et al. (2021a), the helmet use fluctuations between different times of day might arise from larger shares of private e-scooter riders being observed during commuting peaks in Copenhagen.

6.3. Limitations

There are some potential limitations to this study, both for the developed algorithm, as for the resulting helmet use data. For the detection algorithm, a potential limitation of the study is the application of the computer vision detection algorithm to video data without the means to assess the quality of the detection. While we base our estimation of good accuracy of helmet use on the data of the annotated test dataset, it seems beneficial to evaluate the detection accuracy on longer durations of video data on which the algorithm is applied.

In addition, the assessment of e-scooter helmet use in Copenhagen is subject to additional limitations. While video data was collected over multiple days at two observation sites in Copenhagen, a general helmet use rate for Copenhagen or Denmark can not be inferred from this. Future studies should include more observation sites to provide a broader evidence base for e-scooter helmet use assessment. Similarly, the installed video cameras did not produce high-quality video data at night, potentially missing present active e-scooters. This is especially important to consider in light of the very small number of detections in the early morning hours. A main reason for this might be the lack of visibility of e-scooters due to the camera system. Infrared cameras or well-lit sites could be chosen to improve night-time video quality.

7. Conclusion and practical applications

This study assessed the impact of a mandatory e-scooter helmet use law in Denmark. Through video-based observation and computer vision analysis, helmet use data was collected and analyzed. The results showed a significant increase in helmet use following the law's implementation, highlighting the effectiveness of legislation in promoting safety practices among e-scooter riders. The findings have practical implications for policymakers, urban planners, and safety advocates. The successful use of computer vision technology demonstrates its potential for accurately assessing helmet use compliance and can be adopted in other urban areas. The study underscores the importance of legislation in influencing riders' behavior and encourages policymakers to implement similar regulations in regions with high e-scooter usage. Further research is needed to address the low overall compliance rate and explore strategies for improving helmet use, such as educational campaigns.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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