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Data Descriptor

Traffic Sign Detection and Classification on the Austrian Highway Traffic Sign Data Set

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Abstract: Advanced Driver Assistance Systems rely on automated traffic sign recognition. Today, Deep Learning methods outperform other approaches in terms of accuracy and processing time; however, they require vast and well-curated data sets for training. In this paper, we present the Austrian Highway Traffic Sign Data Set (ATSD), a comprehensive annotated data set of images of almost all traffic signs on Austrian highways in 2014, and corresponding images of full traffic scenes they are contained in. Altogether, the data set consists of almost 7500 scene images with more than 28,000 detailed annotations of more than 100 distinct traffic sign classes. It covers diverse environments, ranging from urban to rural and mountainous areas, and includes many images recorded in tunnels. We further evaluate state-of-the-art traffic sign detectors and classifiers on ATSD to establish baselines for future experiments. The data set and our baseline models are freely available online.

Dataset: https://doi.org/10.53177/ATSD

Dataset License: Permissive license that allows to use the data set free of charge. Full license text: https://contentportal.asfinag.at/assets/pdf/Bedingungen_VZK%20ASFINAG_20210726_en.pdf

Keywords: traffic scene; traffic sign detection; traffic sign classification

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1. Summary

Traffic sign detection and classification is one of the big challenges in Autonomous Driving and Advanced Driver Assistance Systems (ADAS). Current approaches are based on Machine Learning, in particular Deep Neural Networks, and therefore require large, diverse and curated data sets on which the prediction models can be trained. Although in recent years the number of such data sets has been growing steadily, many aspects of the wide variety of traffic sign classes and design variations are not yet sufficiently covered. This, in particular, includes country-specific phenomena, such as traffic sign classes that exist only in one single country, or subtle differences in the pictogram design that may have a considerable impact on automated recognition systems [1].

In this paper, we present a new data set, the *Austrian Highway Traffic Sign Data Set* (ATSD), composed of annotated images of traffic scenes of Austrian highways, as well as labeled traffic-sign patches. It is the first Austrian data set of this kind, and as such fills some gaps in the current landscape of traffic sign/scene data sets as outlined above. For instance, in contrast to most other data sets it contains many images acquired in tunnels, where traffic signs are typically displayed on LED panels. It furthermore includes Austrian specialties, such as the 'IG-L' additional panel, which marks speed limits that are activated and deactivated depending on the current air quality. Although all traffic scenes stem from highways, they are still pretty diverse thanks to the fact that almost all highway segments (and traffic signs therein) in Austria are covered. Examples can be found in Figure 1.

Figure 1. Some example scenes of ATSD, highlighting the diversity of the data set. It covers rural, urban and mountainous areas, and lots of tunnels.

Every traffic sign in ATSD was annotated manually, to avoid all kinds of automation bias. Annotations do not only capture the position of signs within scene images and the classes they belong to, but also metadata such as the type of the signs (plate/LED/...), whether they are damaged, whether they are located in tunnels, and many more. Whenever several signs are semantically associated (such as additional panels and the corresponding 'main' signs they refer to), each of them was annotated separately and assigned a group-ID for making the association explicit.

The ultimate goal of ATSD is to stimulate research in traffic sign recognition. To that end, we evaluated state-of-the-art detectors and classifiers on the data set and report their performance in the paper, setting a baseline for future experiments. Moreover, about 20% of the data are completely held back in an internal test set, thereby allowing us to rigorously and independently assess the quality of traffic sign recognition systems developed on (the published part of) ATSD or other data bases. We report baseline model performance on the internal test set as reference marks, but remark that these results are not reproducible. A similar strategy of holding back data is pursued in related data sets, too [2]. To facilitate working with ATSD it adheres to the FAIR data principles [3]: every version of the data set has its own persistent Digital Object Identifier (DOI) that links to a landing page where the corresponding version of the data set can be downloaded. Furthermore, Python code for loading, preparing and augmenting the data is provided in a GitHub repository (https://github.com/risc-mi/atsd; accessed on 4 December 2022), and so are the baseline detection and classification models.

Systems based on artificial intelligence, such as ADAS, are only accepted by the general public if they are *trustworthy*. This entails the need for *transparency* in the data sets these systems are based on. ATSD was created in close cooperation with experts in ethics, to ensure a concise and thorough documentation of all aspects of the data set. This not only concerns the decision which traffic sign classes to include or exclude, and for what reasons, but also the disclosure of weaknesses and limitations inherent to the data.

The main contributions of this paper and the underlying data set can be summarized as follows:

- First-ever publicly available data set of annotated traffic scene images from Austrian highways;
- Diverse scenery and traffic signs, including tunnels, temporary signs at construction sites, etc.;
- Large number of additional panels, which add extra complexity to detection and classification tasks;
- Rich meta information about each annotation;

- Evaluations of state-of-the-art detection and classification models to set strong baselines for future developments.

Related Work

Many real-world data sets for traffic sign detection and classification exist. The most widely used are perhaps the German Traffic Sign Detection Benchmark (GTSDB) [4] and the German Traffic Sign Recognition Benchmark (GTSRB) [5], which are composed of traffic scene and sign images, respectively, collected in urban areas in Germany. The Mapillary Traffic Sign Dataset [2] constitutes the most extensive data set to date, with highly diverse traffic scenes from all parts of the world. Table 1 lists other publicly available traffic sign data sets and compares them to ATSD. Some of them are particularly similar to ATSD: STSD and MTSD contain highway traffic scenes as well, but ATSD is exclusively made up of highway scenes. MTSD presumably includes images recorded on Austrian roads, but fails to properly capture Austrian specialties such as the large number of additional panels, LED panels and tunnel scenes. Just like ATSD, MTSD is split into training, validation and test sets, but all traffic scene images are made public and only the *annotations* of the 10.544 test images are withheld.

In addition to data sets focusing on traffic signs, there are other traffic-related image data sets as well: CityScapes [6] and KITTI Vision [7] contain traffic scene images with pixel-level annotations of relevant objects (cars, pedestrians, cyclists, signs, etc.) that can be used for semantic segmentation; CULane [8] and TuSimple [9] are data sets targeted at lane detection; and Street View Text [10], ASAYAR [11] and the data sets collected by Gonzalez et al. [12] and Rong et al. [13] are concerned with localizing and reading text in traffic panels.

Besides real-world data sets, synthetic data sets generated from photo-realistic renderings of 3D scenes are becoming more and more popular [14–18]. The major downside of synthetic data sets is the apparent domain gap between photographs/videos and 3D renderings, which is why we think real-world data sets such as ATSD are still relevant.

Table 1. Publicly available real-world traffic sign detection and recognition data sets. Entries with—in the 'Scenes' column only contain traffic sign images. * 45 classes have more than 100 instances. † 53,377 additional, partly annotated scenes. ‡ 169,447 additional annotated signs not belonging to the 400 classes. § 108 classes partitioned into 10 main categories.

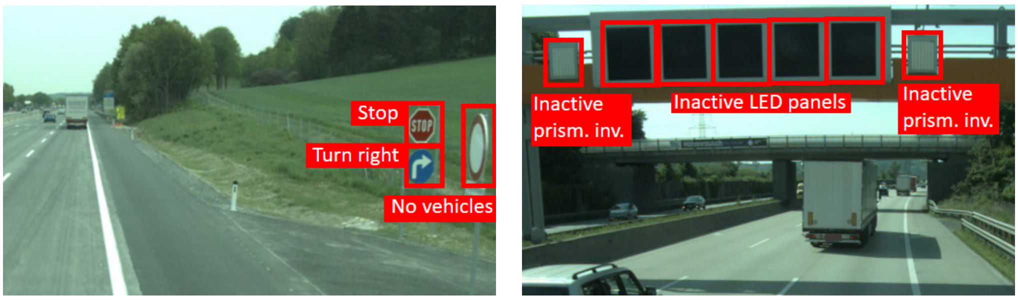
Name	Scenes	Signs	Classes	Region	Year	Note
RUG [19]	48	48	3	Netherlands	2003	
BTS [20]	9006	13,444	108	Belgium	2009	
BTSC [20]	-	7125	62	Belgium	2009	
MASTIF-2009 [21]	-	6423	97	Croatia	2009	rural
Stereopolis [22]	847	273	10	France	2010	urban
STSD [23]	19,236	3777	19	Sweden	2011	highways and urban
MASTIF-2010and11 [21]	4875	6613	88	Croatia	2011	rural
GTSRB [5]	-	51,840	43	Germany	2011	urban
LISA [24]	6610	7855	49	US	2012	
GTSDB [4]	900	1206	3	Germany	2013	urban
TT-100K [25]	100,000	30,000	* 221	China	2016	
CTSD [26]	1100	1574	48	China	2016	
DITS [27]	2100	9200	58	Italy	2016	day and night, urban
RTSD [28]	179,138	104,358	156	Russia	2016	summer and winter, urban and rural
CCTSDB [29]	10,000	13,361	3	China	2017	
ETSD [30]	-	82,476	164	Europe	2018	includes GTSRB, Stereopolis, RUG, BTSC, STSD, MASTIF
IceVisionSet [31]	29,051	71,634	35	Russia	2019	winter, day and night
Cure-TSR-Real [32]	896,700	648,186	14	Belgium	2019	based on BTS, with synthetic challenging conditions added
DFG [33]	6957	13,239	200	Slovenia	2020	polygon bounding boxes, urban and rural
MTSD [2]	† 52,453	‡ 88,094	400	World	2020	
ATSD-Scenes-v1 (ours)	7454	27,521	§ 108	Austria	2021	highways
ATSD-Signs-v1 (ours)	-	20,683	60	Austria	2021	highways

2. Data Description

ATSD consists of two parts: (i) *ATSD-Scenes*, containing 7454 traffic scene images, and (ii) *ATSD-Signs*, containing 20,683 traffic sign image patches extracted from ATSD-Scenes. All images are saved in the widespread JPEG format. In addition, metadata are contained in tables stored as CSV files. Therefore, all data can easily be opened without the need for special software.

2.1. Annotations

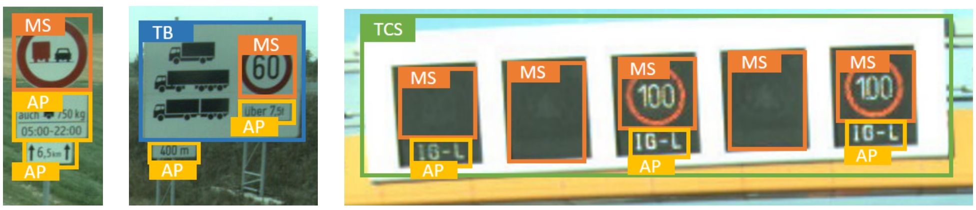
Each traffic scene image in ATSD is annotated with the exact location and size, class and further metadata of all traffic signs visible in it, regardless of their applicability to the main (highway) road. This is the reason why the data set contains traffic sign classes such as 'Stop' that can normally not be found on highways (Figure 2a). Furthermore, included are inactive LED panels and prismatic inverters, although they do not constitute any 'traffic sign' in the usual sense (Figure 2b). Direction signs and road-specific signs (displaying street names/numbers, for instance) are excluded.



(**a**) (**b**)

Figure 2. 'Atypical' annotations. (**a**) Traffic signs were annotated even if they do not apply to the main road/lane. (**b**) Inactive (switched-off) LED panels and prismatic inverters were annotated as well.

In general, there are four main sorts of traffic signs: *main traffic signs* (MS), *additional panels* (or *additional information*) (AP), *traffic boards* (TB) and *traffic control systems* (TCS); see Figure 3 for an overview and clarification of the terminology. The generic notion *traffic sign* (TS) is used as an umbrella term that applies to each of these sorts. Traffic boards and traffic control systems contain other traffic signs (usually main traffic signs and additional information) as sub-elements, whereas additional panels are typically mounted below the traffic sign they refer to. All four sorts are annotated, with information about which groups of traffic signs semantically belong together (e.g., a main traffic sign and an additional panel, or a traffic board and its sub-elements).



(**a**) (**b**) (**c**)

Figure 3. Different sorts of traffic signs. (**a**) Main sign (MS) with two additional panels (AP). (**b**) Traffic board (TB) with MS and AP, which itself has an AP attached to it. (**c**) Traffic control system (TCS), which is an ensemble of (overhead) LED panels; LED panels can consist of MS and AP.

Every annotation has a vast amount of metadata attached to it. This includes the position of the TS in the image by means of a tight *bounding box* (as can be seen on in

Figures 2 and 3, for instance), the aforementioned grouping information, and of course the *category* and *class* of the traffic sign (e.g., 'Stop' or 'Speed limit: 100 km/h'; Figure 4). APs and TBs/TCSs have their own categories, so they can easily be distinguished from MSs. Annotations of MSs and APs furthermore contain information about the *type* (material) of the sign (plate, LED panel, prismatic inverter, back-lit; Figure 5a), and whether any one of eleven binary attributes is set (Figures 6 and 5b).

Every TS category is further subdivided into individual classes. In total, there are 108 distinct TS classes, including 'other', 'not recognizable' and TBs/TCSs. Excluding these 'improper' classes leaves 91 proper traffic sign classes. Some of them are very uniform, e.g., all 'Speed limit: 100 km/h' look more or less the same (disregarding perspective and lighting). Others, in particular some APs, exhibit a large intra-class variability.

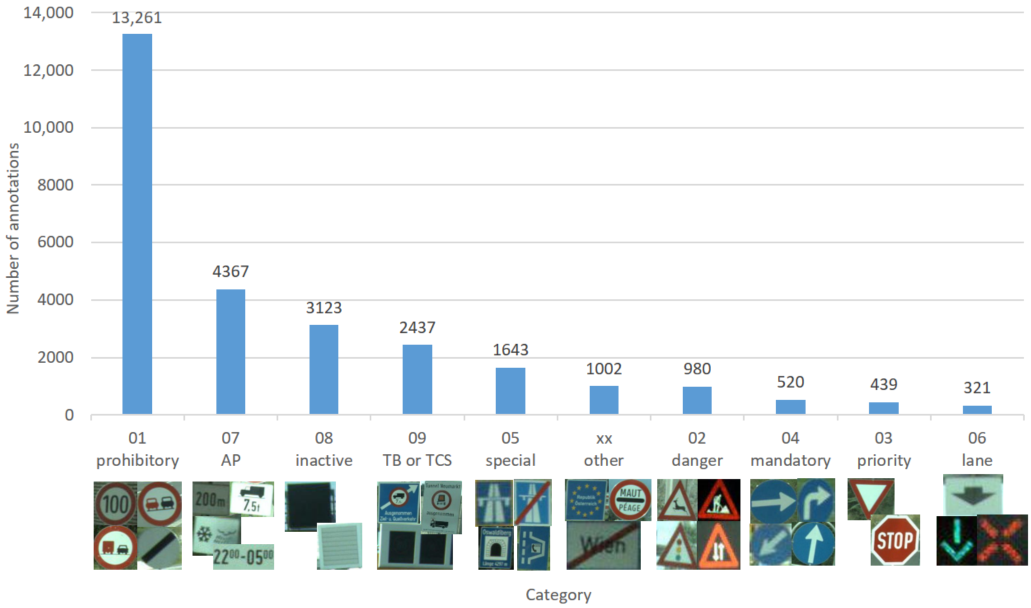
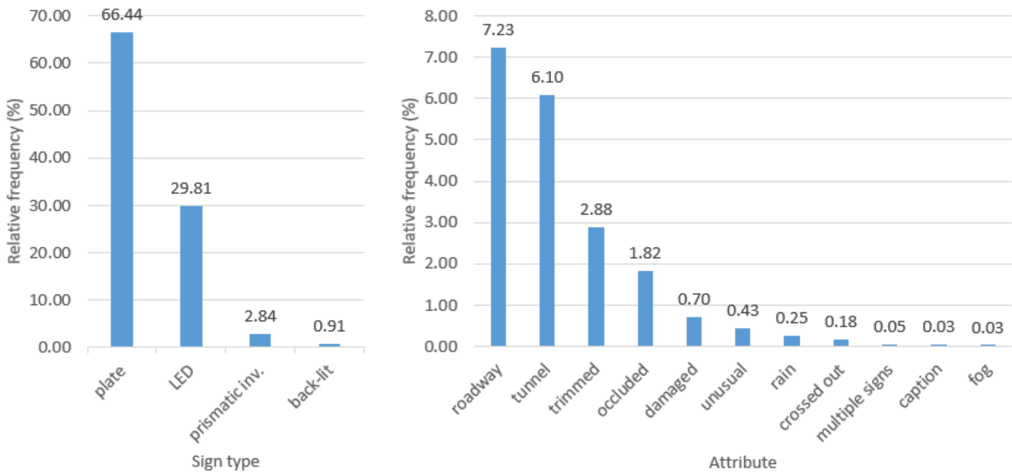


Figure 4. Traffic sign categories, sorted by frequency.



(**a**) (**b**)

Figure 5. Frequency of (**a**) sign types and (**b**) attributes.

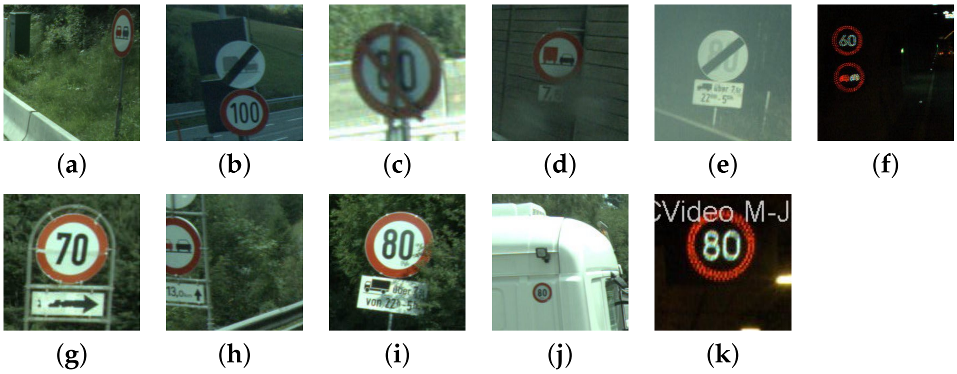


Figure 6. Attributes of TS annotations. (**a**) Not normal to roadway, (**b**) multiple signs, (**c**) crossed out, (**d**) rain, (**e**) fog, (**f**) tunnel, (**g**) damaged, (**h**) trimmed, (**i**) occluded, (**j**) unusual sign (located on the back of a truck) and (**k**) figure caption.

2.2. Train, Test and Internal Sets

ATSD is split into a training, test and internal sets, the first two of which are publicly available. The split respects the geographic proximity of traffic scene images by putting all images of the same *highway segment* into the same subset. This avoids data leakage from the test into the training set, since otherwise images showing roughly the same scene (but from slightly different viewpoints or angles) could end up in different sets.

The splits were carefully created manually based on the following considerations: (i) the training set should encompass roughly 55% of all data, the test set about 20%, and the internal set about 25%; (ii) the relative frequency of the TS classes should be similar across the three sets; and (iii) the relative frequency of certain attributes, most notably 'tunnel', should also be similar. Due to the construction of the splits based on highway segments rather than individual images not all goals could be achieved equally well. In particular, this means that some classes may be under- or over-represented in one of the sets, and that some variants of a class (sign type, design, etc.) may only appear in one set (typically because they can only be found in one particular highway segment). The latter point is crucial, since it implies that detection and classification systems either cannot be trained on some TS variants, or cannot be tested on them. One concrete example is the 'Speed limit: 40 km/h' class, all LED-versions of which appear in the test set only. Without going into details, analogous issues are present in the internal set as well, but fortunately there are not too many of them.

2.3. ATSD-Scenes

ATSD-Scenes consists of 7454 traffic scene images together with the corresponding TS annotations as described in Section 2.1. Every image is a high-resolution RGB image with 1596 × 1196 pixels, as depicted in Figure 1. The training set contains 4068 images, the test set contains 1443 images and the internal set contains 1943 images. Table 2 summarizes the three sets. As can be seen, there are only a few images without any TS annotations.

Table 2. ATSD-Scenes statistics. Annotations per image are displayed as *median (min-max)*.

	Train	Test	Internal	Total
Images	4068 (54.57%)	1443 (19.36%)	1943 (26.07%)	**7454**
Annotations	15,042 (54.66%)	5485 (19.93%)	6994 (25.41%)	**27,521**
Annotations per image	3 (0–20)	3 (0–17)	3 (0–18)	**3 (0–20)**
Images w/o annotations	55	16	26	**97**

Figure 7 depicts the relative frequency of each TS category in the three sets. It can be seen that all categories are distributed more or less evenly across the sets, with minor deviations only in categories 07, 08, 09, 05 and 06.

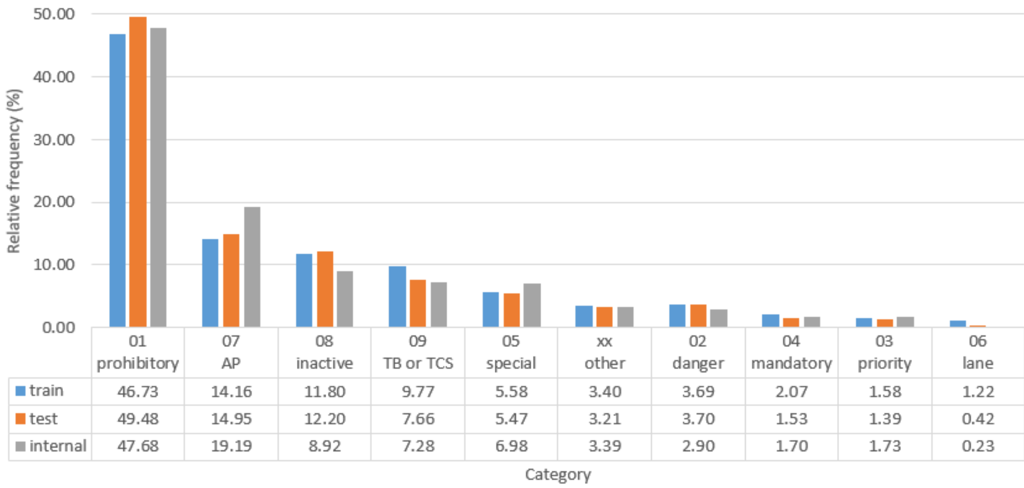


Figure 7. Relative frequency of TS categories in the three sets.

2.4. ATSD-Signs

ATSD-Signs consists of 20,683 traffic sign images extracted from the 7454 traffic scene images in ATSD-Scenes and 101 extra scene images not included in ATSD-Scenes. Of the 91 proper TS classes (excluding 'other', 'not recognizable', TBs and TCSs) only the 60 most frequent and most important ones were selected for inclusion in the data set, which explains the considerable drop from 27,521 annotations to only 20,683 images. Furthermore, only those TS not marked as 'crossed out', 'unusual', 'multiple signs' or 'caption' were considered, which reduced the number of images slightly further by 89 instances. Every traffic sign image is contained in the same set as the scene image it was extracted from, leading to 11,056 images in the training set, 4310 in the test set and 5317 in the internal set (Table 3).

Table 3. ATSD-Signs statistics. Image size refers to square root of the area, in pixels, and is displayed as *median (min-max)*.

	Train	Test	Internal	Total
Images	11,056 (53.45%)	4310 (20.84%)	5317 (25.71%)	**20,683**
Image size	62.1 (7.5–326.9)	63.5 (8.2–326.3)	65.6 (8.4–324.0)	**63.2 (7.5–326.9)**

A traffic sign class is included if at least 35 instances appear in the combined training and test set (52 classes), or if it is deemed particularly important (8 further classes). There is no deeper reason behind the value '35' of the threshold, except that it ensures that sufficiently many instances appear in the training-, test- and internal sets. More concretely, the minimum number of instances per class is seven in the training set, three in the test set and two in the internal set. Every class has a unique identifier consisting of the two-character category string (see Figure 4) and another two-character class string, separated by an underscore. Figure 8 shows one example of every class. As can be seen, inactivate LED panels and prismatic inverters are included as well, although they strictly speaking do not constitute any 'real' traffic sign classes.

Figure 9 depicts the relative frequency of each of the 60 classes in the training and test sets. As can be seen the data set is quite imbalanced, with a few classes appearing considerably more often than the others. The six most frequent classes are 'Speed limit: 100 km/h', 'Inactive LED panel', 'No overtaking for trucks whose weight exceeds 3.5 tonnes', 'Speed limit: 80 km/h', 'No overtaking' and 'Speed limit: 60 km/h'. We deliberately do not disclose any detailed information about the distribution of TS classes in the internal set, as this would contradict its purpose. We do remark, however, that the distribution is similar to those in the other sets.

Figure 8. One example for each of the 60 traffic sign classes contained in ATSD-Signs.

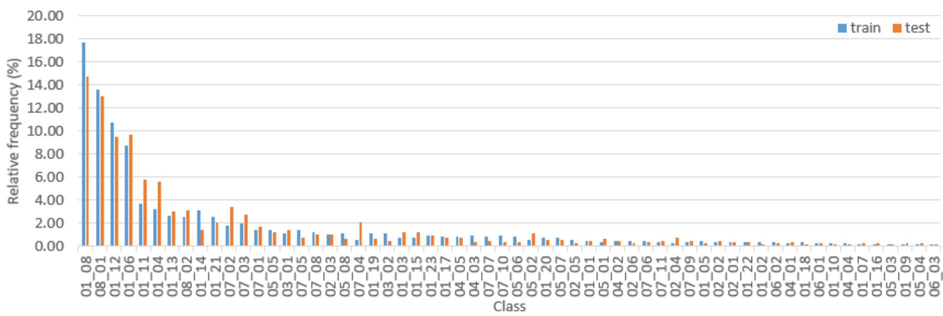


Figure 9. Relative frequency of traffic sign classes in the training and test sets.

3. Methods

3.1. Data Set Creation

The raw data underlying ATSD are HD videos of Austrian highways. They cover most of the 2249 km long ASFINAG (Austrian highway operator, www.asfinag.at/en; accessed on 4 December 2022) highway network consisting of motorways and dual carriageways. From these videos, 7555 frames containing traffic signs were extracted and de-identified (blurring license plates, faces and some advertisements on trucks). Every physical sign is visible in at most four distinct frames. The frames were then annotated, resulting in a total of 28,093 annotations of traffic signs (see Section 2.1 for details). Afterwards, the frames were split into training, test, and internal sets (Section 2.2). After discarding 101 'invalid' frames, the remaining 7454 frames (together with the corresponding 27,521 traffic sign annotations) make up the *ATSD-Scenes* data set (Section 2.3). A frame is invalid if it contains a heavily damaged or outdated traffic sign that has been replaced in the meantime. Finally, extracting patches from the frames showing actual traffic signs yields the *ATSD-Signs* data set (Section 2.4). Figure 10 summarizes the whole data generation process.

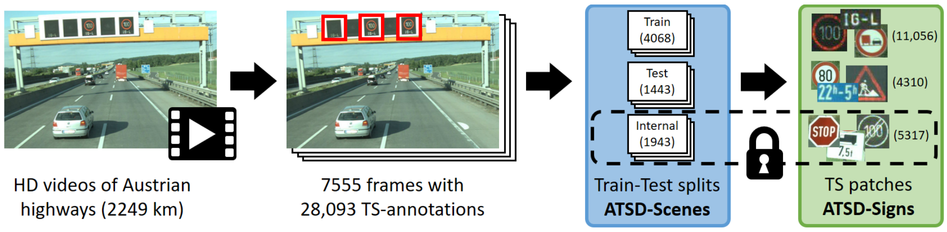


Figure 10. Development of ATSD. 7555 frames containing traffic signs were extracted from HD videos and then annotated. After filtering invalid images, the remaining 7454 frames were then split into training, test and internal sets, forming *ATSD-Scenes*. *ATSD-Signs* consists of traffic sign patches extracted from the frames in the respective splits.

The original traffic scene videos are a by-product of the last complete highway scan conducted by *RoadSTAR* in the year 2014. *RoadSTAR* is a high-performance measurement vehicle equipped with state-of-the-art sensors, satellite navigation and camera technology used for traffic infrastructure maintenance (www.ait.ac.at/en/solutions/road-condition-monitoring; accessed on 4 December 2022). The forward-facing camera for recording the videos is mounted on the roof of the vehicle, at a height of about 3.30 m. The view slightly differs compared to normal cars, because the original purpose of the videos was not traffic sign recognition but traffic infrastructure maintenance. Although we do not expect this to be problematic when deploying detectors trained on our data in car-mounted devices, a thorough investigation of this question remains future work.

The annotation process was carried out by four employees of RISC Software GmbH (www.risc-software.at/en; accessed on 4 December 2022), using the Computer Vision Annotation Tool [34]. Frequent auditing rounds were implemented to maintain a high and consistent annotation quality.

3.2. Evaluation of Baseline Traffic Sign Recognition Systems

3.2.1. Traffic Sign Detection on ATSD-Scenes

To detect the traffic signs in the scenes we used the darknet detection framework, which is the basis for YOLO (You Only Look Once) detectors [35]. To reduce model size and lower detection times we chose the Yolov4-tiny architecture. Compared to classic Yolov4 the average precision is reduced significantly for general detection tasks, but initial experiments revealed that Yolov4-tiny is sufficient for simple shapes such as traffic signs. The Yolov4-tiny model combines a target area and target category prediction into a single neural network, which results in a single step to obtain regions of interest (ROIs) and their respective category (e.g., prohibitory). Supplementary Figure S1 shows the full architecture of the used network.

For training the detector we used a subset of the available categories, excluding 'TB or TCS' and 'other' due to their reduced relevance for real world applications. The model was trained for 250 epochs using the default darknet online augmentation methods: saturation, exposure and hue. The loss function that was minimized is Complete Intersection over Union (CIoU) [36], which takes the overlapping area, the central point and the aspect ratio differences of the true and predicted bounding boxes into account.

Evaluations were performed with respect to an IoU-threshold of 50% and confidence-threshold of 25%. We trained three independent models (with same hyperparameters but different random seeds) on the training set of ATSD-Scenes and evaluated them both on the public and internal test set. This resulted in a mean average precision (mAP) of 85.39 ± 2.33% on the public test set and 86.40 ± 3.44% on the internal set. To also show the potential results when using the entire publicly available data we trained three more models on the training and test set and evaluated them on the internal set, yielding a mAP of 90.07 ± 0.3%.

Supplementary Figure S2 shows the per-category average precision of the trained models.

3.2.2. Traffic Sign Classification on ATSD-Signs

We trained classifiers on the traffic sign patches in ATSD-Signs employing the model architecture developed by Li and Wang [37], which achieves 99.66% accuracy on GTSRB [5]. The model is a 19-layer CNN with asymmetric convolutions [38]. We slightly deviated from the originally proposed training strategy in that we trained the models for a total of 101 epochs (instead of 230) and enabled on-line data augmentation from the beginning. We furthermore increased the batch size from 16 to 32 and put more weight on underrepresented classes to counter the considerable class imbalance (Figure 9).

We first trained models on the training set of ATSD-Signs and evaluated them both on the public- and the internal test set. We then also trained models on the union of training and test set, and evaluated them only on the internal set. This should give an idea of what can be achieved (on the internal set) when making use of all publicly available data, a likely scenario for potential future challenges in connection with ATSD. In any case, during training we put aside 20% of the training data into a validation set used for monitoring the training progress and adjusting hyperparameters. Neither training- nor validation accuracy change significantly after about 60 epochs.

Besides the standard on-line data augmentation during model training (small random rotations, shifts, shearing and scaling; see [37]) we tried traffic-sign specific augmentation strategies as well. For instance, images of some classes can be flipped and/or rotated by 90°/180°/270° while either preserving the class label or changing the label to a different class among those included in ATSD-Signs.

As explained in Section 2.2, not all sign variants of every class appear in all three sets. A prominent example is 'Speed limit: 40 km/h' whose LED-versions are all contained in the test set. In our initial experiments we found that vanilla classification models consistently confuse LED-versions of classes they have never seen during training with other (similar) classes for which LED-versions exist in the training set.As a countermeasure we applied color transformations to non-LED images to make them look LED-like, and vice versa, and augmented the training data with these new images. Although the conversion is based on a simple linear transformation in LAB color space, the results look reasonable, as can be seen in Supplementary Figure S3. More sophisticated approaches, e.g., based on *generative adversarial networks* (GANs), are certainly conceivable. The list of classes treated in this way can be found in github.com/risc-mi/atsd/blob/main/Classification_Preparation.ipynb, accessed on 4 December 2022. Note that it consists of those classes for which an LED conversion might seem reasonable to someone without access to the internal set, i.e., there are also cases where such a conversion would not have been necessary for improving the classification accuracy on the internal set. Furthermore, note that besides LED vs. non-LED there are many other sign variants that could be addressed in a similar manner.

The top-performing models trained on the training set achieve an accuracy of 97.61 ± 0.24% on the test set and 97.20 ± 0.21% on the internal set. When training on all publicly available data, the accuracy on the internal set increases to 98.27 ± 0.25%. In either case, both geometric and LED augmentation were employed. Detailed results can be found in Supplementary Table S3.

3.2.3. Full Detection and Classification Pipeline

We combined the detectors presented in Section 3.2.1 with the classifiers presented in Section 3.2.2 to obtain a full *traffic sign recognition pipeline*.

The detectors were trained to detect all classes contained in the eight categories from '01' to '08' (Figure 4), but the classifiers can only distinguish between the 60 classes contained in ATSD-Signs (Figure 8). Therefore, in order to assess the performance of the full pipeline in a fair way, we discard all detections of traffic signs whose classes are not included in ATSD-Signs. The same applies to all signs with attributes 'crossed out', 'unusual', 'multiple signs' or 'caption', because they are not included in ATSD-Signs either. In other words, a detection is only considered if (i) if it is a true positive and the true class is one of the 60 ATSD-Signs classes or (ii) it is a false positive, i. e., a detection that cannot be assigned to a ground truth annotation, meaning that there is no true class. Alternative evaluation protocols are conceivable as well, for instance borrowing ideas from *Open Set Recognition* to 'tweak' the existing classifiers to automatically identify unknown traffic sign classes rather than wrongly assign them one of the known classes [39]. We leave this for future work.

Another question concerns the treatment of disagreements between detector and classifier. If the traffic sign category predicted by the detector differs from the category of the class predicted by the classifier, this might indicate a false positive detection. Suppressing such detections can potentially improve the overall recognition performance, so we evaluated this approach in our experiments as well.

With an IoU threshold of 50% and the confidence of the classifiers as final recognition confidence, the top-performing models trained on the training set achieve a mAP of $87.87 \pm 2.29\%$ on the test set and $90.07 \pm 1.96\%$ on the internal set. When training on all publicly available data, the mAP on the internal set increases to $92.46 \pm 0.68\%$. Detailed overall results can be found in Supplementary Table S4, and per-class average precision is shown in Supplementary Figure S4.

The size of the ground truth annotations has a considerable effect on recognition performance. When only considering small signs whose area does not exceed 45×45 pixels (first quartile over ATSD-Signs), the mean average precision drops to $68.32 \pm 2.84\%$ on the public test set.

Figure 11 shows the result of applying one of the pipelines to an image from the public test set. Most traffic signs are correctly recognized, but there are also one false positive detection, one misclassified sign, and one missed sign. The false-positive detection, shown in red, is predicted as 'Speed limit: 100km/h' (01_08) with low detection but high classification confidence, despite its rectangular shape. The partly occluded sign shown in orange belongs to class 'No vehicles' (01_14) but is wrongly classified as 'Speed limit: 100km/h', too. The missed sign, shown in magenta, belongs to class 'No vehicles whose height exceeds n meters' (01_17) and is indeed barely visible.

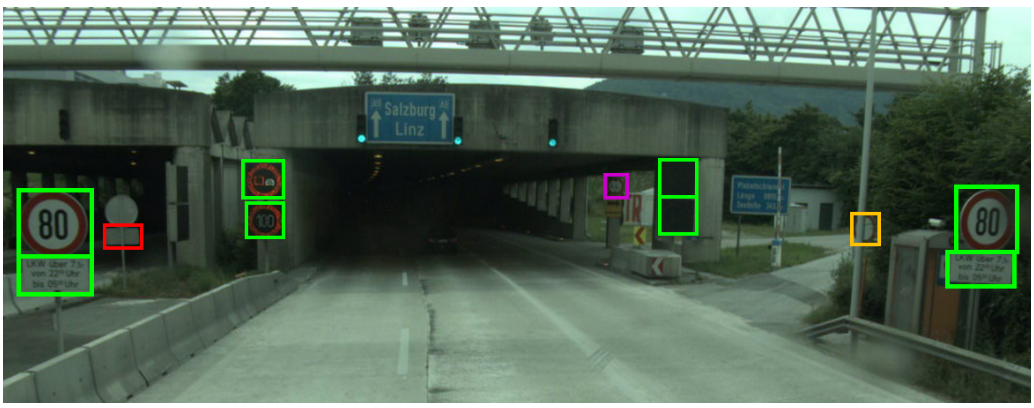


Figure 11. Example scene with recognition results. True positives are shown in green, false positives in red, false negatives in magenta and misclassifications in orange. Image was cropped to focus on relevant parts.

4. User Notes

Download ATSD and extract all files and folders from the archive. The only file formats appearing in the data set are JPEG and CSV files, which makes it particularly easy to handle.

Both ATSD-Scenes and ATSD-Signs are split into a training set and a test set, contained in sub-directories 'train' and 'test', respectively. Keep in mind that the internal set is not available for download. The 'train' and 'test' folders contain the actual images; in case of ATSD-Scenes, they are all stored in sub-directory 'imgs', in case of ATSD-Signs they are grouped according to the traffic sign class they belong to and stored in sub-directories with corresponding names. Directory structures like this are widely used in machine learning for image classification. The 'train' and 'test' folders additionally contain a table 'meta_train.csv' or 'meta_test.csv', respectively, with metadata about the images. Details about these metadata tables and how they can be linked to the individual images can be found in Supplementary Tables S1 and S2.

No special software is needed to open the image and metadata files. Still, for large-scale analyses and experiments we recommend using Python. To that end, https://github.com/risc-mi/atsd, accessed on 4 December 2022, contains a couple of Jupyter notebooks illustrating how images and metadata can be loaded, analyzed and prepared for subsequent model training; how trained detectors and classifiers can be applied to the data set (and others with similar structure); and how the results can be effectively evaluated with respect to the provided ground truth annotations. The repository additionally contains trained network weights of some of the models presented in Section 3.2.

5. Conclusions

We presented a novel, publicly available data set of annotated traffic scene and traffic sign images. The data set covers almost all traffic signs on Austrian highways and provides rich meta information about them, in addition to bounding box and object class. Furthermore, our experiments with state-of-the-art traffic sign detection and classification models showed that the data set is challenging for various reasons, including different sign types (metal plate, prismatic inverter, LED), images acquired in tunnels and pronounced class imbalance.

ATSD shall support research on traffic sign recognition by adding Austrian varieties and specialties to the pool of public available catalogs. On Austrian highways, additional signs that restrict the meaning to selective classes of vehicles, e.g., 'trucks only', are quite common. Anecdotal evidence shows that traffic sign recognition systems used in currently available cars routinely ignore such information. This already had some minor impact, as cars automatically slowed down or accelerated due to traffic signs not meant for them (information provided by the customer management center of ASFINAG). We want to encourage research on the recognition of additional panels by providing ample examples in ATSD.

Insights gained during the publication of ATSD showed that the introduction of new traffic signs or a new design for some existing class will most probably require retraining of classifiers to preserve performance. New traffic signs or designs will show up only gradually 'in the wild'. We believe that providing images of them well before in a catalog might improve the performance of classifiers on day 1 significantly. We therefore plan to add synthetic images of new traffic signs that are going to be deployed on Austrian highways to future versions of ATSD before they are actually deployed.

In general, extending ATSD with more data and/or more fine-grained annotations constitutes the main direction of future work. As each traffic scene image corresponds to a video frame, more data can easily be acquired by annotating a small number of frames before and after each currently annotated frame. Moreover, since highway traffic scene videos are systematically recorded on a regular basis, the currently used data from 2014 can be enriched by more recent data. How this can be achieved with minimum manual annotation effort yet avoiding automation bias is an interesting research direction on its own.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/data8010016/s1, Table S1: Schema of ATSD-Scenes metadata tables; Table S2: Schema of ATSD-Signs metadata tables; Table S3: Detailed classification results; Table S4: Detailed results of the full detection and classification pipeline; Figure S1: Architecture of the used Yolov4-tiny detection model; Figure S2: Average precision of each category; Figure S3: Exemplary results of our LED augmentation approach; Figure S4: Average precision of each TS class.

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Data Availability Statement: The public part of the data presented in this paper is available at https://doi.org/10.53177/ATSD, accessed on 4 December 2022. The held-back internal part is not publicly available, as this would contradict its very purpose of objectively and independently evaluating the quality of camera-based traffic sign recognition systems. Software for working with the data, as well as trained baseline detection- and classification models are available at https://github.com/risc-mi/atsd, accessed on 4 December 2022.

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Abbreviations

The following abbreviations are used in this manuscript:

ADAS	Advanced Driver Assistance Systems
AP	Additional panel
ASFINAG	Austrian highway operator
ATSD	Austrian Highway Traffic Sign Data Set
CSV	Comma-separated values
CVAT	Computer Vision Annotation Tool
FAIR	Findability, Accessibility, Interoperability, Reuse
JPEG	Joint Photographic Experts Group
LED	Light-emitting diode
mAP	Mean average precision
MS	Main traffic sign
TB	Traffic board
TCS	Traffic control system
TS	Traffic sign
YOLO	You Only Look Once (image detection framework)

References

1. Maletzky, A.; Thumfart, S.; Wruß, C. An Evaluation of the Machine Readability of Traffic Sign Pictograms using Synthetic Data Sets. In Proceedings of the OAGM Workshop 2021: Computer Vision and Pattern Analysis Across Domains, St. Pölten, Austria, 24–25 November 2021; Seidl, M., Zeppelzauer, M., Roth, P.M., Eds.; Verlag der TU Graz: Graz, Austria, 2022; pp. 9–15. [CrossRef]
2. Ertler, C.; Mislej, J.; Ollmann, T.; Porzi, L.; Neuhold, G.; Kuang, Y. The Mapillary Traffic Sign Dataset for Detection and Classification on a Global Scale. In Proceedings of the Computer Vision—ECCV 2020, Glasgow, UK, 23–28 August 2020; Vedaldi, A., Bischof, H., Brox, T., Frahm, J.M., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2020; pp. 68–84. [CrossRef]
3. Wilkinson, M.D.; Dumontier, M.; Aalbersberg, I.J.; Appleton, G.; Axton, M.; Baak, A.; Blomberg, N.; Boiten, J.W.; da Silva Santos, L.B.; Bourne, P.E.; et al. The FAIR Guiding Principles for scientific data management and stewardship. *Sci. Data* **2016**, *3*, 160018. [CrossRef] [PubMed]
4. Houben, S.; Stallkamp, J.; Salmen, J.; Schlipsing, M.; Igel, C. Detection of traffic signs in real-world images: The German traffic sign detection benchmark. In Proceedings of the 2013 International Joint Conference on Neural Networks (IJCNN), Dallas, TX, USA, 4–9 August 2013; pp. 1–8. [CrossRef]
5. Stallkamp, J.; Schlipsing, M.; Salmen, J.; Igel, C. Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition. *Neural Netw.* **2012**, *32*, 323–332. [CrossRef] [PubMed]
6. Cordts, M.; Omran, M.; Ramos, S.; Rehfeld, T.; Enzweiler, M.; Benenson, R.; Franke, U.; Roth, S.; Schiele, B. The Cityscapes Dataset for Semantic Urban Scene Understanding. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 3213–3223.
7. Geiger, A.; Lenz, P.; Stiller, C.; Urtasun, R. Vision meets robotics: The KITTI dataset. *Int. J. Robot. Res.* **2013**, *32*, 1231–1237. [CrossRef]
8. Pan, X.; Shi, J.; Luo, P.; Wang, X.; Tang, X. Spatial As Deep: Spatial CNN for Traffic Scene Understanding. In Proceedings of the AAAI Conference on Artificial Intelligence (AAAI), New Orleans, LA, USA, 2–7 February 2018.
9. TuSimple Lane Detection Challenge. 2017. Available online: https://github.com/TuSimple/tusimple-benchmark/tree/master/doc/lane_detection (accessed on 4 December 2022).
10. Wang, K.; Belongie, S. Word Spotting in the Wild. In Proceedings of the Computer Vision—ECCV 2010, Heraklion, Greece, 5–11 September 2010; Daniilidis, K., Maragos, P., Paragios, N., Eds.; Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2010; pp. 591–604. [CrossRef]
11. Akallouch, M.; Boujemaa, K.S.; Bouhoute, A.; Fardousse, K.; Berrada, I. ASAYAR: A Dataset for Arabic-Latin Scene Text Localization in Highway Traffic Panels. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 3026–3036. [CrossRef]
12. González, A.; Bergasa, L.M.; Yebes, J.J. Text Detection and Recognition on Traffic Panels From Street-Level Imagery Using Visual Appearance. *IEEE Trans. Intell. Transp. Syst.* **2014**, *15*, 228–238. [CrossRef]
13. Rong, X.; Yi, C.; Tian, Y. Recognizing Text-Based Traffic Guide Panels with Cascaded Localization Network. In Proceedings of the Computer Vision—ECCV 2016 Workshops, Amsterdam, The Netherlands, 8–10. 15–16 October 2016; Hua, G., Jégou, H., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2016; pp. 109–121. [CrossRef]
14. Cognata Traffic Sign Datasets. 2021. Available online: https://www.cognata.com/traffic-sign-datasets/ (accessed on 4 December 2022).
15. Ros, G.; Sellart, L.; Materzynska, J.; Vazquez, D.; Lopez, A.M. The SYNTHIA Dataset: A Large Collection of Synthetic Images for Semantic Segmentation of Urban Scenes. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016; pp. 3234–3243. [CrossRef]
16. AI.Reverie. 2021. Available online: https://aireverie.com/ (accessed on 4 December 2022).
17. Anyverse. 2021. Available online: https://anyverse.ai/ (accessed on 4 December 2022).
18. CVEDIA. 2021. Available online: https://www.cvedia.com/ (accessed on 4 December 2022).
19. Grigorescu, C.; Petkov, N. Distance sets for shape filters and shape recognition. *IEEE Trans. Image Process.* **2003**, *12*, 1274–1286. [CrossRef] [PubMed]
20. Timofte, R.; Zimmermann, K.; Van Gool, L. Multi-view traffic sign detection, recognition, and 3D localisation. *Mach. Vis. Appl.* **2014**, *25*, 633–647. [CrossRef]
21. Šegvić, S.; Brkić, K.; Kalafatić, Z.; Stanisavljević, V.; Ševrović, M.; Budimir, D.; Dadić, I. A computer vision assisted geoinformation inventory for traffic infrastructure. In Proceedings of the 13th International IEEE Conference on Intelligent Transportation Systems (ITSC), Funchal, Portugal, 19–22 September 2010; pp. 66–73.
22. Belaroussi, R.; Foucher, P.; Tarel, J.P.; Soheilian, B.; Charbonnier, P.; Paparoditis, N. Road Sign Detection in Images: A Case Study. In Proceedings of the 20th International Conference on Pattern Recognition, Istanbul, Turkey, 23–26 August 2010; pp. 484–488. [CrossRef]
23. Larsson, F.; Felsberg, M. Using Fourier Descriptors and Spatial Models for Traffic Sign Recognition. In Proceedings of the Image Analysis, 17th Scandinavian Conference, SCIA 2011, Ystad, Sweden, 23–27 May 2011; Heyden, A., Kahl, F., Eds.; Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2011; pp. 238–249. [CrossRef]
24. Møgelmose, A.; Trivedi, M.M.; Moeslund, T.B. Vision based Traffic Sign Detection and Analysis for Intelligent Driver Assistance Systems: Perspectives and Survey. *IEEE Trans. Intell. Transp. Syst.* **2012**, *13*, 1484–1497. [CrossRef]

25. Zhu, Z.; Liang, D.; Zhang, S.; Huang, X.; Li, B.; Hu, S. Traffic-Sign Detection and Classification in the Wild. In Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016; pp. 2110–2118. [CrossRef]
26. Yang, Y.; Luo, H.; Xu, H.; Wu, F. Towards Real-Time Traffic Sign Detection and Classification. *IEEE Trans. Intell. Transp. Syst.* **2016**, *17*, 2022–2031. [CrossRef]
27. Youssef, A.; Albani, D.; Nardi, D.; Bloisi, D.D. Fast Traffic Sign Recognition Using Color Segmentation and Deep Convolutional Networks. In Proceedings of the Advanced Concepts for Intelligent Vision Systems, Lecce, Italy, 24–27 October 2016; Blanc-Talon, J., Distante, C., Philips, W., Popescu, D., Scheunders, P., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2016; pp. 205–216. [CrossRef]
28. Shakhuro, V.; Konushin, A. Russian traffic sign images dataset. *Comput. Opt.* **2016**, *40*, 294–300. [CrossRef]
29. Zhang, J.; Huang, M.; Jin, X.; Li, X. A Real-Time Chinese Traffic Sign Detection Algorithm Based on Modified YOLOv2. *Algorithms* **2017**, *10*, 127. [CrossRef]
30. Gámez Serna, C.; Ruichek, Y. Classification of Traffic Signs: The European Dataset. *IEEE Access* **2018**, *6*, 78136–78148. [CrossRef]
31. Pavlov, A.L.; Karpyshev, P.A.; Ovchinnikov, G.V.; Oseledets, I.V.; Tsetserukou, D. IceVisionSet: Lossless video dataset collected on Russian winter roads with traffic sign annotations. In Proceedings of the 2019 International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada, 20–24 May 2019; pp. 9597–9602. [CrossRef]
32. Temel, D.; Chen, M.H.; AlRegib, G. Traffic Sign Detection Under Challenging Conditions: A Deeper Look into Performance Variations and Spectral Characteristics. *IEEE Trans. Intell. Transp. Syst.* **2019**, *21*, 3663–3673. [CrossRef]
33. Tabernik, D.; Skočaj, D. Deep Learning for Large-Scale Traffic-Sign Detection and Recognition. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 1427–1440. [CrossRef]
34. Sekachev, B.; Manovich, N.; Zhiltsov, M.; Zhavoronkov, A.; Kalinin, D.; Hoff, B.; TOsmanov; Kruchinin, D.; Zankevich, A.; DmitriySidnev; et al. Opencv/Cvat: V1.1.0. 2020. Available online: https://zenodo.org/record/4009388#.Y7JwZBVBxPY (accessed on 4 December 2022). [CrossRef]
35. Redmon, J. Darknet: Open Source Neural Networks in C. 2013–2016. Available online: http://pjreddie.com/darknet/ (accessed on 4 December 2022).
36. Zheng, Z.; Wang, P.; Ren, D.; Liu, W.; Ye, R.; Hu, Q.; Zuo, W. Enhancing Geometric Factors in Model Learning and Inference for Object Detection and Instance Segmentation. *IEEE Trans. Cybern.* **2021**, *52*, 8574–8586. [CrossRef] [PubMed]
37. Li, J.; Wang, Z. Real-Time Traffic Sign Recognition Based on Efficient CNNs in the Wild. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 975–984. [CrossRef]
38. Szegedy, C.; Vanhoucke, V.; Ioffe, S.; Shlens, J.; Wojna, Z. Rethinking the Inception Architecture for Computer Vision. In Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016; pp. 2818–2826. [CrossRef]
39. Vaze, S.; Han, K.; Vedaldi, A.; Zisserman, A. Open-Set Recognition: A Good Closed-Set Classifier is All You Need? *arXiv* **2022**, arXiv:2110.06207.