# A Two-stage Learning Approach for Traffic Sign Detection and Recognition

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Abstract: With the progress of advanced driver assistance systems (ADAS), the development of assisted driving technologies is becoming more and more important for vehicle subsystems. The traffic signs are designed to remind the drivers of possible situations and road conditions to avoid traffic accidents. This paper presents a two-stage network to detect and recognize the traffic sign images captured by the vehicle on-board camera. In the detection network, we adopt Faster R-CNN to detect the location of the traffic signs. For the classification network, we use SVM, VGG, and ResNet for validation and testing. We compare the results and integrate the detection and classification systems. The datasets used in this work include TT100K and our own collected Taiwan road scene images. Our technique is tested using the videos acquired from the highway, suburb and urban scenarios. The results using Faster R-CNN for detection combined with VGG17 for classification have demonstrated superior performance compared to YOLOv3 and Mask R-CNN.

## 1 INTRODUCTION

In advanced driver assistance systems (ADAS), one specific important module is for the detection and recognition of traffic signs. It provides the indispensable information for the drivers or autonomous vehicles to comply with the traffic laws and regulations (Lin et al., 2020). Major traffic accidents might be occurred if drivers do not pay attention to the road signs. Since most of the signs are in the outdoor scenes, the detection and recognition have many difficulties such as occlusion, distortion, lighting and color fading, etc. In the past few decades, there are many traditional methods utilizing image features, including color, shape and gradient, to detect and recognize traffic signs (Huang et al., 2017).

Recently, machine learning based methods have made significant progress on object recognition. They are also successfully adopted to many vehicle related applications. The detection and classification of traffic signs have been greatly improved with the continuous development of deep learning techniques. In (Tabernik and Skočaj, 2020), Tabernik and D. Skǒcaj present an approach for large scale traffic sign detection and classification. It is based on Mask R-CNN and Detectron (He et al., 2017; Girshick et al., 2018), with the online hard-example mining (OHEM) module (Shrivastava et al., 2016). Their datasets are collected by dashcam recorders for more than 200 types. One major drawback of the proposed method is the detection time of 0.5 seconds per image. Zhang *et al.* modify YOLOv2 with several changes to the network architecture and compare the accuracy and recall (Zhang et al., 2017; Redmon and Farhadi, 2017). The traffic signs are only divided into three categories, namely 'mandatory', 'danger' and 'prohibitory', for detection and classification. Rajendran *et al.* improve the accuracy of YOLOv3 by changing the size of anchor boxes (Rajendran et al., 2019; Redmon and Farhadi, 2018). In addition to the above literatures, there are also many works using public datasets for traffic sign detection (Yuan et al., 2019; Philipsen et al., 2015; Liu et al., 2019). Since most of the public datasets are created with the road scenes in Europe and the US, there exist some variations for the traffic sign detection in different countries. Table 1 shows the comparison of various public datasets currently available.

In this paper, we propose a two-stage network for traffic sign detection and recognition. We adopt Faster R-CNN implemented in Detectron as the backbone of our detection framework (Ren et al., 2015). A fairly loose criterion is first used to detect any possible traf-

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Table 1: The comparison of various public datasets for traffic sign detection and recognition. GTSDB (Houben et al., 2013), GTSRB (Stallkamp et al., 2012), DFG (Tabernik and Skočaj, 2020), LISA (Mogelmose et al., 2012), TT100K (Zhu et al., 2016).

| | GTSDB | GTSRB | DFG | LISA | TT100K |
|---|---|---|---|---|---|
| Resolution | $1360 \times 800$ | $15 \times 15$ \| $250 \times 250$ | $1920 \times 1080$ | $640 \times 640$ \| $1024 \times 522$ | $2048 \times 2048$ |
| Number of Images | 900 | over 50,000 | 7,000 | 6,610 | 100,000 |
| Number of Classes | 3 | 43 | 200 | 47 | 221 |
| Usage | Detection | Classification | Detection | Detection | Detection |
| Area | Germany | Germany | Slovenian | USA | China |

fic signs with the miss rate as low as possible in the first stage. This might contain many false positives corresponding to the background regions similar to the traffic signs. The detection results are then sent to the second stage for road sign recognition. Many approaches, including SVM (support vector machine) and CNN (convolutional neural network), are adopted for image classification. The public dataset TT100K is mainly used for training and testing (Zhu et al., 2016). However, we also collect our own traffic scene dataset since the road signs are not identical for different countries (Chiu et al., 2019). Moreover, it is required to increase the number of samples for network training.

For the traffic sign detection, the images with the resolution of $512 \times 512$ in the datasets are used in the first stage. The cropped road sign regions derived from the first stage are used in the second stage as the training and testing data. Due to the blur or occlusion, it is difficult to classify small size road sign images into specific categories. Thus, we set the minimum size of $25 \times 25$ pixels for recognition, which corresponds to about 50 – 60 meters from the camera. According to the frequency appeared in the road scenes, there are 22 types of traffic signs considered for detection and recognition currently. In the future, as the growth of image data and annotation, the number of categories will be gradually increased.

# 2 METHOD

To improve the accuracy of traffic sign detection and recognition, this work proposes a new two-stage approach. Figure 1 shows the flowchart of the proposed technique. The first stage mainly detects the locations of the traffic signs, followed by the second stage of using the cropped regions for image classification. The proposed traffic sign detection framework is different from the commonly adopted two-stage detectors such as R-CNN, Faster R-CNN, etc. (Girshick et al., 2014; Ren et al., 2015). Our first stage is designed to have a very low miss rate and disregard the number of false positives. The second stage is then carried out for the validation and classification of traffic signs.

## 2.1 Detection Network

Our detection network is based on Detectron (Girshick et al., 2018), with Faster R-CNN+ResNet50. It is mainly used to detect the possible traffic signs and derive the miss rate (or false negative rate, FNR) given by

$$FNR = \frac{FN}{FN+TP} \tag{1}$$

where FN and TP are the numbers of false negatives and true positives, respectively. Compared with the previous works, the most common problem encountered in traffic sign detection is the misunderstanding of signboard and similar shapes.

Faster R-CNN is adopted in this work due to its low miss rate and high accuracy. One of the most important architectures is the Region Proposal Network (RPN). It uses softmax to determine the foreground and background, and bounding box regression to correct the anchor position. The RPN contains two paths and a proposal layer to eliminate smaller and out-of-bounds proposals. We also added the Feature Pyramid Network (FPN), by fusing the higher level features with low-level features (Yang et al., 2016). The semantic features of the high convolutional layer are combined with the features from low convolutional layers to improve the accuracy of target detection.

## 2.2 Classification Network

The traffic signs detected in the first stage are cropped from the images, and only the classes of interest are used for training in the second stage. We select a total of 22 most common road sign types plus an additional non-sign category for classification. They are further divided into 1 category for danger sign, 2 categories for mandatory signs and 19 categories for prohibition signs.

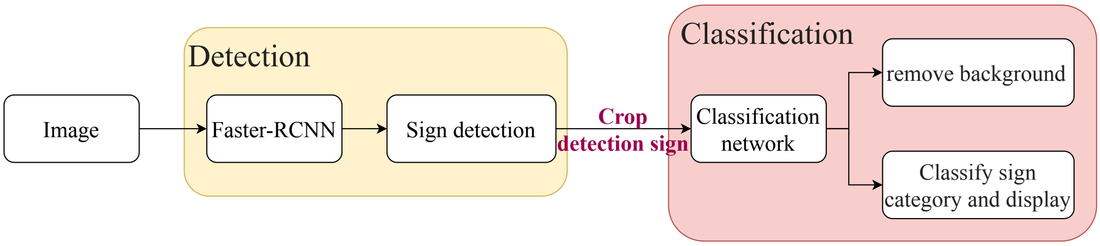
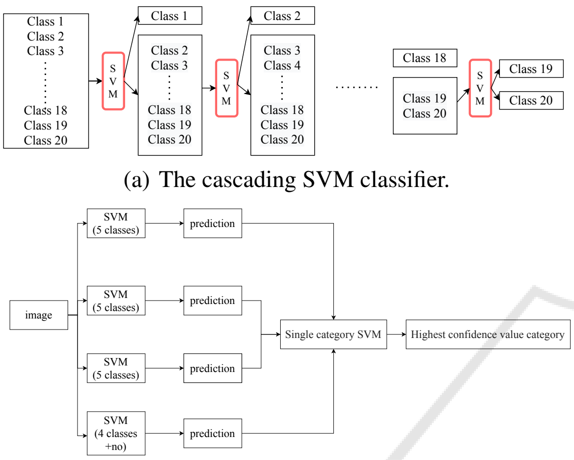



Figure 1: The flowchart of the proposed two-stage traffic sign detection and recognition.




(a) The cascading SVM classifier.

(b) The parallel SVM classifier.

Figure 2: Two different SVM variations (cascading and parallel) used for the second stage.

In the second stage, SVM, VGG16, ResNet and SE-ResNet are adopted for traffic sign classification. For SVM classifiers, the HOG (Histogram of Oriented Gradient) features are used for training (Wahyono et al., 2014; Zaklouta and Stanciulescu, 2012). One approach is to set one category versus the rest, and all SVMs are connected in series as shown in Figure 2(a). The other is to use parallel SVMs for the initial predictions, followed by another SVM to select the one with the highest confidence value, as illustrated in Figure 2(b). Due to the execution speed of these two methods, other machine learning techniques are further investigated.

Both VGG16 and ResNet have good performance in the ImageNet classification competition. The network structure of VGG16 is relatively simple, including 13 convolutional layers, 3 fully connected layers and 5 pooling layers. In our implementation, the input image size, batch size and learning rate are set as $224 \times 224$, 32 and 0.002, respectively. We trained the network with roughly 900 epochs and the weights are stored for every 300 epochs. Finally, the one with the highest accuracy is used for testing. ResNet is a residual network which solves the problem of information loss caused by too many convolutional layers.

SE-ResNet inserts the SE (Squeeze-and-Excitation) module into the residual structure of ResNet. By controlling the scale size, important and unimportant features are enhanced and weakened. In ResNet and SE-ResNet, the network parameters are as follows: the input image size for training: $40 \times 40$, the batch size: 64, the learning rate: 0.002, the training epoch: 3000. The weights are also stored for every 300 epochs.

## 3 TRAFFIC SIGN DATASET

Most of the public datasets for traffic sign detection are collected in Europe and the United States. However, Taiwan has the road scene complexity different from Europe and the US. There are many motorcycles on the streets in the urban areas, but less in other countries. TT100K is by far the most suitable dataset to train the networks for Taiwan's traffic sign detection. Figure 3 shows all types traffic signs in TT100K. Since there still exist discrepancies between our application scenario and the dataset (such as no danger signs in the dataset), we further include self-labeled Taiwan road scene images for training and testing. For the testing videos, the image sequences are captured by an on-board digital video recorder (DVR). The original image size is $1280 \times 800$.

The dataset contains 23 categories (including 1 non-sign category) for the first stage detection, with 29,659 images for training and 15,766 images for testing. To better detect the traffic sign locations and increase the accuracy, the images are cropped into multiple $512 \times 512$ regions. The cropping process is carried out in a sliding window fashion, starting from the upper left corner to detect the traffic signs in the region. To ensure that no signs will be missed, the stride is set as 400 and each movement follows an overlap of 112 pixels. If there is a sign in the ROI, it will be cropped into a $512 \times 512$ image.

In the second stage classification, the traffic sign images are cropped from TT100K and our dataset. There are 10,474 images for training (including 711 background images) and 4,496 images for testing (including 55 background images). The background im-

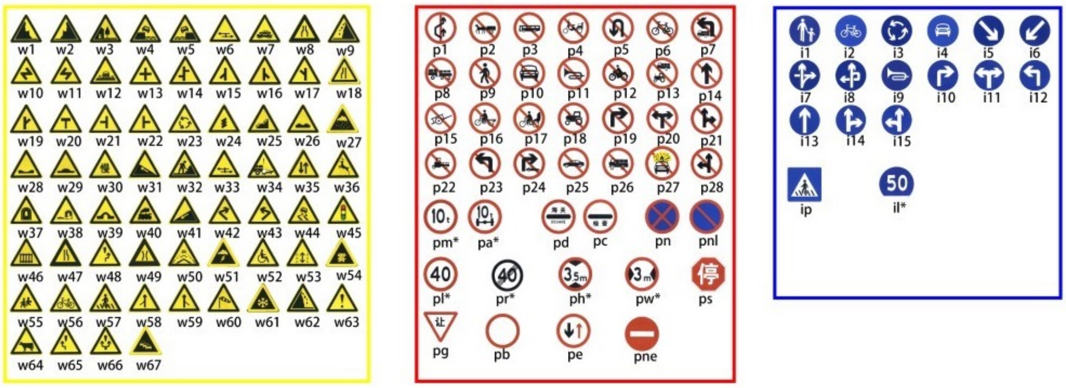
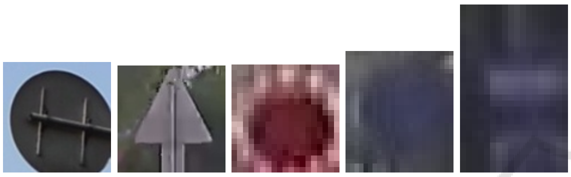



Figure 3: All types of traffic signs in the public dataset TT100K. It is mainly used in this work.



(a) (b) (c) (d) (e)

Figure 4: Some false positives in the first stage detection used as the training samples in the second stage classification.

ages are used to eliminate the false positives (FP) appeared during the detection stage. They are cropped from the false detection results, and used to train the classification network. Figure 4 shows some false positives of the traffic signs detected in the first stage and used as the training samples in the second stage classification.

We are mainly interested in the traffic sign detection from car digital video recorders. However, TT100K covers about 80% of images for network training. The dataset contains still images which are different from the image sequences acquired when the vehicle is moving (with more severe blur and noise). The images captured by the car digital video recorder are blurry and noisy compared to the TT100K images. Thus, image processing is carried out to make the dataset images close to the recorded video data. The two-stage processing flowchart with three-category detection is shown in 5. To provide a more realistic testing environment for traffic sign detection algorithms, we create three types of testing videos including highways, suburbs and urban areas. There are two image sequences generated for each scenario with a total of six testing videos. The video playback is speeded up for the areas without traffic signs. Each video is 3-minute long, and contains 5,400 image frames. The image resolution of $1280 \times 800$ is cropped into a $612 \times 612$ ROI. Since the sidewalks and opposite lanes are removed, the detection speed and accuracy can be greatly improved (Chiu et al., 2019).

# 4 EXPERIMENTS

For the detection networks, we compare three methods: YOLOv3, Faster R-CNN in Detectron, and the approach described in (Zhu et al., 2016). The traffic signs are also divided into three categories, 'mandatory', 'prohibitory' and 'danger', for evaluation. In the first stage, the main objective is to have a very low miss rate. Table 2 shows the comparison of the miss rate for three networks using the urban testing videos. Among them, Faster R-CNN is evaluated with additional 3 categories. It is indicated in the table that the low miss rate usually comes with more false positives. The results also show that Faster R-CNN often recognizes the signboards or circular shapes as traffic signs, but is capable of detecting obscured signs. It is suitable for our first stage detection since the major concern is low FNR instead of low FDR (false discovery rate).

For the classification networks, we compare two different approaches. One is to test with a still image set containing 80% and 20% of images from TT100K and our dataset, respectively. The other is to test with the 6 video sequences created for highway, suburb and urban road scenes as described in the previous section. Since the test sets are the output of the first stage detection and marking, the accuracy evaluation of this stage is purely for the classification results.

In the implementation, there are two approaches for the first stage. One is to detect the traffic signs without classification, and the other is to detect and classify the traffic signs into three categories, 'mandatory', 'danger' and 'prohibition'. Thus, there are four different classification networks trained separately. It

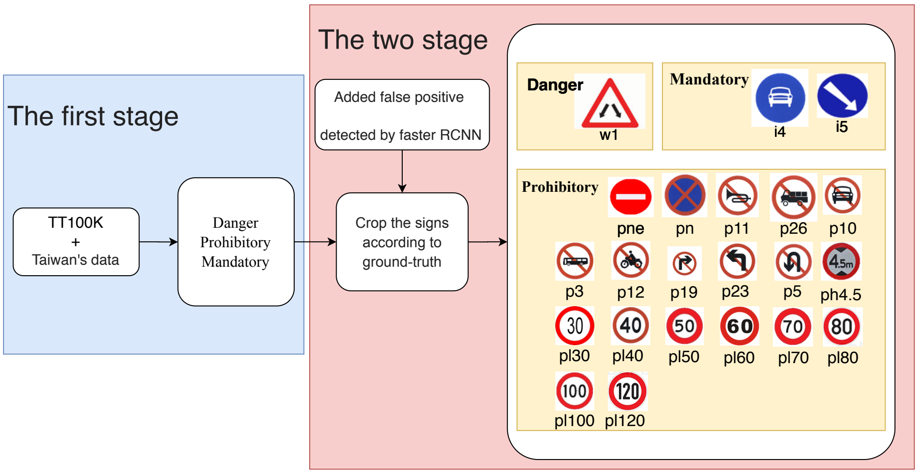



Figure 5: The two-stage processing flowchart with three-category detection. The network training of the first stage is for all signs or three categories. In the second stage, the background false positives are added for training.

Table 2: The comparison of the miss rate for three networks using the urban testing videos. Faster R-CNN is also evaluated with additional 3 categories. It is indicated in the table that the low miss rate usually comes with more false positives. Only the traffic signs larger than $25 \times 25$ in the videos are considered.

| | Miss Rate | Number of Signs | Number of Missed | False Positive |
|---|---|---|---|---|
| YOLOv3 | 0.0796 | 1,257 | 100 | 1,766 |
| Mask R-CNN | 0.0387 | 1,257 | 68 | 1,995 |
| Faster R-CNN | 0.0135 | 1,257 | 17 | 1,985 |
| Faster R-CNN (3class) | 0.0220 | 1,257 | 50 | 1,436 |



Table 3: The evaluation of Image Test and Video Test using two classifiers, ResNet18 and SVM for the mandatory category. ‘i4’ and ‘i5’ are the traffic signs shown in Figure 5. ‘i4’ is not available in Video Test because it does not appear in our test video. The input image size to ResNet18 is $40 \times 40$.

| | Image Test | | Video Test | |
|---|---|---|---|---|
| Classifier | ResNet18 | SVM | ResNet18 | SVM |
| mAP | 81.53% | 79.387% | 95.42% | 95.38% |
| i4 | 86.06% | 93.97% | – | – |
| i5 | 86.07% | 98.37% | 97.35% | 99.77% |
| non-sign | 72.45% | 45.79% | 93.49% | 91.00% |

should be noted that if the wrong category is assigned from the second approach, the subsequent classification network will not be able to obtain the correct results. The first approach has no such issue but usually results in a higher false positive rate.

We first consider the classification for the mandatory category. Currently there are two different signs, ‘i4’ and ‘i5’, as shown in Figure 5. Table 3 shows the results of Image Test and Video Test using two classifiers, ResNet18 and SVM. It can be seen that the video inputs have better accuracies than the still images. This is due to some unusual viewpoints of traffic signs in the testing data of TT100K. In our video testing dataset, the images are all captured with the camera facing the traffic signs. For the danger category, there is only one traffic sign ‘w1’ as shown in Figure 5. The classification results using ResNet18 and SVM are tabulated in Table 4 for Image Test and Video Test. The table shows the accuracy of SVM is higher in Image Test while the accuracy of ResNet18 is higher in Video Test. This is caused by many triangular signs detected in the first stage (as shown in Figure 6), and considered as ‘w1’ for training in the second stage.

(a) w1 (b) x (c) x (d) x

Figure 6: The correct and incorrect triangular signs detected in the first stage.

There are a total of 19 types of prohibitory traf-

Table 4: The evaluation of Image Test and Video Test using two classifiers, ResNet18 and SVM for the danger category. 'w1' is the traffic signs shown in Figure 5. The input image size to ResNet18 is $40 \times 40$.

| | Classifier | mAP | w1 | non-sign |
|---|---|---|---|---|
| Image Test | ResNet18 | 83.6% | 90.01% | 77.2% |
| | SVM | 97.46% | 98.55% | 96.36% |
| Video Test | ResNet18 | 75.77% | 98.33% | 53.21% |
| | SVM | 46.23% | 72% | 20.45% |

Table 5: The evaluation of Image Test and Video Test using several SVM implementations, VGG16, ResNet18 and SE-ResNet50 for the prohibitory category.

| Classifier | Input Image Size | Image Test | Video Test |
|---|---|---|---|
| Linear SVM | $40 \times 40$ | 75.66% | 40.16% |
| RBF SVM | $40 \times 40$ | 76.66% | 47.07% |
| Cascaded SVM classifier | $64 \times 64$ | 89.85% | 61.77% |
| Cascaded SVM classifier | $40 \times 40$ | 85.22% | 52.35% |
| Parallel+Cascaded SVM | $64 \times 64$ | 89.78% | 60.99% |
| VGG16 | $224 \times 224$ | 80.63% | 66.46% |
| ResNet18 | $40 \times 40$ | 76.25% | 56.9% |
| SE-ResNet50 | $40 \times 40$ | 76.77% | 66.9% |

fic signs for testing, and it is much more challenging than danger and mandatory. Several classifiers are tested, including several SVM implementations, VGG16, ResNet18 and SE-ResNet50, and the comparison is tabulated in Table 5. The table shows a big difference between the accuracies of Image Test and Video Test. It is mainly due to the low image quality of the video testing data compared to the TT100K training dataset. To deal with the problem, Gaussian blur and Gaussian noise are added to TT100K images for training. Figure 7 shows some examples of the processed images, which can be considered as the transferred version of TT100K dataset images to car camera images.

To evaluate the effectiveness of this pre-processing approach on the dataset images, we perform another Image Test and Video Test using only the pre-processed TT100K images (without including Taiwan road scene images) for training. The mAPs of Image Test and Video Test without image pre-processing using ResNet18 are 79.42% and 42.67%, respectively. After the dataset images are processed for training, the mAPs become 79.88% and 45.61%, respectively. This shows the slight improvement on Video Test using ResNet18. The comparison with our traffic sign dataset included is shown in Table 6. When examining the result images, it is found that some detection results are worse if the pre-processed training data are used. This is due to the over-filtering on some low quality images in TT100K dataset. Thus, image sharpness and Laplacian edge blur degree are used as thresholds for image filtering. Table 7 shows the comparison of SE-ResNet50 and VGG16 with various dataset image alteration.


Figure 7: The processed TT100K images with Gaussian blur and Gaussian noise for network training.

For the traffic sign detection on the three categories separately, VGG16 has the best detection accuracy on the prohibitory signs. Thus, it is used as the framework for the direct detection for all signs (23 classes) without an initial mandatory, danger and prohibitory classification. The input image size for training is also $224 \times 224$. The mAP of Image Test and Video Test are 83.41% and 78.57% respectively. Compared to the approach separating three categories in the first stage, the miss rate is lower but with a similar classification mAP.

For the two-stage network using Faster R-CNN combined with classifiers, we adopt SE-ResNet50. The mAP is 80.86% for the evaluation on urban scene videos, and the detailed comparison is shown in Table 8. The first and second rows show our results using Faster R-CNN+VGG16 without and with setting 3 categories for detection. The third row shows the results using Mask R-CNN (Tabernik and Skočaj, 2020) and trained on our dataset. The fourth and last rows are the result of using Faster R-CNN and YOLOv3, respectively.

Finally, we retrain the proposed method using

Table 6: The evaluation of the pre-processing approach on the dataset images using ResNet18. The training data are TT100K combined with Taiwan road scene images. The input image size is $40 \times 40$.

| Classifier | Categories for Pre-processing | Image Test | Video Test |
|---|---|---|---|
| ResNet18 | – | 76.25% | 56.9% |
| ResNet18 | all | 76.74% | 64.13% |
| ResNet18 | pl40, pl50, pl60, p12 (Gaussian Blur) | 76.12% | 56.74% |
| ResNet18 | pl40, pl50, pl60, p12 (Motion Blur) | 74.6% | 62.99% |

Table 7: The evaluation and comparison of SE-ResNet50 and VGG16 with various dataset image alteration.

| Classifier | Input Image Size | Categories for Pre-processing | Image Test | Video Test |
|---|---|---|---|---|
| SE-ResNet50 | 40 | – | 76.77% | 64.42% |
| SE-ResNet50 | 40 | pl40, pl50, pl60, p12 | 78.63% | 75.34% |
| SE-ResNet50 | 40 | all | 79.41% | 71.34% |
| VGG16 | 224 | no | 80.63% | 66.64% |
| VGG16 | 224 | all | 83.54% | 77.9% |

Table 8: The comparison of the proposed two-stage network using Faster R-CNN combined with classifiers evaluated on urban scene videos. The first and second rows show our results using Faster R-CNN+VGG16 without and with setting 3 categories for detection. The third row shows the results using Mask R-CNN and trained on our dataset. The fourth and last rows are the result of using Faster R-CNN and YOLOv3, respectively. The computation time is given per fame.

| | mAP | p23 | p5 | i5 | p19 | pl50 | Computation Time |
|---|---|---|---|---|---|---|---|
| Faster R-CNN (1class) with VGG16 | 80.86% | 0.81% | 0.74% | 0.87% | 0.91% | 0.71% | 0.087+0.02 sec. |
| Faster R-CNN (3class) with VGG16 | 72.05% | 0.77% | 0.77% | 0.36% | 0.84% | 0.87% | 0.087+0.02 sec. |
| Mask R-CNN | 54.92% | 0.57% | 0.6% | 0.57% | 0.5% | 0.5% | 0.94 sec. |
| Faster R-CNN | 61.6% | 0.76% | 0.28% | 0.88% | 0.52% | 0.28% | 0.10 sec. |
| YOLOv3 | 53.55% | 0.74% | 0.33% | 0.6% | 0.52% | 0.48% | 0.03 sec. |



GTSDB and GTSRB and compare with (Yang et al., 2016). The paper adopts a color probability model to extract traffic signs, and use SVM to classify into three categories, followed by a CNN for the recognition of individual signs. Our classification accuracies using VGG16 in the GTSRB are 97.68% in prohibition and restriction, 86.33% in compliance, and 93.62% in warning categories, respectively.

## 5 CONCLUSIONS

In this paper, we present a two-stage approach for the detection and recognition of traffic signs using Faster R-CNN combined with a classifier. In the first stage, Faster R-CNN is used and a lower threshold is used to detect any possible traffic signs. In the second stage, the classifier is used to recognize the type of a specific traffic sign. We analyze the discrepancy between the training dataset and the road scene images acquired by on-board camera. A pre-processing stage is carried out to make the image quality of the public dataset similar to the testing data. Our method has achieved the mAP of 80.86% on the testing videos, compared to 53.55% from YOLOv3 and 54.92% from Mask R-CNN.

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## REFERENCES

Chiu, Y. C., Lin, H. Y., and Tai, W. L. (2019). Implementation and evaluation of cnn based traffic sign detection with different resolutions. In *2019 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, pages 1–2.

Girshick, R., Donahue, J., Darrell, T., and Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In *2014 IEEE Conference* *on Computer Vision and Pattern Recognition*, pages 580–587.

Girshick, R., Radosavovic, I., Gkioxari, G., Dollár, P., and He, K. (2018). Detectron. https://github.com/facebookresearch/detectron.

He, K., Gkioxari, G., Dollár, P., and Girshick, R. (2017). Mask r-cnn. In *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 2980–2988.

Houben, S., Stallkamp, J., Salmen, J., Schlipsing, M., and Igel, C. (2013). Detection of traffic signs in real-world images: The german traffic sign detection benchmark. In *The 2013 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8.

Huang, S. C., Lin, H. Y., and Chang, C. C. (2017). An in-car camera system for traffic sign detection and recognition. In *2017 Joint 17th World Congress of International Fuzzy Systems Association and 9th International Conference on Soft Computing and Intelligent Systems (IFSA-SCIS)*, pages 1–6.

Lin, H.-Y., Chang, C.-C., Tran, V. L., and Shi, J.-H. (2020). Improved traffic sign recognition for in-car cameras. *Journal of the Chinese Institute of Engineers*, 43(3):300–307.

Liu, C., Li, S., Chang, F., and Wang, Y. (2019). Machine vision based traffic sign detection methods: Review, analyses and perspectives. *IEEE Access*, 7:86578–86596.

Mogelmose, A., Trivedi, M. M., and Moeslund, T. B. (2012). Vision-based traffic sign detection and analysis for intelligent driver assistance systems: Perspectives and survey. *IEEE Transactions on Intelligent Transportation Systems*, 13(4):1484–1497.

Philipsen, M. P., Jensen, M. B., Møgelmose, A., Moeslund, T. B., and Trivedi, M. M. (2015). Traffic light detection: A learning algorithm and evaluations on challenging dataset. In *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, pages 2341–2345.

Rajendran, S. P., Shine, L., Pradeep, R., and Vijayaraghavan, S. (2019). Real-time traffic sign recognition using yolov3 based detector. In *2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, pages 1–7.

Redmon, J. and Farhadi, A. (2017). Yolo9000: Better, faster, stronger. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 6517–6525.

Redmon, J. and Farhadi, A. (2018). Yolov3: An incremental improvement.

Ren, S., He, K., Girshick, R., and Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. In *Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 1*, NIPS'15, page 91–99, Cambridge, MA, USA. MIT Press.

Shrivastava, A., Gupta, A., and Girshick, R. (2016). Training region-based object detectors with online hard example mining. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 761–769.

Stallkamp, J., Schlipsing, M., Salmen, J., and Igel, C. (2012). Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition. *Neural Networks*, 32:323 – 332. Selected Papers from IJCNN 2011.

Tabernik, D. and Skočaj, D. (2020). Deep learning for large-scale traffic-sign detection and recognition. *IEEE Transactions on Intelligent Transportation Systems*, 21(4):1427–1440.

Wahyono, Kurnianggoro, L., Hariyono, J., and Jo, K. (2014). Traffic sign recognition system for autonomous vehicle using cascade svm classifier. In *IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society*, pages 4081–4086.

Yang, Y., Luo, H., Xu, H., and Wu, F. (2016). Towards real-time traffic sign detection and classification. *IEEE Transactions on Intelligent Transportation Systems*, 17(7):2022–2031.

Yuan, Y., Xiong, Z., and Wang, Q. (2019). Vssa-net: Vertical spatial sequence attention network for traffic sign detection. *IEEE Transactions on Image Processing*, 28(7):3423–3434.

Zaklouta, F. and Stanciulescu, B. (2012). Real-time traffic-sign recognition using tree classifiers. *IEEE Transactions on Intelligent Transportation Systems*, 13(4):1507–1514.

Zhang, J., Huang, M., Jin, X., and Li, X. (2017). A real-time chinese traffic sign detection algorithm based on modified yolov2. *Algorithms*, 10(4).

Zhu, Z., Liang, D., Zhang, S., Huang, X., Li, B., and Hu, S. (2016). Traffic-sign detection and classification in the wild. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2110–2118.