Traffic sign recognition using convolutional neural networks

Kaoutar Sefrioui Boujemaa, Afaf Bouhoute, Karim Boubouh and Ismail Berrada
LIMS Laboratory, Dhar El Mehraz Science Faculty,
Université Sidi Mohamed Ben Abdellah
Fez, Morroco

Kaoutar.sefriouiboujemaa@usmba.ac.ma, afaf.bouhoute@usmba.ac.ma
boubouhkarim@gmail.com, iberrada@univ-lr.fr

***Abstract*—Traffic sign recognition (TSR) represents an important feature of advanced driver assistance systems, contributing to the safety of the drivers, pedestrians and vehicles as well. Developing TSR systems requires the use of computer vision techniques, which could be considered fundamental in the field of pattern recognition in general. Despite all the previous works and research that has been achieved, traffic sign detection and recognition still remain a very challenging problem, precisely if we want to provide a real time processing solution. In this paper, we present a comparative and analytical study of the two major approaches for traffic sign detection and recognition. The first approach is based on the color segmentation technique and convolutional neural networks (C-CNN), while the second one is based on the fast region-based convolutional neural networks approach (Fast R-CNN).**

Keywords—traffic sign recognition; convulotional neural network; color segmentation; region proposal.

I. INTRODUCTION

Recently the number of road vehicles has increased enormously thanks to the technological achievements in the motor industry and very precisely the availability of low rates. With this remarkable growth, the number of accidents is as well in an infinite raise year after year, due to different causes, in which the ignorance of traffic signs is considered as a major cause of these lasts.

Developing automated traffic sign recognition systems helps assisting the driver in different ways in order to guarantee his/her safety, which preserves as well the safety of other drivers and pedestrians. These systems have one main goal: detecting and recognizing traffic signs during the driving process. With these functionalities the system can guide and alert the drivers to prevent danger. Even though it is possible to develop a system that can recognize traffic signs, it doesn't mean that any sign can be correctly recognized by the system due to some traffic environmental challenges, for example: lightning variations, bad illumination, weather changes and signs in a ruined condition.

Figure 1. Examples of traffic signs subjected to lightning variations & weather conditions (GTSRB).

Traffic signs (TS) are generally divided into three main categories according to theirs functions: regulatory signs to give notice of traffic laws or regulation, warning signs to give notice of a situation that might cause danger and finally guide signs to show information about route destinations, distances, …etc. In each mentioned TS category, there are different subclasses with similar generic shape and appearance but different details. This suggests that traffic sign recognition should be carried out in two phases: the first phase consists of detecting traffic signs in a video sequence or an image using image processing algorithms that are generally based on shape and color segmentation. The second one is normally related to recognition of the detected signs in the first step, by applying a classification algorithm. Various methods have been developed in this area on top of them, artificial neural networks.

In this paper, we present an analytical study and its experimental results comparing the two major approaches: color segmentation and convolutional neural network (C-CNN) approach and fast region proposal convolutional neural network (Fast R-CNN) approach. The C-CNN method consists of selecting a set of regions for interest (ROIs) by applying a color tresholding on the input image, thus reducing the search space. Then, a trained CNN is used to classify the ROI (whether it contains a traffic sign or not), followed by another CNN with the same architecture that is used to recognize the detected traffic signs. According to [28], the Fast R-CNN method employs several techniques to improve training and testing speed while also increasing detection accuracy, it trains the very deep VGG16 [47] network 9× faster than the regular R-CNN

978-1-5386-2123-3/17/$31.00 ©2017 IEEE

[28] and it is 213× faster at test-time. In order to test and compare the performance of the implemented approaches we

used the GERMAN TRAFFIC SIGN datasets, for detection (GTSDB) [40] and for recognition (GTSRB) [41].

The rest of the paper is organized as follows. Section 2 provides a brief overview of the state of the art methods for traffic signs detection and classification in single images. Both of the approaches we studied and tested are presented in section 3, while the experimental results, carried out on GTSRB and GTSDB datasets are presented in Section 4. Finally, conclusions and future works are drawn in Section 6.

II. RELATED WORK

There are many researches in the literature dealing with Road Traffic Sign Recognition (TSR) problem. According to [1], the very first work on automated traffic sign detection was presented in Japan in 1984. Different researchers introduced several methods afterwards, to develop an efficient traffic sign recognition and detection (TSDR) system and to minimize all of the issues mentioned above. An efficient TSDR system can be divided into several phases, starting with preprocessing, detection, tracking, and recognition.

In the preprocessing phase, the main goal is to enhance the visual appearance of images. Different approaches are used to minimize the effect of environment on the test images based on two important features: color and shape [6–3]. Traffic sign detection aims to identify regions of interest (ROIs) in which it is supposed to find a traffic sign that is verified after a large-scale search for candidates (TS) within the input image [4]. To detect these ROIs, different techniques were proposed. The most popular color based thresholding methods are HIS/HSV transformation [5-6], Colour Indexing [8], YCbCr color space transform [9] and Region Growing [7]. Shape based algorithms were introduced to reinforce the detection phase since color information can be easily impacted due to a bad illumination or weather changes. There are different approaches for shape detection that are well known with their efficiency and processing time speed. The most popular are: Hough Transformation [10–11], Similarity Detection [12], Distance Transform Matching [13], and Edges with Haar-like features [14].

The tracking phase is really important to ensure real-time recognition, however not all of the existing TSDR approaches use tracking. Tracking helps to reduce the amount of traffic sign candidates that can be passed to the recognition step by detecting and following the object [15]. The most common adapted tracker is the Kalman filter [14, 17, 18].

The last step in any TSDR system as we mentioned is recognition. Ohara et al. [19] and Torresen et al. [20] used the template matching technique, which is a straight forward and a very fast method. Aoyagi and Asakura [21] and De la Eccalera et al. [22] used a genetic algorithm to deal with the illumination problem. Li et al. [24] used AdaBosst that is known and confirmed with its simplicity, generalization, and feature selection for large dataset. Greenhalgh and Mirmehdi [25] studied four important classifiers: SVM, MLP, HOG-based and Decision Trees. After a comparison between these classifiers, they found that a Decision Tree has the highest accuracy rate and the lowest computational time.

In fact it is impossible to discuss recognition algorithms and approaches without mentioning CNNs. After their use in [26] for image classification, the interest in using CNN was rekindled and quickly researchers started adapting CNNs more and more for object detection and recognition. Sermanet et al. observed that convolutional networks are generically efficient when they are used in a sliding window fashion, as many computations can be reused in overlapping regions. They demonstrated a network that can detect and recognize an object additionally to its bounding box coordinates so that the recognized object can be finally presented with its class label and a box drawn around it. Another widely used strategy using CNNs is to first calculate some random object proposals and perform classification only on these candidates. R-CNN [28] was the first to use this strategy, but it is very slow for two reasons. Firstly, generating category-independent object proposals is costly; it takes about 3s to generate 1000 proposals for the Pascal VOC 2007 images [45]. Secondly, it applies a whole deep convolutional network to every candidate proposal calculated, which is obviously very inefficient and time consuming. To improve efficiency, the spatial pyramid-pooling network (SPP-Net) [46] calculates a convolutional feature map for the entire image and extracts feature vectors from the shared feature map for each proposal. This speeds up the R-CNN approach about 100 times. Girshick et al. have proposed the Fast R-CNN model [29], which is a faster version of the R-CNN approach. Ren et al. proposed region proposal networks (RPNs), which generate object proposals using convolutional feature maps. This allows the generator of the object proposal to share the convolutional features of the whole image with the detection network. With this technique Ren et al's detection system can achieve a frame rate of 5 fps on a powerful GPU. Szegedy et al. [34] improved the network architecture, to achieve a frame rate of 50 fps in testing, with competitive detection performance.

III. COLOR SEGMENTATION & CNN BASED APPROACH

In this section we will describe the C-CNN based approach. A flowchart of the main phases of this last is shown in Figure 2.

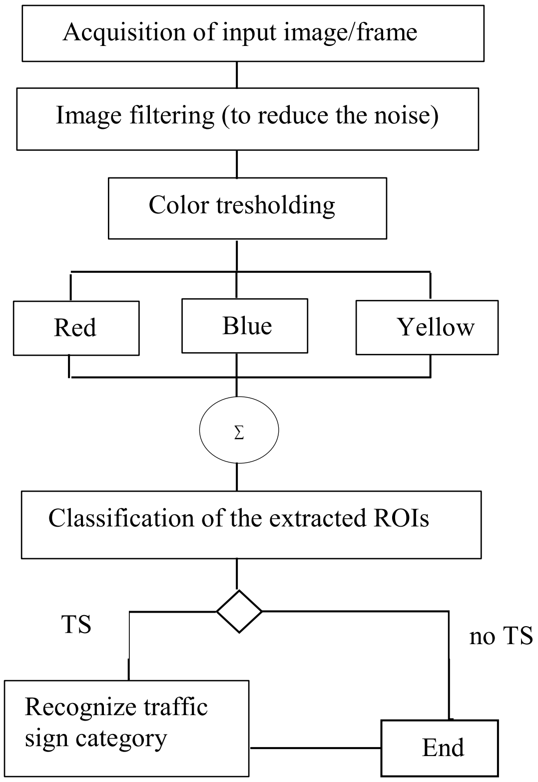

Figure 2. Flowchart of the C-CNN process.

Traffic sign detection stage for this study basically depends on color and feature analysis. Using the HSV features and grayscale color spaces, color thresholding can be applied to a given image or frame. After color detection, an additional step is required in order to verify if the corresponding regions ROIs are a traffic sign or not, by using a CNN model as a classifier. A simple Image demo of the detection process is given in Figure 3.

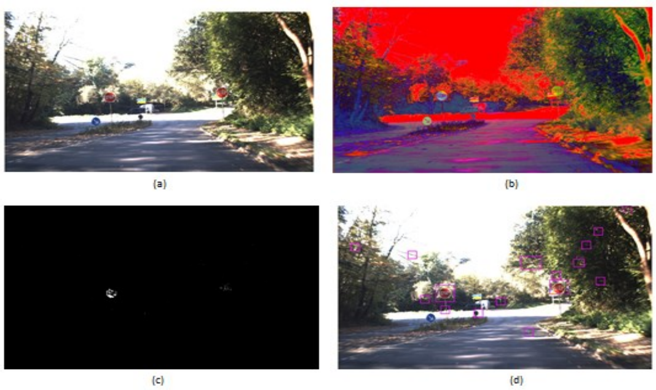

Figure 3. A demo of the detection process, (a) represent the input image (from the GTSDB), (b) is the image after converting it to the HSV color space, (c) is the binary image after extracting only red color and (d) represents all the ROIS that might contain a red traffic sign, which will be passed to a CNN to eliminate regions with no traffic sign in.

The first methodology in the detection stage of the C-CNN approach is color segmentation which is applied by extracting color features of traffic signs images after being transmitted from RGB color space to HSV color. In some color spaces, the hue plays an important role in the color detection. This is because it is invariant to lightning conditions as it is also invariant to scale and under saturation changes. However the hue coordinate is unstable, mentioning that any small changes in the RGB may cause strong variation in hue [36]. The hue generally faces three problems. Firstly, the hue becomes meaningless when the intensity is high or very low. Secondly, when the saturation is very low, it also makes the hue meaningless. Thirdly, when the saturation value is less than a certain threshold, in this case the hue becomes unstable. Vitabile et al. [37] defined three different areas in the HSV color space:

- The achromatic area characterized by $S \leq 0.25$ or $V \leq 0.2$ or $V \leq 0.9$.
- The unstable chromatic area characterized by $0.25 \leq S \leq 0.5$ and $0.2 \leq V \leq 0.9$.
- The chromatic area characterized by $S \geq 0.5$ and $0.2 \leq V \leq 0.9$.

In order to reduce the problems that might be caused by the changes in external light conditions, the areas mentioned above should be taken into consideration in any color segmentation system. Table 1 shows the HSV values we used for red, blue and yellow colors.

Table 1. HSV values for color thresholding.

	H	S	V
Red	[150, 179]	[100, 100]	[255, 255]
Blue	[100, 150]	[100, 255]	[38, 255]
Yellow	[20, 30]	[100, 100]	[255, 255]

A frame taken by a camera is represented using the collection of three parameters (R, G, B). As a first step, a median filter is used to reduce the noise while preserving the edges of the objects, by moving through each pixel and replacing the current pixel value with the median value of the neighboring pixels. The RGB color space is then converted to the HSV color space and the desired colored regions of the image are extracted. Any other color than red, blue or yellow is suppressed, so the remaining image carries only red, blue and yellow colors with its intensity information. To remove intensity effect, grayscale is subtracted from the detected color components of RGB color space, so the result is pure color information. After that, we extract our regions of interest, so we can decide for each region whether it contains a traffic sign or not, by applying a CNN. This CNN is used as a model, which was inspired by Pierre Sermanet & Yan LeCun [27]. It is fairly simple and has 7 layers: 3 convolutional layers, 3 maxpooling layers for feature extraction and one fully connected layer as a classifier. The CNN was trained to recognize two classes: traffic sign / no traffic sign. For that, we merged two datasets: the GTSRB dataset [41] and 30.000

random samples of the Cifar-10 dataset [39]. After classifying the extracted ROIs, we apply a second CNN with same architecture of the first one, to recognize the detected traffic signs in the ROIs. This second CNN was trained only on the GTSRB dataset.

IV. FAST R-CNN BASED APPROACH

In this section, we will describe briefly the Fast R-CNN based approach. According to [29], Fast R-CNN was proposed to fix the disadvantages of R-CNN [28] and SPPnet [46], while improving their speed and accuracy. The Fast R-CNN method has several advantages:

- Higher detection quality than R-CNN, and SPPnet,
- Training is single-stage, using a multi-task loss.
- No disk storage is required for feature caching.
- Training can update all network layers.

According to [29], the Fast R-CNN network takes as input an entire image and a set of object proposals that are calculated by an external algorithm. The network first processes the whole image with several convolutional (conv) and max pooling layers to produce a conv feature map. Then, for each object proposal a region of interest (ROI) pooling layer extracts a fixed-length feature vector from the feature map. Each feature vector is fed into a sequence of fully connected (fc) layers that finally branch into two sibling output layers:

- One that produces softmax probability estimates over K object classes plus a catch-all "background" class.
- Another layer that outputs four real-value numbers for each of the K object classes. Each set of 4 values encodes refined bounding-box positions for one of the K classes.

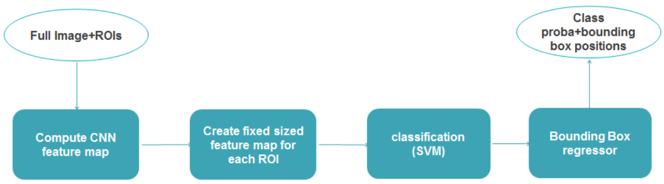

Figure 4. Flowchart of the Fast R-CNN architecture.

V. EXPERIMENTAL RESULTS

This section presents the series of experiments carried out to validate the studied approaches (C-CNN & Fast R-CNN) for detection and recognition of road signs.

We discuss at first the datasets used in our experiments and the recognition results. We used python language for implementation. For color segmentation, we used the OpenCv API [42] and the well-known deep learning API Keras [43] with Tensorflow backend [44] were used to train the CNNs models in both approaches.

1) GTRSB dataset visualization

The German Traffic Sign dataset is composed of 43 different traffic sign categories with each image 32×32×3 array of pixels, represented in RGB color space as integer values in the range [0,255]. This dataset has 39,209 images as training data and 12,630 images as a test data. Figure 5 shows the 43 classes of the dataset.

Figure 5. Traffic signs classes of the GTRSB.

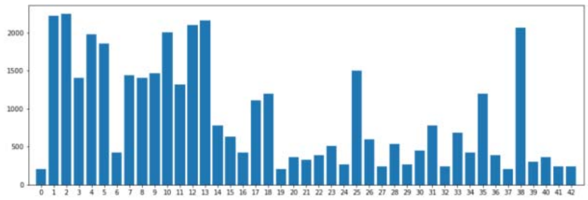

Figure 6. Class distribution across training GTSRB dataset.

As it is shown above (Figure 6), the training data class distribution is highly skewed.

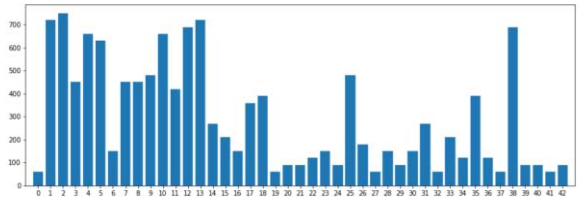

Figure 7. Class distribution across test GTSRB dataset.

We see in Figure 7 that the test data is also skewed. The only difference is that the individual counts for each class are less, as expected. If we aim to maximize the accuracy on the testing data, then it will not make any sense to balance the class distribution on the training set, since the test set is imbalanced in the same way as the training set.

2) C-CNN approach results

As mentioned in section 2, we trained two CNNs with the same architecture, the first one for classifying the ROIs extracted after applying the color segmentation on input frames and the second one to recognize the detected traffic signs. The training time took 6 hours on an Intel core i7 3612QM 8GB 1T.

Table 2. CNNs trained in C-CNN approach summary.

	Batch size	Epochs	Training	Test

		number	dataset size (image)	accuracy
CNN1	32	150	93583	93
CNN2	32	150	63583	95

Figure 8. Examples of C-CNN results.

3) *Fast R-CNN approach results*

With the Fast R-CNN approach, we could achieve 94.8% accuracy on test set (the GTSDB). The training time took 3 days, on a server with a GTX 1080 TI ROC - 11GO graphic card (see Table 3).

Table 3. Fast R-CNN settings.

Epochs size	Anchor box sizes	Training dataset size (image)	Test accuracy
300	[128,256,512]	600	94%

Even though the Fast R-CNN is a very good approach and showed interesting results in pattern detection & recognition in general, but if the training dataset is not balanced and big, that limits the performance of the approach. Figure 9 shows an example of false positive detected as a stop sign.

Figure 9. Example Fast R-CNN false detection.

VI. CONCLUSION & FUTURE WORKS

This paper presented an analytical study of two effective and efficient road sign detection and recognition approaches.
The experimental results achieved after testing both of the methods on the German Traffic Sign Detection & Recognition datasets, conclude that the Fast R-CNN is so much faster than the C-CNN method, also it is invariant to illumination changes (as long as this type of images is available in the training dataset). On the other hand, even though the C-CNN approach is slow and sensitive to weather conditions, it is invariant to scale and viewing angle.

This project is a part of bigger one called vCar. The project "vCar" is an open source platform for the analysis and visualization of driving data. It implements some useful tools to help us in analysis phase. vCar is wildly open to more functionalities through a flexible plugin system that allow integration of new algorithms out of the box as independent plugins. The work presented in this article, is a plugin in the platform that is dedicated to only traffic sign recognition. The user can access the different datasets used, the techniques based in the project and also can create his own project in the platform and make use of the plugin as an api to access the different functionalities, for example color segmentation, TR detection…etc. We aim to study other approaches and propose a new one using CNNs for sure, to make a real time traffic sign detection and recognition system that is more flexible and effective in the real world driving environment and conditions.

REFERENCES

[1] P. Pacl´ık, J. Novoviˇcov´a, and R. P. W. Duin, “Building roadsign classifiers using a trainable similarity measure,” IEEE Transactions on Intelligent Transportation Systems, vol. 7, no. 3,pp. 309–321, 2006.

[2] Ruta, Y. M. Li, and X. H. Liu, “Detection, tracking and recognition of traffic signs from video input,” in Proceedings of the 11th International IEEE Conference on Intelligent Transportation Systems (ITSC ’08), pp. 55 60, IEEE, Beijing, China, December 2008.

[3] G. A. Tagunde and N. J. Uke, “Detection, classification and recognition of road traffic signs using color and shape features,” International Journal of Advanced Technology & EngineeringResearch, vol. 2, no. 4, pp. 202–206, 2012.

[4] H.G¨und¨uz, S. Kaplan, S.G¨unal, and C. Akinlar, “Circular traffic sign recognition empowered by circle detection algorithm,” in Proceedings of the 21st Signal Processing and Communications Applications Conference (SIU ’13), pp. 1–4, IEEE, New York, NY, USA, April 2013.

[5] S. Maldonado-Basc´on, S. Lafuente-Arroyo, P. Gil-Jim´enez, H. G´omez-Moreno, and F. L´opez-Ferreras, “Road-sign detection and recognition based on support vector machines,” IEEE Transactions on Intelligent Transportation Systems, vol. 8, no. 2, pp. 264–278, 2007.

[6] G.A. Tagunde andN. J.Uke, “Detection, recognition and recognition of road traffic signs using colour and shape features,” International Journal of Advance Technology & Engineering Research, vol. 2, no. 4, pp. 202–206, 2012.

[7] L. Priese and V. Rehrmann, “On hierarchical color segmentation and applications,” in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR ’93), pp. 633–634, IEEE, New York, NY, USA, June 1993.

[8] M. J. Swain and D. H. Ballard, “Color indexing,” International Journal of Computer Vision, vol. 7, no. 1, pp. 11–32, 1991.

[9] Hechri and A.Mtibaa, "Automatic detection and recognition of road sign for driver assistance system," in Proceedings of the 16th IEEE Mediterranean Electrotechnical Conference (MELECON'12), pp. 888–891, Yasmine Hammamet, Tunisia, March 2012.

[10] G. Overett and L. Petersson, "Large scale sign detection using HOG feature variants," in Proceedings of the IEEE Intelligent Vehicles Symposium (IV '11), pp. 326–331, Baden-Baden, Germany, June 2011.

[11] Møgelmose, M. M. Trivedi, and T. B. Moeslund, "Visionbased traffic sign detection and analysis for intelligent driver assistance systems: perspectives and survey," IEEE Transactions on Intelligent Transportation Systems, vol. 13, no. 4, pp. 1484–1497, 2012.

[12] S. Vitabile, G. Pollaccia, G. Pilato, and E. Sorbello, "Road signs recognition using a dynamic pixel aggregation technique in the HSV color space," in Proceedings of the 11th International Conference on Image Analysis and Processing (ICIAP '01), pp. 572–577, Palermo, Italy, September 2001.

[13] D. M. Gavrila, "Traffic sign recognition revisited," in Mustererkennung 1999: 21. DAGM-Symposium Bonn, 15.-17. September 1999, pp. 86–93, Springer, Berlin, Germany, 1999.

[14] B. H¨o4ferlin and K. Zimmermann, "Towards reliable traffic sign recognition," in Proceedings of the IEEE Intelligent Vehicles Symposium, pp. 324–329, Xi'an, China, June 2009.

[15] V. A. Prisacariu, R. Timofte, K. Zimmermann, I. Reid, and L. Van Gool, "Integrating object detection with 3D tracking towards a better driver assistance system," in Proceedings of the 20th International Conference on Pattern Recognition (ICPR '10), pp. 3344–3347, IEEE, Istanbul, Turkey, August 2010.

[16] M. A. Hannan, A. Hussain, and S. A. Samad, "Decision fusion via integrated sensing system for a smart airbag deployment scheme," Sensors and Materials, vol. 23, no. 3, pp. 179–193, 2011.

[17] C.-Y. Fang, S.-W.Chen, and C.-S. Fuh, "Road-sign detection and tracking," IEEE Transactions on Vehicular Technology, vol. 52, no. 5, pp. 1329–1341, 2003.

[18] S. Lafuente-Arroyo, S. Maldonado-Bascon, P. Gil-Jimenez, H. Gomez-Moreno, and F. Lopez-Ferreras, "Road sign tracking with a predictive filter solution," in Proceedings of the 32nd Annual Conference on IEEE Industrial Electronics (IECON '06), vol. 1–11, pp. 3314–3319, IEEE, Paris, France, November 2006.

[19] Y. H. Ohara, I. Nishikawa, S. Miki, and N. Yabuki, "Detection and recognition of road signs using simple layered neural networks," in Proceedings of the 9th International Conference on Neural Information Processing (ICONIP '02), vol. 2, pp.626–630, IEEE, 2002.

[20] J. Torresen, J.W. Bakke, and L. Sekanina, "Efficient recognition of speed limit signs," in Proceedings of the 7th International IEEE Conference on Intelligent Transportation Systems (ITSC '04), vol. 90, pp. 652–656,Washington, DC, USA, October 2004.

[21] Y. Aoyagi and T. Asakura, "A study on traffic sign recognitionin scene image using genetic algorithms and neural networks,"in Proceedings of the IEEE 22nd International Conference on Industrial Electronics, Control, and Instrumentation (IECON'96), vol. 3, pp. 1838–1843, IEEE, Taipei, Taiwan, August 1996.

[22] De la Eccalera, J. M. Arminogol, and M. A. Salichs, "Traffic sign detection for driver support systems," in Proceedings of the International Conference on Field and Service Robotics (FSR '01), Helsinki, Finland, June 2001.

[23] L.Chen, Q. Li,M. Li, L. Zhang, andQ.Mao, "Design of a multisensory cooperation travel environment perception system for autonomous vehicle," Sensors, vol. 12, no. 9, pp. 12386–12404,2012.

[24] Y. Li, P. Sharath, andW. Guan, "Real-time traffic sign detection: an evaluation study," in Proceedings of the 20th International Conference on Pattern Recognition (ICPR '10), pp. 3033–3036,Istanbul, Turkey, August 2010.

[25] J. Greenhalgh and M. Mirmehdi, "Traffic sign recognition using MSER and Random Forests," in Proceedings of the 20th European Signal Processing Conference (EUSIPCO'12), pp. 1935–1939, August 2012.

[26] Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. Burges, L. Bottou, and K. Weinberger, editors, Advances in Neural Information Processing Systems 25, pages 1097–1105. Curran Associates, Inc., 2012.

[27] P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. LeCun. Overfeat: Integrated recognition, localization and detection using convolutional networks. CoRR, abs/ 1312.6229, 2013.

[28] R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2014.

[29] R. Girshick, J. Donahue, T. Darrell, and J. Malik. Region based convolutional networks for accurate object detection and segmentation. TPAMI, 2015

[30] G. Overett and L. Petersson, "Large scale sign detection using HOG feature variants," in Proceedings of the IEEE Intelligent Vehicles Symposium (IV '11), pp. 326–331, Baden-Baden, Germany, June 2011.

[31] Møgelmose, M. M. Trivedi, and T. B. Moeslund, "Visionbased traffic sign detection and analysis for intell

[32] S. Vitabile, G. Pollaccia, G. Pilato, and E. Sorbello, "Road signs recognition using a dynamic pixel aggregation technique in the HSV color space," in Proceedings of the 11th International Conference on Image Analysis and Processing (ICIAP '01), pp. 572–577, Palermo, Italy, September 2001.

[33] D. M. Gavrila, "Traffic sign recognition revisited," in Mustererkennung 1999: 21. DAGM-Symposium Bonn, 15.-17. September 1999, pp. 86–93, Springer, Berlin, Germany, 1999.

[34] Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, Alex Alemi, "Inception-v4 Inception-ResNet and the Impact of Residual Connections on Learning", August 2016.

[35] Y. Li, P. Sharath, andW. Guan, "Real-time traffic sign detection: an evaluation study," in Proceedings of the 20th International Conference on Pattern Recognition (ICPR '10), pp. 3033–3036, Istanbul, Turkey, August 2010.

[36] S. Vitabile, G. Pollaccia, G. Pilato, and E. Sorbello, "Road signs recognition using a dynamic pixel aggregation technique in the HSV color space," in Proceedings of the 11th International Conference on Image Analysis and Processing (ICIAP '01), pp. 572–577, Palermo, Italy, September 2001.

[37] B. Soheilian, N. Paparoditis, and B. Vallet, "Detection and 3D reconstruction of traffic signs frommultiple view color images,"Mathematical Problems in Engineering 1 ISPRS Journal of Photogrammetry and Remote Sensing, vol.

[38] https://www.cs.toronto.edu/~kriz/cifar.html

[39] "the German Traffic sign recognition benchmark" http://benchmark.ini.rub.de/?section=gtsdb&subsection=news

[40] "the German Traffic sign detection benchmark" http://benchmark.ini.rub.de/?section=gtsrb&subsection=news

[41] http://opencv.org/

[42] "keras api documentation" https://keras.io/

[43] https://www.tensorflow.org/

[44] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The PASCAL Visual Object Classes (VOC) Challenge. IJCV,2010.

[45] K. He, X. Zhang, S. Ren, and J. Sun. Spatial pyramid pooling in deep convolutional networks for visual recognition. In ECCV, 2014.

[46] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In ICLR, 2015