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Automatic Traffic Sign Detection Practices: A Review

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ABSTRACT

Traffic sign detection and recognition plays an important part in today's technology driven world. The purpose of traffic signs is to help drivers as well as pedestrians for safe navigation. The two major phases involved in traffic sign detection and recognition are : identifying the region of interest and proceeding to detect any and all signs that might be present, and further, classifying the detected signs into their respective classes. This paper attempts to review all the existing methods/practices for the detection of signs(real-time).

KEYWORDS:*Trafficsign detection, detection methods, traffic signs.*

I. INTRODUCTION

Traffic/ road signs offer information about traffic rules, conditions of roads as well as different directions of routes. It can have various applications in real life ranging from autonomous driving to helping visually impaired people in navigating their environments. With population, and with it, traffic increasing almost everyday, the need for easy to understand signs or otherwise simplified and standardized signs increased as well, so as to reduce barriers in language, and boost traffic safety. Such signs employ various methods, such as using specific colours and/or signs, to make it easy for users to recognise them at a single glance. After being initially developed in Europe, these signs have now been embraced by most countries to different extents.

Traffic signs are placed along the roads with the function of informing drivers about the front road conditions, directions, restrictions or text information. Though traffic signs have different structures and appearances in different countries, the most essential types of traffic signs are prohibitory, danger, mandatory and text-based signs. The prohibitory, danger or mandatory signs often have standard shapes, such as circle, triangle and rectangle, and often have standard colors such as red, blue and yellow. The text-based signs usually do not have fixed shapes and contain informative text[1]. Due to such conventions already in play when it comes to traffic signs, it becomes easier to detect and recognize them as the constraints defined limit the number of aspects we need to keep in check.

The applications of traffic sign detection and recognition are many[1, 2], and some of them are listed below:

• Driver Assistance: Traffic sign detection could assist drivers in many ways, especially in making drives more comfortable as well as safer.

• Autonomous Vehicle: Self driving cars, as they do not require any human intervention, will need to implement traffic sign detection and recognition technology in order to recognise signs as it travels on roads. Official future estimates are positive that cars with at least semi-automated features will be launched by the end of 2020, and most cars are expected to have full automation by 2035[14].

• Assistance of visually impaired people: Navigation can be made easier for visually impaired people on roads with the help of such methods, which can alert them to oncoming signs and guide them onto safer routes.

• Maintenance of road signs: Traffic sign recognition systems can be used to check the quality and the condition of different road signs[15,16].

• Engineering measurements. The locations of traffic signs were obtained using detection and recognition of signs. This was achieved with the help of Google Street View, and these locations were used for measurements in engineering[17].

Due to the usefulness of all such applications in the real world, traffic sign recognition has become all the more important, and as such , requires the best possible systems in order to be of utmost help and relevance in today's society.

This paper is organised as follows: Section II through V provide a brief review of the existing methods involved in the traffic sign detection and Section VI provides the conclusion.

II. Color Based Detection

As the name suggests, color based detection practices utilize the color as the distinguishing feature in order to detect the area in the picture or frame which might contain a traffic sign. As already mentioned above, traffic signs have distinctive colors based on the type of information they convey, and as a result, our search space is lessened considerably and the detected color can also help us in further classifying it into a reduced set of signs. The main advantage of color based detection is that traffic signs are usually designed to have easily noticeable colors, and in stark contrast to their surroundings, so that they are hard to miss.

As discussed in [1], color based detection can be divided into a few categories, namely, RGB Based thresholding, Hue and Saturation Thresholding, Chromatic/Achromatic Decomposition and Pixel Classification.

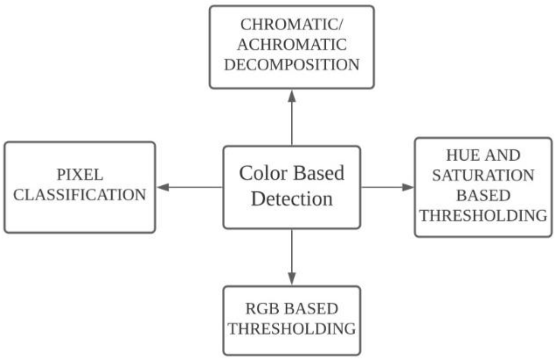

Fig. 1 Types of Color Based Detection Methods

Thresholding:

As described in [6], thresholding is an image segmentation method, done on the basis of pixel distribution. In this process, we switch an image which is in color to one that is binary, i.e., black and white. This is done to make the analysis of the image easier. For images, thresholding is basically of two types: RGB based and HSV based.

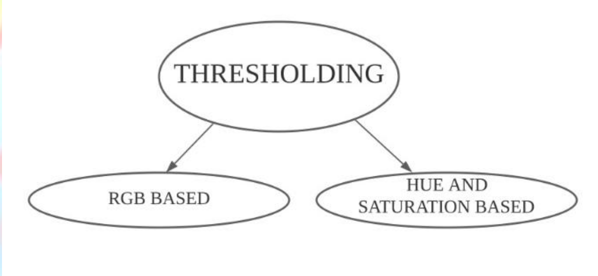

Fig. 2 Types of Thresholding Methods

• **RGB BASED THRESHOLDING:**

Using only a specific color space is a great way to segment the colors that we require. So, it is only fitting that we use the most basic color space, RGB, to achieve this in images and videos. However, this is a very primitive solution and is subject to many changes depending on surrounding conditions, like the sensitivity to illumination, which could be a problem especially if we are dealing with real time images and videos. [1] suggests a work-around for this, namely, a Normalized version of RGB called NRGB, which works with only two channels to figure out the rest of the channels, and as a result, factors such as illumination changes do not have a profound effect.

For attaining the different color masks, the expressions deployed are listed below:

$$\text{Red}(i,j) = \begin{cases} \text{True}, & \text{if } r(i,j) \geq ThR \\ & \text{and } g(i,j) \leq ThG \\ \text{False}, & \text{otherwise} \end{cases}$$

$$\text{Blue}(i,j) = \begin{cases} \text{True}, & \text{if } b(i,j) \geq ThB \\ \text{False}, & \text{otherwise} \end{cases}$$

$$\text{Yellow}(i,j) = \begin{cases} \text{True}, & \text{if } (r(i,j) + g(i,j)) \geq ThY \\ \text{False}, & \text{otherwise.} \end{cases}$$

The threshold values(ThR, ThG, Thb and ThY) can be inferred from [8].

• HUE AND SATURATION BASED THRESHOLDING:

Continuing our discussion with illumination changes, the channels of hue and saturation in the HSV/HSI color space are even more unaffected by them. These channels can be determined with the help of RGB, although this leads to an increase in the time required for processing.

Similar to color based detection, the color masks by means of hue and saturation thresholding can be listed as:

$$\text{Red}(i,j) = \begin{cases} \text{True}, & \text{if } H(i,j) \leq ThR_1 \\ & \text{or } H(i,j) \geq ThR_2 \\ \text{False}, & \text{otherwise} \end{cases}$$

$$\text{Blue}(i,j) = \begin{cases} \text{True}, & \text{if } H(i,j) \geq ThB_1 \\ & \text{and } H(i,j) \leq ThB_2 \\ \text{False}, & \text{otherwise} \end{cases}$$

$$\text{Yellow}(i,j) = \begin{cases} \text{True}, & \text{if } H(i,j) \geq ThY_1 \\ & \text{and } H(i,j) \leq ThY_2 \\ & \text{and } S(i,j) \geq ThY_3 \\ \text{False}, & \text{otherwise.} \end{cases}$$

ThRi , ThBi and ThYi are the fixed values of the different thresholds, which can be acquired from [8].

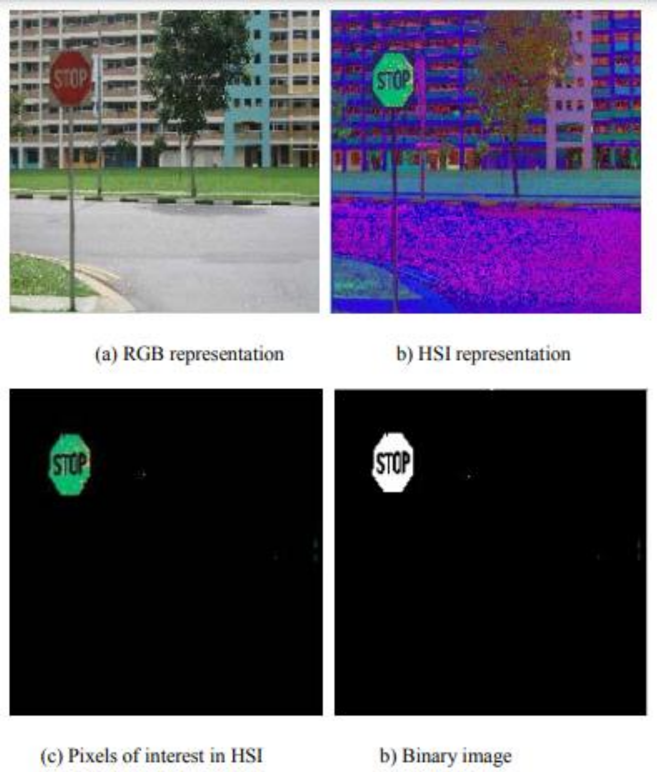

Fig 3. Result of HSI color space segmentation, courtesy[28]

• CHROMATIC/ACHROMATIC DECOMPOSITION

Color based detection is intended for basic colors, including but not limited to yellow, blue and red. Chromatic/Achromatic decomposition approach attempts to locate those pixels which do not have any color information. A thorough explanation of such methods is given in [8], and they are listed as Ohta components method, saturation and intensity-based approach, normalized RGB differences, RGB differences method and chromatic/achromatic index method. In all of these techniques, various thresholds are applied on disparate color spaces to determine white color.

• PIXEL CLASSIFICATION

As we have seen above, the thresholds that are being used need to be altered on the basis of color spaces. These alterations/ fine tunings depend solely on the trained images and cannot be generalized. Some authors have attempted to turn this into a pixel classification problem from a color extraction one. SVM classification was used in [8] and [18], to classify different color pixels in comparison to background pixels. In other works, such as [19], input pixels were utilized for training a neural network for the same classification(color pixels). Since these methods are classifying every single pixel in the image, they will be considerably slower as compared to other methods.

TABLE 1. Comparison of color based detection methods(for the color red), Courtesy[1]

Methods	Detection Rate
RGB	97.23 %
HSV	88.92%
HIS	95.56%
Ohta	90.03%

III. Shape Based Detection

Along with distinct colors, traffic signs have definite shapes like circle, triangle, rectangle, octagon etc. As a result, it is a feature that can be used to detect and classify different signs. The different shape-based detection methods have been described below:

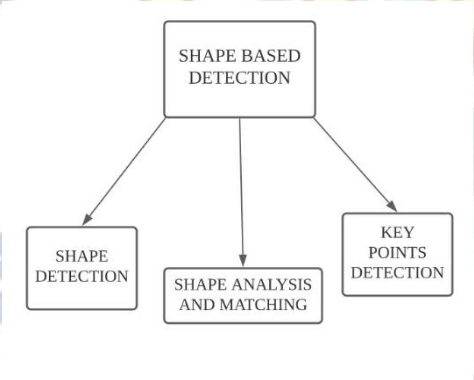

Fig. 4 Types of Shape Based Detection Methods

- **SHAPE DETECTION**

  Traffic signs with basic shapes are so designed that they can be easily detected by shape detection methods. One such method, Hough detection[9] is used to identify special shapes. However, they are generally slow when it comes to processing sizeable images. Based on the generalization of the hough method, Barrile et al.[10] refined road sign characterization so as to identify the different signs. Another derivation of the Hough method is fast radial symmetry[11], which uses the voting mechanism of radial symmetry to detect different signs present in the frame.

- **SHAPE ANALYSIS AND MATCHING**

  Detection of signs can also be done by analysing and matching different shapes with distinct edges. In [20], Fang et al. designed intricate shape models for circular, octagonal and triangular signs. These shape models however, were sensitive to noise and shape changes. The design for a decomposition approach was proposed in [21], to signify shapes that are complex using several simpler components.

- **KEY POINTS DETECTION**

  Key points detection can be used to detect the singularities as well as angular edges of traffic signs, which can further be used to represent traffic signs. A common key point descriptor, Scale Invariant Feature Transform(SIFT) can be used to achieve this, since it is both invariant to scale and rotation. In [22], Khan et al. used the Gabor filtering method to obtain local features that were also stable pertaining to the points of interest that were detected, and hence proceeded to develop a clustering method for traffic sign detection.

IV. Color and Shape Based Detection

In an attempt to reduce the amount of interferences incurred while separately gaining the information about both the color and the shape of different signs, methods which simultaneously use the shape and color information are preferred. As is natural, this would involve two main stages : first segmenting the color of the sign into a specific color space and thereafter detecting the shape of the sign.

Fig. 5 Results of traffic sign detection using both color and shape information, Courtesy: [29]

V. Machine Learning and Deep Learning Based Detection

- **ADABOOST BASED**
  AdaBoost, short for adaptive boosting, was developed by Freund and Schapire, and is a method used to enhance the working of machine learning algorithm. It is especially helpful when used with weak classifiers ,and then use them to make a single strong classifier for detection. Although such detection is considerably fast, scanning images and videos of high resolution still take a lot of time. In such scenarios, providing the AdaBoost detection process with already extracted Regions of Interest(ROI) or doing color extraction beforehand can be beneficial[23]. In some approaches, AdaBoost based detectors are used for coarse detection and then the images are further processed by other detection methods, like CNN or SVM.

- **SVM**
  The SVM and Histograms of Oriented Gradients (HOG) [4] based detection structure was first proposed to detect pedestrians and has been commonly used in different detection problems in the past decade. This structure utilizes HOG-like features to express the objects and treats the object detection problem as an SVM classification problem, in which each candidate is classified into objects or backgrounds. The SVM based detection structure has been successfully applied in TSD problems. The introduction of HOG-like features is the key of the success of SVM based detection methods. The HOG feature [4] is the most popular feature used in different detection problems. Using classical HOG features, the HOG+SVM based detection methods [31], [60] can achieve high detection results. Different features have been derived from HOG features.

CNN Based Methods:
The use of convolutional neural networks for traffic sign detection is especially beneficial since they are able to learn a whole hierarchy of features, owing to the fact that they can build high-level features derived from low-level features. The different CNN based methods for sign detection are listed below:

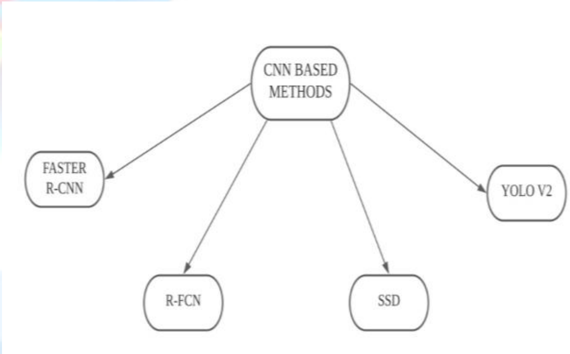

Fig. 6 Types of CNN Based Detection Methods

- **FASTER R-CNN**
  Faster R-CNN [24] presents a Region Proposal Network (RPN), a fully convolutional neural network(CNN) that has the ability to predict objectiveness score and object bounding boxes at the same time. Due to this, the model becomes completely trainable as the detection network get access to convolutional feature maps of the full images. These proposals are created in a sliding window approach, by sliding the output feature map under a small network, and the map is of the most

recent convolutional map. The RPN makes predictions for various region proposals at each of the locations of the sliding window, with a maximum number of possible proposals, at each location, denoted as k. These proposals are then factored with respect to k boxes of reference termed anchors. All of these individual anchor boxes are linked with a scale and aspect ratio, and their centre is designated at the location of the sliding window. For the purpose of reducing repetitiveness of the RPN proposals that might overlap, an algorithm termed Non-Maximum Suppression is first implemented on the regions of proposal based on the scores of their objectiveness. The above-mentioned algorithm performs the important function of merging several detections belonging to the identical objects. Once this action is complete, a particular number of the top ranked regions of proposal are dispatched to the detection network, and this ultimately leads regression of the bounding boxes and the classification of all the regions into specific object classes.

Fig. 7 Result of Faster R CNN sign detection method , Courtesy[30]

- **R-FCN**

Region-based Fully Convolutional Networks (R-FCN) [25] have the same architecture as that of RCNN but only with CNNs. That is to say, this approach employs a detector, based on regions, that is fully conventional and whose computation is revealed throughout the image, thus, removing the demand for the computation of subnetworks in every region, to be done multiple time for every image. Authors have suggested score maps(positive-sensitive) to tackle a problem that may arise amongst invariance of translation in classification of images and variance of translation in object detection. Hence, the R-FCN approach take on a chronological two- stage process of region proposal as well as classification, and here, the candidate regions are obtained with the help of a RPN that is fully convolutional.

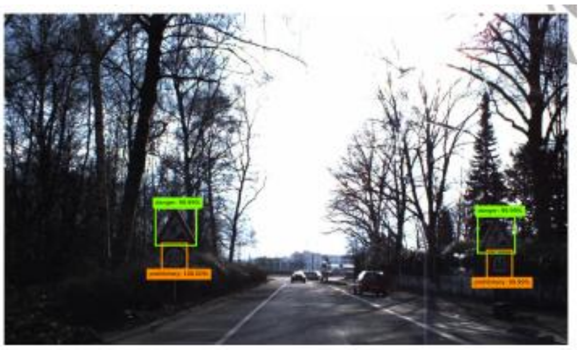

Fig. 8 Result of Faster R FCN sign detection method, Courtesy[30]

- **SSD**

As compared to the above two methods, SSD[26] wraps up all the computational works in a single feed forward CNN with the motive of directly inferring box offsets as well as category scores of objects. As a result, the stage of generating bounding box proposals and further resampling of features or pixels is not needed. This method uses a set of standard boxes (termed anchor boxes/anchors) that are chosen carefully by the developers themselves who have to notice the size of the objects being detected, and this has to be done beforehand. The aim of these boxes is to approximate the output space of bounding boxes over different aspect and scale ratios at every location on the map. To be precise, at each of the feature map cells, SSD can make predictions about the offsets, in relation to the anchor shapes in the cell, including the category scores that specify the occurrence of object classes in every one of the anchors. Furthermore, for object handling of different sizes, SSD combines its estimates/predictions from the feature maps. The initial network layers of the SSD model are formed on the basis of a standard architecture that is used to classify images of high quality. After this, a supplementary structure is attached to the network for the purpose of producing feature maps which are multi-scalable, and to be used for detection. This structure consists of feature layers (convolutional) and their goal is to reduce the size of the feature maps gradually and to permit detection predictions on various scales.

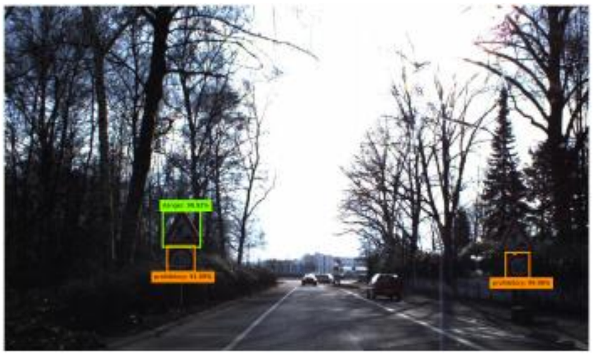

Fig. 9 Result of Faster SSD sign detection method, Courtesy[30]

- **YOLO V2**

The motivation being YOLO V2[13] is the RPN of Faster R-CNN, which uses anchor boxes that are hand-picked to make predictions on bounding boxes on the basis of the offsets to the anchors at every feature map location. Even so, on one hand, this approach runs k-means clustering, by utilizing a distance metric that is customized, and does so on the bounding boxes present in the training set (Eq. 1), and the reason behind doing this is to find good anchor boxes automatically instead of having to choose them manually. Choosing anchor boxes that are better makes it simpler for the network to learn how to make good detection predictions, whereas on the other hand, to stop any anchor box from inadvertently finding itself at any point in the image, the width and height of the box is predicted from the centroids of the cluster and the coordinates of the location , relative to the location of the grid cell, and with the application of a logistic activation to restrain the network predictions to always be between 0 and 1.

d(box, centroid) = 1 − IoU(box, centroid) (1)

the model for classification that is put to use as the base of YOLO V2 is termed Darknet-19. Additionally, batch normalization is also used by YOLO V2, which serves the purpose of model regularization and thus helps in improving the convergence, and does so while the model is being stabilized[27].

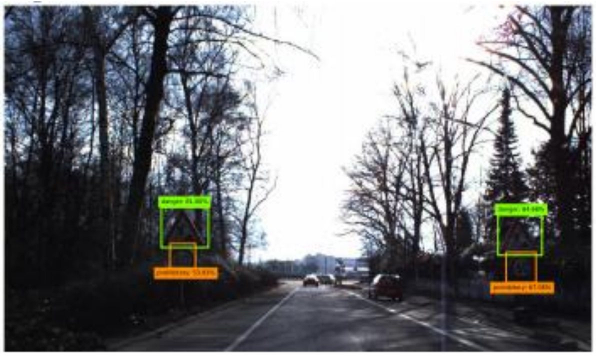

Fig. 10 Result of Faster YOLO V2 sign detection method, Courtesy[30]

VI. Conclusion

In this paper, a brief review on the existing methods for the traffic sign detection are discussed. We divide the traffic sign detection methods into four categories: color based methods, shape based methods, color and shape based methods, machine learning and deep learning based methods. The report lists research work carried out in this area. As we can see, the color based methods are easy to implement as well as fast. The shape detection methods are not very commonly used but can still be useful in detecting signs. The color and shape based methods usually need a good color enhancement process. The machine learning and deep learning methods give us the best results.

References

[1] Liu, C., Li, S., Chang, F. and Wang, Y., 2019. Machine vision-based traffic sign detection methods: Review, analyses and perspectives. *IEEE Access*, *7*, pp.86578-86596.

[2] Gudigar, A., Chokkadi, S. and Raghavendra, U., 2016. A review on automatic detection and recognition of traffic sign. *Multimedia Tools and Applications*, *75*(1), pp.333-364.

[3] Vennelakanti, A., Shreya, S., Rajendran, R., Sarkar, D., Muddegowda, D. and Hanagal, P., 2019, January. Traffic sign detection and recognition using a cnn ensemble. In *2019 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 1-4). IEEE.

[4] Tabernik, D. and Skočaj, D., 2019. Deep learning for large-scale traffic-sign detection and recognition. *IEEE Transactions on Intelligent Transportation Systems*, *21*(4), pp.1427-1440.

[5] Swathi, M. and Suresh, K.V., 2017, February. Automatic traffic sign detection and recognition: A review. In *2017 International Conference on Algorithms, Methodology, Models and Applications in Emerging Technologies (ICAMMAET)* (pp. 1-6). IEEE.

[6] Di Martino, F. and Sessa, S., 2020. PSO image thresholding on images compressed via fuzzy transforms. *Information Sciences*, *506*, pp.308-324.

[7] Lafuente-Arroyo, S., García-Díaz, P., Acevedo-Rodríguez, F.J., Gil-Jiménez, P. and Maldonado-Bascón, S., 2004. Traffic sign classification invariant to rotations using

support vector machines. *Proceedings of Advabced Concepts for Intelligent Vision Systems, Brussels, Belgium.*
[8] Gomez-Moreno, H., Maldonado-Bascon, S., Gil-Jimenez, P., & Lafuente-Arroyo, S. (2010). *Goal Evaluation of Segmentation Algorithms for Traffic Sign Recognition. IEEE Transactions on Intelligent Transportation Systems, 11(4), 917–930.*
[9] Yakimov, P. and Fursov, V., 2015, July. Traffic signs detection and tracking using modified hough transform. In *2015 12th International Joint Conference on e-Business and Telecommunications (ICETE)* (Vol. 5, pp. 22-28). IEEE.
[10] Barrile, V., Meduri, G.M. and Cuzzocrea, D., 2012. Automatic recognition of road signs by hough transform: Road-gis. *Journal of Earth Science and Engineering*, *2*(1), pp.42-50.
[11] Barnes, N., Zelinsky, A. and Fletcher, L.S., 2008. Real-time speed sign detection using the radial symmetry detector. *IEEE Transactions on Intelligent Transportation Systems*, *9*(2), pp.322-332.
[12] Freund, Y. and Schapire, R.E., 1997. A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, *55*(1), pp.119-139.
[13] Redmon, J. and Farhadi, A., 2017. YOLO9000: better, faster, stronger. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 7263-7271).
[14] Bimbraw, K., 2015, July. Autonomous cars: Past, present and future a review of the developments in the last century, the present scenario and the expected future of autonomous vehicle technology. In *2015 12th international conference on informatics in control, automation and robotics (ICINCO)* (Vol. 1, pp. 191-198). IEEE.
[15] González, Á., Garrido, M.Á., Llorca, D.F., Gavilán, M., Fernández, J.P., Alcantarilla, P.F., Parra, I., Herranz, F., Bergasa, L.M., Sotelo, M.Á. and De Toro, P.R., 2011. Automatic traffic signs and panels inspection system using computer vision. *IEEE Transactions on intelligent transportation systems*, *12*(2), pp.485-499.
[16] Šegvić, S., Brkić, K., Kalafatić, Z., Stanisavljević, V., Ševrović, M., Budimir, D. and Dadić, I., 2010, September. A computer vision assisted geoinformation inventory for traffic infrastructure. In *13th International IEEE Conference on Intelligent Transportation Systems* (pp. 66-73). IEEE.
[17] Yan, W.Y., Shaker, A. and Easa, S., 2013. Potential accuracy of traffic signs' positions extracted from Google street view. *IEEE Transactions on Intelligent Transportation Systems*, *14*(2), pp.1011-1016.
[18] Gomez-Moreno, H., Gil-Jimenez, P., Lafuente-Arroyo, S., Vicen-Bueno, R. and Sanchez-Montero, R., 2003. Color images segmentation using the support vector machines. *Recent Advances in Intelligent Systems and Signal Processing*, pp.151-155.
[19] Zhang, K., Sheng, Y. and Li, J., 2012. Automatic detection of road traffic signs from natural scene images based on pixel vector and central projected shape feature. *IET Intelligent Transport Systems*, *6*(3), pp.282-291.
[20] Fang, C.Y., Chen, S.W. and Fuh, C.S., 2003. Road-sign detection and tracking. *IEEE transactions on vehicular technology*, *52*(5), pp.1329-1341.
[21] Xu, S., 2009. Robust traffic sign shape recognition using geometric matching. *IET Intelligent Transport Systems*, *3*(1), pp.10-18.
[22] Khan, J., Bhuiyan, S. and Adhami, R., 2014. Hierarchical clustering of EMD based interest points for road sign detection. *Optics & Laser Technology*, *57*, pp.271-283.
[23] Liu, C., Chang, F. and Chen, Z., 2014. Rapid multiclass traffic sign detection in high-resolution images. *IEEE Transactions on Intelligent Transportation Systems*, *15*(6), pp.2394-2403.
[24] Ren, S., He, K., Girshick, R. and Sun, J., 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems* (pp. 91-99).
[25] Dai, J., Li, Y., He, K. and Sun, J., 2016. R-fcn: Object detection via region-based fully convolutional networks. In *Advances in neural information processing systems* (pp. 379-387).
[26] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.Y. and Berg, A.C., 2016, October. Ssd: Single shot multibox detector. In *European conference on computer vision* (pp. 21-37). Springer, Cham.
[27] Ioffe, S. and Szegedy, C., 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*.
[28] Nguwi, Y.Y. and Kouzani, A.Z., 2006, July. Automatic road sign recognition using neural networks. In *The 2006 IEEE International Joint Conference on Neural Network Proceedings* (pp. 3955-3962). IEEE.
[29] Zheng, Z., Zhang, H., Wang, B. and Gao, Z., 2012, September. Robust traffic sign recognition and tracking for advanced driver assistance systems. In *2012 15th International IEEE Conference on Intelligent Transportation Systems* (pp. 704-709). IEEE.
[30] Arcos-Garcia, A., Alvarez-Garcia, J.A. and Soria-Morillo, L.M., 2018. Evaluation of deep neural networks for traffic sign detection systems. *Neurocomputing*, *316*, pp.332-344.