An overview on various methods of detection and recognition of traffic signs by Autonomous Vehicles

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Abstract— **The improvement of traffic signs detection and recognition by autonomous vehicles has reached high level of development in recent years. It is an important concept to provide more safety and comfortability for the passengers during the driving task. Researchers started to work on increasing autonomous vehicle detecting performance, by conducting suitable solutions to overcome visibility constraints of the traffic signs, such as, weather conditions, air pollution, color fade after long exposure to sunlight and different types of obstacles. These solutions represented by introducing several color spaces to have preferable traffic sign segmentation, for a data set of captured images and videos. Afterwards, they have been processed to classifier models to recognize and classify the categories of traffic signs in an accurate manner. This paper summarizes the recent studies on traffic signs detection and recognition by autonomous vehicles; it provides a comparison to the used methodologies and applications, and refers to their respective outreach and limitations. Recommendations for future developments were also presented in this study.**

Keywords— Autonomous vehicles; traffic sign detection; color space; traffic sign recognition

I. INTRODUCTION

Traffic signs are visual objects existed at road sides to provide information, navigation rules, restrictions and warnings to drivers. They are usually designed with great visual properties to be easily noticed and recognized by the drivers. With the rapid development of economy and technology in the modern society, self-driving technology can assist, or even independently complete the driving operation, which is of remarkable importance to mitigate physical fatigues of human bodies, and considerably reduce accidents. However, it should be taken into consideration that the autonomous vehicles (AVs) are still in the test phase to alter the conventional vehicles in transportation system. This highly depends on some socio-demographic characteristics for example: age, which significantly influence expectations and acceptability in terms of perception and attitude towards AVs [1]. AVs capabilities promise high development in technology, when the vehicles provide groups of distributed sensors which have the ability to scan the vicinity, and also have the responsibility of controlling driving speeds, braking, and path tracking systems autonomously. The development also includes a crucial side represented by traffic sign detection and recognition which will directly affect the implementation of driving behaviors. Traffic sign detection stands for the process of an accurate extraction of objects that matched the traffic signs, from the actual surroundings, usually depending on the color, shape and texture of signs' descriptive symbols. While sign recognition technology usually refers to recognizing traffic signs based on the information included in their pictograms. Recently, it has been demonstrated that the sensory cognitive process of human brains can be well simulated via forward learning and feedback mechanism, thereby gradually improving the ability of traffic sign classification [2]. One of the primary goals of Cognitive Infocommunications is to provide augmentation to the sensory capabilities of both the human user and the artificially cognitive system so that they can communicate with each other at a higher level in order to mitigate the difficulties of human-virtual machine interaction and the conflicting goals of situation awareness [3]. Therefore, enabling the computers to extract information from digital images or videos is rapidly growing along-side the rise of deep learning and is used in conjunction with numerous problems within artificial intelligence. Nowadays, the popularity and substantial research in deep learning have enabled Convolutional Neural Network to surpass human image classification performance [4]. This paper reviews the algorithms and models developed so far, with the aim to summarize their findings and to evaluate their outreach and limitations.

II. SELECTION OF TRAFFIC SIGN CATEGORIES

A large and growing body of literature has investigated the performance of autonomous vehicles to detect and recognize various types of road sings. Several categories of traffic signs have been studied by the researchers depending on their importance and priority. De La Escalera et al. [5] addressed four types of traffic sings according to their form and shape:

- Warning signs which have equilateral triangular shape with one vertex upwards.
- Prohibition signs that have white round shape enclosed with red borders.
- Obligation sings which are circular and have blue background.

- Informative signs include blue or green rectangular boards refer to general places and facilities.

The authors referred to two exceptions, although they are important signs, but they do not undergo the above categories. These are: YIELD signs, which has an inverted triangular shape, and STOP signs with an octagonal shape.

More recent attention has focused on specified selections for the types of road traffic signs. Zaklouta and Stanciulescu in [6] focused on the shape of traffic sign to be selected more than the information inside. They have selected a data set of 24 classes of traffic signs, 12 circular and 12 triangular shaped signs, to represent speed limit and warning signs respectively. Similarly, García-Garrido et al. [7] studied four types of signs existing in the Spanish driving code, prohibition, obligation, warning, and informative. The study considered the octagonal STOP sign as a circular in shape for the detection issues. On the other hand, some researchers worked only on one type of traffic signs, like Vishwanathan et al. [8] who had selected the ocatgonal STOP sign to be the studied sign, and had used different methods of edge detection, and applied a comparison between them to obtain the most accurate results. While Zhang [9] has tested STOP signs and yellow warning signs for the detection performance.

Zhu et al. [10] have covered three categories of traffic sign include warning signs, prohibition signs and mandatory. They have used a large scale of image data set in China with a benchmark named Tsinghua-Tencent 100K. Later, Lai et al. [11] have has studies the same three categories of traffic signs with less number of images (1000 images), which have been trained and tested to get better accuracy rates of detection and classification. Similarly, a total number of 2718 images were collected in Saudi Arabia by Alghmgham et al. [12] from a database named (Saudi Arabia Traffic and Road signs). These images are divided into 24 most available Arabian traffic signs, that undergo the categories of warning signs, and speed limits and mandatory signs.

In contrast to earlier selections, Ellahyani et al. [13] and Cao et al. [14] gave more interest to the selection of traffic signs, when six subset categories of traffic signs have been chosen during their studies. These are: speed limit, other prohibitory, derestriction, mandatory, danger, and unique signs. This will ensure recognizing any type of traffic signs, that belongs to the German Traffic Sign Recognition Benchmark (GTSRB). See Fig. 1.

Fig. 1. Subsets of traffic signs in GTSRB data set. (a) Speed limit signs. (b) prohibition signs. (c) Derestriction signs. (d) Mandatory signs. (e) Danger signs. (f) unique signs. [13]

Collectively, these studies addressed different selections of the most common types of traffic signs for the purpose of detection and recognition. But in fact, there might be other types of traffic sings, for example, word message traffic sings, that should also be considered in future studies. The impact of these signs is highly affecting on driving behavior, and understanding this type of traffic signs varies according to different languages at different regional areas.

III. Detection of Traffic Sings

Traffic sign detection and recognition systems started to be appeared at the late 80's, but it has not been an actual use until recent times when real time performing systems have been successfully achieved [15],[16]. This achievement plays an important role in enhancing car safety and driving comfort using ADAS. In order to understand the process of detecting various categories of traffics signs, two important aspects that have been intensively studied by the researchers should be discussed: determination of category location and detection technique.

A. Category determination using shapes and color spaces

Road traffic signs are usually installed in order to provide an entire visual information to human driving task. This information includes the current state of the road, restrictions, limitations and other warnings. The easiest way to deliver this information to the driver represented by recognizing the shape of the signs and its color.

Automated Driving, on the other hand, has a great challenge to recognize currently available road signs. Bearing in mind, that the analysis of human behavior helps the computers to respond more. Collaboration, in turn, only works when both sides are aware of each other's limits [17]. Multiple systems were used to simplify the process of color analyzing by autonomous vehicles. De La Escalera et al. [5] have used the most intuitive RGB color space. In this system, every pixel is defined by three components: red, green, and blue. In addition, corner detection has also been applied for the purpose of image identification. After applying RGB color space to the images, the authors indicates that this color space seems to be invariant, and it could be affected by lighting changes to a great extent. This indication was also approved by Vishwanathan et al. [8] who gave less interest to color space, when he applied Gray scale to a number of images and videos taken for car's surroundings, captured by a mounted camera fixed on a test vehicle. The reason behind that, was to mostly depend on the edge detection of the STOP sign, rather than depending on color information. While Alghmgham et al.[12] made a transformation from RGB system to Gray scale color space, for the traffic sign images before being processed to feature extraction.

More works has been pursued to conduct new systems to get better image segmentation. Lai et al. [11] introduced YCbCr color space to divide the color channels for feature extraction. Where Y stands for represents the illumination factor, Cb and Cr represent the blue-difference and red-difference components. This color space was mainly applied for continuous image processing in a recorded video.

Soheilian et al. [18] cited by Ellahyani et al [13], stated that Color segmentation algorithms are affected by various parameters, such as, seasonal climate conditions, brightness or darkness during the day, shadows, inclined and tilted road signs, the influence of other objects existing on the street which has the same color of the signs, and many other parameters. Because of this, color information has been adopted only to extract region of interest (RIO), but not for image classification, to overcome the circumstances. Therefore, Ellahyani et al [13] proposed the main three shapes of signs: circular, triangular and rectangular, to be adapted during image segmentation process. In recent years, Hue, Saturation, Value (HSV) color space were used to overcome the inconvenience of other color space, related to illumination difficulties and visual deterioration of the signs. Cao et al. [14] for example, used HSV color space because it has faster speed detection, as compared to the color spaces used in other approaches. See Fig. 2

In General, the researchers had used the most common color spaces in order to get an accurate detection of the image colors, and then conduct segmentation to the ROIs. Each has its own advantages, but the fact that HSV color space has distinguished traits, cannot be overlooked. In addition, it has provided great features, that may help to later perform the detection and recognition processes of road signs in the best possible manner.

B. *Detection Techniques*

Traffic sign detection is the technology that aims to identify traffic signs, through certain digital images taken on the street during the movement of an autonomous vehicle. The detecting process usually conducted by applying certain mathematical algorithms, to extract the interesting traffic sign regions from those images sufficiently.

A number of techniques and methodologies have been used in the past to achieve acceptable results of detecting road traffic signs. Zhang [9] have selected only 20 images to be tested for the detection by conducting Hough transform method. García-Garrido et al. [7] have also used restricted Hough transform for circumferences in order to detect circular signs, and then used straight lines for triangular ones. This method relies on preserving contours, which is very important for detecting traffic signs using shape information. It has the ability to detect any kind of signs, except the informative ones, even in adverse weather conditions, as shown in Fig. 3.

Canny [19], Zhang et al. [20] and Sobel [21] cited by Vishwanathan et al. [8], have applied different methods of image edge detection. Canny's method main criteria was to lower the error rate, where the distance between the points marked by the detector and the center of the true edge is minimized. Zahng's method, on the other hand, followed the principle of linear prediction for the future values of a signal image. The method relied on the fact that edge points in the image have sharp changes in intensity, therefore, large prediction errors occur at these points compared with gradual changes in intensity found in other points. Hence, the method aimed to optimize filter coefficients in order to reduce the prediction errors. While Sobel's method followed the principle of image gradient for edge detection. Where the gradient magnitude of each point on the image was calculated. If the gradient of a specific point exceeds some threshold, then the edge location is declared. Vishwanathan et al. in [8] made a comparison to evaluate the performance of each of the three methods, and reached the best obtained results among them.

Zaklouta and Stanciulescu [6] stated that during segmentation process, the number of true detections decreases, and morphological operators falsely eliminating road sign images with a low contrast to the background, or due to poor illumination or deterioration of the sign itself. This might be the reason behind using red color enhancement segmentation technique similar to [5], but taking into consideration, the use of Histogram of Oriented Gradients (HOG), which is fast to compute and robust changes in illumination.

Cao et al. in [14] explained that during the driving task of an autonomous vehicle in the streets. All existing objects, not just traffic signs, are observed. For example, the colored clothes of pedestrians, outdoor advertising billboards and other led posters might be existed. The interference between these colors and the colors of traffic signs will cause blurring for the vehicle detection. Therefore, there will be a need of filtering the surrounding environment from useless objectives, in order to obtain the required visibility and the effective detection of Region of Interests (ROIs). The authors illustrated

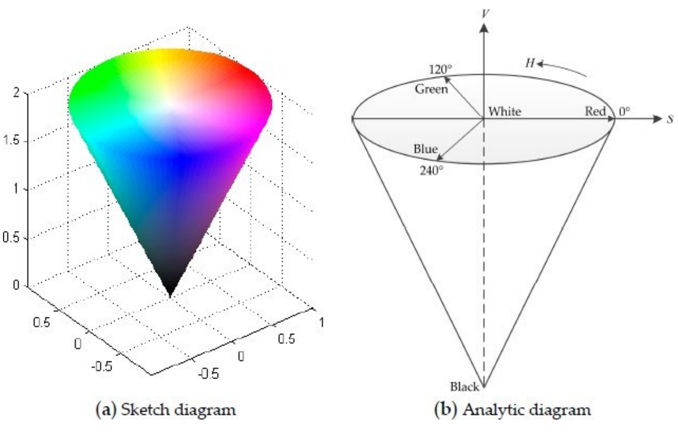

Fig. 2. HSV Color Space [14]

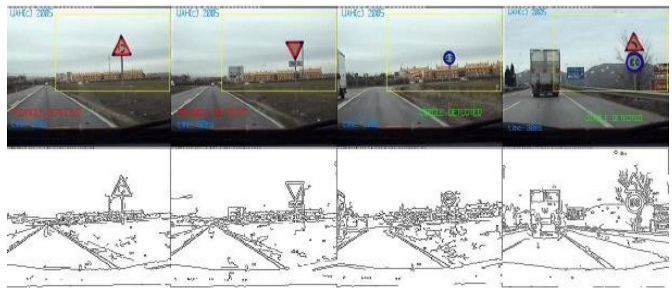

Fig. 3. Real images sequence, detected on the road, with the search area within each image outlined (square window), and Canny image used for contour information search. [7]

the procedures of passing the image of a circular traffic sign through a corrosion and expansion processes. Both procedures are conducted together to filter the interference and produce the desired shape. Sometimes the ROI cannot be completely appeared because of the faded color of the traffic sign, or the sign itself might be blocked by an obstacle. For this reason, filling process is applied to overcome these conditions, and to complete visualization of the traffic sign. At the end, the effective detection of traffic signs is realized.

Lim et al. [22] presented a General Purpose Graphics Processing Unit (GPGPU) based real-time traffic sign detection and recognition method that is robust against illumination changes due to weather or time of day, and also to overcome problems related to low image quality at high speeds.

Wang et al. [23] in their study, conducted an algorithm that deals with 3D object detection, as it represents an essential task for autonomous driving. The authors distinguished their work among relevant approaches by the conclusion that says that the representation of most of the data could be accounted while the data quality has no influence. This could be discovered through the use of convolutional neural networks and understanding the inside work. The study used pseudo-Lidar in order to conduct a conversion for the image-based maps to new representations, basically simulating the LiDAR signal. At the end, remarkable improvements have been achieved by using these representations to apply various Lidar based detection algorithms on KITTI benchmark.

Houben et al. [24] came with a great evolution to the field of traffic signs detection and recognition. The authors have separate sign detection from sign classification, this is by introducing a traffic sign data set that helps to conduct the detection process on real-world benchmark. The authors have selected the evaluation metric carefully and considered a web-interface to complete the process of comparison of various approaches. The study evolved three selected detection algorithms: A Viola-Jones detector, a linear classifier based on HOG features, and a model-based approach including number of comparable algorithms that have been suggested lately. The obtained results were very promising and will guarantee an evolution for traffic sign detection general industry.

Recent advanced methods have facilitated investigation of providing faster and clearer sign detection. Ruta et al. [25] have introduced a novel method for image representation and discriminative local feature selection which is utilized in a traditional three-stage framework involving detection, tracking and recognizing a dataset of 13287 images. The detector captures instances of equiangular polygons in the scene which is first appropriately filtered to extract the relevant color information and establish the regions of interest. a distance metric based on the Color Distance Transform (CDT) is used to predict the position and the scale of the detected sign candidate over time to reduce computation.

Satılmış et al. [26] have created a traffic sign dataset from ZED stereo camera mounted on a mini autonomous vehicle and used Tiny-YOLO real-time object detection and classification system to detect and classify traffic signs. The dataset consists of seven traffic sign classes, most of them belongs to the mandatory category, then, an Intersection over Union (IOU) have been used as an evaluation metric to assess the accuracy of an object detector.

A focus should also be applied to the data source, the architecture with its common data model, and the main implementation steps of the system. Sik et al. [27] Proposed to create an online tool where users could parametrize their trips around the city using the live information, and then visualize them on a map. It will be possible to extract ROIs, also access and get other live public transportation data.

Overall, various methods have been used for traffic sign image detection in the presented studies, but it is difficult to decide which approach is supposed to be the leading one, to explain the most precise detection process. Mainly because few standard databases of traffic sign images are available, and it is hard to conduct comparison to the study achievements. In addition, it is well known that the compilation of a set of road scene images is a very time-consuming task, this might be the reason behind the difficulty to evaluate results fineness for some studies which are based on a small set of images.

IV. Recognition and Classification of Trffic Signs

Most of the road signs contain a pictogram, a string of characters, or both. Different classifiers which have been fed with different features are representing the recognition modules used to identify the detected road signs [13]. Prior studies have noted the importance of applying neural networks on the detected sign image to classification successfully. De La Escalera et al. in [5] used two different detection algorithms according to the shape of the sign, either circular or triangular. Therefore, two neural networks were trained for the image through presenting the image as the input pattern, to perform the classification of the signs. The procedures include image normalization and obtained 1620 training patterns, with an acceptable sign slope of $\pm 6^{\circ}$.

The present studies are designed to determine the effect of using the most common classifier models and establishing comparison between them. Ellahyani at el. In [13] have used Random Forest and SVM classifiers on different features, such as Histogram of Oriented Gradient (HOG), Local Binary Pattern (LBP), and Local Self-Similarity (LSS). The authors started to try the features independently with Random Forests Classifier, then those features were combined to create a new one. The interest of using Random Forests has been obviously increased, because they can be more accurate and robust to noise than single classifiers [6]. On one hand, Random Forest consists of an arbitrary number of simple trees, where the final predicted class for a test object is the mode of the predictions of all individual trees [28]. On the other hand, the basic concept of SVM is to transform the input vectors to a higher dimensional space by a nonlinear transform, and then data will be separated by the use of a hyperplane. At the end of their work, the authors stated that Random Forest classifier with HIS-HOG+LSS features have been adopted as a proposed recognition method to classify the detected shapes.

Zaklouta and Stanciulescu in [6] have observed a distinct difference between tree classifiers and machine learning classifiers. Tree classifiers have the advantage of being easy to train and update. Therefore, the authors conducted a comparison between the tree classifiers k-d and random forest, and SVM classifier. The also article declared that the spatial weighting of the HOG features in the K-d tree improves the classification accuracy by over 20%, attaining the best overall rate of 80.90%. This outperforms the Random Forest by about 10%. Fig. 4 illustrates the process of segmenting, detecting and recognizing a speed limit sign image conducted by this study. Lai et al. in [11] have presented a traffic sign recognition and classification method based on Convolutional Neural Network and Support Vector Machine (CNN-SVM). The method procedures include collecting 1000 training images, mainly obtained from mobile phone shootings.

Along the same lines, Cao et al. in [14] have used classic LeNet-5 network model for the recognition and classification of a single target. A considerable improvement has been made to the robustness and stability of the training network, as well as the overall convergence speed, to further expand the outstanding advantages of CNN in graphics recognition.

Many researchers have used GTSRB data base to evaluate the recognition and classification algorithms. The internal traffic signs are collected from the real road traffic environment that covered large spaces in Germany, later it has been considered as a common traffic sign dataset which can be highly recommended and used by experts in computer vision, self-driving and other fields. GTSRB includes 43 classes of traffic signs, divided into six categories: speed limit, danger, mandatory, prohibitory, derestriction and unique traffic signs. The same type of traffic signs includes different resolutions, changes in illumination conditions, weather conditions, occlusion rate and tilt levels which make the dataset similar to the actual road scenes [14].

Other researchers, like Alghmgham et al. [12] proposed a study to develop a new database for Arabic Traffic and Road Signs using Deep CNN. This study considered as the first trial to conduct a complete database for the traffic signs in Arab countries region. Therefore, the authors collected a dataset consists of 2,728 images captured for 24 traffic signs in Saudi Arabia and transformed into grayscale color space to be processed to CNN for sign classification.

Zhu et al. [10] have demonstrated how a robust end-to-end convolutional neural network (CNN) can simultaneously detect and classify traffic signs. using a dataset of a large traffic sign benchmark from 100000 Tencent Street View panoramas, as mentioned earlier. While, Lim et al. [22] applied a hierarchical classifier structure using SVM and CNN on a dataset, which uses the Vienna convention traffic rules in different areas in Germany and South Korea.

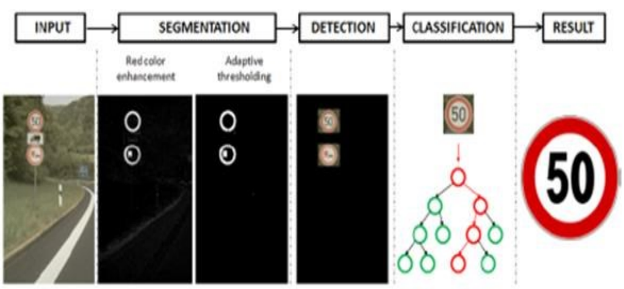

Fig. 4. Three stage approach proposed for Traffic Sign Recognition (TSR): (i) segmentation (ii) detection using HOG/SVM, (iii) classification using tree classifiers.[6]

Ruta et al. [25], introduced a novel feature selection algorithm that extracts for each sign a small number of critical local image regions including the variation between this sign and all other signs. Within these regions, robust image comparisons are made using a distance metric based on a (CDT), which enables efficient pictogram classification. Fig. 5 represents a screenshot illustrates how the used system detects and recognizes a sign in a sample frame of the input video.

Behloul et al. [29], have chosen SURF descriptor during the recognition phase, because of the its superiority against other descriptors in terms of the runtime performance and robustness to illumination changes. This is very important to overcome high sensitivity to the background noise present when the matching measure is used between the query image and the images in the database.

Tabernik et al. [30] presented a novel dataset, termed the DFG traffic sign dataset for the purpose of detection and recognition of a large number of traffic sign categories includes 200 traffic sign categories spread over 13,000 traffic sign instances and 7000 high-resolution images. The authors proposed several adaptations to Mask R-CNN that improve the learning capability on the domain of traffic signs.

Farag in [31] proposed and developed a Convolutional Neural Network based classifier "WAF-LeNet" to be used in traffic signs recognition and identification as an empowerment of autonomous driving technologies. GTSRB have been used during image training, validation and testing. The proposed approach proved successful in identifying correctly 96.5% of the tested data set

V. Summarized Results of Reviewed Research

The results of detection, recognition and classification of traffic signs, and the processing speed achieved by the reviewed studies are summarized in Table 1. Where various conducted methods, features and applied data set are included.

Fig 5. The process of traffic sign recognition shown in a screenshot. The appeared candidates represent the best obtained scores. [25]

TABLE 1. DETECTION, RECOGNIITION AND CLASSIFICATION RESULTS OF REVIEWD REASEARCH

Authors	Application	Method/Algorithm/Feature	Rate %	Time	Dataset
De La Escalera et al. [5]	Classification	CNN	97.00	30-40 ms	1620 training images
Zaklouta and Stanciulescu [6]	Detection	HOG/linear SVM	90.90	55.54	14,763 training images
	Classification	k-d tree	88.73	------	GTSRB
	Classification	Random Forest	97.20	-----	GTSRB
García-Garrido et al. [7]	Detection	Hough transform	99.00	33 ms	Spanish driving code
Vishwanathan et al [8]	Detection	Linear Prediction Method	-----	-----	-----
Zhang [9]	Detection	Hough transform	80.00	-----	20 images
Zhu et al. [10]	Detection	CNN	84.00	-----	Tsinghua-Tencent 100K
	Classification	CNN	88.00	-----	Tsinghua-Tencent 100K
Lai et al. [11]	Classification	CNN	98.18	-----	1000 images
	Classification	CNN-SVM	98.60	-----	1000 images
Alghmgham et al. [12]	Recognition	CNN	100.00	-----	2718 images (ATRS)
Ellahyani et al. [13]	Detection	HSI-HOG	91.13	8-10 ms	GTSDB
	Detection	HSI-HOG	90.27	-----	STS
	Classification	HSI-HOG+LSS/Random Forest	97.43	28.93 ms	GTSRB
	Classification	HSI-HOG+LSS/ SVM	96.91	53.12 ms	GTSRB
Cao et al. [14]	Recognition	LeNet-5 CNN	99.75	5.4 ms	GTSRB
Lim et al. [22]	Classification	CNN-SVM	97.60	14.42	German – Day testset
	Classification	CNN-SVM	99.03	14.12	Korea – Day testset
	Classification	CNN-SVM	97.91	13.94	Korea – Night testset
Wang et al. [23]	Detection	pseudo-LiDAR	74.00	-----	KITTI 3D Benchmark
Houben et al. [24]	Detection	HOG + LDA	91.30	-----	GTSDB (Prohibition)
	Detection	Hough-like	55.30	-----	GTSDB (Prohibition)
	Detection	Viola-Jones	98.80	-----	GTSDB (Prohibition)
Ruta et al. [25]	Detection	Color Distance Transform CDT	90.30	-----	13,287 images
	Classification	CNN	90.20	-----	13,287 images
Satılmış et al. [26]	Classification	Tiny-YOLO	99.97	-----	3566 images
Behloul et al. [29]	Detection	BoxOut	95.65	-----	48 images
	Classification	SURF	97.72	80 ms	48 images
Tabernik et al. [30]	Detection	Mask R-CNN	97.50	-----	STS
	Detection	Mask R-CNN	96.50	-----	DFG 200 categories
Farag [31]	Classification	WAF-LeNet CNN	96.50	-----	GTSRB -test data
	Classification	WAF-LeNet CNN	100.00	-----	GTSRB - robustness data

According to the obtained studies' results, three groups can be obviously noticed representing detection, recognition, and classification rates. The first group is low accuracy rate group (less than 90%), represented by [9], [10] and [23], in this group, various reasons were behind getting low rates, such as the small size of used data set of traffic sign images, and also because of the limitations present in the used detection and recognition algorithms to the quality and resolution of these images. The second group is moderate to high accuracy rate group (greater than 90% and less than 99%). The majority of the studies falls in this group, mainly because the researchers tried to bring up the newest knowledge and ideas to the traffic signs detection and recognition field of study. Eventually, the applied methodologies and the machine-learning techniques which have been used were comparable to a great extent and led to close range of accuracy. The third group is the high accuracy rate (more than 99%), where researchers in [7], [12], [14], [22], [26] and [31] have achieved high records of detection and classification rates. This leads to the conclusion that tells a robust technological assurance will be offered for the further development of advanced driving assistance systems.

Despite the fact that deferent performance metrics have been used by the researchers, but the majority of the studies promises distinguished results in terms of detection and recognition accuracy rates which leads to provide sufficient comfortability to the development of automotive industry. It is obvious that most of the reviewed research seem to be recently published, this is because the fact that tells a fast- growing field of study.

VI. Conculsion

This paper has reviewed a brief state of art in traffic sign detection and recognition by autonomous vehicles. This topic enhances traffic safety by informing the driver of speed limits or possible dangers such as icy roads, imminent road works or pedestrian crossings. Most of the applied algorithms of the presented studies consist of three stages: segmentation of the ROIs, shape detection for the sign image, and recognition and classification stage to identify the type of the sign. Some of the researchers have faced several difficulties during conducting their methodologies, such as poor quality of the sign image due to low resolution, bad weather conditions, high or low illumination, as well as tilting, rotation, occlusion and deterioration of the traffic signs. Other researchers suffered from limited memory and processing capacities in real-time applications of Advanced Driver Assistance Systems (ADAS). Different models were used in the recent studies to achieve remarkable advantages of classification accuracy and algorithm time-consuming.

However, detection and recognition methods achieved a high accuracy rate, mostly varied from 90% to 100%, but in fact, they are still far from a real-time ADAS applications where the road traffic sign should be detected and classified in real time. Therefore, considerably enhancing the driving safety of intelligent vehicles in the actual driving environments and effectively meeting the real-time target requirements of smart cars are highly recommended.

Regarding the traffic sign recognition and classification accuracy, as well as the needed processing speeds to conduct the relevant algorithms, the imposed question by the community could be confidently answered in this manner, that recent traffic sign detection and classification methods has proven the same performances in real-world application and has outstanding advantages. Mainly based on increasing the autonomous vehicles safety during the driving task in an actual environment. In addition, the real-time objective needs of those intelligent vehicles can be efficiently met to ensure better technological enhancement.

In the future works, the inclusiveness and anti-error recognition of the traffic signs, can be further optimized and improved to contribute the overall performance of detection and recognition algorithms.

References

[1] D. Földes, C. Csiszár, and A. Zarkeshev, “User expectations towards mobility services based on autonomous vehicle,” 2018.

[2] Q. Liu *et al.*, “A review of image recognition with deep convolutional neural network,” in *International conference on intelligent computing*, 2017, pp. 69–80.

[3] P. Baranyi and Á. Csapó, “Definition and synergies of cognitive infocommunications,” *Acta Polytech. Hungarica*, vol. 9, no. 1, pp. 67–83, 2012.

[4] R. Kalliomäki, “Real-time object detection for autonomous vehicles using deep learning.” 2019.

[5] A. De La Escalera, L. E. Moreno, M. A. Salichs, and J. M. Armingol, “Road traffic sign detection and classification,” *IEEE Trans. Ind. Electron.*, vol. 44, no. 6, pp. 848–859, 1997.

[6] F. Zaklouta and B. Stanciulescu, “Real-time traffic sign recognition in three stages,” *Rob. Auton. Syst.*, vol. 62, no. 1, pp. 16–24, 2014.

[7] M. Á. García-Garrido, M. Á. Sotelo, and E. Martín-Gorostiza, “Fast road sign detection using hough transform for assisted driving of road vehicles,” in *International Conference on Computer Aided Systems Theory*, 2005, pp. 543–548.

[8] H. Vishwanathan, D. L. Peters, and J. Z. Zhang, “Traffic sign recognition in autonomous vehicles using edge detection,” in *Dynamic Systems and Control Conference*, 2017, vol. 58271, p. V001T44A002.

[9] S. Zhang, “Traffic sign detection for vision-based driver's assistance in land-based vehicles,” Technical report, School of Aeronautics and Astronautics-Stanford University, 2016.

[10] Z. Zhu, D. Liang, S. Zhang, X. Huang, B. Li, and S. Hu, “Traffic-sign detection and classification in the wild,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 2110–2118.

[11] Y. Lai, N. Wang, Y. Yang, and L. Lin, "Traffic Signs Recognition and Classification based on Deep Feature Learning.," in *ICPRAM*, 2018, pp. 622–629.

[12] D. A. Alghmgham, G. Latif, J. Alghazo, and L. Alzubaidi, "Autonomous traffic sign (ATSR) detection and recognition using deep CNN," *Procedia Comput. Sci.*, vol. 163, pp. 266–274, 2019.

[13] A. Ellahyani, M. El Ansari, and I. El Jaafari, "Traffic sign detection and recognition based on random forests," *Appl. Soft Comput.*, vol. 46, pp. 805–815, 2016.

[14] J. Cao, C. Song, S. Peng, F. Xiao, and S. Song, "Improved traffic sign detection and recognition algorithm for intelligent vehicles," *Sensors*, vol. 19, no. 18, p. 4021, 2019.

[15] D. M. Gavrila, U. Franke, C. Wohler, and S. Gorzig, "Real time vision for intelligent vehicles," *IEEE Instrum. Meas. Mag.*, vol. 4, no. 2, pp. 22–27, 2001.

[16] N. Barnes and A. Zelinsky, "Real-time radial symmetry for speed sign detection," in *IEEE Intelligent Vehicles Symposium, 2004*, 2004, pp. 566–571.

[17] A. Torok, "From human-computer interaction to cognitive infocommunications: A cognitive science perspective," in *2016 7th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, 2016, pp. 433–438, doi: 10.1109/CogInfoCom.2016.7804588.

[18] B. Soheilian, N. Paparoditis, and B. Vallet, "Detection and 3D reconstruction of traffic signs from multiple view color images," *ISPRS J. Photogramm. Remote Sens.*, vol. 77, pp. 1–20, 2013, doi: https://doi.org/10.1016/j.isprsjprs.2012.11.009.

[19] J. Canny, "A Computational Approach to Edge Detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-8, no. 6, pp. 679–698, 1986, doi: 10.1109/TPAMI.1986.4767851.

[20] J. Z. Zhang, P. C. Tay, and R. D. Adams, "A novel image edge detection method using Linear Prediction," in *2010 53rd IEEE International Midwest Symposium on Circuits and Systems*, 2010, pp. 620–623, doi: 10.1109/MWSCAS.2010.5548904.

[21] I. Sobel, "Camera Models and Machine Perception," 1970.

[22] K. Lim, Y. Hong, Y. Choi, and H. Byun, "Real-time traffic sign recognition based on a general purpose GPU and deep-learning," *PLoS One*, vol. 12, no. 3, p. e0173317, 2017.

[23] Y. Wang, W.-L. Chao, D. Garg, B. Hariharan, M. Campbell, and K. Q. Weinberger, "Pseudo-lidar from visual depth estimation: Bridging the gap in 3d object detection for autonomous driving," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019, pp. 8445–8453.

[24] S. Houben, J. Stallkamp, J. Salmen, M. Schlipsing, and C. Igel, "Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark," in *The 2013 international joint conference on neural networks (IJCNN)*, 2013, pp. 1–8.

[25] A. Ruta, Y. Li, and X. Liu, "Real-time traffic sign recognition from video by class-specific discriminative features," *Pattern Recognit.*, vol. 43, no. 1, pp. 416–430, 2010.

[26] Y. Satılmış, F. Tufan, M. Şara, M. Karslı, S. Eken, and A. Sayar, "CNN based traffic sign recognition for mini autonomous vehicles," in *International Conference on Information Systems Architecture and Technology*, 2018, pp. 85–94.

[27] D. Sik, K. Csorba, and P. Ekler, "Implementation of a geographic information system with big data environment on common data model," in *2017 8th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, 2017, pp. 181–184, doi: 10.1109/CogInfoCom.2017.8268238.

[28] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.

[29] A. Behloul and Y. Saadna, "A Fast and Robust Traffic Sign Recognition," *Int. J. Innov. Appl. Stud.*, vol. 5, no. 2, p. 139, 2014.

[30] D. Tabernik and D. Skočaj, "Deep learning for large-scale traffic-sign detection and recognition," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 4, pp. 1427–1440, 2019.

[31] W. Farag, "Recognition of traffic signs by convolutional neural nets for self-driving vehicles," *Int. J. Knowledge-based Intell. Eng. Syst.*, vol. 22, no. 3, pp. 205–214, 2018.