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Classification of Traffic Signs Using Deep Learning based Approach for Smart Cities

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Abstract

Various traffic sign recognition systems have been proposed during the past few years. The current study provides an overview of a few effective, contemporary techniques for identifying and categorising traffic signs. In fact, localising regions of interest including traffic signs is the primary objective of detection techniques, and we classify detection techniques into three broad categories: color-based (classified according to the colour space), shape-based, and learning-based methods (including deep learning). The traffic sign detection and recognition (TSDR) technology is a vital component of these systems for assuring vehicle safety. This research offers a thorough analysis of image and video-based traffic sign detection and identification systems. Our primary goal is to outline the current trends and difficulties associated with creating an effective TSDR system. This will be followed by a thorough comparison of numerous recognised techniques employed by various scholars. The conclusion is followed by some future recommendations for creating an effective TSDR system. In the future, a successful traffic sign detection and identification system that ensures driver safety will be developed, perhaps as a result of this study.

Keywords: *Traffic sign classification, Traffic sign detection, Object detection, Image processing.*

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1. INTRODUCTION

In recent years, the ability to read traffic signs has drawn more and more attention; it is now even seen as a crucial component of intelligent cars. Due to driver weariness or when looking for an address, drivers may ignore traffic signs even when they provide significant important information. These drivers are also more inclined to ignore traffic signs when driving in hazardous conditions. Therefore, enhancing automatic detection and traffic sign recognition systems coupled with driving safety measures is increasingly essential to reducing the number of fatalities on the road. These improvements, however helpful they may seem, address a number of external, non-technical obstacles such changes in size and weather, occlusions and rotations, which may eventually result in a reduction in the performance of traffic sign identification systems. By detecting and identifying such traffic signals, the TSDR system may provide useful information about the flow of traffic and the area around a vehicle as it is moving along the road [1]. Images captured by cameras or certain imaging sensors can contain traffic indicators that an autonomous TSDR system can recognise and categorise [2].

This system's primary goal is to ensure driving safety by comprehending this visual language, providing information on the state and flow of traffic, and warning the driver to any dangerous situations. The development of a TSDR system is difficult for a number of reasons, including motion artefacts, noisy backdrop and foreground scenery, fluctuating lighting conditions, and inconsistent intensity [3]. Additionally, traffic signs that are broken, partially hidden, faded, or blurry, as well as comparable man-made things nearby, might affect how well the TSDR system performs [4]. Over the past 20 years, there has been extensive research done on the difficult task of creating a reliable TSDR [5]. As computer processing capacity grows daily, it is becoming more practical. To increase the effectiveness of the TSDR system, several researchers have been creating various alternatives.

Localization, detection, and classification are the three primary phases of traffic sign recognition systems. Due to the fact that the classifier is not often trained on false alarms, performance will be worse in the classification stage if there is any false alarm in the detection stage. Road signs are classed based on a number of distinguishing characteristics. There are five primary categories of signs, identified by their forms and colours: warning signs (red triangular), prohibition signs (red round), reservation signs (blue rectangle), required signs (blue circle), and temporary signs (yellow triangle). Fig. 1 displays examples of traffic signs for each of the aforementioned categories.

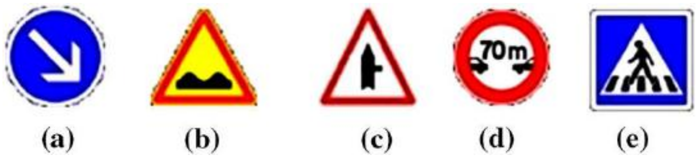

Figure 1: Different types of Traffic signs: (a) Mandatory, (b) Temporary, (c) Warning, (d) Prohibition, (e) Reservation

Challenges and Current Trends:

The primary goal of an ADAS system is to protect drivers. As a traffic sign depicts the area around the car, it is a crucial component of ADAS. Given how quickly the environment is changing, developing an automated TSDR system is challenging [6]. One of the main issues with the TSDR system is reliability [7]. Researchers attempted to combine colour and shape information for the creation of the TSDR system since colour information is extremely inaccurate and shape may alter due to a variety of circumstances. Researchers apply SVM, Neural Network, and Hough Transform techniques to lessen the impact of illumination on TSDR systems. The main techniques employed by various researchers to reduce the impact of diverse illumination include the SVM approach for classification [16-17], neural networks [8-10], self-organizing maps (SOM) [11], AdaBoost [12-13], and joint transform correlation (JTC) [14]. Other machine learning techniques developed by the researchers include MSER-based HOG [18], Low Rank Matrix Recovery (LRMR) [19], The Karhunen-

Loeve transform [20], and Fuzzy c Means (FCM) [21]. However, in order to be used in real time, a TSDR system must take into account all potential problems. The following list of factors provides an overview of the TSDR system development considerations:

- ***Affected vision:*** For a real-time application, shadows and the light emitted by arriving cars' headlights can both reduce visibility. Rain, clouds, snow, and fog can all reduce visibility.
- ***Effects of fading and blurring:*** Another significant problem for TSDR systems is sunlight and rain illumination. Traffic sign fading and blurring brought on by sunlight and rain might result in erroneous detection, which makes the TSDR system ineffective. The adaptive thresholding approach is excellent for this. Recent studies have used the Hough transformation, which is reliable under various lighting conditions and levels of illumination [12].
- ***Variable lighting condition:*** Variable lighting condition: While developing a TSDR system, variable lighting condition is one of the main problems. One of the two key characteristics of a traffic sign is its distinctive hue, which sets it out from the surroundings. The varying lighting conditions have a significant impact on this colour information. The impact of light varies with the time of day and the climate [6].
- ***Signs that appear multiple time***s: When many traffic signs show simultaneously, they may overlap with one another due to similar-looking man-made objects, which may result in a false detection. Rotation, translation, scaling, and partial occlusion are other factors that might impact the detecting process. The accuracy rate in different weather conditions is as follows: 95.49% for bright conditions, 93.02% for cloudy conditions, and 89.82% for rainy conditions. Li et al. employed the HSI transform and Fuzzy shape recognizer in [22], which are robust and unaffected by these issues.
- ***Motion aberrations:*** When a moving car is on a highway, motion artefacts start to work and cause blurry photos to be captured. Images that are noisy and blurry might also result from using low resolution cameras. In order to lessen the impact of motion blurr, rotation, and scaling problems, Prisacariu et al. employ the PWP3D method for tracking together with Haar-like features and SVM for classification in [23].
- ***Real-time application:*** While the car is driving on the highways, a quick algorithm is required for real-time application. For real-time applications, a quick method with a very low processing time, such as SVM, is required.
- ***Sign that has been damaged and is partially concealed:*** If the system has a shape recognizer, traffic signs that have been damaged and partially obscured are another issue for detection and recognition. It decreases system effectiveness and raises the rate of erroneous detection. The Soheilian et al. 3D reconstruction approach [16] can identify damaged signs in a real-time context.
- ***Problem with the background and chaotic viewing angle:*** Running down the street when the background and foreground are chaotic makes it harder to recognise objects. When employing color-based techniques, backdrop traffic sign objects of a similar hue produce colour overlapping. Therefore,

these techniques are unable to identify the intended Region of Interest (ROI), which might result in a false positive for the system.

- ***Absence of public database:*** This study subject has encountered difficulties due to the absence of any free and adequately arranged public databases. There are presently only a very small number of well-known publicly accessible datasets, such as GTSRB, KUL, and STS.

Comparative Assessment:

Researchers use various combinations of machine learning algorithms to address various system-related problems. For example, Sheng et al. [10] use probabilistic neural networks to detect and recognise traffic signs in background that is somewhat distorted, noisy, or blurry as well as under varying lighting conditions. A quick algorithm is required to use the TSDR system in real-time environments. A thorough comparison of SVM, MLP, HOG-based classifiers, and decision trees is offered in [12]. The trial findings revealed that the decision tree has the greatest accuracy rate of all, at around 93.89%, followed by the SVM's accuracy of 85.79% and the MLP's accuracy of 90.19%. The SVM requires 115.87 milliseconds of calculation for a single classification, followed by the MLP at 1.45 milliseconds and the quickest decision tree at 0.15 milliseconds. SVM or a decision tree are better options for spotting speed limit signs than the Hough transform or a neural network. Neural networks require the entire dataset to be modified in order to add new classes, which requires more computing effort than SVM.

In [24], a genetic algorithm is utilised for detection following RGB picture segmentation for post-processing. The total detection rate is high because genetic algorithms may handle problems in several dimensions and directions and are not dependent on the error surface. In order to find and extract the anticipated ROI, self-adaptive image segmentation is first introduced in [10] and is then followed by a geometrical form analysis. Sheng employed the Probabilistic NN to recognise the symbol after removing the predicted ROI. Image normalisation and YCbCr colour space modification are employed by Hechri et al. [25] to lessen the impact of varying illumination, blurring, and fading. By using the bootstrap technique on the system, neural networks increase the system's accuracy. Another well-liked approach for creating a TSDR system is Support Vector Machine (SVM). SVM is used by Wu et al. [15] and Bascon et al. [16] to identify speed limit signs. Gil-Jimenez et al. [26] employed SVM with a Gaussian Kernel to extract 134 blob pictures with a 90% success rate from an image database in order to detect and recognise the speed limit signs. When recognising speed limit signs on highways, Prisacariu et al. [27] employed SVM for classification and Haar-like characteristics for detection. Additionally, this approach is invariant to partial occlusion and motion blur. The system has a hardware implementation that can handle 640x480 pictures at 20 frames per second. Fig. 2 displays a case in point.

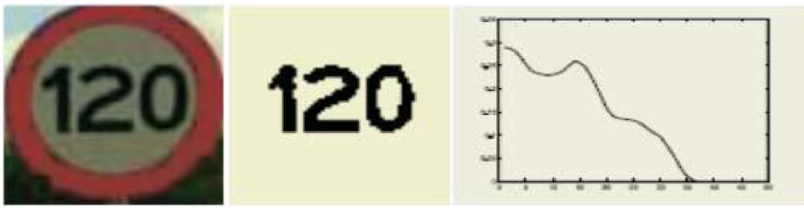

Figure 2: SVM-based identification of speed limit signs

In [18], Greenhalgh et al. deploy a Hough-based SVM that is invariant to changes in translation, rotation, illumination, scaling, partial occlusion and viewing angle. For robustness and lighting, gamma compression and picture normalisation are utilised in the pre-processing step. Tri-linear interpolation of the pixel's weight into the spatial orientation histogram is employed in the HoG method, which has an accuracy rate of 98.59%–99.43%, to reduce the viewing angle and partial occlusion problem. SIFT matching-based SVM was utilised by Pei et al. in [19] for the detection and identification of broken signs. In this method, pictures are taken using an on-board camera, readjusted to a standard camera axis using the SIFT matching technique, and then compared to a reference image using SVM.

The fundamental drawback of this approach, as utilised by Wang et al. [21], is its chromatic-adaptation transform, known as the Bradford transform. It uses the CIE XYZ transform in LCH spacing. Then, a shape analysis using the FOSTS model is performed. By comparing the 49-dimensional vectors of the current picture with template vectors kept in the database and categorised with an accuracy of 95% into various color/shape subgroups, the recognition process is carried out. For identification and rearrangement, Li et al. [12] employed a fuzzy shape recognizer and the HSI transform. Three weather categories—sunny, wet, and cloudy—have been used to categorise the research's results. The convex hull is calculated using Graham's scan technique, which is then handed on for confirmation and identification to the fuzzy shape recognizer. Fig. 3 depicts an illustration of the segmentation procedure of a slightly obscured sign in bright weather.

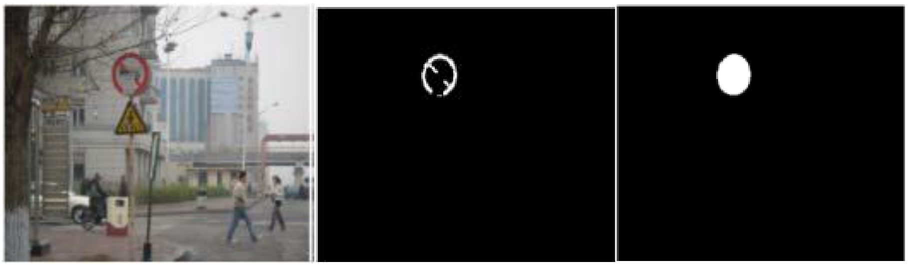

Figure 3: Process of segmenting a partially obscured sign

Gonzalez-Reyna et al. [20] employ the Eigen Vector Gradient Orientation and Karhunen-Loeve transform, which is effective in identifying blur signs. The Eigen vector approach is also invariant to changes in illumination, background noise, and viewing angle. Li et al. [22] employ the 3D reconstruction approach, a particularly customised technique, to find broken and partially obscured indications. The ROI is extracted using the fitting ellipse approach, and the texture analysis is performed using template matching. The sign is then recovered and recognised using a 3D reconstruction technique. According to Pacl et al. [23], the colour feature was extracted using the Gabor filter, and Joint Transform Correlation (JTC), which has a great capacity to distinguish between object and non-object, was then used. Additionally, this system is invariant to rotation, scaling, transformation, and viewing angle. Greenhalgh et al. adopt MSER-based HoG in [18] because of its resilience in varying illumination, blurring, and fading effects. Di et al. [24] employ the AdaBoost approach, which is quick and useful at detecting blurry and fading signs as well as under varied lighting conditions. [25] uses 936 speed limit signs and 2056 random pictures with no road signs, respectively, for positive and negative samples for the AdaBoost training, with an accuracy rate of 95.35%.

While creating a successful TSDR system, all the concerns listed above have to be taken into account. The strategies that are most often used by researchers all have disadvantages that lower the system's effectiveness. Greenhalgh et al. [18] employ the Hough Transform, which has a high processing time requirement and input data dependence as its primary drawbacks. Dr. Kang-Hyun Jo and his teams have been working for a number of years to improve the system's effectiveness and resilience in a variety of environmental conditions [25–27]. Combination of Shifted Filter Responses (COSFIRE), which has a classification rate of 98.95%, is introduced by Azzopardi et al. In [48]. A SIFT matching-based technique was utilised by Yang et al. [49] to categorise damaged and broken indications. For the use of an efficient TSDR system in the real-time environment, more research ought to be required.

Ref. No.	**Methodology used**	**Affected Vision**	**Affects of fading and blurring**	**Variable lighting condition**	**Signs that appear multiple times:**	**Motion aberrations**	**partially concealed signs**	**Noisy background**	**chaotic viewing angle**
[2]	Genetic Algorithm + Probabilistic NN	√	√	√				√	
[5]	MSER based HOG + Decision tree	√	√			√	√		
[11]	Karhunen-Loeve transform + Gradient Orientation	√		√		√			√
[14]	Probabilistic NN + Genetic Algorithm		√		√	√			√
[16]	YCbCr + Image Normalization+NN	√	√		√	√			√
[17]	Haar like features + SVM	√		√	√	√	√		
[22]	SVM		√		√			√	
[24]	Hough based SVM	√	√		√		√		√
[25]	3D reconstruction method			√		√			√

[26]	AdaBoost + CHT		√	√			√		
[27]	Gabor Filter + Joint Transform Correlation	√			√		√		√

Prospects for future research:

The issue with the state-of-the-art at the moment is the lack of a global dataset that incorporates signs from various locations, including those that do not adhere to The Vienna Convention on Road Signs and Signals, and that were collected in various environments. We believe that a new, more sophisticated universal dataset is required since the number of accessible datasets has hit its limit. A new balanced dataset is needed to address this issue since the distribution of samples in the class of traffic signs in the datasets that are currently available is unbalanced, which can have a detrimental influence on classification performance.

If we assume that the automobile is travelling at 100 km/h and that the sign is 26 m distant from the car, then this sign will be passed in 1 s in future study, utilising the high-resolution picture in the detection dataset. Images from the collection should be of a high resolution in order to clearly discern distant indicators. Researchers may concentrate more on the tracking module to follow signals because if the system employs a camera with 30 shot frames per second, it should be able to detect and recognise all signs of 30 frames in 1 s; however, with the tracking module, songs identified and tracked will not be reclassified in each frame taken but just once until the arrival of a new sign.

Systems for recognising traffic signs include detection and classification phases. The optimum approach must be chosen carefully since classification performance depends on detection outcomes. As was shown in the introduction, achieving a high accuracy is more important than simply being able to recognise traffic signs with a high recall rate. We propose that research be concentrated on reducing false alarms in traffic sign detection.

Researchers should concentrate more on looking for and studying more discriminant characteristics that may better reflect the various classes of traffic signs in order to improve the accuracy of the classification stage. Deep features now outperform hand-crafted ones in terms of discrimination; however, there are no studies on learning methods that demonstrate their scalability for new datasets, opening the door for future study.

2. CONCLUSION

This paper's main goal is to examine the major trends in the area of autonomous traffic sign detection and identification. This publication gives a summary of the study on the Automatic TSDR system along with some of the existing problems and difficulties, as well as the researchers' responses. The evolution of the Automatic TSDR system has been divided into four key stages, including the early stage, intermediate stage, saturation era, and current age, after a thorough analysis of a large number of papers. The steps are covered in more detail in the sections that follow, along with in-depth comparisons of the approaches now in use.

No human-machine interaction is shown in the state-of-the-art, which leaves room for future study as it is crucial for an effective ADAS system. The availability of public databases is another important issue that has to be resolved. There are various publicly accessible databases that simply include the Vienna Convention-Complaint and are still not very popular. Future study might include certain combinational techniques to reduce problems with real-time applications, particularly the dependability element. Additionally, for precise recognition, traffic signs might be represented by GPS or RFID. Additionally, inter-vehicle communication via RFID or sonar is used while running on the roadway to increase driver safety.

A robust and effective TSDR system will hopefully be developed as a result of the review of the research, comparative analysis, and challenges that are discussed in the field of automatic TSDR in this paper along with some future recommendations.

REFERENCES

[1] Larsson F., Felsberg M., Using Fourier Descriptors and Spatial Models for Traffic Sign Recognition, Image Analysis Lecture Notes in Computer Science, 6688 (2011) 238–49.

[2] Ren F.X., Huang J.S., Jiang R.Y., Klette R., General Traffic Sign Recognition by Feature Matching, (2009).

[3] Ohgushi K., Hamada N., Traffic Sign Recognition by Bags of Features, IEEE Region 10 Conference, 1-4, (2009), 1352–7.

[4] Gu Y.L., Yendo T., Tehrani M.P., Fujii T., Tanimoto M., Ieee., A New Vision System for Traffic Sign Recognition, 2010 IEEE Intelligent Vehicles Symposium (Iv), (2010) 7–12.

[5] Paclik P., Novovicova J., Road Sign Classification without Color Information, Proceedings of the 6th Conference of Advanced School of Imaging and Computing, (2000).

[6] Wali, Safat, Mohammad A Hannan, Shahrum abdullah, AiniHussain S.A.S., Shape Matching and Color Segmentation Based Traffic Sign Detection System, PrzeglD Elektrotechniczny, 1 (2015) 38–42.

[7] Hussain A., Hannan M.A., Mohamed A., Sanusi H., Ariffin A.K., Vehicle crash analysis for airbag deployment decision, International Journal of Automotive Technology, 7 (2006) 179–85.

[8] Safat B.W., Ridwanur R., Ahsan Z., J. Ahmed M., A Neural network Based System Architecture of An Automatic Traffic Sign Detection and Recognition System, Australian Journal of Basic and Applied Sciences, 8 (2013) 102–5.

[9] Mohammad A Hannan, Safat Bin Wali, Tan J. Pin, Aini Hussain S.A.S., Traffic Sign Classification based on Neural Network for Advance Driver Assistance System, PrzeglD Elektrotechniczny, 1 (2014) 169–72.

[10] Sheng Y.H., Zhang K., Ye C., Liang C., Li J., Automatic detection and recognition of traffic signs in stereo images based on features and probabilistic neural networks. In: Schelkens P, Ebrahimi T, Cristobal G, Truchetet F, editors. Optical and Digital Image Processing, vol. 7000, Bellingham: Spie-Int Soc Optical Engineering (2008).

[11] Prieto M.S., Allen A.R., Using self-organising maps in the detection and recognition of road signs, Image and Vision Computing, 27 (2009) 673–83.

[12] Li Y., Pankanti S., Guan W., Real-Time Traffic Sign Detection: An Evaluation Study. 2010 20th International Conference on Pattern Recognition, (2010), 3033–6.

[13] Chen L., Li Q., Li M., Zhang L., Mao Q., Design of a multisensor cooperation travel environment perception system for autonomous vehicle, Sensors, (Basel, Switzerland) 12 (2012) 12386–404.

[14] Khan J.F., Bhuiyan S.M. a., Adhami R.R., Image Segmentation and Shape Analysis for Road-Sign Detection, IEEE Transactions on Intelligent Transportation Systems, 12 (2011) 83–96.

[15] Wu J., Tseng C., Chang C., Road sign recognition system based on GentleBoost with sharing features, IEEE International Conference on System Science and Engineering, (2011) 410–5.

[16] Bascon S.M., Rodriguez J.A., Arroyo S.L., Caballero A.F., Lopez-Ferreras F., An optimization on pictogram identification for the road-sign recognition task using SVMs, Computer Vision and Image Understanding, 114 (2010) 373–83.

[17] Garcia-Garrido M.A., Ocana M., Llorca D.F., Sotelo M.A., Arroyo E., Llamazares A., et al., Robust Traffic Signs Detection by means of Vision and V2I Communications, 2011 14th International IEEE Conference on Intelligent Transportation Systems, (2011), 1003–8.

[18] Greenhalgh J., Mirmehdi M., Ieee., TRAFFIC SIGN RECOGNITION USING MSER AND RANDOM FORESTS. 2012 Proceedings of the 20th European Signal Processing Conference, Los Alamitos: Ieee Computer Soc; (2012), 1935–9.

[19] Pei D.L., Sun F.C., Liu H.P., Supervised Low-Rank Matrix Recovery for Traffic Sign Recognition in Image Sequences, IEEE Signal Processing Letters, 20 (2013) 241–4.

[20] Gonzalez-Reyna S.E., Avina-Cervantes J.G., Ledesma-Orozco S.E., Cruz-Aceves I., Eigen-Gradients for Traffic Sign Recognition, Mathematical Problems in Engineering, (2013) 6.

[21] Wang W., Wei C.-H., Zhang L., Wang X., Traffic-signs recognition system based on multi-features, 2012 IEEE International Conference on Computational Intelligence for Measurement Systems and Applications (CIMSA) Proceedings, (2012), 120–3.

[22] Li L., Li J., Sun J., Robust traffic sign detection using fuzzy shape recognizer. In: Ding M, Bhanu B, Wahl FM, Roberts J, editors, in proc. Pattern Recognition and Computer vision, 7496 (2009), 74960Z – 74960Z – 8.

[23] Pacl P., Novoviˇ J., Vitabile S., Gentile A., Sorbello F., Torresen J., et al., Real-Time Detection and Recognition of Road Traffic Signs, Robotics and Autonomous Systems, 13 (2012) 86–93.

[24] De la Escalera A., Armingol J.M., Mata M., Traffic sign recognition and analysis for intelligent vehicles, Image and Vision Computing, 21 (2003) 247–58.

[25] Hechri A., Mtibaa A., Automatic Detection and Recognition of Road Sign for Driver Assistance System, 2012 16th IEEE Mediterranean Electrotechnical Conference,(2012), 888–91.

[26] Gil-Jimenez P., Lafuente-Arroyo S., Maldonado-Bascon S., Gomez-Moreno H., Shape classification algorithm using support vector machines for traffic sign recognition. In: Cabestany J, Prieto A, Sandoval F, editors. Computational Intelligence and Bioinspired Systems, Proceedings, vol. 3512, Berlin: Springer-Verlag Berlin; (2005), 873–80.

[27] Prisacariu V.A., Timofte R., Zimmermann K., Reid I., Gool L. Van., Integrating Object Detection with 3D Tracking Towards a Better Driver Assistance System, 2010 20th International Conference on Pattern Recognition, (2010), 3344–7.