Proceedings of the Fifth International Conference on Computing Methodologies and Communication (ICCMC 2021)
IEEE Xplore Part Number: CFP21K25-ART

Traffic Sign Recognition using Deeplearning for Autonomous Driverless Vehicles

Suriya Prakash A
Department of ECE
Sri Krishna College of Engineering and Technology
Coimbatore, India
17euec157@skcet.ac.in

Vigneshwaran D
Department of ECE
Sri Krishna College of Engineering and Technology
Coimbatore, India
17euec171@skcet.ac.in

Seenivasaga Ayyalu R
Department of ECE
Sri Krishna College of Engineering and Technology
Coimbatore, India
17euec136@skcet.ac.in

Jayanthi Sree S
Department of ECE
Sri Krishna College of Engineering and Technology
Coimbatore, India
jayanthisrees@skcet.ac.in

2021 5th International Conference on Computing Methodologies and Communication (ICCMC) | 978-1-6654-0360-3/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICCMC51019.2021.9418437

Abstract - **Recently, the smart world, smart cars, and so on plays a major role. To ensure Traffic Safety, the development of smart cars requires the detection and recognition of traffic signs. The algorithm is the extended work on the classical LeNet-5 CNN model. The proposed technique makes use of Gabor based kernel followed by a normal convolutional kernel after the pooling layer. The optimizer technique used here is the Adams method. Hue, Saturation Value color space features have a speed of detection is faster and low suffering from illumination. The proposed technique for traffic sign recognition is evaluated using the German Traffic Sign Recognition Benchmark. The proposed technique gives an accuracy of nearly 99%.**

Keywords— traffic sign detection; traffic sign recognition; smart cars; LeNet-5 Conv.NN; Hue, Saturation Value Color Space; pooling layer; Traffic Safety

I. INTRODUCTION

Though the popularity of cars has introduced appreciable luxury and comfort to individuals, it is one of the sources of traffic safety issues that cannot be unheeded, like tie-up and frequently happening accidents. Traffic queries of safety area unit mostly caused by reasons related to driving processes, like basic cognitive process without proper knowledge of driving and not following the traffic rules and the smart vehicle became efficient so that these human factors can be eliminated[1]. Auto-driving technology will assist, and do the driving process completely, which is very important to liberate the physical structure and significantly cut back the number of accidents [2]. Traffic sign recognition is critical in the development of smart vehicles, which will result in significant changes in driving style. Intelligent vehicles use a camera to provide real traffic information and synthesize control motion for smart cars or vehicles for a safe driving experience. A Capsule network was proposed by Kumar et al for traffic sign detection [3]. This network understands the automatic feature extraction, which that is very stable. The whole process of traffic sign detection technique was proposed by Yuan et al using a multi-feature fusion network [4]. The literature survey gives many traffic sign recognition techniques with good results, but there are some drawbacks in these algorithms, which can be limiting the conditions like disturbances, like inclemency conditions, fading, and changes in lighting conditions of a sign will cause a transparent decline of accuracy in recognition rate and poor environmental adaptability [5]. Moreover, most of the recognition algorithms which are recognition images have high accuracy but there are disadvantages, like increased algorithms complexity and heavy system hardware requirement, and different preprocessing for training data are necessary. Adaboost and SVM are combined for road traffic sign recognition by Yuan et al. [6] in which though the accuracy rate was high, the processing time was also very high. Another method used fusion network formation to obtain features of the signs and background statistics around the observed image, but the complexity was high.

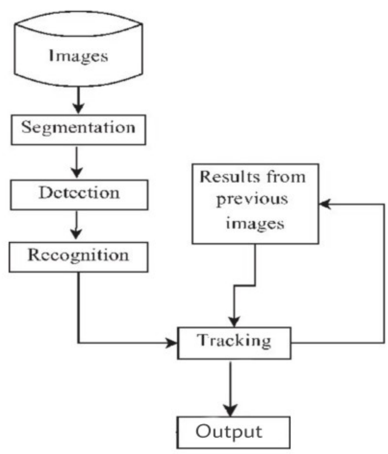

Fig 1:

Initially, the spatial threshold segmentation is used by Hue, Saturation Value color space. Secondly, the LeNet-5 Conv.NN is extended by Gabor kernel and optimizer algorithm. Finally, the evaluation of the proposed technique is performed on GTSRB[7]. This article is organized as follows: Introduction of the traffic sign detection is discussed in Section I. Section II describes the detection of a traffic sign. Section III extended LeNet is elaborated for traffic sign recognition followed by results in Section IV. Finally, Section V draws the conclusion of the research work.

II. DETECTION OF TRAFFIC SIGN

A camera is mounted on the intelligent vehicle is used to capture the traffic sign which is placed on the road. The traffic sign image detected by the camera is extracted and recognized by the algorithm. Somewhere, in real-time conditions, the traffic sign pictures are not similar, in terms of color, shape, and quality of the image. The preprocessing traffic sign images include color space processing and detection of traffic signs supported by various shape features.

A. Color Space

Color is one of the necessary feature of a road signs might be rapidly located by distribution of color. Comparing HSI and RGB color spaces, the Hue, Saturation Value colour space features have a speed of detection is faster and low suffering from illumination [17-18].

The HSV colour model is a cylinder colour model that remaps RGB primary colours into more human-friendly proportions. The angle of colour on the RGB colour wheel is defined by its hue. Red is formed by a 0° hue, green by 120°, and blue by 240°[8]. Saturation controls the quantity of colour used. 'H' represents the color swap of the image. The co-ordinates of the chromatic color are given by gradient, and various color gain corresponds to the various gradient. 'S' represents the proportion of current color integrity to a maximum of 1 to minimal of 0. 'V' indicates the image brightness. White is 1 which indicates maximum value and therefore black is 0 which indicates minimum values respectively. In the Hue Saturation Value color space, as long as 'V' is fixed and 'H' and 'S' are mostly unrelated. Therefore, Hue, Saturation value color space has better illumination flexibility whenever the conditions change. The processing complication is also less, which is favorable for segmentation for traffic sign detection [9].

III. TRAFFIC SIGN RECOGNITION

A. LeNet-5 CNN Model

The effective algorithm requires recognizing real-time traffic signs using dataset resources to detect the traffic signs much quicker. Furthermore, Conv.NN do not get to extract the features manually[10]. The sensor operation of human brains is often well-replicated along with forwarding, learning, and reaction mechanism, thereby continuously enhancing the power of the road by recognizing the traffic sign. In this part, the drawbacks of the classical LeNet-5 are reviewed, and extended to add the advantages of Conv.NN in graphics identification.

For the solitary targets, recognition and characterization have a good impact in the LeNet-5 model. Nonetheless, in the rush hour gridlock, signs recognition preparing is hard to guarantee a sufficiently accurate recognition rate, the preparation network cannot merge, and the recognition productivity of the organization diminishes drastically.

B. Extended LeNet-5 Model

Recognition of road traffic signs depends on obtained dataset assets and utilizations powerful grouping calculation to perceive distinguished and criticism to shrewd vehicles precisely progressively[11]. Conv.NN separates includes straightforwardly from information recognition picture and yields the characterization results through the prepared classifier dependent on picture highlights. This condition demonstrates that Conv.NN has great realistic recognition execution. A tactile cycle of the human mind can be all around mimicked by means of forwarding learning and criticism instrument, in this manner slowly improving the quality of road traffic sign arrangement, recognition, and detection. In this area, the deficiencies of the traditional LeNet-5 organization pattern are analyzed, and model is impressively improved to additionally extend the extraordinary focal points of Conv.NN in illustration recognition. The traffic sign training image has ROI and some edge background information. Therefore, image pre-processing is necessary.

a) Image Cropping may be a particularly important step within image processing. 10% of the entire image which is the background part of traffic signs are not used for recognition[12]. The bounding box coordinates recovered by ROI are used for proportional cropping. The cropping of unnecessary region reduces information and increase the network's training capability.

b) The recognition of the same traffic signs under various illumination conditions is significantly different. The noise in the image is reduced using various image enhancement techniques. Traditional conversion technique is employed to regulate grey value. The quality of the image is improved and the computational load of the network (n/w) is reduced by this method.

c) There are different sizes of the same traffic signs[14]. The different feature sizes may result in different sized training images during the Convolutional Neural network training process results in difficulties within the detection and recognition.

Fig . 2 Six categories of Different Training Images of Traffic sign DataBase

TABLE I. PARAMETERS USED FOR THE PROPOSED EXTENDED LENET

Layer	Layer Type	Feature Map Number	Convolutional Kernel Size	Feature Map size
1	Convolutional Layer	6	5 x 5	28 x 28
2	Pooling Layer	6	2 x 2	14 x 14
3	Convolutional Layer	12	5 x 5	10 x 10
4	Pooling Layer	12	2 x 2	5x 5
5	Fully Connected Layer	120	1 x 1	1 x 1
6	Fully Connected Layer	84	1 x 1	1 x 1
7	Output Layer	43	-	-

IV. EXPERIMENTAL RESULTS AND DISCUSSION

From Internal road traffic signs are collected from the important road traffic environment, and it has become a standard road traffic-sign dataset used in self-driving and other fields. A total of 20,000 and 10,000 images are used for training and testing sets approximately 76% and 24% respectively. The spitting image size is not equal and the larger and smaller images are 250 × 250 and 15 × 15 pixels, respectively. The road traffic sign images are collected from video recorded by the camera in the vehicle. Corresponding to each road traffic sign, a Comma-separated values file is included to interpret with a category label. With respect to the different instruction contents. A similar type of traffic signs contains various resolutions, illumination conditions, weather conditions, and other images for creating more amount of data with real-time examples[15]. The different resolution sample images of different categories of a traffic sign are given in Figure 1. After picture preprocessing, a counterfeit dataset should be produced for GTSRB. The different layer parameters of the improved Lenet – 5 [16]. The recognition accuracy for different categories of the images is given in the Table below. It can be seen that improved Le-Net provides better accuracy for different categories of the images. This method was accomplished via continual computing of the network model. Accuracy reaches 99.75% from the prediction, and the average frame processing rate is 8 ms.

TABLE II. RECOGNITION RATES FOR SIX CATEGORIES OF TRAFFIC SIGN

Traffic signal type	**Table Column Head**		
	TP	***FN***	***Accuracy(%)***
Speed limit	997	3	99.70
Danger	999	1	99.90
Mandatory	998	2	99.80
Prohibitory	994	6	99.40
Derestriction	1000	0	100.00
Unique	997	3	99.70

1. Accuracy (all correct / all) = TP + TN / TP + TN + FP + FN
2. Misclassification (all incorrect / all) = FP + FN / TP + TN + FP + FN
3. Precision (true positives / predicted positives) = TP / TP + FP
4. Sensitivity aka Recall (true positives / all actual positives) =TP / TP + FN
5. Specificity (true negatives / all actual negatives) =
   a. `TN / TN +FP

V. CONCLUSION

In this study, smart cars can detect and recognize traffic signs by the proposed algorithm. Initially, spatial threshold segmentation is employed by the HSV color space, and traffic signs are effectively detected to support the features. Secondly, the classical LeNet-5 Conv.NN model is extended to improve the recognition rate. Finally, the detection, recognition, and classification of traffic signs are conducted to support the GTSRB. In Lenet-5 Conv.NN Model, more layers were used to check for the accuracy is improved. This is done by using a trained algorithm, the real-time data is processed to capture from a different environment. The performance of the model examines great when compared to other models. This algorithm has good efficiency so the recognition rate and average time interval are significantly improved. In the future, the performance and further optimization of the algorithm will be error-free. It will be useful in driving the safety of autonomous vehicles.

References

[1] Aziz S, Mohamed E, Youssef F (2018) Traffic sign recognition based on multi-feature fusion and ELM classifier. Proc Comput Sci 127:146–153

[2] Jang, C., Kim, H., Park, E., Kim, H. (2016). Data debiased traffic sign recognition using MSERs and CNN. In 2016 International Conference on Electronics, Information, and Communications (ICEIC), Da Nang, Vietnam, pp. 1-4. https://doi.org/10.1109/ELINFOCOM.2016.7562938

[3] Lai, Y., Wang, N., Yang, Y., & Lin, L. (2018). Traffic signs recognition and classification based on deep feature learning. In 7th International Conference on Pattern Recognition Applications and Methods (ICPRAM), Madeira, Portugal (pp. 622-629).

[4] Rosario G, Sonderman T, Zhu X. (2018) Deep Transfer Learning for Traffic Sign Recognition[C]//2018IEEE International Conference on Information Reuse and Integration (IRI). IEEE: 178–185. MLA

[5] Hatolkar, Y., Agarwal, P., & Patil, S. (2018). A Survey on Road Traffic Sign Recognition System using Convolution Neural Network.

[6] Huang, Z., Yu, Y., Gu, J., & Liu, H. (2017). An efficient method for traffic sign recognition based on extreme learning machine. IEEE transactions on cybernetics, 47(4), 920-933.

[7] Li, C., Hu, Y., Xiao, L., Tian, L. (2012). Salient traffic sign recognition based on sparse representation of visual perception. In 2012 International Conference on Computer Vision in Remote Sensing, Xiamen, China, pp. 273-278. https://doi.org/10.1109/CVRS.2012.6421274.

[8] Shi W, Xin L, Yu Z et al (2017) An FPGA-based hardware accelerator for traffic sign detection. IEEETransactions on Very Large Scale Integration Systems 4:1362–1372

[9] Rosario G, Sonderman T, Zhu X. (2018) Deep Transfer Learning for Traffic signal Recognition[C] 2018 IEEE International Conference on Information Reuse and Integration

[10] Li, H., Gong, M. (2017). Self-paced Convolutional Neural Networks. In IJCAI, pp. 2110-2116.

[11] Yang, Y., Luo, H., Xu, H., Wu, F. (2015). Towards real-time traffic sign detection and classification. IEEETransactions on Intelligent Transportation Systems 17(7):20222031.https://doi.org/10.1109/TITS.2015.2482461

[12] Yi, K., Jian, Z., Chen, S., Chen, Y., & Zheng, N. (2018). Knowledge-based Recurrent Attentive Neural Network for Traffic Sign Detection. arXiv preprint arXiv:1803.05263.

[13] Promlainak, S.; Woraratpanya, K.; Kuengwong, J.; Kuroki, Y. Thai tra_c sign detection and recognition for driver assistance. In Proceedings of the 7th ICT International Student Project Conference (ICT-ISPC),Nakhon Pathom, Thailand, 11–13 July 2018; pp. 1–5.

[14] Yuan, Y.; Xiong, Z.T.;Wang, Q. An incremental framework for video-based tra_c sign detection, tracking,and recognition. IEEE Trans. Intell. Transp. Syst. 2017, 18, 1918–1929

[15] Sermanet, P., LeCun, Y. (2011). Traffic sign recognitionwith multi-scale convolutional networks. In The 2011International Joint Conference on Neural Networks, SanJose, CA, USA, pp. 2809-2813.https://doi.org/10.1109/IJCNN.2011.6033589.

[16] A. Shustanov, P. Yakimov, "CNN Design for Real-Time Traffic Sign Recognition," 3rd International Conference "Information Technology and Nanotechnology," ITNT-2017, 25-27 April 2017, Samara, Russia.

[17] Dhaya, R. "CCTV Surveillance for Unprecedented Violence and Traffic Monitoring." Journal of Innovative Image Processing (JIIP) 2, no. 01 (2020): 25-34.

[18] Vijayakumar, T., and R. Vinothkanna. "Retrieval of complex images using visual saliency guided cognitive classification." J Innov Image Process (JIIP) 2, no. 02 (2020): 102-109.