

Road Sign Recognition Technology Integrating Deep Learning

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Abstract: At present, research work on pedestrian detection, forward collision avoidance and other applications emerges in an endless stream, but there is not much work on road signal detection and recognition. As a public facility that provides drivers with basic road information, the importance of traffic signs is unquestionable. The purpose of this paper is to study road sign recognition techniques incorporating deep learning. A method that combines traditional image processing is proposed. After the redundant elements in the dataset images are removed and learned by the network model, the network model combining the residual network concept and SENet concept is compared in day and night scenes, and the recognition accuracy proves the effectiveness of the proposed algorithm. The trained road sign recognition network is used to complete offline video road sign recognition experiments at all levels, and the experimental results are analyzed. In the daytime scene, a recall rate of 0.96 and a precision rate of 0.98 were obtained. In the night scene, a recall rate of 0.89 and a precision rate of 0.91 were obtained.

1. Introduction

Traffic sign detection and recognition research has good application prospects. Not only is it an important part of driver assistance systems, it can also serve as one of many inputs to environment perception systems. Efficient and accurate traffic sign detection and recognition will certainly be of great help to this research [1-2]. In the road navigation function of electronic maps, the detection and recognition of road traffic signals will also provide very important information for the driver's positioning and route planning [3-4].

Traffic signs are a mandatory feature of global road traffic regulations. Automatic detection and recognition of traffic signs by vehicles can improve driver and passenger safety levels. BA Akgül has developed a DL-based RT-TSR system due to its high recognition rate and fast execution.

Additionally, CV methods have been included in software developed to enable RT classification and support digital imaging. Due to its low computational cost and high performance, the developed system is able to run smoothly in embedded systems with mobile GPUs or CPUs. The coding is done using the python programming language under the TensorFlow and OpenCV frameworks, and the CNN is trained using a parallel architecture. Experimental results show that the developed CNN architecture achieves 99.71% accuracy and confirms the high efficiency of the system [5]. To avoid problems on the road, Kumar KA contributes to the embedded control and image processing of Traffic Sign Detection (TSD), a technology that detects traffic signs and enables drivers to drive in a comfortable zone and avoid accidents [6]. In a word, road sign recognition, as an important branch in the field of artificial intelligence, is of great scientific nature and needs to do related research work.

With the deepening of the network model, its training time is also increasing, and there is also a phenomenon of "degeneration", that is, with the deepening of the network, the accuracy of training begins to decline. In view of this problem, this paper proposes an improved deep learning road traffic representation recognition algorithm. The improved algorithm integrates traditional image processing knowledge and deep learning network model framework. On the basis of using shallow network structure and low training time, to achieve a high recognition rate.

2. Research on Road Sign Recognition Technology Integrating Deep Learning

2.1. Image Preprocessing

In the collection of road traffic sign images, factors such as illumination, shooting angle, and shooting environment often affect the collected images, which increases the difficulty of subsequent image recognition. The preprocessing of image lighting based on multi-color space depends on Threshold processing of the color space of the output image, the original color image collected in the actual road scene often contains a large amount of information, and is easily affected by complex conditions such as illumination and weather, which hinders the target detection results, in order to reduce the subsequent image processing [7]. Image grayscale is to represent the parameters of each pixel in the original scene in the RGB color model with a fixed gray value through a specific function transformation. This paper is mainly carried out in RGB and YCbCr color space [8-9]. In the manipulation and processing of digital images, the RGB color space is the most commonly used color space. However, the RGB color space cannot represent the overall brightness information of a digital image, and changing the color characteristics will change the overall color of the image. Changing the details of the original image is not what we want. Therefore, we introduce the YCbCr color, where Y represents the image brightness information, and Cb and Cr represent the density variation of blue and red, respectively, chromaticity [10-11].

2.2. Deep Learning Network Model

(1) Gradient descent algorithm

In the neural network model, we introduce the activation function to solve the problem that the nonlinear function cannot be learned in the neural network model [12-13]. After we introduced several activation functions, we also mentioned the operations that need to use the gradient descent algorithm. Specifically, the gradient descent algorithm and the activation function complement each other. The derivative of the activation function can provide the gradient descent algorithm with the gradient that can be calculated, so as to guide the correct convergence of the model objective, and the gradient descent algorithm is to optimize the objective function to make it reach the ideal value [14].

(2) Residual connection and Squeeze-and-Excitation module

In mathematical operations, it is difficult to directly fit some layers into the maximum identity graph function $H(x)=x$, but the network is modeled as $H(x)=F(x)+x$, which can be changed to Learn a residual $F(x)=H(x)-x$, that is, since $F(x)=0$, if $F(x)$ is not equal to 0 but close, then the identity image $H(x)=x$ is 0, and the network system only needs to learn The differential part can simplify the learning objective, prevent the gradient dispersion problem, and at the same time ensure that the network system maintains the deep learning characteristics and is close to the original input results [15-16].

The core of the Squeeze-and-Excitation module is a computational unit, which can be defined as any type:

$$Ftr : X \rightarrow U \quad (1)$$

$$X \in R^{H \times W \times C} \quad (2)$$

$$U \in R^{H \times W \times C} \quad (3)$$

We treat Ftr as a convolution operation, let $V=[v_1, v_2, \dots, v_c]$ denote the set of filter kernels, and v_c denote the parameters of the c -th layer filter. We can express the output result Ftr as $U=[u_1, u_2, \dots, u_c]$, where:

$$u_c = v_c * X = \sum_{s=1}^C v_c^s * x^s \quad (4)$$

Squeeze operation: To address the channel dependency problem, the Squeeze function works by compressing global spatial information into channel descriptors, which is achieved by using global mean pooling to generate channel statistics [17-18].

Excitation operation: To use the information collected in Squeeze mode, we use Excite mode to fully extract channel dependencies.

3. Investigation and Research on Road Sign Recognition Technology Integrating Deep Learning

3.1. A road Sign Recognition Algorithm Combining Image Processing and Deep Learning

This paper proposes a road traffic sign recognition algorithm that combines image processing and deep learning. The algorithm integrates various preprocessing operations and algorithm formulas for data set images, including exposure adjustment, image size adjustment, and data with a small amount of data. Then, combined with the convolutional neural network model, adjust the network structure and related parameters, and integrate the residual connection to obtain the algorithm of this paper. The specific algorithm flow is as follows. Figure 1 shows the entire algorithm flow chart:

Step 1: uses multi-color space to batch preprocess the illumination level of the dataset and remove the background;

Step 2: Normalize dataset images and perform data refinement for identifiers with less data.

Step 3: Fully train the network structure by combining residual connectivity, structure tuning, parameter selection, and Squeeze-and-Excitation module concepts with the dataset.

Step 4: identifies any road sign image.

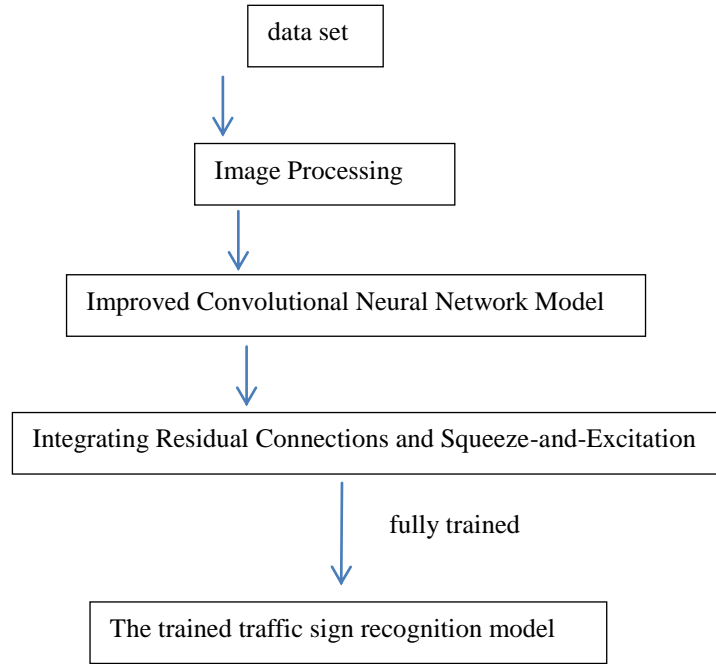


Figure 1. A road sign recognition algorithm combining image processing and deep learning

3.2. Experimental Setup

In this paper, the network trained and tested on GPU is applied to the recognition of road signs on the actual road. The test is the offline video collected by the driving recorder, including day, night, and rainy scenes. The frame rate of the driving recorder is 30fps, the processing speed of the improved deep learning network is 4 frames/s, and one frame is selected for processing every 5 frames. For a road sign detection, considering the location interval of the actual road sign setting, this speed can fully meet the requirements, and does not need to be processed every frame, which improves the detection and recognition efficiency of road signs.

4. Analysis and Research of Road Sign Recognition Technology Integrating Deep Learning

4.1. Road Sign Recognition Experiments in Different Scenes during the Day

The light in the daytime scene is good, the video collected by the driving recorder is of good quality, the image is clear, and the road sign detection performance is good. Label, so it is not detected, and the road sign is partially occluded and not detected. If it rains during the day, the rain will blur the front glass of the car, resulting in the obtained road signs may be partially or completely occluded, which will affect the detection performance of the network. Therefore, the recall rate and accuracy rate in rainy days are slightly lower than those in the daytime, 0.90 and 0.91, respectively.

Table 1. Daytime road sign recognition performance

Scenes	Recognition efficiency (frame/s)	Recall	Accuracy
Daytime	4	0.96	0.98
Rainy day	4	0.90	0.91

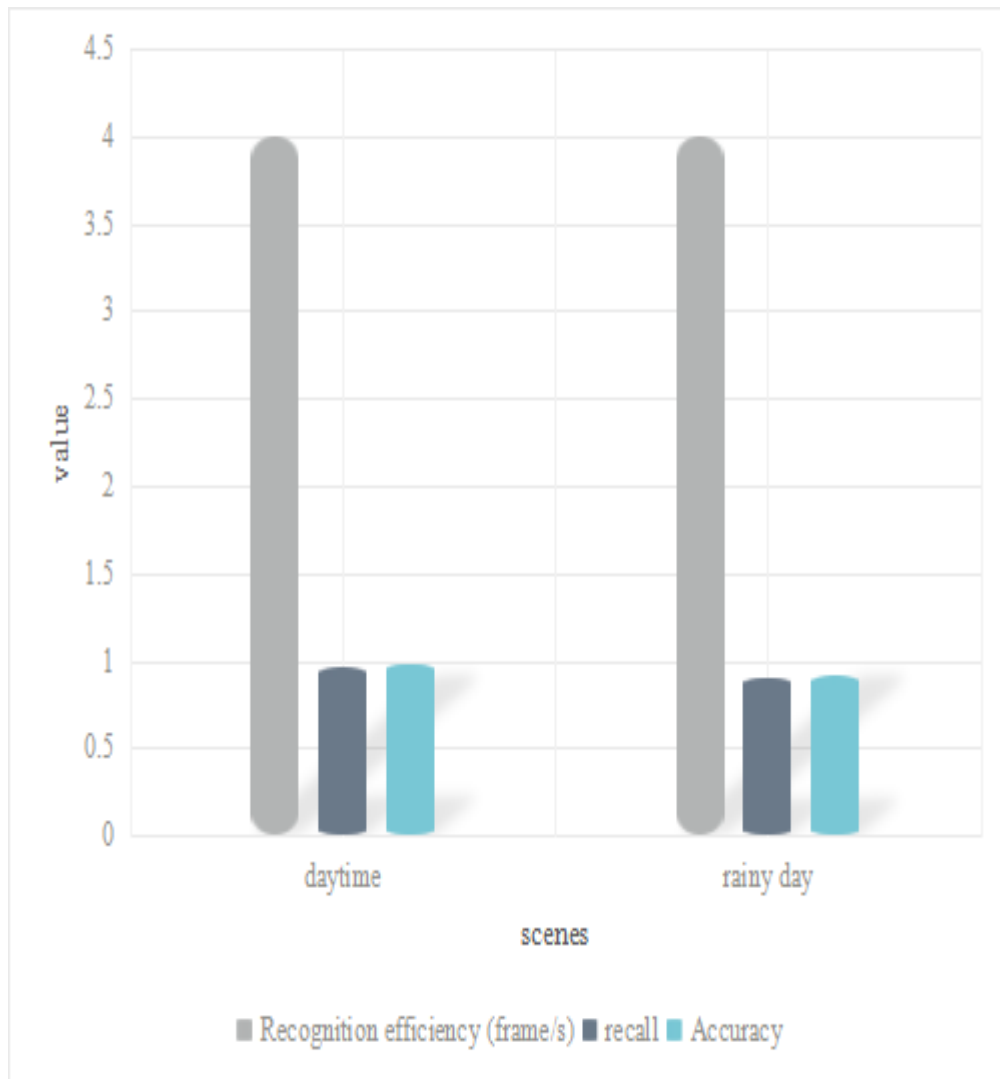


Figure 2. Road sign recognition results in different scenes during the day

4.2. Road Sign Recognition Experiment in Different Scenes at Night

The night light is not good, coupled with the influence of street lights and other vehicle lights, the video image quality collected by the driving recorder is not good, which has a great impact on the recognition of road signs. Due to the dim light and reflection at night, some road signs cannot be detected. The recall and precision of road sign detection at night are only 0.89 and 0.91. If it rains at night, the acquired images are more blurry, and the rain and lights make road signs more difficult to detect, so the recall and accuracy rates on rainy nights are only 0.85 and 0.86.

Table 2. Night road sign recognition performance

Scenes	Recognition efficiency (frame/s)	Recall	Accuracy
Night	4	0.89	0.91
Rainy night	4	0.85	0.86

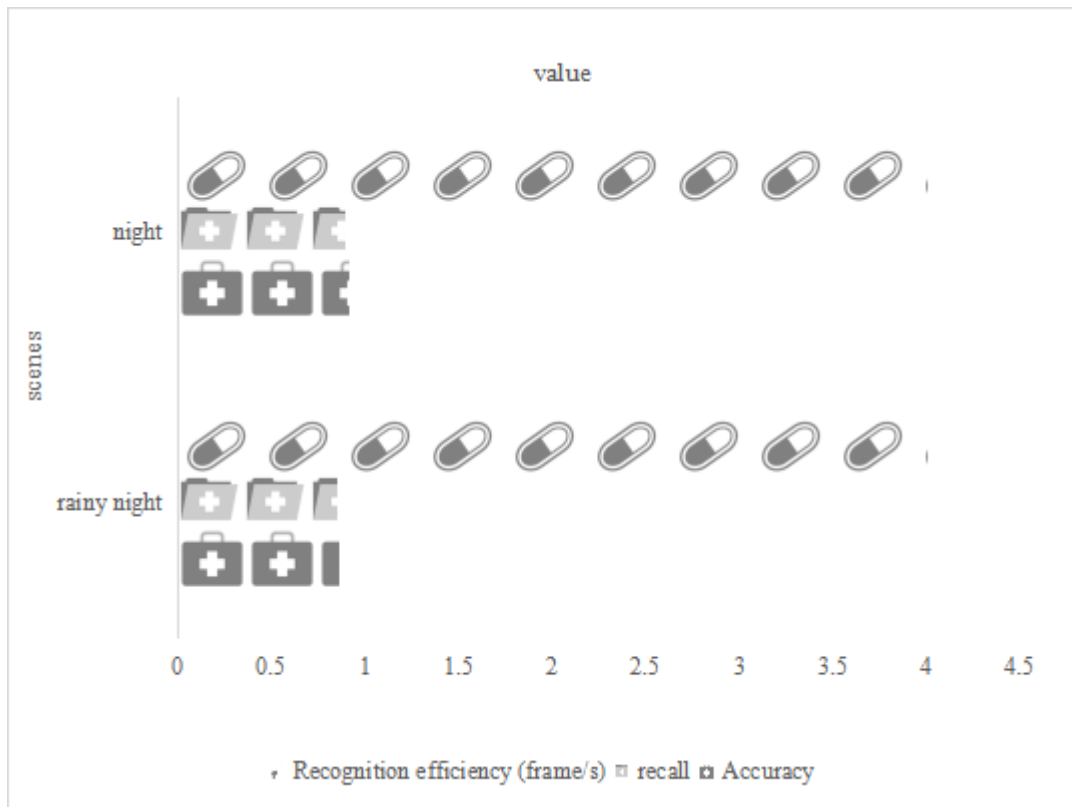


Figure 2. Road sign recognition results in different scenes at night

4.3. Error Analysis of Road Sign Recognition

Due to the complexity of the real scene, especially in the night and other bad weather such as heavy rain, the road signs in the video images captured by the driving recorder will be unclear or even distorted to a certain extent, and due to limited time, many road signs are missed and falsely detected in the process of being identified. For example, the driving recorder is too far from the road sign, and the collected image road sign is too small, resulting in the detection failure, but when the driving recorder gradually approaches the road sign, the road sign can be recognized. For example, although the road sign with a height limit of 6 meters has been detected, the detection category is ph5. In the database annotation, the ph5 category represents the height limit of 5 meters. Since the shapes and colors of the two road signs are similar, there is no height limit 6 in the database. meters, resulting in a false detection of this road sign.

5. Conclusion

If road markings can be accurately identified under complex conditions such as different road conditions, lighting, and weather, it will make a great contribution to the field of autonomous driving and make driving safer. This paper proposes a road sign recognition algorithm that integrates deep learning. Although the algorithm proposed in this paper has outstanding performance in road sign recognition, it is not perfect due to the time relationship, and there are still many areas worthy of improvement. For example, in the classification stage, you can try the ResNeXt and DenseNet algorithms. Since there are many deformed landmarks in the dataset, the technology of STN can also be added.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

- [1] Faiedh H, Hamdi S, Bouguezzi S, et al. Architectural exploration of multilayer perceptron models for on-chip and real-time road sign classification:. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 2018, 232(6):772-783. <https://doi.org/10.1177/0959651818778478>
- [2] Akshay G, Dinesh K, Nagaraj. Road sign recognition system using raspberry PI. *International Journal of Pure and Applied Mathematics*, 2018, 119(15):1845-1850.
- [3] Hasegawa R, Iwamoto Y, Chen Y W. Robust Japanese Road Sign Detection and Recognition in Complex Scenes Using Convolutional Neural Networks. *Journal of Image and Graphics*, 2020, 8(3):59-66. <https://doi.org/10.18178/joig.8.3.59-66>
- [4] Al-Shamayleh A S, Ahmad R, Jomhari N, et al. Automatic Arabic Sign Language Recognition: A Review, Taxonomy, Open Challenges, Research Roadmap And Future Directions. *Malaysian Journal of Computer Science*, 2020, 33(4):306-343. <https://doi.org/10.22452/mjcs.vol33no4.5>
- [5] BA Akgül, Haznedar B, Hasoglu M F, et al. Development of a Real-Time Traffic Sign Recognition System Based On Deep Learning Approach with Convolutional Neural Networks and Integrating to The Embedded Systems. *Euroasia Journal of Mathematics Engineering Natural and Medical Sciences*, 2020, 8(14):46-64.
- [6] Kumar K A, Gowtham S, Kumar M M, et al. Automatic recognition of sign-boards using myRIO. *International Journal of Pure and Applied Mathematics*, 2018, 119(12):14555-14562.
- [7] Hasegawa R, Iwamoto Y, Chen Y W. Robust Japanese Road Sign Detection and Recognition in Complex Scenes Using Convolutional Neural Networks. *Journal of Image and Graphics*, 2020, 8(3):59-66. <https://doi.org/10.18178/joig.8.3.59-66>
- [8] Khayeat A, Abdulmunem A A, Al-Shammari R, et al. Traffic Sign Detection and Classification based on Combination of MSER Features and Multi-language OCR. *Webology*, 2020, 17(2):394-403. <https://doi.org/10.14704/WEB/V17I2/WEB17040>
- [9] Kamruzzaman M M. Arabic Sign Language Recognition and Generating Arabic Speech Using Convolutional Neural Network. *Wireless Communications and Mobile Computing*, 2020, 2020(6):1-9. <https://doi.org/10.1155/2020/3685614>
- [10] Kim H G, Jeong H, Lim H T, et al. Binocular Fusion Net: Deep Learning Visual Comfort Assessment for Stereoscopic 3D. *IEEE Transactions on Circuits and Systems for Video Technology*, 2019, 29(4):956-967. <https://doi.org/10.1109/TCSVT.2018.2817250>
- [11] Lavinia Y, Vo H, Verma A. New colour fusion deep learning model for large-scale action recognition. *International journal of computational vision and robotics*, 2020, 10(1):41-60. <https://doi.org/10.1504/IJCVR.2020.104356>
- [12] Siddiqui S Y, Naseer I, Khan M A, et al. Intelligent Breast Cancer Prediction Empowered with

- Fusion and Deep Learning*. Cmc -Tech Science Press-, 2020, 67(1):1033-1049. <https://doi.org/10.32604/cmc.2020.013952>
- [13] Abdi A, Shamsuddin S M, Hasan S, et al. Deep learning-based sentiment classification of evaluative text based on Multi-feature fusion. *Information Processing & Management*, 2019, 56(4):1245-1259. <https://doi.org/10.1016/j.ipm.2019.02.018>
- [14] Khayyat M M, Elrefaei L A. Manuscripts Image Retrieval Using Deep Learning Incorporating a Variety of Fusion Levels. *IEEE Access*, 2020, PP(99):1-1. <https://doi.org/10.1109/ACCESS.2020.3010882>
- [15] Saba T, Mohamed A S, El-Affendi M, et al. Brain tumor detection using fusion of hand crafted and deep learning features. *Cognitive Systems Research*, 2020, 59(Jan.):221-230. <https://doi.org/10.1016/j.cogsys.2019.09.007>
- [16] Wekesa J, Meng J, Luan Y. Multi-feature fusion for deep learning to predict plant lncRNA-protein interaction. *Genomics*, 2020, 112(5):2928-2936. <https://doi.org/10.1016/j.ygeno.2020.05.005>
- [17] Usama M, Xiao W, Ahmad B, et al. Deep Learning based Weighted Feature Fusion Approach for Sentiment Analysis. *IEEE Access*, 2019, 7(99):140252-140260. <https://doi.org/10.1109/ACCESS.2019.2940051>
- [18] Lahaye N, Ott J, Garay M J, et al. Multi-Modal Object Tracking and Image Fusion with Unsupervised Deep Learning. *Selected Topics in Applied Earth Observations and Remote Sensing*, *IEEE Journal of*, 2019, 12(8):3056-3066. <https://doi.org/10.1109/JSTARS.2019.2920234>