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Journal of Advances in Artificial Life Robotics
Vol. 4(2); September (2023), pp. 80–88
ON LINE ISSN 2435-8061; ISSN-L 2435-8061
https://alife-robotics.org/jallr.html

Research Article

Optimizing Traffic Sign Detection System Using Deep Residual Neural Networks Combined with Analytic Hierarchy Process Model

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ARTICLE INFO

Article History
Received 05 December 2022
Accepted 07 October 2023

Keywords
Traffic sign detection system
Residual neural network (ResNet)
Analytic hierarchy process (AHP)

ABSTRACT

This paper utilises image pre-processing techniques and deep residual neural networks to enhance the traffic sign detection system. A novel Analytic Hierarchy Process (AHP) model for performance evaluation has been proposed and utilised to determine the optimal parameter configuration of the learning models. Four evaluation metrics, namely accuracy, stability, response time, and system capability, have been defined for AHP measurements. The experiments were conducted using a comprehensive dataset, with VGG-16 and Google Net implemented for comparisons. Finally, the combination of ResNet-50 and the AHP model yielded the best results, achieving a 98.01% accuracy rate, 0.09% false alarm rate, and 1.28% undetection rate.

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1. Introduction

Deep Learning plays a pivotal role in current frontier science and finds widespread applications in sectors such as manufacturing, agriculture and transportation. In the content of urban transportation, it is of great significance to leverage deep learning approaches for the Traffic Signs Detection System (TSDS), which normally comprises two related domains: Traffic Sign Detection (TSD) and Traffic Sign Recognition (TSR). However, TSDS application demand high accuracy and precision while minimising detection and recognition time. As an alternative to conventional detection methods, deep learning-based approaches appear to be a promising option for efficient traffic sign detection [1], [2], [3]. According to existing research, to address the challenge of traffic sign detection and recognition, Suriya Prakash, *et al.* [4] proposed a LeNet-5 Convolutional Neural Network (CNN) model that possessed a very high detection accuracy of nearly 98.8%. Changzhen, *et al.* [5] implemented an advanced detection method based on a deep CNN model which achieved a result of over 99.0% recognition precision.

Despite the impressive performance of deep learning models, the effectiveness of the CNN model will decrease when confronted with trickier recognition challenges which require deeper layers and more computing resources [3]. The Residual Neural Network (ResNet) was proposed by He, *et al* [6] to resolve the problem that the performance decreases with the deepening of network training. This model employs a residual learning approach that substantially mitigates the the challenges of training deep networks. Moreover, ResNet models have been widely applied in various research works. Zakaria, *et al.* [7] utilized ResNets in the medical field to recognize and classify medical images. Li and Rai [8] optimized and enhanced the model

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structures in the study of fruit leaf disease recognition and classification, yielding an impressive accuracy rate exceeding 98.2%.

This paper leverages the deep residual neural networks to explore state-of-the-art solutions for traffic sign detection. In this work, image pre-processing techniques and ResNet models were implemented to conduct detection experiments. In addition, a novel Analytic Hierarchy Process (AHP) model was introduced for performance assessment and comparison. Extensive experiments based on real-world datasets were performed to validate the effectiveness of proposed method.

The rest of this paper is organized as follows. Secton 2 provides a brief introduction to related research. Section 3 outlines the workflow and structure of the proposed detection system. Section 4 presents the performance evaluation method based on the AHP model. Section 5 is dedicated to the discussion of experimental results and finally, Section 6 summarises the conclusions of this paper.

2. Related Works

2.1. *Traffic Sign Detection System (TSDS)*

Traffic signs play a crucial role in providing essential information for safe driving in real-world scenarios. Variousmethods and algorithms have been developed to detect and recognize different traffic signs in many countries and regions. In general, the TSDS concern two related aspects: Traffic Sign Detection (TSD), which aims to accurately locate traffic signs in the physical environment, and Traffic Sign Recognition (TSR), which focuses on identifying the meaning of specific traffic signs such as speed limits, stop signs, and directional signs. As for existing works, Lu, *et al.* [9], Wali, *et al.* [10] and Arcos-García, *et al.* [11] have conducted comprehensive surveys of state-of-the-art techniques in the field of TSDS.

As illustrated in Table 1, this paper provides an extensive review of relevant literature. In the realm of conventional TSDS methods, the majority of research efforts concentrate on color segmentation, image shape, and texture features [12], [13], [14], [15], [16], [17]. Nevertheless, these conventional approaches heavily rely on image quality, rendering them vulnerable to variations caused by factors such as daylight conditions and the impact of environmental pollutants on sign paint. Recognizing these limitations, Fleyeh, *et al* [1] conducted an exhaustive overview of the traditional methods and pointed to many problems regarding traditional image detection and recognition methods. Given the limitations of conventional methods, most have gradually been replaced by new learning-based models, which optimise performance and effectiveness by using existing datasets and prior experience.

Over the past two decades, numerous learning-based approaches have been introduced to tackle intricate TSDS challanges. Support Vector Machine (SVM) models have been utilized in Spanish traffic sign detection to issue alerts to drivers [18]. Neural network models also gained extensive attention in this domain, often combined with techniques such as Hough transformation, corner detection and projection methods. Models proposed by Kuo and Lin [19] achieved good accuracy of nearly 95.5% based on the traffic sign datasets in Taiwan, China. However, as traffic senariors become more complex and the number of signal categories increases, conventional machine learning models struggle to handle more intricate challenges, like contaminated, multi-object, and large-scale sign detection and recognition [9].

2.2. *Deep Learning Technique*

Deep learning (DL) techniques have been at the forefront of computer vision, finding extensive applications in image detection and classification [2]. Among the various DL approaches, Convolutional Neural Networks (CNN) are one of the most prominent models in the field of TSDS.

Suriya Prakash, *et al.* [4] extended and enhanced the classical LeNet-5 CNN model by incorporating a Gabor-based kernel followed by a standard convolutional kernel after the pooling layer. Their proposed CNN model was evaluated using the German Traffic Sign Benchmark, achieving an accuracy of approximately 98.9%.

Furthermore, Changzhen, *et al.* [5] introduced a novel algorithm based on deep CNN with a Region Proposal Network (RPN) for the detection of all Chinese traffic signs. The experiments demonstrated that their model achieved near real-time detection speed and precision exceeding 99.0%.

To achieve improved detection response times, K R, *et al.* [20] introduced a combined approach that utilises both Faster Region-based Convolution Neural Network (R-CNN) and RPN network. Additionally, the Random Forest algorithm is employed for classification and regression within the provided dataset. These composite methods substantially decreased the resource demands for training deep learning models while increasing accuracy to up to 99.9%.

Many existing methods typically concentrate on a restricted set of traffic sign classes, covering around 50 out of several hundred categories found in various regions. To improve this limitation, Tabernik and Skocaj [21] proposed an enhanced mask R-CNN model to resolve the challenge of detecting a large-scale range of traffic sign categories. Their experiments were conducted on a large-scale sign dataset, and the results demonstrated an average error rate below 3% in real-world detections. However, it is noted that a systematic performance evaluation method is still lacking in most of the research [22].

Table 1 A summary of related research works

Techniques	Descriptions
Colour Segmentation [12], [13]	Easily affected by daylight conditions
Texture Features [16], [17]	Highly reliant on the quality of the images
SVM Classifier [18]	Good classification accuracy but low speed
NN Models [19]	High accuracy, but large resources are required
LeNet-5 CNN [4]	Using Gabor Based Kernel. High accuracy
CNN+RPN [5]	Fast real-time sign detection speed
R-CNN+RF [20]	High accuracy, recall and F1-score
Mask R-CNN [21]	Implemented based on a large-scale dataset
ResNet+AHP [22]	Proposed a systematic evaluation model

2.3. *Research Gap and Further Work*

To date, there has been limited research dedicated to the training and testing ResNet models using comprehensive traffic sign datasets that encompass a wide range of categories. This paper introduces deep ResNets to address the challenges of large-scale sign detection, and experiments are conducted to validate its effectiveness in enhancing the TSDS. Furthermore, despite the favorable detection results obtained in previous research, the majority of evaluations have concentrated exclusively on essential metrics such as detection accuracy, precision, and response time. This paper presents a novel AHP approach to evaluate the practical performance of deep learning models across different parameters and optimizers.

3. Proposed Methodology

In this paper, the ResNet models with 50, 101, and 152 layers of CNN-based architectures were established and evaluated using a novel AHP method. The Tsinghua-Tencent 100K dataset [23], comprising approximately 100k images with about 30k traffic signs, was employed for training and testing. The workflow of poposed traffic sign detection system is shown in Fig. 1, with 80% of the dataset used for model training and the remaining 20% for performance evaluation.

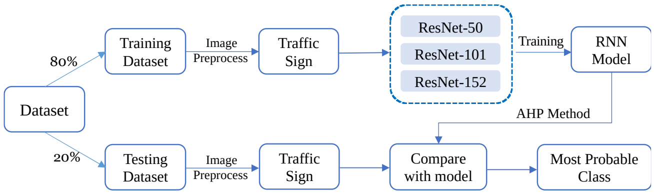

Fig. 1. Workflow of model training and testing process

3.1. *Image Pre-processing*

The first stage of the TSDS workflow is the image pre-processing. Given that pixels with sudden changes in brightness in an image usually represent the contours of an object, precise localization of these pixels allows for accurate recognition and prediction of actual signs [21]. To extract image features, this paper primarily employed edge detection and corrosion expansion. The flowchart of the image pre-processing techniques is illustrated in the following Fig. 2.

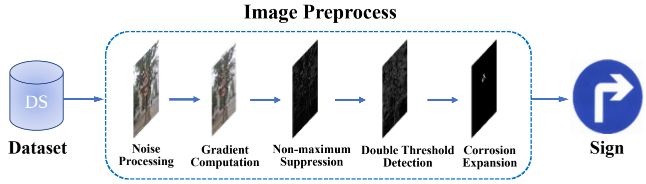

Fig. 2. Flowchart of the image pre-processing

3.1.1. Edge Detection

(i) Noise processing & Gradient computation

In images, pixels exhibiting pronounced variations in grayscale values may manifest as noise, which can appear randomly. Such noise can be generated from various sources, including image acquisition, transmission, and quantization. To mitigate the impact of noise, this paper employs a Gaussian filter for noise reduction. It is important to note that while the Gaussian filter effectively reduces noise, it can have an adverse effect on image definition and sharpness. To address this, gradient computation is subsequently applied to extract object outlines within the image. These two sequential processes enhance the saliency of image features, rendering them more suitable for subsequent processing procedures.

(ii) Non-maximum suppression

After gradient computation, the features of the main object are enhanced, and the non-maximal value suppression is used to eliminate the influence of other non-target objects. This technique retains only local maximum gradient values, indicating the positions of the strongest image features. In areas with multiple traffic signs, over-lapping detections may occur. Non-maximal values help identify the optimal target boundary frame and remove redundant boundary boxes.

(iii) Double threshold detection

The final step in edge detection involves differentiating objects from the background. It utilizes the grayscale contrast between the target and its background in the image to extract the desired traffic signs. This is achieved by classifying pixel values into multiple categories through thresholding, thereby effectively separating objects from the background.

3.1.2. *Corrosion expansion*

After edge detection, the next step involves corrosion expansion, which entails selecting the maximum value within the neighborhood of each pixel to determine the output grayscale value. This expansion process enhances the overall brightness of the image, making brighter objects appear larger, while darker objects may be reduced or even eliminated. By merging the outcomes of image processing with the location identified through color thresholding, a sign devoid of background noise is obtained.

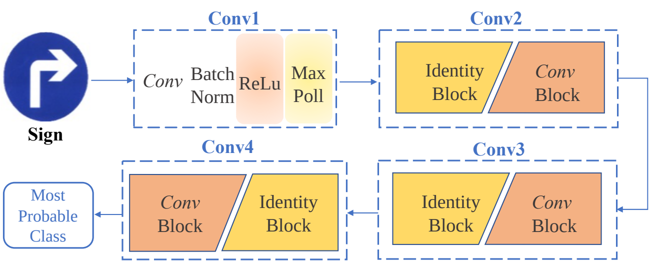

Fig. 3. Architecture of the applied ResNet models

3.2. *Residual Neural Network (ResNet)*

Following image pre-proposssing, the next stage is to classify the traffic sign into the most probable category. In this work, the sign recognition is conducted using ResNet model, which consists of two different layers, known as the *conv* block and identity block. These blocks serve as shortcuts in residual blocks and are arranged in the order shown in Fig.3.

Fig. 4 illustrates the structures of the identity and *conv* blocks. Each residual block consists of a stack of three layers: 1×1, 3×3, and 1×1 convolution layers. The 1×1 layers are responsible for dimension reduction and subsequent dimension expansion, while the 3×3 layer operates with smaller input and output dimensions.

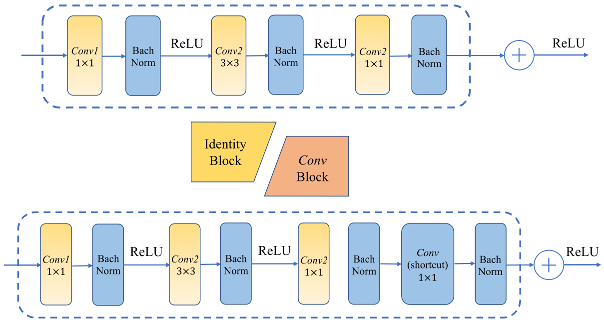

Fig. 4. Structures of the identity and *conv* blocks

4. Analytic Hierarchy Process (AHP)

To effectively access the maturity level of different process component and parameter configuration, this paper used the AHP to develop a maturity evaluation model. AHP leverages straightforward mathematical tools in conjunction with operational concepts to break down intricate problems into individual elements and construct hierarchies based on their interdependencies. The key mathematical notations utlized in this paper are provided in the following Table 2.

Table 2. Notations of the AHP method

Symbol	Description	Unit
$Score$	Total score	1
RT	Response time score	1
SB	Stability score	1
AC	Accuracy score	1
SC	System capability score	1
PS	Process Speed	Piture/ms
CPR	Computing Requirement	FLOPS

4.1. ***Maturity level evaluation model***

This paper defines four evaluation indicators to calculate the maturity level score of different models. These four sub-indicators are given as follows: Accuracy (*AC*), Stability (*SB*), Response Time (*RT*) and System Capability (*SC*).

Accuracy (*AC*)

The most crucial criterion for evaluating the model is the accuracy. Therefore, the ratio between the number of correct detection and the total dataset is used to normalize the performances of images in different scales. The corresponding score in Table 3 is calculated as follows:

$$AC = \frac{Correct\ number}{Total\ number} \times 100\% \tag{1}$$

Table 3 Accuracy score table

Accuracy	*AC (Score)*
Less than 75%	0
75% ~ 80%	1
80% ~ 85%	2
85% ~ 90%	3
90% ~ 95%	4
More than 95%	5

Stability (*SB*)

The stability of detection model is crucial in various working conditions. However, unexpected factors can disrupt the detection process in realistic scenarios, such as low-light environments, incomplete images, and damaged traffic signs. To assess stability, this paper calculates the ratio between accuracy under realistic conditions and accuracy under ideal conditions. The *SB* score in Table 4 can be calculated by:

$$SB = \frac{Practical\ accuracy}{Theatrical\ accuracy} \times 100\% \tag{2}$$

Table 4 Stability score table

Stability	*SB (Score)*
Less than 60%	0
60% ~ 65%	1
68% ~ 78%	2
78% ~ 88%	3
88% ~ 95%	4
95% ~ 100%	5

Process Speed (*PS*) & Response Time (*RT*)

To ensure the efficiency of the process parts, the response time is a critical factor. The training speed is determined by the time of processing 1000 images based on Equation (3). A shorter training time results in a higher score, as indicated in Table 5.

$$PS = \frac{Response\ time}{1000} \tag{3}$$

Table 5 Response time score table

Process Speed	*RT (Score)*
More than 3.00s	0
2.40 ~ 3.00s	1
1.80 ~ 2.40s	2
1.20 ~ 1.80s	3
0.60 ~ 1.20s	4
0.00 ~ 0.60s	5

System capability (*SC*)

Hardware requirements are essential factors that limit the performance of models. These requirements are determined by the computing power requirement (CPR). Floating-point operations per second (FLOPS) are often used to estimate the performance of computer, especially in scientific computing scenarios, where many floating-point arithmetic operations are performed. Therefore, this paper also employs FLOPS to evaluate the level of CPR, as illustrated in Table 6.

Table 6 System capability score table

CPR	*SC (Score)*
More than 3.50G	0
2.00 ~ 3.50G	1
1.50 ~ 2.00G	2
1.00 ~ 1.50G	3
0.50 ~ 1.00G	4
0.00 ~ 0.50G	5

4.2. ***Weight Determination***

In this study, the judgment matrix for the indicators is constructed using a nine-point scale, as presented in Table 7. This matrix is used to compare the four indicators in pairs and generate the judgment matrix. Noted that each element in the matrix should adhere to the following conditions:

$$x_{ij} > 0,\ \ x_{ij} = \frac{1}{x_{ji}}, (i, j = 1,2,3,4) \tag{4}$$

Table 7 Nine-point table of the AHP model

Scaling	Definition
1	Factor i is as important as factor j
3	Factor i is slightly more important than factor j
5	Factor i is significantly more important than factor j
7	Factor i is much more important than factor j
9	Factor i is extremely more important than factor j
2,4,6,8	The scale value of the importance of factor i over factor j is between the above two adjacent levels
Reciprocal of scaling value	Inverse comparison of factor i and j: $x_{ij} = 1/x_{ji}$

The weight vector can be calculated by arithmetic mean:

$$\omega_{1i} = \frac{1}{n}\sum_{j=1}^{5} \frac{x_{ij}}{\sum_{k=1}^{5} x_{ki}} (i = 1,2,3,4) \tag{5}$$

Also, the geometric mean method is expressed as follows:

$$\omega_{2i} = \frac{\left(\prod_{j=1}^{5} x_{ij}\right)^{\frac{1}{5}}}{\sum_{k=1}^{5} \left(\prod_{j=1}^{5} x_{ij}\right)^{\frac{1}{5}}}, (i = 1,2,3,4) \tag{6}$$

The arithmetic mean and the geometric mean are used to calculate the weight vectors, ω_{1i}, ω_{2i} $(i = 1,2,3,4)$, and then these vectors are averaged to obtain the final weight vector, as illustrated in Table 8. After obtaining the weight for evaluation indicators, the next step is to test for consistency. In this paper, the consistency test of the judgment matrix yields a value less than 0.1, indicating the obtained weight data are valid. The evaluation model is given as follows:

$$Score = 0.275RT + 0.211SB + 0.342AC + 0.172SC \tag{7}$$

Table 8 Weight bar graph

Indicator	*Weight*
RT	0.275
SB	0.211
AC	0.342
SC	0.172

5. Experimental Result and Analysis

This section describes the evaluation metrics utilized to assess the performance and provides a detailed analysis of the experimental result. Noted that the experiment was performed using the following hardware specifications:Intel i5-10400F Processor, 16GB RAM, Windows 10 64-bit OS, and the NVIDIA GeForce RTX 2080 GPU.

Table 9 Confusion matrix for performance evaluation

Input Data	Positive Predictive	Negative Predictive
Positive Sample	True Positive (TP)	False Nagatice (FN)
Negative Sample	False Positive (FP)	True Negative (TN)

5.1. *Evaluation Metrics*

The experiment result of training and testing are assessed by metrics derived from the confusion matrix, as shown in Table 9. As mentioned in Section 3, to simulate the real-world traffic detection scenario, the dataset was deliberately designed to be unbalanced, with a significantly larger number of normal road images (~70%) than road images with traffic signs (~30%) [23]. Therefore, the general metric of accuracy is not representative to evaluate the performance of detection system. To ensure an unbiasedanalysis, credible metrics namely False Alarm Rate (FAR) and Un-Detection Rate (UND),were used to evaluate the performance. Table 10 illustrates these metrics and corresponding formulas.

Table 10 Evaluation metrics and relevant explanations

Evaluation Metrics	Corresponding Formula	
Accuracy	$\frac{1}{n}\sum_{1}^{n} \frac{TP+TN}{TP+TN+FP+FN} \times 100\%$	(8)
False Alarm Rate (FAR)	$\frac{1}{n}\sum_{1}^{n} \frac{FP}{FP+TN} \times 100\%$	(9)
Un-Detection Rate (UND)	$\frac{1}{n}\sum_{1}^{n} \frac{FN}{FN+TP} \times 100\%$	(10)

5.2. *Experimental Results*

Using the Tsinghua-Tencent 100k dataset, this work employed ResNet-50, ResNet-101, and ResNet-151 models for training and conducting traffic sign recognition experiments. In addition, VGG-16 [24] and GoogLeNet [25] models were implemented for comparison with the proposed method. Table 11 presents a performance comparison for these different models, with the ResNet-50 combined with AHP model achieving the best testing results, boasting an accuracy of 98.01%, a FAR of 0.09%, and an UDN of 1.28%. Furthermore, this paper selected the optimal parameters of the ResNet models with the best performance leveraging the AHP evaluation model. By comparing the results of different parameter configrations in the training and testing process, the optimal parameters of ResNet were listed in Table 12.

6. Conclusion

In this study, the method based on image pre-processing techniques and deep learning were applied to enhance the traffic sign detection system. Moreover, this paper presented a novel AHP model to evaluate the performance of learning models and determine the optimal parameter configuration strategy. Four evaluation indicators, namely accuracy, stability, response time, and system capability, were used for AHP measurement. The experimental results demostrated that the ResNet-50 combined with the AHP model achieved the best performance, with the highest accuracy, lowest false alarm rate, and lowest un-detection rate. These findings emphasize the efficacy of the proposed method in improving the reliability and efficiency of traffic sign detection systems, making it a promising solution for real-world applications.

Acknowledgements

This work was supported by the Chinese National Undergraduate Innovation Training Program (No. 202310386056)

Table 11 Experimental results of training and testing

Evaluation Metrics		**Deep Learning Models**		
		VGG-16	**GoogLeNet-22**	**ResNet-50+AHP**
Training (80%)	**Accuracy**	98.24%	98.89%	99.03%
	FAR	0.06%	0.03%	0.01%
	UND	0.87%	0.86%	0.41%
Testing (20%)	**Accuracy**	83.60%	96.62%	98.01%
	FAR	2.47%	0.19%	0.09%
	UND	56.73%	2.94%	1.28%

Table 12 Optimal parameters of ResNets chosen by the AHP model

Model Parameters	**Parameter 1 (Chosen)**	**Parameter 2**	**Parameter 3**
Convolution Layers	**ResNet-50**	ResNet-101	ResNet-152
Learning Rate	**Step**	Low	High
Split Strategy	**Classification Split**	Random Split	
Image Enhancement	**Brightness Enhancing**	Image Scale	Contrast Enhancing
Colour Processing	**HSV**	RGB	

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