Deep Residual Neural Network for Efficient Traffic Sign Detection

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Abstract

This paper established three deep residual neural network models with different architectures for traffic sign detection. Also, a new systematic analytic hierarchy process method for model performance evaluation has been proposed, which was utilized to determine the configuration of the deep learning model. In this paper, four evaluation metrics were used for analytic hierarchy process measurement, they are accuracy, stability, response time, and system capability. Based on the Tsinghua-Tencent 100K dataset, experimental results verified the feasibility of the proposed models for traffic sign detection and recognition which has training and testing accuracy of 99.03% and 98.01% respectively.

Keywords: Traffic Sign Detection System; Residual Neural Network (RNN); Analytic Hierarchy Process (AHP).

1. Introduction

Deep Learning (DL) plays a non-negligible role in current frontier science, which has been widely used in agriculture, and transportation industries. As for the application in urban transportation, it is of great significance to utilise related DL approaches for the Traffic Signs Detection System (TSDS), which normally consists of two related domains: Traffic Sign Detection (TSD) and Traffic Sign Recognition (TSR). However, TSDS requires high accuracy and precision while exploiting the shortest possible detection and recognition time. As an alternative to conventional machine learning schemes, deep learning-based schemes appear to be a promising option for efficient traffic sign detection[1],[2],[3]. According to recent literature works, 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 high detection accuracy of nearly 98.8%. Changzhen, *et al.*[5] implemented an advanced detection method based on a deep CNN model which also achieved a satisfactory result of above 99.0% recognition precision.

Despite the good performance of deep learning models, the effectiveness of this CNN model will decrease when facing trickier image recognition challenges which require deeper layers and more computing resources [3]. The Residual Neural Network (RNN) or in short, ResNet, approach was proposed by He, *et al.*[6] to resolve the problem that the performance decreases with the deepening of network training. RNN models adopt a residual learning methodology that significantly reduces the difficulty of the deep networks training process. Besides, RNN models have been widely applied in some research works, Zakaria, *et al.*[7] utilized RNN models in the medical field to recognize and classify medical images. Li and Raim made optimization and improvement combined with the actual applications, which obtained very good results of over 98.2% accuracy for fruit leaves detection and recognition.

This paper applies RNN approaches to explore state-of-the-art solutions for efficient traffic sign detection. In this work, a deep RNN is built to address the TSDS challenges. Experiments have been conducted to verify the feasibility of implementing the RNN model for TSD and TSR problems. Also, another contribution of this paper is to propose a new performance evaluation method for a RNN with different parameters and optimizers. An optimal configuration scheme for RNN models was suggested through a large number of experiments based on representative datasets.

2. Related Works

This section goes through the key concepts of this paper, including TSDS and DL. Furthermore, many related research works have been explicitly reviewed, and the gaps in existing knowledge have been identified.

2.1. *Traffic Sign Detection System (TSDS)*

Traffic signs provide paramount information for real-world driving, and a variety of methods and algorithms have been implemented to detect and recognize different traffic signs in different countries and regions. The TSDS concern two related subjects: TSD and TSR, where TSD aims to find an accurate location of the sign in the physical transportation environment and TSR mainly focus on identifying the meaning of specific traffic signs (e.g., Speed Limit, Stop and Direction). As for existing knowledge in the area of TSDS, Lu, *et al.*[9] Wali, *et al.*[10] and Arcos-García, *et al.*[11] have proposed comprehensive surveys of some state-of-the-art techniques for TSDS purposes.

As shown in Table 1, many related works have been explicitly reviewed in this paper. As for the conventional methods for TSDS, most of the research works focus on the methods of colour segmentation, image shape and texture features[12],[13],[14],[15],[16],[17]. However, these traditional approaches are highly dependent on the quality of the images, which can be easily affected by daylight conditions and the reaction of the paint to the pollutants in the air. Fleyeh and Dougherty[1] proposed an exhaustive overview of the traditional methods and pointed to many problems regarding traditional image detection and recognition methods. Considering the validity of the TSDS, most of the conventional methods have been gradually replaced by new learning-based models, which can optimize model performance and effectiveness through learning the existing datasets and previous experience.

Over the past two decades, many learning-based approaches have been proposed to address complex TSDS problems. Support Vector Machine (SVM) models have been applied in Spanish TSDS to provide alerts to the drivers[18]. Neural network models also gained extensive attention in this domain, which can be combined with Hough transformation, corner detection and projection methods. The Neural Network (NN) models proposed by Kuo and Lin[19] have achieved good accuracy of nearly 95.5% based on the traffic sign datasets in Taiwan, China. However, since the emergence of trickier traffic scenarios and the increase of different signal categories, general ML models get exhausted when facing more complicated challenges, such as contaminated, multi-object and large-scale sign detection and recognition[9].

2.2. *Deep Learning Technique*

DL technique has been the core topic in computer vision, which has been highly applied in image detection and classification[2]. CNN and RNN models are the most prominent DL approaches in the field of traffic sign detection and recognition.

Suriya Prakash, *et al.*[4] extended and developed a classical LeNet-5 CNN model, which makes use of Gabor based kernel followed by a normal convolutional kernel after the pooling layer. Their proposed CNN model was evaluated using the German Traffic Sign Benchmark and gave an accuracy of nearly 98.9%.

Also, Changzhen, *et al.*[5] suggested a new algorithm based on deep CNN using Region Proposal Network (RPN) to detect all Chinese traffic signs. Experiments show that their model has real-time detection speed and above 99.0% precision.

Considering better detection response time, K R, *et al.*[20] have proposed a combined scheme utilizing Faster Region-based Convolution Neural Network (RCNN) and RPN network. Besides, the Random Forest algorithm is used to perform classification and regression in the given dataset. Their composite methods significantly reduced the resource requirements used for training the deep learning models and the accuracy increased up to 99.9%.

However, most of the existing methods suggested are based on a limited number of traffic signs (about 50 classes out of several hundred in different regions). Tabernik and Skocaj[21] proposed several improvements using CNN and mask R-CNN approach to resolve the issue of detecting large-scale traffic sign categories. The experiments are conducted on large-scale traffic signs detection and results show that the detection has a 2–3% average error rate in actual detections.

Table 1 A summary of related literature works

Techniques	Descriptions
Colour Segmentation [12][13]	Easily affected by daylight conditions.
Texture Features [16][17]	Highly depending on the quality of the images.
SVM Classifier [18]	Good classification accuracy, but low speed.
NN Models [19]	High accuracy, but a large resource is required.
LeNet-5 CNN [4]	Utilizing Gabor Based Kernel, high accuracy
CNN+RPN [5]	Very high real-time detection speed.
R-CCN+RPN [20]	Very high accuracy, close to 99.9%.
Mask R-CNN [21]	Based on highly challenging datasets.

2.3. *Research Gap*

To date, there is limited research that has focused on training and testing the RNN model based on representative traffic sign datasets including large-scale categories. In this paper, a deep RNN is proposed to address the large-scale detection challenges. Experiments are conducted to verify the effectiveness of implementing the RNN model to advance TSDS.

Although the existing research works have achieved a good detection result, most of the works are only evaluated by detection accuracy, precision, and response time, which are all in the same key. In this paper, a new analytic hierarchy process (AHP) method for RNN with different parameters and optimizers is proposed to deploy in the practical performance measurement of the deep learning model.

3. The Proposed Method

This work utilizes the Tsinghua-Tencent 100k dataset proposed in [22], which provides 100k images containing 30k different traffic signs. The RNN with respectively 50, 101, and 152 layers of CNN-based architecture has been established for training and testing. Fig. 1 illustrates the workflow of the model training and testing process. The training dataset is composed of 80% of the total dataset, which is used to train the proposed RNN model. While the testing dataset consists of the remaining 20%, which is used to evaluate the performance of the trained RNN model.

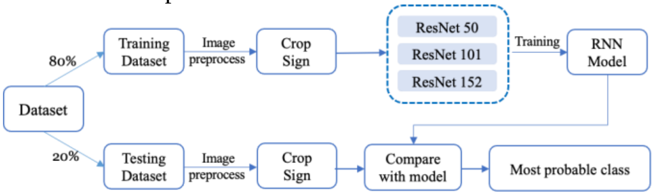

Fig. 1. Workflow of model training and testing process

3.1. *Image Pre-processing*

The first step of the TSDS system workflow is image pre-processing. Considering that a collection of pixels in an image with a sharp change in brightness is often the outline of an object. Being able to locate them accurately means that the actual signs can be located and predicted[21]. To extract the features in the image, this paper mainly utilized edge detection and corrosion expansion. Fig. 2 shows the specific workflow of the image pre-processing, including noise processing, gradient computation, non-maximum suppression, double threshold detection and corrosion expansion.

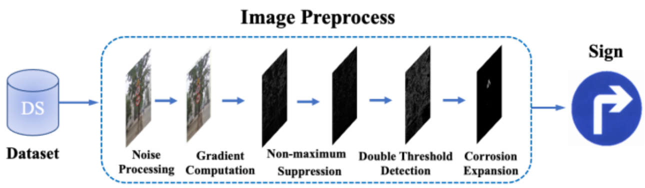

Fig. 2. Flowchart of the image pre-processing

Edge Detection

Noise processing and gradient computation

In the image, the pixels with large grayscale changes appear randomly and gene the noise. And the noise comes from various situations, including image acquisition, transmission, and quantization. In order to minimize the noise, this paper applied the Gaussian filter to minimise the noise. The gaussian filter will give a negative impact on the definition and sharpness of images, therefore, the gradient computation is conducted to extract the outline of the objects in the image. These two steps make the features of the image more prominent and suitable for subsequent processing.

Non-maximum suppression

After the gradient computation, the features of the main objects in the images will be highlighted. In this case, non-maximal value suppression is utilized to eliminate the influence of other non-target objects. It suppresses all the gradient values other than the local maximum and indicates the position of the strongest strength of the image. In the location of the traffic sign detection, a large number of traffic signs in the location of the same target will be detected, and these traffic signs may overlap between them. The non-maximal values can be used to prevent the finding of the best target border frame and eliminate the redundant boundary boxes.

Double threshold detection

The final step of edge detection is to distinguish the objects from the background. The grey difference between the target and the corresponding background in the image is used to extract the targeted traffic signs and divide the pixel level into several classes by setting the threshold in order to achieve the separation of the objects and the background.

Corrosion expansion

After the edge detection, the next procedure is corrosion expansion, which selects the maximum value in the neighbourhood of each position as the output grey value. After expansion, the overall brightness of the image will be improved. The size of the brighter object in the graph will be larger, while the size of the darker object will be reduced or even disappear. According to the result of image processing and the location determined by the colour threshold, the traffic sign without background noise is obtained.

3.2. *Residual Neural Network (RNN)*

The proposed RNN architecture has two layers, called *conv* block and identity block, which serve as shortcuts in residual blocks and are included in an order, as shown in Fig.3.

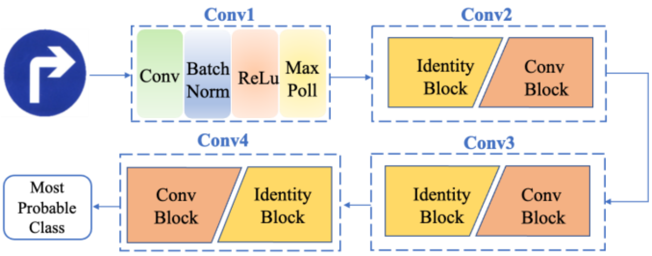

Fig. 3. Architecture of proposed ResNet

Fig. 4 presents the structures of the identity and *conv* blocks respectively. A stack of three layers was used for each residual block. The 1×1, 3×3, and 1×1 layers are three convolution layers. The 1×1 layers focus on first reducing and then increasing the dimensions, and the 3×3 layer has smaller input and output dimensions.

4. Analytic Hierarchy Process

To accurately measure the maturity level of different process parts, the Analytic Hierarchy Process (AHP) is proposed to establish a maturity evaluation model. AHP applies simple mathematical tools combined with operational thoughts to decompose complex issues into individual constituents, and form hierarchies according to the disposable relationship group.

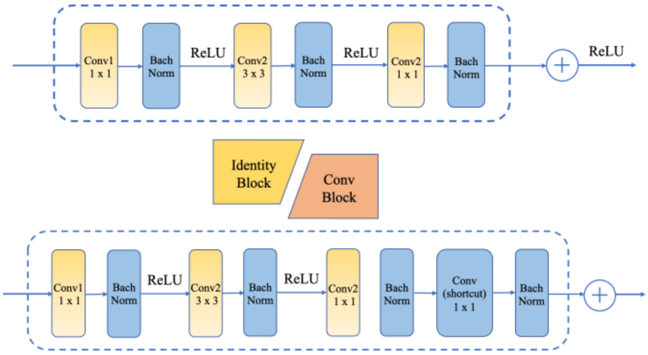

Fig. 4. Structures of the identity and *conv* blocks

The key mathematical notations used in this sector are listed in 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*

Indicator selection

This paper designs four sub-indicators to calculate the maturity level score of different parts. These four sub-indicators are Accuracy (*AC*), Stability (*SB*), Response Time (*RT*) and System Capability (*SC*).

Accuracy (AC)

The most important standard to judge the model is the accuracy. Therefore, the ratio between the number of correct detection and the total set is used to normalize the performances of different scale pictures. 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 0.75	0
0.75-0.80	1
0.80-0.85	2
0.85-0.90	3
0.90-0.95	4
More than 0.95	5

Stability (SB)

The model must keep relatively high stability in all working conditions. But unexpected things would disturb the detection process in many realistic cases, like dim environments, incomplete pictures, and broken traffic signs. So, the ratio between the accuracy of realistic and theoretical conditions is considered to obtain the *SB*. The *SB* score in Table 4 is calculated using:

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

Table 4 Stability score table

Stability	*SB (Score)*
Less than 75%	0
75%-80%	1
80%-85%	2
85%-90%	3
90%-95%	4
95%-100%	5

Process Speed (PS) & Response Time (RT)

To guarantee the efficiency of the process parts, the response time is a very important factor. The training speed is determined by the time of processing 1000 images using eq. 3. The shorter the training time, the higher the score, as shown in Table 5.

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

Table 5 Response time score table

Process Speed	*RT (Score)*
More than 5s	0
4-5s	1
3-4s	2
2-3s	3
1-2s	4
0-1s	5

System capability (SC)

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

Table 6 System capability score table

CPR	*SC (Score)*
More than 3.5G	0
2.0-3.5G	1
1.5-2.0G	2
1.0-1.5G	3
0.5-1.0G	4
0-0.5G	5

4.2. *Weight Determination*

In this work, the judgment matrix of the indicators is constructed according to the nine-point scale, as shown in Table 7, to compare the five sub-indicators in the scores pairs to obtain the judgment matrix. Among them, the elements in the matrix should satisfy:

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

Table 7 Nine-point table

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 factor j: $x_{ij} = 1/x_{ji}$

The weight vector can be obtained by the arithmetic mean below

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

And the geometric mean method to find the weight vector is

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

The arithmetic mean and the geometric mean are used to explore the weight vector, ω_{1i}, ω_{2i} $(i = 1,2,3,4)$, then average them to obtain the weight vector. It can be seen from Table 8 that the weight of *RT*, *SB*, *AC*, and *SC* are similar, and *AC* has the largest weight on $Score$.

The model must guarantee the accuracy of traffic sign detection. The detection must get the command during the right driving time. The consistency test of the judgment matrix is less than 0.1, indicating that the weight data obtained are valid. The evaluation model is shown as follows:

$$Score = 0.275RT + 0.211SB + 0.342AC + 0.172SC \quad (7)$$

Table 8 Weight bar graph

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

5. Experiment and Analysis

This section describes the results of experiments using selected models and the application of the analysis of the results with the performance evaluation indicators presented in this paper.

5.1. *Basic result analysis*

The experiment result of training and testing is usually assessed by metrics derived from the confusion matrix, as shown in Table 9.

Table 9 Confusion matrix for performance evaluation

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

In order to avoid a biased analysis, credible metrics namely False Alarm Rate (FAR) and Un-Detection Rate (UND) metrics were used to evaluate the performance. Table 10 illustrates several evaluation metrics and their corresponding formulas.

Table 10 Evaluation metrics and 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. *Result Analysis*

This paper provides a unique performance evaluation standard by combining practical application scenarios and various factors. For the effects between different parameters in the same case, the comparison results were tabulated in Table 11.

Furthermore, this paper selects the RNN model with the best execution effect as the training model. By comparing the results of different parameters in the training process, the optimal parameters were listed in Table 12. The RNN model has the highest training and testing accuracy which are 99.03% and 98.01% respectively.

6. Conclusion

In this paper, the RNN with different architectures has been established for resolving traffic signal detection challenges. Also, this paper designed a new AHP method to evaluate the performance of the proposed RNN models with different parameters, so that the configuration of the start-of-the-art model can be determined. Four evaluation metrics were utilized for AHP measurement: accuracy, stability, response time and system capability.

Based on the Tsinghua-Tencent 100k dataset, the training and testing of the proposed models were conducted and analysed. The RNN model has the highest training and testing accuracy which are 99.03% and 98.01% respectively. Experimental results verified the feasibility of the proposed model for traffic sign detection and recognition.

Table 11 Experimental results of training and testing

Evaluation Metrics		Deep Learning Models		
		VGG	**GoogleNet**	**RNN**
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 Parameter list of the AHP method

Training Parameters	Parameter 1	Parameter 2	Parameter 3
Convolution Layers	**RNN 50**	RNN 101	RNN 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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