Deep Residual Neural Network for Efficient Traffic Sign Detection

Hanlin Cai, Zheng Li, Jiaqi Hu, Wei Hong Lim,
Sew Sun Tiang, Mastaneh Mokayef, Chin Hong Wong

Fuzhou University, China

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About the Presenter

Hanlin Cai 蔡汉霖

- A junior student majoring in Robotics and Intelligent Devices at Fuzhou University.
- I am extremely fortunate to be advised by Chin Hong Wong and Zhezhuang Xu.
- Currently, I am interested in Machine Learning and its applications on the Internet of Things (IoT).
- hanlin.cai@ieee.org
- `https://caihanlin.com`

1. Research Overview
2. Proposed Methodology
3. Experimental Results
4. Conclusion and Plan

1. Research Overview
   - Background
   - Literature Review
   - Gaps in existing works
2. Proposed Methodology
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Background

Neural Network for Traffic Sign Detection.

- **Traffic Sign Detection System (TSDS)**
  1. Traffic Sign Detection (TSD)
  2. Traffic Sign Recognition (TSR)
  3. Traffic Sign Classification (TSC)
- **Famous Neural Network for Image Processing**
  1. VGGNet[1]
  2. GoogLeNet[2]
  3. ResNet[3] (SOTA)
- **Significance of Related Works**
  1. Increase the efficiency and safety of urban transportation
  2. Bring the development of self-driving cars that are able to detect traffic.

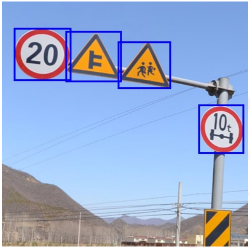

Figure 1: Traffic Sign Example

$$\text{Problem} \Rightarrow \begin{cases} \text{TSD} \xrightarrow{\text{YOLO}} \text{Search for the Signs} \\ \text{TSR} \xrightarrow{\text{RNN}} \text{Understand the Signs} \\ \text{TSC} \xrightarrow{\text{RNN}} \text{Classify the Signs} \end{cases} \xrightarrow{\text{How to get}} \text{Optimization}$$

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Literature Review

$$\text{Review} \Rightarrow \begin{cases} \text{Traditional Method} \xrightarrow{\text{2003-2009}} \text{Color, Features} \\ \text{Machine Learning} \xrightarrow{\text{2010-2015}} \text{Classifier, NN} \\ \text{Deep Learning} \xrightarrow{\text{2016-2022}} \text{CNN, RNN Model} \end{cases}$$

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.

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Research Gaps and Contributions

Gaps in existing knowledge

- Large-scale categories datasets for training and testing
- Systematic evaluation method for configuration optimization

Contributions of this works

- The model training and testing are based on large-scale datasets (Tsinghua-Tencent 100k).
- A new systematic analytic hierarchy process (AHP Method) for model evaluation has been proposed.

Overview of Our Works

Deep Residual Neural Network for Efficient Traffic Sign Detection*

- **Traffic Sign Detection System**
  1. Traffic Sign Detection (TSD)
  2. Traffic Sign Recognition (TSR)
- **Analytic Hierarchy Process Method**
  1. Accuracy (Performance Metrics)
  2. Stability
  3. Response
  4. System Capability

$$\text{Our works} \Rightarrow \begin{cases} \text{TSD} \xrightarrow{\text{YOLO}} \text{Search Sign} \\ \text{TSR} \xrightarrow{\text{RNN}} \text{Understand} \end{cases} \xrightarrow{\text{AHP method}} \text{Optimization}$$

Traffic Sign Detection System (TSDS)

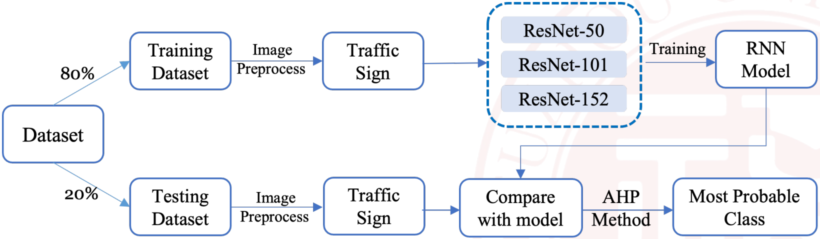


Figure 2: Flowchart of the proposed system

$$\text{Our works} \Rightarrow \begin{cases} \text{TSD} \xrightarrow{\text{YOLO}} \text{Search Sign} \\ \text{TSR} \xrightarrow{\text{RNN}} \text{Understand} \end{cases} \xrightarrow{\text{AHP method}} \text{Optimization}$$

Step 1: Pre-processing

Image Pre-processing

- Edge Detection
  1. Noise processing and gradient computation
  2. Non-maximum suppression
  3. Double threshold detection
- Corrosion Expansion
- After that, a traffic sign without background noise is obtained.

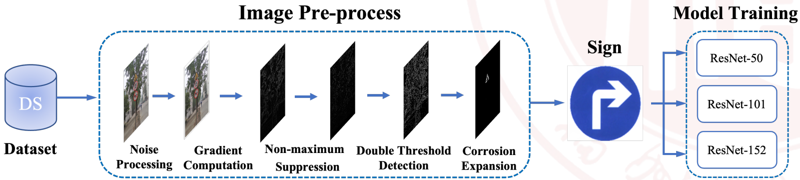


Figure 3: Flowchart of the pre-process

Proposed ResNet Models

- Three ResNet models with different architecture
  1. ResNet 50
  2. ResNet 101
  3. ResNet 152
- Two main types of blocks used in ResNet
  1. Identity Block: Input activation $\xleftrightarrow{\text{same dimension}}$ Onput activation
  2. Conv Block: Input activation $\xleftrightarrow{\text{not match}}$ Onput activation

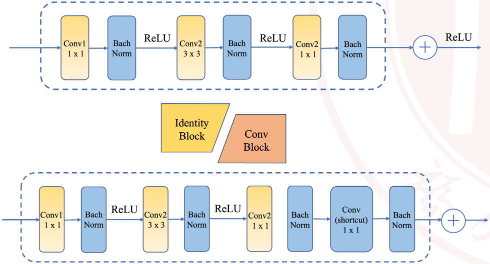
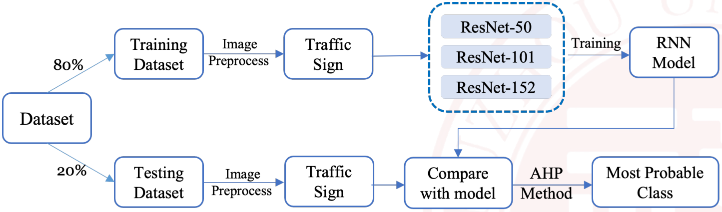
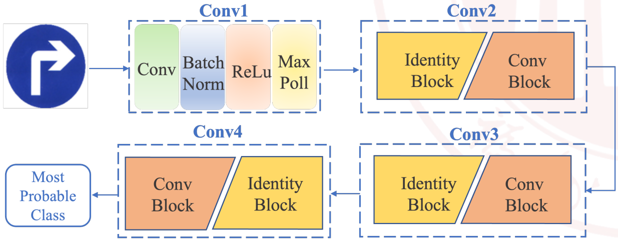


Figure 4: Structures of ResNet blocks

Model Training and Testing





1 Research Overview

2 Proposed Methodology
- Overview of Our Works
- Step 1: Image Pre-processing
- Step 2: Residual Neural Network
- Step 3: Analytic Hierarchy Process

3 Experimental Results

4 Conclusion and Plan

AHP Method

Analytic Hierarchy Process Method

- Maturity level evaluation model
  1. Accuracy (AC)
  2. Stability (SB)
  3. Response Time (RT)
  4. System capability (SC)
- Weight Determination
  1. Indicator judgment matrix
  2. Weight of each indicator

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

Step 3-1: Maturity level evaluation model

- Four performance indicators
  1. Accuracy: Correct detection / Total datasets
  2. Stability: Realistic accuracy / Theoretical accuracy
  3. Response Time: Time of processing 1000 images
  4. System capability: Floating-point operations per second (FLOPS)

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

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

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

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

Step 3-2: Weight Determination

- Weight Determination
  1. Indicator judgment matrix
  2. Weight of each indicator

The judgment matrix of the indicators is constructed according to the nine-point scale (Table 7), to compare the four indicators in the scores pairs.

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

Step 3-2: Weight Determination (Proof)

The elements in the matrix should satisfy:

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

The weight vector can be obtained by the arithmetic mean below

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

And the geometric mean method to find the weight vector is

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

Step 3-2: Weight Determination

- Weight of each indicator in AHP evaluation model
  1. Accuracy: 0.342
  2. Stability: 0.211
  3. Response Time: 0.275
  4. System capability: 0.172

The consistency test of the judgment matrix is less than 0.1, indicating that the weight data obtained are valid.

Table 8: Weight of indicators

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

Methodology of Results Analysis

The experiment result of training and testing is usually assessed by metrics derived from the confusion matrix:

Table 9 Confusion matrix for performance evaluation

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

1. TP: Number of positive samples correctly classified as positive.
2. TN: Number of negative samples correctly classified as negative.
3. FN: Number of positive samples incorrectly classified as negative.
4. FP: Number of negative samples incorrectly classified as positive.

Three evaluation metrics

In order to avoid a biased analysis, credible metrics namely False Alarm Rate and Un-Detection Rate metrics were used:

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)

- Three evaluation metrics
  1. Accuracy
  2. False Alarm Rate
  3. Un-Detection Rate

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The experimental results were proposed by comparing the training and testing results of different models based on the same datasets:

Table 11 Experimental results of training and testing

Evaluation Metrics		VGG	GoogleNet	RNN
		Deep Learning Models		
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%**

- Result of ResNet-50 (Training and Testing, Best)
  1. Accuracy: 99.03% and 98.01%
  2. False Alarm Rate: 0.01% and 0.09%
  3. Un-Detection Rate: 0.41% and 1.28%

By comparing the testing results of different parameters, this work also proposed the optimal parameters configurations.

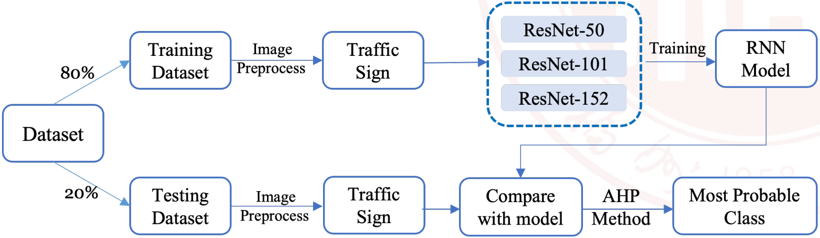
Table 12 Parameter list of the AHP method

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	

- Optimal configurations:
  1. Model Layers: ResNet-50
  2. Learning Rate: Step
  3. Split Strategy: Classification Split
  4. Image Enhancement: Brightness Enhancing
  5. Colour Processing: HSV

Conclusion and Future Plan

- **Conclusion**
  1. Proposed ResNet-50 model got the highest accuracy of 99.03% and 98.01%.
  2. Optimal configurations were suggested through AHP method.
- **Future Plan**
  1. Training and testing based on more complex and large-scale datasets.
  2. Implement image classification capabilities.



Thanks for Listening !