EE301FZ Signals and Systems

<<Deep Residual Neural Network for Efficient Traffic Sign Detection System >>

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A. Declaration

We hereby certify that this material, which we now submit for assessment on the program of study as part of BSc in Robotics and Intelligent Devices qualification, is *entirely* our own work and has not been taken from the work of others - save and to the extent that such work has been cited and acknowledged within the text of our work.

We hereby acknowledge and accept that this thesis may be distributed to future first year students, as an example of the standard expected first year projects.

Signed: Date:

Deep Residual Neural Network for Efficient Traffic Sign Detection System (Student Abstract)

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***Abstract*—This paper has proposed a deep residual neural network (RNN) model for traffic signs detection system (TSDS) research. Experiments are conducted to verify the feasibility of implement RNN model for traffic sign detection and recognition. Moreover, a new systematic analytic hierarchy process (AHP) method for model performance evaluation have been suggested, which is sufficient for deployment in the practical performance measurement of deep learning model.**

***Index Terms*—Traffic Sign Detection System, Residual Neural Network (RNN)**

I. INTRODUCTION

Deep learning plays a non-negligible role in current frontier science, which has been widely used in the area of agriculture, industry and transportation. As for the application in transportation, it is of great significance to utilized related DL approaches for 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 [1-3]. 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 very high detection accuracy of nearly 98.8%. Changzhen, et al. [5] implemented an advanced detection method based on deep CNN model which also achieved satisfactory result of above 99.0% recognition precision.

Despite the good performance of deep learning models, the effectiveness of these conventional neural network (NN) models will decrease when facing trickier image recognition challenges which requires deeper layers and more computing resources [3]. In this context, the Resnet neural network (RNN) 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 deep networks training process. Besides, RNN models have been widely applied in some literature works, Zakaria, et al. [7] utilized RNN models in the medical field to recognize and classify medical images. Li and Rai [8] 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.

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

II. LITERATURE REVIEW

This section goes through the key concepts of this paper, including Traffic Sign Detection System (TSDS) and Deep Learning Technology. Furthermore, many related literature works have been explicitly reviewed, and the gaps in existing knowledge have been identified.

[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. Generally speaking, the TSDS concern two related subjects: Traffic Sign Detection (TSD) and Traffic Sign Recognition (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 purpose.

As shown in the Table 1, many related literature works have been explicitly reviewed in this paper. As for the conventional methods for TSDS, most of research since around 2005 have been based on the methods of colour segmentation, image shape and texture features [12-17]. 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 with the pollutants in the air. Fleyeh and Dougherty [1] proposed an exhaustive overview of the traditional methods, and points 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 existing datasets and previous experience.

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

[2] Deep Learning Technology

Deep learning technology has been the core topic in the area of computer vision, which have been highly applied in the image detection and classification [2]. Generally speaking, convolutional neural network and residual neural network models are the most prominent DL approaches in the field of the traffic sign detection and recognition.

In this case, Suriya Prakash, et al. [4] extended and developed a classical LeNet-5 CNN model, which makes used of Gabor based kernel followed by a normal convolutional kernel after the pooling layer. Their proposed CNN model was evaluated using 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 sign. Experiments show that their model has towards 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 (R-CCN) and RPN network. Besides, the Random Forest algorithm is used for performing classification and regression in the given dataset. Their composite methods significantly reduced the resource requirements used for training the deep learning models and gave an increased accuracy closest to 99.9%.

Despite of their effect, most of existing methods suggested by these studies are based on a relatively small number of all traffic signs (about 50 classed out of several hundred in different regions) and performance on the remaining set of traffic signs are required to train and test, which remains an open question. In this context, Tabernik and Skocaj [21] proposed several improvements using CNN and mask R-CNN approach to resolve the issue of detecting a large-scale traffic sign categories. The experiments are conducted on highly challenging traffic sign categories and the numerical results of below 3.0% error rates verified the effectiveness.

TABLE 1 A SUMMARY OF RELATED LITERATURE WORKS

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

[3] Gaps in Existing Knowledge

To the best of our knowledge, no research has focused on training and testing a residual neural network (RNN) model based on the representative traffic sign datasets including large-scale categories. In this paper, a deep residual neural is established to address the large-scale detection challenges. Experiments are conducted to verify the effectiveness of implement RNN model to advance TSDS research.

Also, although many existing literature works have achieved good performance, most of the works are only evaluated by detection accuracy, precision and response time, which are all in the same key. However, a more reasonable and systematic evaluation methodology is absent in most of the measurement process. Therefore, this paper suggests a new analytic hierarchy process (AHP) method for residual neural with different parameters and optimizers, which is sufficient for deployment in the practical performance measurement of deep learning model.

III. RESIDUAL NEURAL NETWORK

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In this paper, a ResNet model with 50, 101 and 152 layer CNN-based architecture have been proposed to classify various traffic sign, such as speed limit, crosswalk, and traffic, stop signs. The classification flow chart based on ResNet is shown in Figure 1. We pre-process the images to extract traffic signs. Our method is as follows. This part also includes the architecture of ResNet.

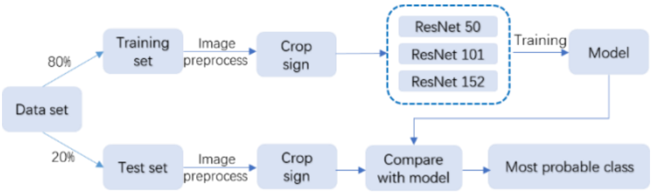

FIGURE 1 CLASSIFICATION FLOW CHART BASED ON RESNET

3.1 Data Pre-process

A collection of pixels in a picture 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. To find the identity in the picture, edge detection is used. There are two steps: Edge detection and Corrosion expansion, as shown in Figure 2.

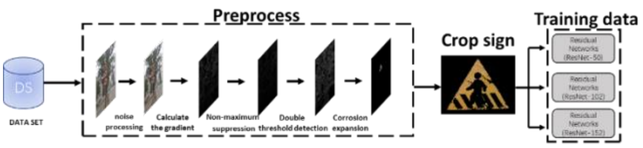

FIGURE 2 IMAGE PRE-PROCESS

3.1.1 Edge Detection

(a) Noise treatment

In the image, the pixels with large grayscale changes appear randomly and form the noise. Noise comes from a variety of situations including image acquisition, transmission, quantization and so on. In this paper, image is used to add Gaussian noise, and then Gaussian filter is used to remove the noise.

(b) Non-maximum suppression

When the image noise is reduced by gaussian filter, the image blur means that the grey change in the contour is not strong. Non-maximal value suppression is used to suppress all the gradient values other than the local maximum, and make it indicate the position of the strongest strength of the strength. In the location of the traffic sign detection, there will be a large number of candidates in the location of the same target, and these candidates may have overlap between them, and then we need to use non-maximal values to prevent the finding of the best target border frame and eliminate the redundant boundary boxes.

(c) Double threshold detection and edge connection

It makes use of the gray difference between the object and the background in the image to be extracted, and divides the pixel level into several classes by setting the threshold, so as to achieve the separation of the object and the background.

3.1.2 Corrosion expansion

Corrosion expansion selects the maximum value in the neighbourhood of each position as the output gray value. After expansion, the overall brightness of the image will be improved, and 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 Thresholder, the original image is cut and the traffic sign is obtained.

3.2 ResNet architecture

The proposed ResNet architecture has two types of layers, namely, conv block and identity block, and these serve as shortcuts in residual blocks and are included in an order, as shown in Figure 3.

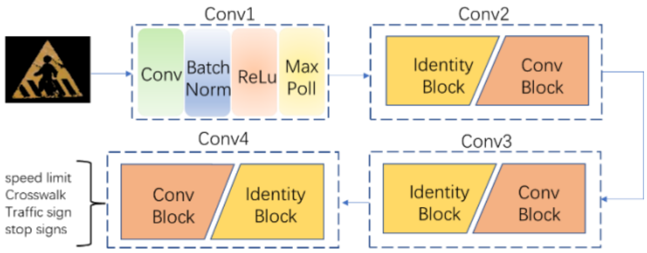

FIGURE 3 ARCHITECTURE OF PROPOSED RESNET

Figures 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 convolutions' 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.

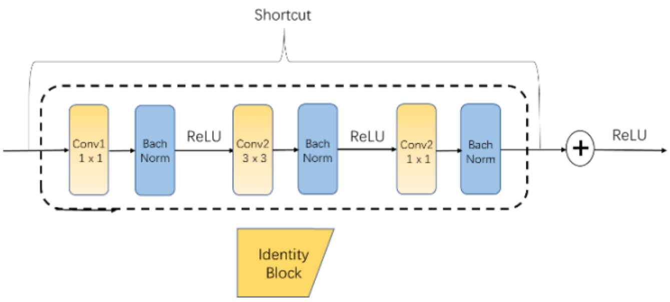

FIGURE 4-1 THE STRUCTURES OF THE IDENTITY BLOCKS

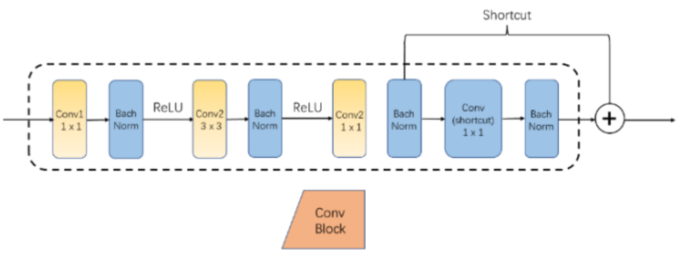

FIGURE 2-2 THE STRUCTURES OF THE CONV BLOCK

IV. EXPERIMENT AND ANALYSIS

V. ANALYTIC HIERARCHY PROCESS

VI. CONCLUSION

REFERENCES

[1] H. Fleyeh and M. Dougherty, "Road and traffic sign detection and recognition," in Proceedings of the 16th Mini-EURO Conference and 10th Meeting of EWGT, 2005, pp. 644-653.

[2] M. Pak and S. Kim, "A review of deep learning in image recognition," presented at the 2017 4th international conference on computer applications and information processing technology (CAIPT), 2017.

[3] V. Feng. "An overview of resnet and its variants." (accessed 2).

[4] A. Suriya Prakash, D. Vigneshwaran, R. Seenivasaga Ayyalu, and S. Jayanthi Sree, "Traffic Sign Recognition using Deeplearning for Autonomous Driverless Vehicles," presented at the 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), 2021.

[5] X. Changzhen, W. Cong, M. Weixin, and S. Yanmei, "A traffic sign detection algorithm based on deep convolutional neural network," in 2016 IEEE International Conference on Signal and Image Processing (ICSIP), 2016: IEEE, pp. 676-679.

[6] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770-778.

[7] N. Zakaria, F. Mohamed, R. Abdelghani, and K. Sundaraj, "Three ResNet Deep Learning Architectures Applied in Pulmonary Pathologies Classification," presented at the 2021 International Conference on Artificial Intelligence for Cyber Security Systems and Privacy (AI-CSP), 2021.

[8] X. Li and L. Rai, "Apple Leaf Disease Identification and Classification using ResNet Models," presented at the 2020 IEEE 3rd International Conference on Electronic Information and Communication Technology (ICEICT), 2020.

[9] Y. Lu, J. Lu, S. Zhang, and P. Hall, "Traffic signal detection and classification in street views using an attention model," Computational Visual Media, vol. 4, no. 3, pp. 253-266, 2018, doi: 10.1007/s41095-018-0116-x.

[10] S. B. Wali et al., "Vision-Based Traffic Sign Detection and Recognition Systems: Current Trends and Challenges," Sensors (Basel), vol. 19, no. 9, May 6 2019, doi: 10.3390/s19092093.

[11] Á. Arcos-García, J. A. Álvarez-García, and L. M. Soria-Morillo, "Evaluation of deep neural networks for traffic sign detection systems," Neurocomputing, vol. 316, pp. 332-344, 2018, doi: 10.1016/j.neucom.2018.08.009.

[12] A. Ruta, Y. Li, and X. Liu, "Detection, tracking and recognition of traffic signs from video input," in 2008 11th International IEEE Conference on Intelligent Transportation Systems, 2008: IEEE, pp. 55-60.

[13] S. Varun, S. Singh, R. S. Kunte, R. S. Samuel, and B. Philip, "A road traffic signal recognition system based on template matching employing tree classifier," in International Conference on Computational Intelligence and Multimedia Applications (ICCIMA 2007), 2007, vol. 3: IEEE, pp. 360-365.

[14] H. Fleyeh, "Color detection and segmentation for road and traffic signs," in IEEE Conference on Cybernetics and Intelligent Systems, 2004., 2004, vol. 2: IEEE, pp. 809-814.

[15] M. Sridharan and P. Stone, "Towards on-board color constancy on mobile robots," in First Canadian Conference on Computer and Robot Vision, 2004. Proceedings., 2004: IEEE, pp. 130-137.

[16] S. Xu, "Robust traffic sign shape recognition using geometric matching," IET Intelligent Transport Systems, vol. 3, no. 1, pp. 10-18, 2009.

[17] N. Barnes, A. Zelinsky, and L. S. Fletcher, "Real-time speed sign detection using the radial symmetry detector," IEEE Transactions on Intelligent Transportation Systems, vol. 9, no. 2, pp. 322-332, 2008.

[18] S. Maldonado-Bascon, S. Lafuente-Arroyo, P. Gil-Jimenez, H. Gomez-Moreno, and F. Lopez-Ferreras, "Road-Sign Detection and Recognition Based on Support Vector Machines," IEEE Transactions on Intelligent Transportation Systems, vol. 8, no. 2, pp. 264-278, 2007, doi: 10.1109/tits.2007.895311.

[19] W.-J. Kuo and C.-C. Lin, "Two-stage road sign detection and recognition," in 2007 IEEE international conference on multimedia and expo, 2007: IEEE, pp. 1427-1430.

[20] S. K R, D. M, and V. D. R S, "Traffic Sign Recognition with Faster RCNN and RPN for Advanced Driver Assistance Systems," presented at the 2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA), 2021.

[21] D. Tabernik and D. Skocaj, "Deep Learning for Large-Scale Traffic-Sign Detection and Recognition," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 4, pp. 1427-1440, 2020, doi: 10.1109/tits.2019.2913588.