OPEN ACCESS
INTERNATIONAL JOURNAL
EIJMRMS
Next Scientists
European International Journal of Multidisciplinary Research and Management Studies
SJIF 5.954 2022

EUROPEAN INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH AND MANAGEMENT STUDIES
ISSN: 2750-8587
DOI: https://doi.org/10.55640/eijmrms-02-05-19
https://eipublication.com/index.php/eijmrms
Volume: 02 Issue: 05 May 2022
Published Date:- 25-05-2022

Page No.-88-94

LIGHTWEIGHT RESIDUAL LAYERS BASED CONVOLUTIONAL NEURAL NETWORKS FOR TRAFFIC SIGN RECOGNITION

Babakulov Bekzod Mamatkulovich

Jizzakh Branch Of The National University, Teacher, Uzbekistan

ABSTRACT: - System for Traffic Sign Recognition and Classification is significantly important for especially traffic safety, traffic surveillance, artificial driver services and by all means, for self-driving cars. Traffic sign recognition plays an important role to tackle the traffic related obstacles. And, as traffic sign recognition is particularly applied to portable devices, lightweight models are essential aspect of the agenda. To overcome the mentioned problems, we propose lightweight convolutional neural networks with residual blocks based deep learning model for traffic recognition systems. We not only present the model efficiency but also show the several conducted experiments will well known deep CNN architectures over publicly available German traffic sign recognition benchmark. Our model showed 99.9 % accuracy by F-score, exceeding other models. At last, our model shows generally validity for traffic sign classification problem.

KEYWORDS: Traffic surveillance, artificial driver services and by all means, for self-driving cars.

INTRODUCTION

Systems for the traffic sign recognition has been an interesting topic among research community for the last three decades. The main reason is the indispensability of protecting human life and saving more people on the road. From one research work to another, the scientists have tried to improve the accuracy and recognition rate of these systems. Suggested models are split into mainly two categories: non-automatic feature approaches and deep learning based automatic methods.

Prior to deep learning, classic recognition models are applied with manual labeling and feature extraction, from particular color acceptance [1] and machine learning based models [2], that extremely decrease model efficiency in both accuracy and speed. As it is obvious, manual labeling upsurge more workload and the models are not guaranteed.

In post deep learning period, the detection and classification methods have changed dramatically. The research of neural networks has gradually become a popular research field for research community. Automation of models can eliminate the laborious manual annotation and automatically extract the features from the input data. Specifically, Convolutional Neural Networks[3] has showed increased accuracy in the field of grid data classification and object detection.

In our paper, we propose a new deep learning model built from lightweight convolutional neural networks (CNNs) with residual blocks to overcome the challenged in the traffic signs. The nominated approach is a robust model that receives raw input images, mostly challenging and process each input data prior to deliver them into a classifier that then gives predicted classes of forty three road signs. Our model consists of two parts: pre-processing part and residual based classification. During first part, the robustness of the model to image noises is improved, especially for images in diverse variations. Putting extra residual layers to CNNs layer boosts model to converge faster and to overcome overfitting. Despite to the fact that our model is lightweight compared to very deep models and has few parameters, it showed efficient results in the given problem. We demonstrated that by choosing convolutional layers carefully, with putting data pre-processing and especially residual blocks, it is possible to get higher results.

The rest of the paper is arranged in that way: Section II review some related works on traffic recognition systems. Dataset is described in Section III. Section IV details proposed model architecture, some essential approaches and provide a detailed explanation of the chosen methods. In Section V, we show the results of conducted experiments on the benchmarks. Finally, conclusion and future work are drawn in Section VI.

Related works

This section highlights some recent related research works on traffic sign recognition.

Methods towards systems for traffic sign recognition expanded from color and shape based models to machine learning and finally deep learning based models. In last decade, CNNs [3] have attracted attention in feature extraction and pattern recognition, and have extensively being applied for classification and detection related works.

One of the most common approaches is color based models. They use variety color spaces for segmentation of the road images such as RGB [8], HSV [5] and HIS [10] among others. Another one is shape based models. [4] is adopted symmetry information of circular, triangular, squared and octagonal shapes, while houghfeature extraction model is proposed by [7]. Last but not least, [1] studied the effect of circular traffic sign recognition system.

Authors of [13] propose fine grained classification applying different methods through a pipeline of three stages: feature extraction, dimensionality reduction and classification. They merged grayscale values of traffic sign images and Histogram of Oriented Gradients (HOG) based features, reducing the dimensionality through Iterative Nearest Neighbors-based Linear Projections (INNLP) and classifying with Iterative Nearest

Neighbors.[6] proposed an approach with shaped based detection algorithms to recognize traffic signs. The authors chose convolutional neural network for the purpose of classification. After simulation they achieved higher accuracy result of the benchmark. As a final word, most researchers are applying convolutional neural networks based models to classify road signs prediction.

Datasets

We applied German Traffic Sign Recognition Benchmark (GTSRB) [9] for training and testing the proposed model. Input images were randomly obtained from the camera in a real-time scene and was first provided by the International Joint Conference on Neural Networks (IJCNN) in 2011. The dataset includes 51838 images in 43 categories of each image resolution is dynamically changed from 15x15 to 250x250 pixels. The images with constantly changing scales increase the richness of the data and can improve the fitting effect of the network. Table 1 shows the distribution of GTSRB dataset for training, validation, and testing. Standard subject - exclusive protocol is defined for the testing part.

Table 1. Distribution of GTSRB benchmark among train, valid and test

Training	Validation	Testing
33326	5882	12630

Figure 1 shows some examples of the dataset. As it is clear from the examples that dataset has different outside variations.

Figure 1. Example images from GTSRB dataset.

Proposed Architecture

We introduce a traffic sign recognition system that carries out fine-grained classification to traffic sign images through a lightweight CNN whose main blocks are convolutional and residual block modules. In order find out and accurate and efficient model for our pursue, we research and discuss mainly two steps: first the effect of processing input data prior to model computation and secondly the structure of the proposed model architecture. Lastly, we will detail how we define initialization of the weights to the model. Figure 2 details our overall architecture.

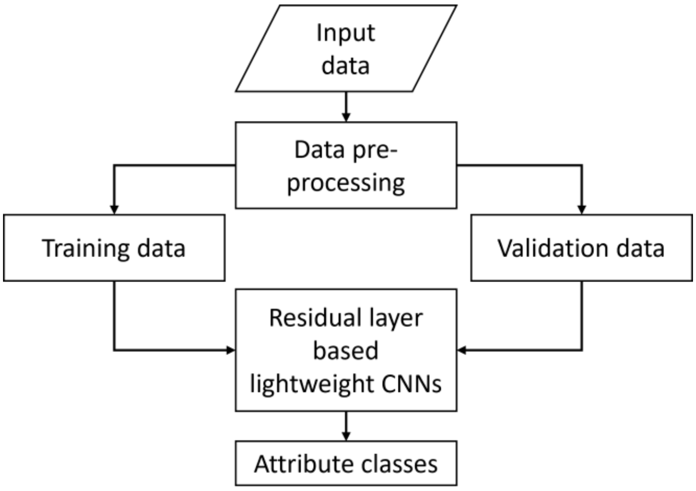

Figure 2. Flowchart of proposed model architecture

Data Pre-processing

Traffic sign samples from GTSRB are raw RGB and sizes vary from 15x15 to 250x250 pixels. To make compatible input data to our model process, all input data are down-sampled or up-sampled to 32x32 pixel size. Furthermore, we also use data normalization method, a specific way to normalize the image pixel value from (0, 255) to (0, 1), that has a similar data distribution for the entire dataset before feeding to the CNNs part. Image normalization process helps the network training to converges faster and better, accelerating the model process speed. The process is run by subtracting the dataset mean from the input and divide it by the standard deviation of that feature as well for each RGB channels:

(3.1)

$$z = \frac{x - mean}{std}$$

z=(x-mean)/std

B.CNN with Residual Blocks.

Our CNN architecture is consisted of overall six feature extraction layers, of which two of them are residual blocks and final layer for classification. Full view of the CNN model is given in Figure 3.

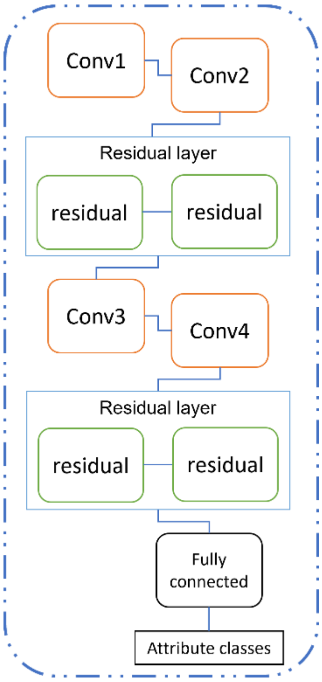

Figure 3. CNN part overview

First Convolution layer is applied 3x3 kernel filters. Max pooling is not applied in order to keep initial features. In the second layer, kernel filters are the same with additional 2x2 max-pooling layer to reduce the dimensionality of the previous layer. Then two-part residual layeris applied for skip connection, especially to avoid degradation in performance. Afterward, two convolutional layers with max-pooling and one more residual block is connected to the model. Finally, dimensional transformation is performed by the fully connected layer on the extracted output features, and apply softmax activation function to classify one of forty three traffic signs.

Number of filters in the first layer is 64, second layer has 192, initial residual blocks 192, while later layers have two 256 layers with the same for the next residual blocks respectively. The model uses only a fraction of the memory in terms of total learnable weights.

We applied Rectified Linear Units (ReLUs) as nonlinearity through each layer and 20% of dropout as regularization step.

C. Weight Initialization.

We train the proposed model only from scratch, without any additional data nor pre-trained weights. Random values with zero mean Gaussian distribution and standard deviation initialize the weights for both convolution and fully connected layers.

V. Experimental Results

The performance of the model is analyzed by conducting extensive experiments on GTSRB dataset. PyTorch [12] open source deep learning framework is adopted forimplementation. For the model cost function, multi-class Cross-entropy loss is applied,

(4.1)

$$L = (\sum_{i=1}^{n} y_i log a_i + (1 - y_i) \log (1 - a_i))$$

All layers are adjusted using Adam (Adaptive moment estimation) optimization technique [11] with 256 batch size. Learning rate is 1e-4, respectively.

First, we evaluate our model with accuracy standard metrics, showing top-1 and top-5 accuracy. Plot of training and validation accuracy is given in Figure 4.

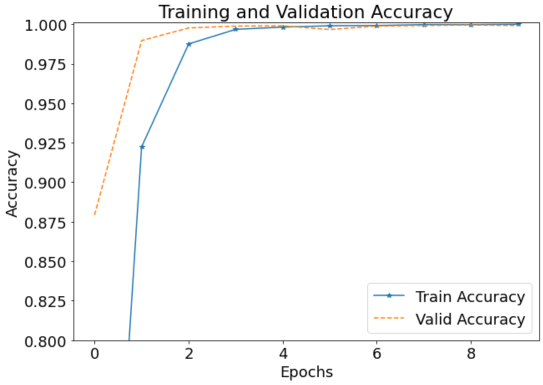

Figure 4. Train and valid accuracy over increasing epochs

To further ensure that our lightweight model is genuinely efficient and competitive with other models, we also conducted experiment with very well-known CNN architectures which are usually state-of-the-art for most benchmarks. Table 2 shows the overall results with comparisons.

Table2. Model Comparison

Models	Loss %	Top_acc_1 %	Top_acc_5 %	Parameters (M)
AlexNet	0.95	73.86	95.31	23.4
VGG13	0.56	90.51	98.48	129
ResNet18	1.44	67.38	91.07	21.3
Proposed model	**0.08**	**97.7**	**99.93**	**3**

As it is clear from the table, our model is not only lightweight with very few parameters but also reached the best in both accuracy and loss among other well-known models.

If our model accuracy is very high, it may be not the best metric to measure the model efficiency. Therefore, we evaluated our model furthermore for recall, precision, and f-score. Table 3 details the desired results.

Table3

Precision	Recall	F1-score
0.999	0.999	0.999

CONCLUSIONS

We propose a lightweight residual layer based convolutional neural networks for traffic signs recognition problem. The proposed model is very fast and uses only a fraction of the memory compared to other deep models. The approach is extremely efficient and highly competitive showing high performance for GTSRB benchmark. Our future work will be to explore other models and to experiment our model in other classification benchmarks.

REFERENCES

1. S.K. Berkaya, H. Gunduz, O. Ozsen, C. Akinlar and S. Gunal, 2016. On circular traffic sign detection and recognition. Expert Systems with Applications, 48, pp.67-75.
2. Y. Yang, H. Luo, H. Xu and F. Wu. Toward real-time traffic sign detection and classification. IEEE Transactions on Intelligent transportation systems, 17(7), pp.2022-2031, 2015.
3. Y. LeCun, Y. Bengio. Convolutional networks for images, speech and time series – The handbook of brain theory and neural networks, 1995.
4. G. Loy, N. Barnes. Fast shape-based road sign detection for a driver assistance system. Intelligent Robots and Sytems, 2004. Proceedings, IEEE/RSJ International Conference on, 1, 70-75 vol.1.
5. W. Shaded, D. Abu-Al-Nadi, M. Mismar. Road traffic sign detection in color images. 10th IEEE International Conference on Electronics, Circuits and Systems, 2003.
6. Yang, WJ., Luo, CC., Chung, PC., Yang, JF.: Simplified Neural Networks with Smart Detection for Road Traffic Sign Recognition. Lecture Notes in Networks and Systems, vol 69. Springer, Cham (2020)
7. N. Barnes, G. Loy, D. Shaw. The regular polygon detector, 2010. Patter Recognition, 43, 592-602.
8. D.L. Escalera, L. Moreno, M. Salichs, J. Armiongol (1997). Road traffic sign detection and classification. IEEE Transactions on Industrial Electronics, 44, 848-859.
9. J. Stallkamp, M. Schlipsing, J. Salmen, C. Igel. The German traffic sign recognition benchmark: a multi-class classification competition. In the 2011 International joint conference on neural networks (pp. 1453-1460), IEEE.
10. S. Maldonado-Bascon, S. Lafuente-Arroyo, P. Gil-Jimenez, H. Gomez-Moreno, F. Lopez-Ferreras. Road-Sign Detection and Recognition Based on Support Vector Machines. Intelligent Transportation Systems, IEEE Transactions on, 8, 264-278, 2007.
11. Kingma, D.P.; Ba, J. Adam: A method for stochastic optimization. In Proceedings of the International Conference for Learning Representations (ICLR), SanDiego, CA, USA, 7–9 May 2015; pp. 1–15.
12. A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen,Z. Lin, N. Gimelshein, L. Antiga, A. Desmaison, A. Kopf, E. Yang, Z. DeVito,M. Raison, A. Tejani, S. Chilamkurthy, B. Steiner, L. Fang, C. Bai, S. Chin-tala: PyTorch: An Imperative Style, High-Performance Deep Learning Library. arXiv:1912.01703, 2019.