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Traffic Sign Recognition Using Small-Scale Convolutional Neural Network

Tejas Chaudhari[1], Ashish Wale, Amit Joshi, Suraj Sawant

Ddepartment of Computer Engineering and IT, College of Engineering Pune, Maharashtra, India- 411005

Abstract

Traffic sign recognition has been of utmost importance ever since the emergence of the need of autonomous vehicles and driver assistance systems. An effective pre-processing of the data is important in autonomous driving system. There is no scope to apply complex transformations or highly computational image processing techniques for such real time purposes. This work presents a approach to recognize traffic signs using small-scale deep convolutional neural networks (CNN) and that can be applied to different applications. The presented solution is implemented using German Traffic Sign Recognition Benchmark (GTSRB) dataset. This dataset is reliable, vibrant and has been used for training of different systems. The proposed system is an Advanced Driver Assistance System (ADAS) based solution to provide an effective assistance. The achieved testing, training and validation accuracies are 97.71 %, 99.19% and 99.61 % respectively.

Keywords- Traffic sign recognition, deep convolutional neural network, Advanced driver assistance system

1. Introduction

Recognition of various traffic signs is becoming essential day by day in deployment of autonomous vehicles, providing assistance to the driver, traffic safety and mapping/navigation. Human beings, even after recognizing traffic signs, can make a lot of errors while driving. Because of this reason and the development of automotive technologies, companies like Tesla, BMW, etc. have been actively investing in research fields of ADAS [1]. ADAS includes recognition of traffic signs for keeping driver's attention at best. With the increase in demands of automation in traveling, it has become necessary to incorporate the requirements of automations using different computer technologies. With ADAS being extensively researched in one hand, on the other hand research in autonomous driving cars is also taking place at great pace. Autonomous racing cars, self-driving cars become one of the prominent areas where TSR is needed [2].

[1] * Corresponding author. Tel. +91 -8554912654;
E-mail address: chaudharits16.it@coep.ac.in

Traffic signs are specifically designed so that they are easily detected and recognized by the driver. They have significant differences in colors between the background and the sign .This one's specialty about traffic signs helps in automated recognition as well.
Nowadays, the results in deep learning are attracting everyone's attention in computer vision bases applications particularly. Significantly improved results of different parameters are obtained in such kind of applications. In deep learning, CNN are quite noticeable. CNN have proven repeatedly their importance and superiority over the other. Traffic sign recognition is also done by using different CNN models such as deep inception based convolutional networks, deep learning for large scale traffic-sign, deformable deep CNN, multi-task cascaded neural network[3][4][5].
The motive of presented solution includes learning of small-scale CNN in faster manner with higher accuracy.

2. Literature Review

Traffic sign recognition is differentiated into two categories. This includes the class of techniques which use classical models which rely on the characteristics of the traffic signs and another class includes the recent deep learning based approaches which learn the general features with help of dataset. The amount of various literature based on traffic sign recognition is no less than an enormous amount because TSR has been a topic of enormous scope and importance ever since the emergence of computer automation and computer vision. Comparing the available literature is difficult because of such a vast amount of research already taken place in the field. Many papers propose a solution using predefined and the most popular among all datasets such as German Traffic Sign Detection Benchmark (GTSDB) and GTSRB [6-8]. Many papers used other datasets such as The Belgium Traffic Signs(BTS) and The Mapping and Assessing the State of Traffic Infrastructure (MASTIF) dataset[9][10]. The Swedish Traffic Sign Dataset (STSD), Laboratory for Intelligent and Safe Automobiles (LISA) are also some predefined datasets used in TSR training process [11] [12]. Some papers use a sampled dataset made by combining these predefined ones. Most use their own specifically defined dataset as well for maximum accuracy and reliability. A very handy and useful feature of private datasets is that it can consist of all the different classes needed as per the requirements.
As per the methodologies used, many approaches exist and have been used. Some used remarkably accurate CNN [13]. Some used Mask R-CNN which is a combination of Region Proposal Network and Fast R-CNN [4]. The convolutional features of both the networks are merged in such a proper way that gives a more efficient and faster CNN approach. The Fast R-CNN module is told where it has to look by the RPN module. Thus, engulfing region of interest and recognizing the same becomes a cooperative work. Approach for traffic sign recognition like a CNN based divide and conquer method has been used recently. It has been observed that recognition of some parts of image is also very much possible and efficient while using CNN. Instead of running the algorithm on the whole image, this approach suggests to run it on equally divided parts of the same image and then running on the image [14]. Training in such manner can significantly improve the accuracy, efficiency and reliability of the system. A noticeable data augmentation method is also used for generating effective training data [21].
Evidently, traffic signs recognition is affected by the translational changes, contrast variation, rotations, etc. These non-uniformities are dealt, by some authors, with an approach of spatial transformer network [3]. Automatic transformation generation of given image is carried out by spatial transformer network. Moreover, this layer is an independent layer and can be inserted anywhere in CNN giving out very low computational overhead.

Many other approaches based on CNN for traffic sign recognition include using of novel method of deep learning architecture also known as capsule networks [13]. Capsule networks do not contain neurons instead they contain capsules. Capsules are able to perform computations on the input and generate the result in the form of a small vector. Inside the capsules, squash functions used for the computations and routing algorithms used.
Many traditional approaches also include Linear Discriminant Analysis (LDA), Histograms of Oriented Gradients (HOG)[15][16]. NARX RNN, MultRT, BagRT are used by some to improvise on RNN based recognition models [17]. Deriving the results of various baseline methods and prominent competition algorithms has also been done concluding that the earlier one falls short when compared to the later one[18]. Color and shape modeling, normalization and classifying with mathematical modeling proved to be prominent in early stages of the research in this field [19]. One of the challenge is to work in bad light conditions. T. Hibi studied bad light conditions traffic sign recognition [20]. Table. 1. shows different recent works carried out.

Table. 1. Different existing techniques with improvements.

Authors names and year	Paper Title	Results	Achieved Improvements
Domen Tabernik Danijel Skočaj (2019)	Deep Learning for Large-Scale traffic sign detection and recognition	Comprehensive analysis about the methods of deep learning and detection of intra-category traffic sign appearance with variation	Reduced error rate to less than 3%
Karsten Behrendt Libor Novak Rami Botros (2017)	A Deep Learning Approach to Traffic Lights: Detection, Tracking and Classification	Detection of traffic lights for small pixel images.	Rate is 10 frames per second on 1280*720 images
Mrinal Haloi (2016)	Traffic Sign Classification Using Deep Inception Based Convolutional Networks	Deformation of input images is achieved.	Accuracy of 99.81% on GTSRB dataset
Arun Nandewal Abhishek Tripathi Satyam Chandrra (2016)	Indian Traffic Sign Detection and Classification Using Neural Network	Can detect images with background similar to traffic signs.	Improvements in recognizing traffic signs in poor lighting and partially occluded image
Amara Dinesh Kumar (2018)	Novel Deep Learning Model for Traffic Sign Detection Using Capsule Networks	Based on the correct classification rate the accuracy achieved is equal to 97.62% using capsule networks	Methods of capsule networks demonstration improved significantly

3. Small-Scale CNN

CNN is a Deep Learning algorithm , in which we can fed the image as input, assign importance (fix the weights and biases) to different objects in the image so as to differentiate the images from one another. CNN are proven best when it comes to image classification.

3.1 Small-Scale CNN

Fig. 1. shows a deep learning CNN model that is considered as a part of this work. The small-scale CNN consists of three convolutional layers followed by two fully connected layers. max pooling is applied after the convolutional layer to provide abstracted form of the representation so as to avoid over-fitting. The small-scale CNN uses a rectified linear (ReLU) activation function in each stage. The final layer gives the softmax probabilities for each 43 classes of traffic signs. In our CNN model, there are total 478, 763 parameters which all are trainable.

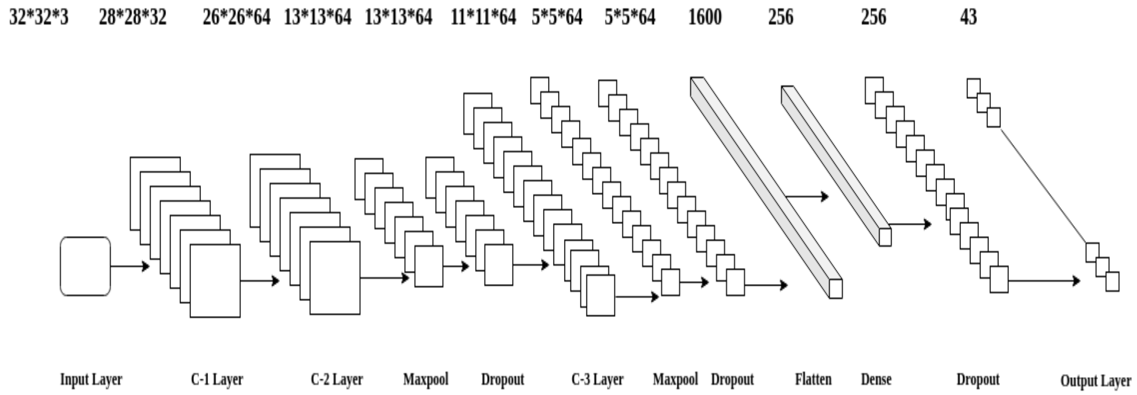

Fig. 1. CNN architecture

3.2. GTSRB Dataset

Generally, traffic signs are framed with particular typical shapes with easily noticeable colors. Fig. 2 shows some of the traffic sign images.

Fig. 2. Samples of Traffic Signs

In our system, traffic signs will be classified using CNN. This neural network will be trained on GTSRB dataset. This GTSRB dataset contains 43 different classes of traffic signs. In this more than 50,000 different images are present in total. We have classified the GTSRB dataset into three categories viz. training data, validation data and testing data. In this dataset , images for each traffic sign are not constant. Fig. 3. shows the distribution of images for each class of traffic signs.

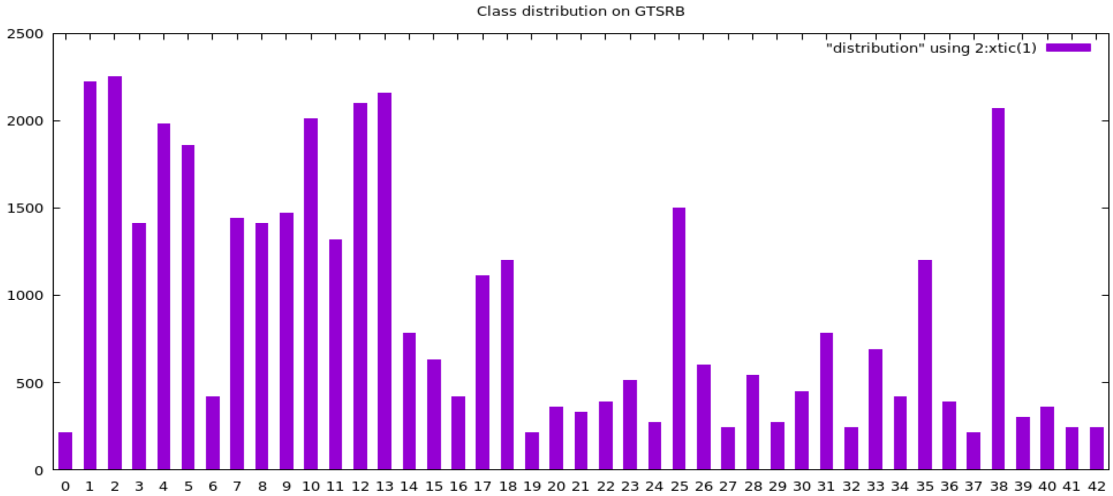

Fig. 3. Distribution of training data

3.3 Loss Function

In the proposed CNN model, we have used categorical cross entropy. The main motivation to use categorical cross entropy is because only one result can be correct in our classification problem. The following loss function is used for training the model.

$$L(y,\hat{y}) = -\sum_{j=0}^{M}\sum_{i=0}^{N}(y_{ij} * log(\hat{y}_{ij})) \tag{1}$$

here ŷ indicates the predicted value.
Categorical cross entropy will compare the distributions of the predictions with the actual distribution. Here, probability of the true class is 1 while that of the other classes 0.

3.4 Optimization

We have used the Adam optimization algorithm in small-scale CNN model. Adam can be considered as combination of Stochastic Gradient Descent and Root Mean Square propagation. Individual learning rates are computed for each different parameters as it adopts an adaptive method for learning. Adam used estimations of first and second moments of gradient to adapt the learning rate for each weight of the neural network.
N^{th} moment of a distribution for a number is given as the expected value of that variable raised to the power n. Mathematically it can be represented as below

$$m_n = E[X^n] \tag{2}$$

m is the moment and X is a random variable.
In neural network, Gradients for the cost function can be taken as a random variable. The update rule for Adam is given by formula shown below.

$$w_t = w_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{3}$$

where w is model weights , η is the step size (depending on the number of iterations).

4. Implementation and Results

4.1. Experimental Setup

We have used google-colab for all the experiments regarding implementation, training and testing. Google-colab provides nearly 12 GB ram which can be extended to 25 GB with GPU support. The whole code for our model is written in python. We have implemented our CNN model using keras API. The images from the dataset are resized to 32*32 with 3 channels so that can be fed to CNN model. The entire GTSRB dataset was uploaded on gitlab so that while running the code on google-colab, it can easily be fetch to load into the memory. This small-scale CNN model is also tested on a system with 8 GB RAM for the purpose of comparison. Traffic sign in bad light conditions such as sunrise time when the traffic sign is reflecting by the sun rays falling on it, sunset time, twilight time and night time were not covered in this work. There is a shortage of data in such challenging conditions and need in depth analysis.

4.2. Results

We trained our model for 50 epochs. Each epoch took nearly 11 sec for the small-scale CNN model to train. The graph is plotted for accuracy and loss for training as well as validation data as plotted in Fig. 4. (a) and Fig. 4. (b).

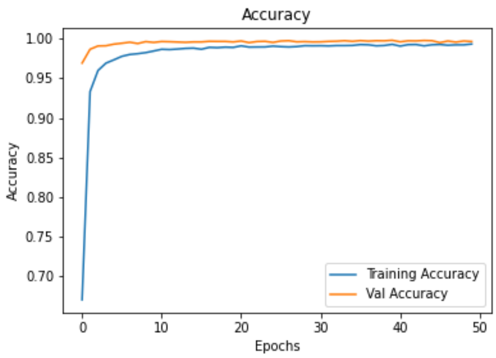

Fig. 4.(a) Accuracy

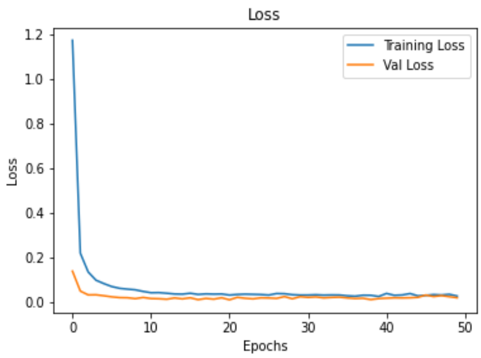

Fig. 4.(b) Loss

In this experimentation 99.19 % training accuracy is achieved with reduced loss of 0.0289. Validation accuracy achieved is 99.62 % with reduced loss of 0.0177. The testing accuracy achieved on the dataset is 97.71 %.
LeNet-5 architecture is having seven layers that is similar to small-scale CNN architecture used in this study. Both the architecture are having similar input size as 32* 32. The testing accuracy achieved with 32*32 input size using LeNet architecture is 90 %.
There is minute difference in training time for the small-scale CNN model using CPU and GPU, which is not of major concern. The small-scale CNN model can be used for real-time purpose either using CPU or GPU. The addition of new sign is not giving any impact on the small-scale CNN model. Recently, IoT based techniques are getting popularized due to its accuracy and remote operation characteristics [22]. In future, proposed system can be designed with IoT enabled capacity for decision making.

5. Conclusion

Traffic sign recognition is a challenging task in autonomous vehicles and driver assisted vehicles. This work gives a focus on study of recent work done for traffic sign recognition. The proposed small-scale CNN model is applied to ADAS-based system using GTSRB dataset. The achieved testing, training and validation accuracies are 97.71 %, 99.19% and 99.61 % respectively. This result gives an important improvement in testing accuracy compared with LeNet deep learning model. Also, small-scale CNN model takes less time of around 10 seconds per one epoch for training purpose. Hence this model can be used for different real-time purposes due to minimum computation time with optimal computational resources.

References

[1] Satılmış, Yusuf, et al. "CNN based traffic sign recognition for mini autonomous vehicles." International Conference on Information Systems Architecture and Technology. Springer, Cham, 2018.

[2] Bechtel, Michael G., et al. "Deeppicar: A low-cost deep neural network-based autonomous car." 2018 IEEE 24th International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA). IEEE, 2018.

[3] Haloi, Mrinal. "Traffic sign classification using deep inception based convolutional networks." arXiv preprint arXiv:1511.02992 (2015).

[4] Tabernik, Domen, and Danijel Skočaj. "Deep learning for large-scale traffic-sign detection and recognition." IEEE Transactions on Intelligent Transportation Systems (2019).

[5] Ouyang, Wanli, et al. "Deepid-net: Deformable deep convolutional neural networks for object detection." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

[6] Shustanov, Alexander, and Pavel Yakimov. "CNN design for real-time traffic sign recognition." Procedia engineering 201 (2017): 718-725.

[7] Stallkamp, Johannes, et al. "Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition." Neural networks 32 (2012): 323-332.

[8] Houben, Sebastian, et al. "Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark." The 2013 international joint conference on neural networks (IJCNN). IEEE, 2013.

[9] Timofte, Radu, Karel Zimmermann, and Luc Van Gool. "Multi-view traffic sign detection, recognition, and 3D localisation." Machine vision and applications 25.3 (2014): 633-647.

[10] Šegvic, Siniša, et al. "A computer vision assisted geoinformation inventory for traffic infrastructure." 13th International IEEE Conference on Intelligent Transportation Systems. IEEE, 2010.

[11] Larsson, Fredrik, and Michael Felsberg. "Using Fourier descriptors and spatial models for traffic sign recognition." Scandinavian conference on image analysis. Springer, Berlin, Heidelberg, 2011.

[12] Mogelmose, Andreas, Mohan Manubhai Trivedi, and Thomas B. Moeslund. "Vision-based traffic sign detection and analysis for intelligent driver assistance systems: Perspectives and survey." IEEE Transactions on Intelligent Transportation Systems 13.4 (2012): 1484-1497.

[13] Kumar, Amara Dinesh. "Novel deep learning model for traffic sign detection using capsule networks." arXiv preprint arXiv: 1805.04424 (2018).

[14] Behrendt, Karsten, Libor Novak, and Rami Botros. "A deep learning approach to traffic lights: Detection, tracking, and classification." 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2017.

[15] Dalal, Navneet, and Bill Triggs. "Histograms of oriented gradients for human detection." 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05). Vol. 1. IEEE, 2005.

[16] Dibua, Ohiremen, Aman Sinha, and John Subosits. "Data-Driven Modeling and Control of an Autonomous Race Car."

[17] Houben, Sebastian, et al. "Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark." The 2013 international joint conference on neural networks (IJCNN). IEEE, 2013.

[18] Bahlmann, Claus, et al. "A system for traffic sign detection, tracking, and recognition using color, shape, and motion information." IEEE Proceedings. Intelligent Vehicles Symposium, 2005.. IEEE, 2005.

[19] T. Hibi, "Vision based extraction and recognition of road sign region from natural color image, by using HSL and coordinates transformation," presented at 29th Inter. Symposium on Automotive Technology and Automation, Robotics, Motion and Machine Vision in the Automotive Industries, ISATA, 1996.

[20] Wu, Yiqiang, et al. "Real-time traffic sign detection and classification towards real traffic scene." *Multimedia Tools and Applications* (2020): 1-19.

[21] Iyer, B., Patil, N. IoT enabled tracking and monitoring sensor for military applications. Int J Syst Assur Eng Manag 9, 1294–1301 (2018). https://doi.org/10.1007/s13198-018-0727-8

[22] P. Deshpande and B. Iyer, "Research directions in the Internet of Every Things(IoET)," *2017 International Conference on Computing, Communication and Automation (ICCCA)*, Greater Noida, 2017, pp. 1353-1357, doi: 10.1109/CCAA.2017.8230008.

Tejas Chaudhari is a student of final year B.Tech (Information Technology) in the Department of Computer Engineering and IT, College of Engineering, Pune. His interests include Deep Learning using GPU. He has been part of COEP's Satellite initiatives as system engineer.

Ashish Wale is a student of final year B.Tech (Information Technology) in the Department of Computer Engineering and IT, College of Engineering, Pune. His interests include Pattern Recognition using Deep Learning.

Amit D. Joshi is working as Assistant Professor in the Department of Computer Engineering and IT, College of Engineering, Pune. He is pursuing Ph. D from National Institute of Technology, Tiruchirappalli, tn. His research interests include Parallel and Distributed Computing, GPU Computing.

Suraj Sawant is working as Assistant Professor in the Department of Computer Engineering and IT, College of Engineering, Pune. He is pursuing Ph. D from Indian Institute of Technology, Roorkee. His research interests include Artificial Intelligence, Deep Learning and GIS.