Traffic-Sign Classification Using Machine Learning Concepts

Mr. A. Obulesh
Department of Computer Science and Engineering, Anurag Group of Institutions, India
obuleshcse@cvsr.ac.in

Ms. P. Sri Sahithi
Department of Computer Science and Engineering, Anurag Group of Institutions, India
16h61a05n4@cvsr.ac.in

Mr. M. Deepesh Kumar
Department of Computer Science and Engineering, Anurag Group of Institutions, India
16h61a05m0@cvsr.ac.in

Ms. S. Pavitra
Department of Computer Science and Engineering, Anurag Group of Institutions, India
16h61a05p2@cvsr.ac.in

ABSTRACT

Traffic signs are an important part of road infrastructure to provide information about the current state of the road, restrictions, prohibitions, warnings, and other helpful information for navigation. Traffic sign classification is the process of automatically recognizing traffic signs along the road, including speed limit signs, yield signs, merge signs, etc. Being able to automatically recognize traffic signs enables us to build "smarter cars". Traffic sign recognition is a two-stage process. Localization and recognition. Localization is detection and localizing where in an input image/frame a traffic sign is. Recognition is taking the localized ROI (Region Of interest) and recognize and classify the traffic sign. With deep learning, we can localize and recognize traffic sign by using convolution neural networks (CNN). The dataset used to train the traffic sign classification is German Traffic Sign Recognition Benchmark (GTSRB). It consists of several pre-cropped and manually labelled traffic signs in the images. Therefore, the proposed approach is used to detect the traffic signs and then classify and recognize different signs with 95% accuracy.

Keywords: Convolutional neural network(CNN), German traffic sign recognition benchmark, ROI (region of interest).

1. INTRODUCTION

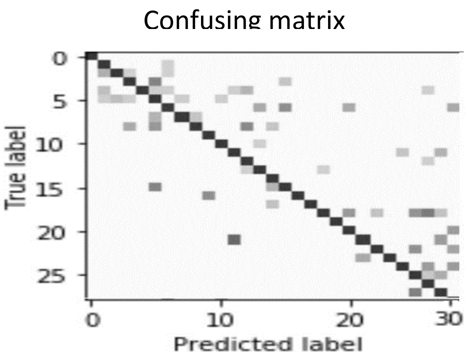
With the rapid development of economy and technology in the modern society, automobiles have become an indispensable means of transportation in the daily travel of people. Although the popularity of automobiles has introduced considerable convenience to people, it has also caused a numerous traffic safety problem that cannot be ignored, such as traffic congestion and frequent road accidents. In the world of Artificial Intelligence and advancement in technologies, many researchers and big companies like Tesla, Uber, Google, Mercedes-Benz, Toyota, Ford, Audi, etc are working on autonomous vehicles and self-driving cars. So, for achieving accuracy in this technology, the vehicles should be able to interpret traffic signs and make decisions accordingly. Traffic safety issues are largely caused by subjective reasons related to the driver, such as inattention, improper driving operation and non-compliance with traffic rules, and smart cars have become an effective means to eliminate these human factors.

2. EXPERMENTAL

We are using Deep learning and Keras for classifying the traffic signs in images. Deep learning object detectors can perform localization and recognition in a single pass of network. There are 3 stages in traffic sign classification. First stage is preprocessing the input image. In the first stage of traffic sign classification the picture is taken as input and pre-process it. Noise is removed from the image and transformed to a gray-scale image. Second stage is detecting the traffic sign in the input. In this step, traffic-signs are first located in the image using Tensorflow. The third stage is classification and recognition the traffic-sign. Classifying the traffic-sign is an important step in the classification of the traffic-sign. It is the method of classifying and identifying various traffic signs by using a trained data set. The dimensions of Input image are 32x32x3. Then we get output image with dimensions 32x32x8.

After batch normalization and pooling:

The dimensions of Input image are 32x32x8. Then, we get output images of dimensions 16x16x8. It uses (5,5) kernel to learn larger features. Compared to other models, here we are using additional preprocessing algorithms that open CV does not provide. Scikit image provides additional preprocessing algorithms. For image improvement we use algorithm called Contrast Limited Adaptive Histogram Equalization. It is found in Scikit image



International Journal of Research
e-ISSN: 2348-6848
p-ISSN: 2348-795X
Volume 07 Issue 05
May 2020

library.

After max pooling:

Dropout-0.5

Batch size-64

Epochs-30

Accuracy -95% (Accuracy = correctly predicted images/ total testing images× 100).

3. RESULTS AND DISCUSSION

In our project, we propose a high-performance traffic sign detection and classification system. In this system, we give image as an input, after giving the input as an image we use predict method to know what sign the image depicts. In Predict Method, we load the images and after loading, the path is set for the images and it starts making the predictions. After Prediction Method, the image undergoes classify model. In classify model we have collections of Road and Traffic Sign Data. It is further proceeded to Feature Extraction. Feature Extraction consists of Loading the label names, Test and Train Data csv files and Scaling of images. In Feature Extraction, Image undergoes through a pre-defined training of the model and it generates image with prediction evaluation. After Feature Extraction, Image undergoes 4 Layer Image Transformation. The 4 Layer Image Transformation consists of techniques like Conv2D, Activation, Batch Normalization and MaxPooling.

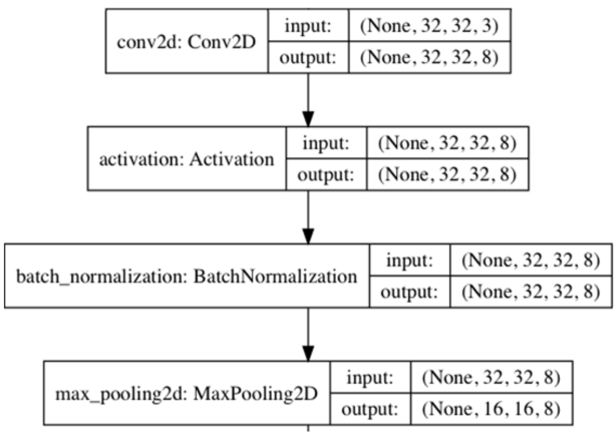


Fig.3.1. Techniques used in 4-layer transformation

2D convolution layer:

A convolution is the simple application of a filter to an input that results in an activation. Repeated application of the same filter to an input results in a map of activations called a feature map, indicating the locations and strength of a detected feature in an input, such as an image.

Activation layer:

In a neural network, the activation function is responsible for transforming the summed weighted input from the node into the activation of the node or output for that input. The rectified linear activation function is a piecewise linear function that will output the input directly if is positive, otherwise, it will output zero. It has become the default activation function for many types of neural networks because a model that uses it is easier to train and often achieves better performance.

Batch normalization:

Batch normalization is a technique for training very deep neural networks that standardizes the inputs to a layer for each mini batch. This has the effect of stabilizing the learning process and dramatically reducing the number of training epochs required to train deep networks.

Max Pooling:

Max pooling is a sample-based discretization process. The objective is to down-sample an input representation (image, hidden-layer output matrix, etc.), reducing its dimensionality and allowing for assumptions to be made about features contained in the sub-regions binned. This part is used in over-fitting by providing an abstracted form of the representation. As well as, it reduces the computational cost by reducing the number of parameters to learn and provides basic translation invariance to the internal representation.

The dataset we'll be using to train our own custom traffic sign classifier is the German Traffic Sign Recognition Benchmark (GTSRB). The GTSRB dataset consists of 43 traffic sign classes and nearly 50,000 images.
We need to load our training and testing split from the GTSRB dataset. Then pre-process the images. Train our model. Then evaluate our model's accuracy. We will create a folder that contains the test images. We load the input image with scikit-image. Then preprocess the image. Make a prediction and grab the class label with the highest probability. Using OpenCV we load, resize, annotate the image with

the label, and write the output image to desired path of the output model. We make predictions on traffic sign data using our trained model.
After all the steps mentioned above, a predicted image of traffic sign is displayed along with the label name.

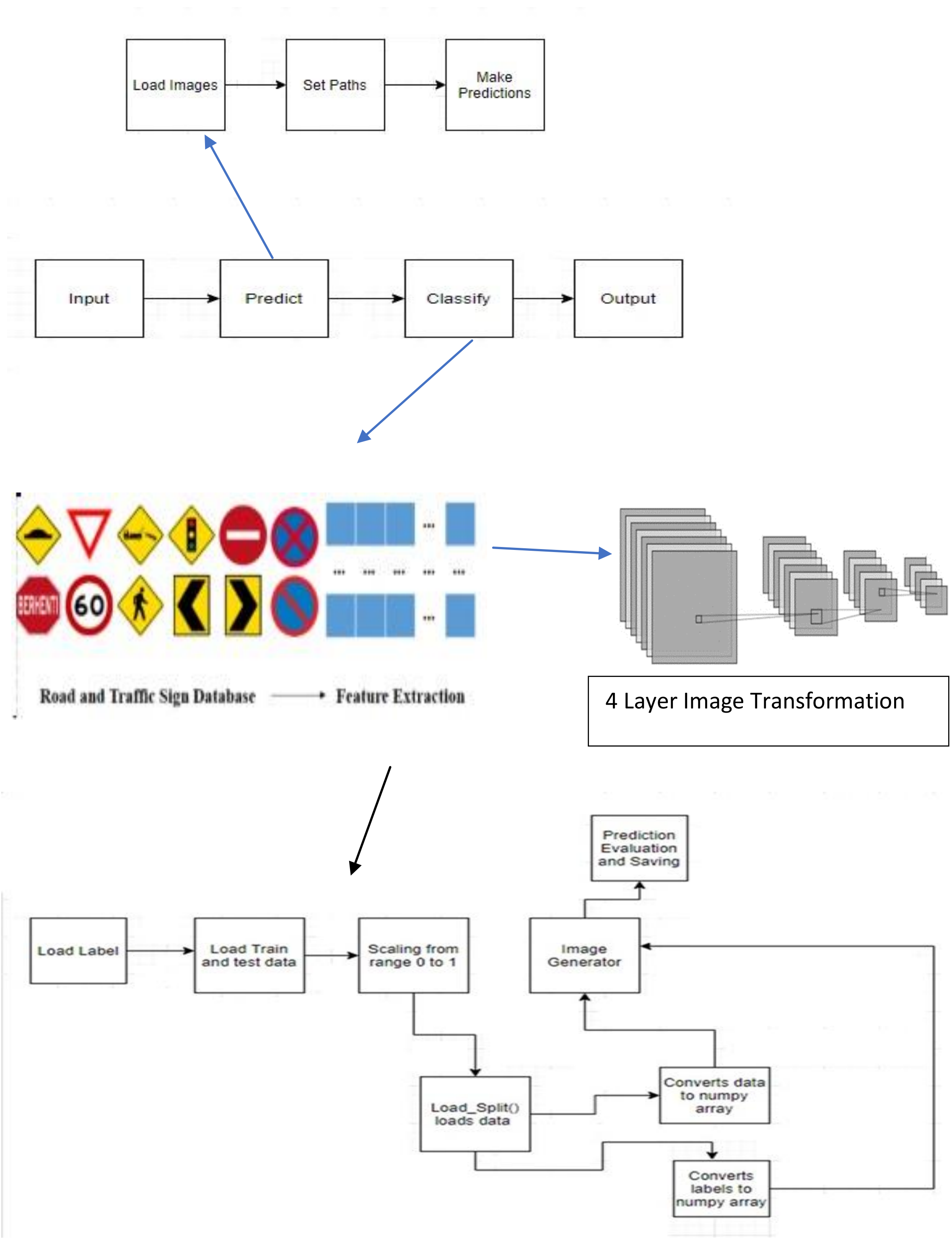


Fig.3.2: Framework for traffic-sign classification using machine learning algorithms.

e-ISSN: 2348-6848
p-ISSN: 2348-795X
Volume 07 Issue 05
May 2020

The images with output.:

Fig.3.3 road work

Fig.3.4 speedlimit(30kms)

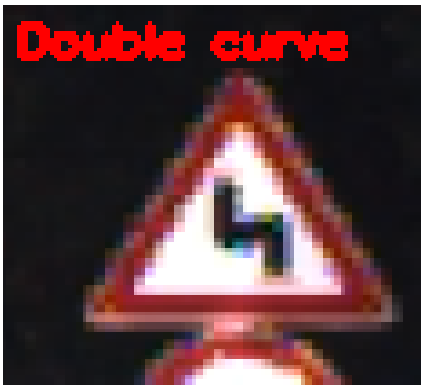


Fig.3.5 double curve

Fig.3.6 roundabout mandatory

Fig.3.7 Turn right ahead

Fig.3.8 Turn left ahead

4. CONCLUSION

In this study, an improved traffic sign detection and recognition algorithm is proposed for intelligent vehicles. The traffic sign classification and recognition experiments are conducted based on the German Traffic Sign Recognition Benchmark (GTSRB). The favorable prediction and accurate recognition of traffic signs are achieved through the continuous training and testing of the network model. The proposed algorithm has more admirable accuracy, better real-time performance, stronger generalization ability and higher training efficiency. The accurate recognition rate and average processing time are significantly improved.

REFERENCES

1. Gudigar A, Chokkadi S, Raghavendra U (2016) A review on automatic detection and recognition of traffic sign. Multimed Tools Appl 75(1):333–364.
2. De la Escalera A, Armingol JM,MataM(2003) Traffic sign recognition and analysis for intelligent vehicles. Image Vis Computer 21(3):247–258
3. Escalera S, Bar X, PujolO,Vitri J, Radeva P (2011) Background on traffic sign detection and recognition. In: Traffic-sign recognition systems. Springer, London, pp 5–13
4. Jin J, FuK, Zhang C (2014) Traffic sign recognition with hinge loss trained convolutional neural networks. IEEE Trans Intell Transp Syst 15(5):1991–2000
5. Aghdam HH, Heravi EJ, Puig D (2016) A practical approach for detection and classification of traffic signs using Convolutional Neural Networks. Robot Auton Syst 84:97–112
6. Qian R, Yue Y, Coenen F, Zhang B (2016) Traffic sign recognition with convolutional neural network based onmax pooling positions. In: 12th International conference on natural computation, fuzzy systems and knowledge discovery (ICNC-FSKD), 2016, IEEE, pp 578–582
7. Mogelmose A, Trivedi MM, Moeslund TB (2012) Vision-based traffic sign detection and analysis for intelligent driver assistance systems: Perspectives and survey. IEEE Trans Intell Transp Syst 13(4):1484–1497.
8. J. Stallkamp, M. Schlipsing, J. Salmen, and C. Igel,“The German traffic sign recognition benchmark: a multi-class classification competition,” in Proc. IEEE IJCNN, 2011.
9. S. Houben, J. Stallkamp, J. Salmen,M. Schlipsing, and C. Igel,[2] “Detection of traffic signs in real-world images: The German traffic sign detection benchmark,” in Proc. IEEE IJCNN, 2013.
10. Towards Real-Time Traffic Sign Detection and Classification by Yi Yang, Hengliang Luo, Huarong Xu and Fuchao Wu,2014, IEEE.
11. C. Fang, S. Chen, and C. Fuh, "Road-sign detection and tracking," IEEE Trans. on Vehicular Technology, vol. 52, pp. 1329-1341, 2003.

12. S. Vitabile, A. Gentile, and F. Sorbello, "A neural network based automatic road sign recognizer," presented at The 2002 Inter. Joint Conf. on Neural Networks, Honolulu, HI, USA, 2002.
13. D. Ghica, S. Lu, and X. Yuan, "Recognition of traffic signs by artificial neural network," presented at IEEE Inter. Conf. Neural Networks, Perth, W.A., 1995.
14. N. Yabuki, Y. Matsuda, Y. Fukui, and S. Miki, "Region detection using color similarity," presented at 1999 IEEE Inter. Symposium on Circuits and Systems, Orlando, Florida, USA, 1999.
15. W. Shadeed, D. Abu-Al-Nadi, and M. Mismar, "Road traffic sign detection in color images," presented at 10th IEEE Inter. Conf. on Electronics, Circuits and Systems (ICECS 2003), Sharjah, United Arab Emirates, 2003.
16. G. Adorni, V. D'Andrea, G. Destri, and M. Mordonini, "Shape searching in real world images: a CNN-based approach," presented at Fourth IEEE Inter. Workshop on Cellular Neural Networks and Their Applications, Seville, Spain, 1996.