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Traffic Sign Classification using Federated Deep Learning Model

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Abstract-For several years, much research has focused on the importance of traffic sign recognition systems, which have played a very important role in road safety. Researchers have exploited the techniques of machine learning, deep learning, and image processing to carry out their research successfully. The new and recent research on road sign classification and recognition systems is the result of the use of federated deep learning-based architectures such as the convolutional neural network (CNN) architectures. In this research work, the goal was to achieve a CNN model that is lightweight and easily implemented for an embedded application and with excellent classification accuracy. We choose to work with an improved network ResNet34 model for the classification of road signs. We trained our model network on the German Traffic Sign Recognition Benchmark (GTSRB) database and also on the Belgian Traffic Sign Data Set (BTSD), and it gave good results compared to other models tested by us and others tested by different researchers. The results we found are efficient, which emphasize the effectiveness of our method

Keywords: Convolution neural network (CNN), Federated deep learning, German Traffic Sign Recognition Benchmark (GTSRB), Belgian Traffic Sign Data Set (BTSD)

1. INTRODUCTION

Traffic signs are an integral part of driving both motor and non-motor vehicles on roads. They direct traffic, they limit the maximum speed and avoid unnecessary collisions and informs the driver about the possible dangers' obstacles on the road.

Today, car transport is one of the most common forms of transport. We meet her on a daily basis in various forms, whether it is on the way to work, school or other daily activities. Every road user (driver) must comply with the road traffic rules of the country in which he is currently located. This is mainly for their own safety and security vis-à-vis other road users. One of the most important components of such an information system is visual image processing. 2 This brings us to the traffic signs that every driver must know in order to be able to orientate themselves in road traffic and to comply with the law on road traffic. Despite the driver's knowledge of traffic signs, it can sometimes happen that the driver can overlook a traffic sign and react incorrectly in a given situation. Which can not only limit and endanger road users but also, in the worst case, cause an accident? This was one of the main reasons why various carmakers began to develop intelligent systems that would be able to recognize the road sign and alert the driver to it in due course, thus preventing a dangerous traffic situation. Those who follow developments in the automotive industry certainly see the efforts of car manufacturers (BMW) as well as companies in the IT sector (GOOGLE) to develop an autonomously controlled vehicle.

The traffic signs can be recognized by using the image processing algorithms and machine learning algorithms using CNN. In this project I am going to use RESNET as the conventional neural network, which is most sophisticated neural network for image processing by using federated learning.

2. METHODOLOGY

The use of a traffic sign recognition system is very challenging. Since the rain, fog, snow etc. Affect the whole system. Another thing is the light variation i.e., shadows, sun, clouds etc. The geometrical shape of the object and the perspective is also a big concern. So, we must be able to come up with a system which can work under light variation and geometrical transformation of the objects in a scene. If we narrow down the scope, we are particularly interested in the detection of these signs under low light condition. In short, our objective is to make the system

very accurate and efficient. In the detection stage, colour information is exploited to detect regions of interest (ROI) that may correspond to traffic signs.

The pictogram contained on each ROI is extracted, analyzed and compared with the pictogram database. The best match between the ROI and database pictogram, if high enough, is considered the sign that is more likely to appear in that ROI. Each recognized sign is part of the output result of the recognition stage.

2.1 Existing Methods

The initial methods for object detection mainly depend on feature extraction methods. People usually took color and shape features into consideration to achieve traffic-sign detection and classification tasks. In terms of color features, the images were transformed to other color spaces like HSV (Hue, Saturation, Values) instead of using RGB (Red, Green, Blue). Wang et al. (2013) pointed out that the computer algorithms based on RGB color spaces could limit the performance of detection traffic signs due to different illuminant conditions. Besides, Li et al. (2014) also proposed a color probability model based on Ohta space to compute the maps of probability for each color belonging to traffic signs (Yang & Wu, 2014). With regard to shape features, traffic signs have various geometries, such as circular, rectangular, triangular or polygonal. People extracted contour lines by Hough transforms and radial symmetry, etc. The circular traffic signs would deform by shooting angle or other external force. In order to tackle this issue, Wang et al. (2014) proposed an ellipsedetection method in their article (G. Wang, Ren, Wu, Zhao, & Jiang, 2014). Moreover, Liang et al. (2013) designed a list of templets for each traffic-sign class to match shape (Liang, Yuan, Hu, Li, & Liu, 2013). The HOG as one of the most widely used features also benefited a lot for the traffic-sign feature extraction. The HOG feature of each cell would be normalized over each of its neighboring blocks to represent more local detail information, but which can lead to redundant dimensions of a feature representation (Yao, Wu, Chen, Hao, & Shen, 2014). Hence, it is challenging to make a trade-off between rich local details and redundancy

3. PROPOSED METHOD

Deep residual networks like the popular ResNet-50 model is a convolutional neural network (CNN) that is 50 layers deep. A Residual Neural Network (ResNet) is an Artifical neural networks(ANN) of a kind that stacks residual blocks on top of each other to form a network.

In recent years, the field of computer vision has undergone far-reaching transformations due to the introduction of new technologies. As a direct result of these advancements, it has become possible for computer vision models to surpass humans in efficiently solving different problems related to image recognition, object detection, face recognition, image classification, etc.

In this regard, the introduction of deep conventional neural networks(CNNs) deserves special mention. These networks have been extensively used for analyzing visual imagery with remarkable accuracy.

But, while it gives us the option of adding more layers to the CNNs to solve more complicated tasks in computer vision, it comes with its own set of issues. It has been observed that training the neural networks becomes more difficult with the increase in the number of added layers, and in some cases, the accuracy dwindles as well.

It is here that the use of ResNet assumes importance. Deeper neural networks are more difficult to train. With Resnet, it becomes possible to surpass the difficulties of training very deep neural networks.

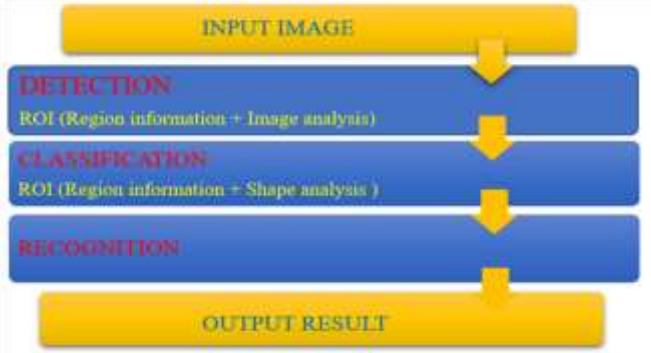

Figure 1: Flowchart of proposed system

4. RESULTS

Figure 3(a): Screen shot of the dataset

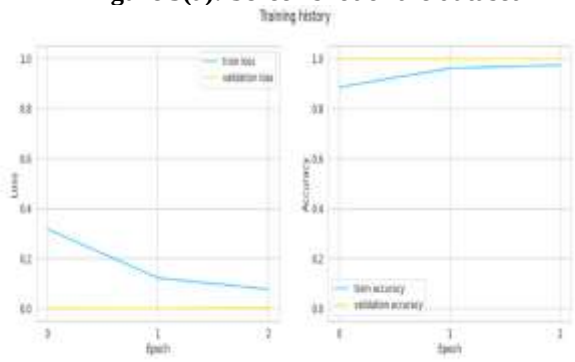

Figure 3(b): Pre-Training

Figure 3(c): Classify Traffic Sign

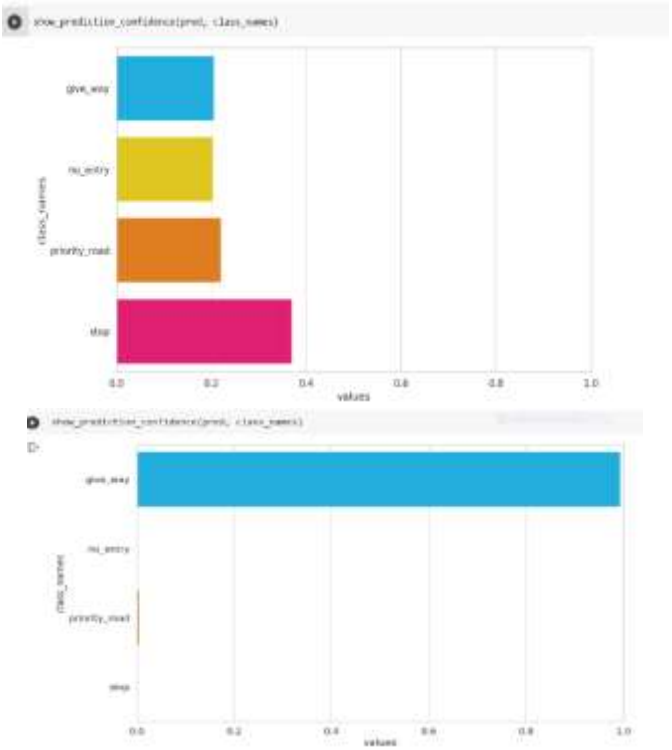

Figure 3(d): Prediction Confidence

Figure 3(e): Predictions

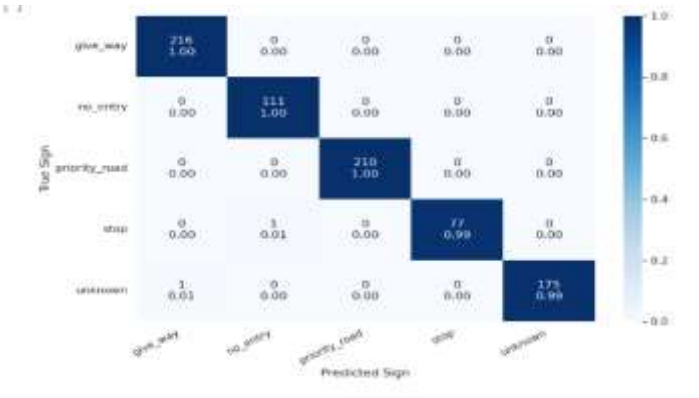

Figure 3(f): Confusion Matrix

5. CONCLUSION

Currently, there are a lot of road accidents happening in the world. This is because the drivers are unable to recognize the traffic signs due to different conditions and the automated vehicles are increasing day by day. So the traffic sign classification mechanism plays a key role in road transport. This mechanism is going to identify the traffic sign on the road even in extreme climatic conditions and give an alert to the driver So that the driver can able to act immediately if he is exceeding the speed limit he will control it if there are any black sports are there he will get an alert and act accordingly. We have used the deep learning algorithm RESNET-34 with which the system can able to detect the traffic sign more efficiently and accurately. Federated learning helps to train the neural network both locally and, in the cloud, so the System will be much more efficiently work.

REFERENCES

[1]. Ameur Zaibi, Anis Ladgham, Anis Sakly, "A Lightweight Model for Traffic Sign Classification Based on Enhanced LeNet-5 Network", Journal of Sensors, vol. 2021, Article ID 8870529, 13 pages, 2021. https://doi.org/10.1155/2021/8870529

[2]. C. Gámez Serna and Y. Ruichek, "Traffic Signs Detection and Classification for European Urban Environments," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 10, pp. 4388-4399, Oct. 2020, doi: 10.1109/TITS.2019.2941081.

[3]. D. Temel, M. -H. Chen and G. AlRegib, "Traffic Sign Detection Under Challenging Conditions: A Deeper Look into Performance Variations and Spectral Characteristics," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 9, pp. 3663-3673, Sept. 2020, doi: 10.1109/TITS.2019.2931429.

[4]. Huang, Shu-Chun, Chih-Yi Li, Huei-Yung Lin, and Wen-Lung Tai. "Traffic sign detection and recognition using image features and convolutional neural network." Shu-Chun Huang, Chih-Yi Li, Huei-Yung Lin, Wen-Lung Tai: 6.

[5]. de la Escalera, A, Moreno, L, Salichs, M, and Armingol, J. Road traf¿c sign detection and classi¿cation. Industrial Electronics, IEEE Transactions on, 44(6):848 –859, December 1997.

[6]. Krizhevsky A, Sutskever I, Hinton G E. ImageNet Classification with Deep Convolutional Neural Networks [J]. Advances in Neural Information Processing Systems, 2012, 25(2):2012.

[7]. K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in International Conference on Learning Representations, May 2015.

[8]. LeCun, Y, Bottou, L, Bengio, Y, and Haffner, P. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11):2278– 2324, November 1998.

[9]. Y. Zhang, T. Xiang, T. M. Hospedales and H. Lu, "Deep Mutual Learning," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, 2018, pp. 4320-4328, doi: 10.1109/CVPR.2018.00454.

[10]. K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90

