SJIF Impact Factor (2024): 8.675| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 9 | Issue: 9 | September 2024 - Peer Reviewed Journal

CNN MODEL FOR TRAFFIC SIGN RECOGNITION

U.Venkateshwarulu[1], Prof. B. Manjunath[2]
[1]School of Computer Science and Applications,REVA University,Bangalore, Karnataka, India
[2]School of Computer Science and Applications,REVA University,Bangalore, Karnataka, India

Article DOI: https://doi.org/10.36713/epra18355
DOI No: 10.36713/epra18355

ABSTRACT

The traffic sign recognition framework (TSRS) is an important component of intelligent transportation systems (ITS). Accurately identifying traffic signs can improve driving safety. This research provides a traffic sign recognition approach based on profound learning. It primarily focuses on the location and order of roundabout signs. First, a photograph undergoes pre-processing to highlight important facts. Hough Transform is used to distinguish and find regions. Finally, the unique street traffic signs are analyzed for further understanding. This paper proposes a photo handling-based traffic sign discovery and distinguishing proof technique that is combined with convolutional brain organization (CNN) to sort traffic signs. CNN is useful for recognizing many PC vision tasks due to its high recognition rate. TensorFlow is used to implement CNN. We have a recognition accuracy of over 98.2% for the roundabout image in the German informative collections.
KEYWORDS——*traffic sign recognition, traffic sign detection, deep learning, convolutional neural network*

I.INTRODUCTION

Traffic sign recognition is important for intelligent driving frameworks like assisted and programmed driving. Manual component procedures and profound learning techniques are the two categories under which street sign acknowledgment approaches fall. For example, explicit variety acknowledgment [10] and other element acknowledgment schemes required manual marking and component extraction, which greatly slowed down the pace of framework activity. Not only was manual marking more work, but it was also more difficult to guarantee accuracy rates. The most common techniques for learning fake elements are SVM and arbitrary backwoods, although this method can be easily understood for images with blurry inclusion boundaries [1].

Traffic signs contain consistent properties that can be used for position and arrangement, including diversity and shape, which can help drivers get street data. Rush hour gridlock signs are similar across countries, with basic colors (red, blue, yellow) and fixed shapes (circles, triangles, square shapes). However, the appearance of traffic signs is often influenced by external factors such as weather patterns. Traffic sign recognition is a challenging and crucial topic in rush hour jam design exams. In [3] and [4], various traffic-sign ID advancements were developed. In paper [5], a CNN with a learning strategy is advanced. Profound CNN is trained on large amounts of data, and viable territorial convolutional neural networks (RCNNs) are discovered using typical traffic preparation methods.

In paper [6], a multi-goal highlight mix network texture is developed to focus on useful elements from small-sized objects. The traffic sign recognition system is also partitioned into spatial succession order and relapse assignments to acquire more data and improve recognition execution. To better comprehend CNN identification and traffic sign recognition. This article uses Hough Transform to recognize and pre-process street traffic signs, enhancing their accuracy and usefulness.

This article covers traffic sign identification in three sections: pre-handling, location, and order. Figure 1 depicts the traffic sign recognition framework procedure. Pre-handling improves the static variety picture and changes the variety space. During the identification stage, street signs are classified based on their shape and variety data. Roundabout traffic signs are then detected using the Hough Transform [7]. During this stage, an image of the region of interest is generated, together with the location of traffic signs. During the recognition and characterization stage, the extracted and sectioned traffic sign region is used as input. A convolutional neural network [8] in deep learning is then used to distinguish and group the recognized data.

CNN has recently gained attention as a topic of study, and many academics are working in this area [6], [7], [8]. CNN has since consistently evolved into PC vision's most typical picture categorization model. Three fundamental components are often included in a complete CNN: the convolutional layer, the pooling layer, and the fully associated layer. The convolutional layer is an important component of CNN. A two-dimensional inclusion map is produced when the convolution piece convolves the relevant region of the image with a preset step size [9]. The image develops from low-dimensional to high-layered, and then it obtains high-dimensional

SJIF Impact Factor (2024): 8.675| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 9 | Issue: 9 | September 2024 - Peer Reviewed Journal

picture highlights. Adding convolutional layers can, in contrast to conventional AI algorithms, eliminate highlights at different levels in the picture and has interpretation invariance to the information picture.

Additionally, the limits of the common are the convolution section in the convolution layer, which significantly reduces the size of the boundaries. In the convolution interaction, the pooling layer can reduce the aspect of the picture, retain the important data, and quicken the organization's preparation. Techniques for normal pools include arbitrary, normal, and biggest pools. The primary goals of pooling, regardless of the approach employed, are to reduce the spatial element aspect, reduce the framework load, and quicken the network preparation speed. At least one fully linked layer usually exists at the end of the brain's organization.Its task is to connect to a single-layered include map, group the image using the high-layered include data that has been separated, use the final fully associated layer as the yield layer, and then the network produces the arrangement result. Moreover, the order initiation capacity may vary across the picture's component data into the (0, 1) span, reducing the amount of PC execution used during the preparatory interaction.

In the identification step, the primary goal is to eliminate the regions of interest from the image and prepare the scene for the layout stage. This work will investigate the finding of traffic signs based on the two data of signs: the variety and shape data. Since each traffic sign has a defined shape and tone, there are two massive data sets related to traffic signs. The goal of area of interest extraction in light of varied data is to extract H and S portions of the image. changed to an HSV variety space. Tone is important because it provides more consistency in the way that illumination circumstances fluctuate and a range of immersion in the shadows or elements behind the scenes. The partition table with according to HSV space.

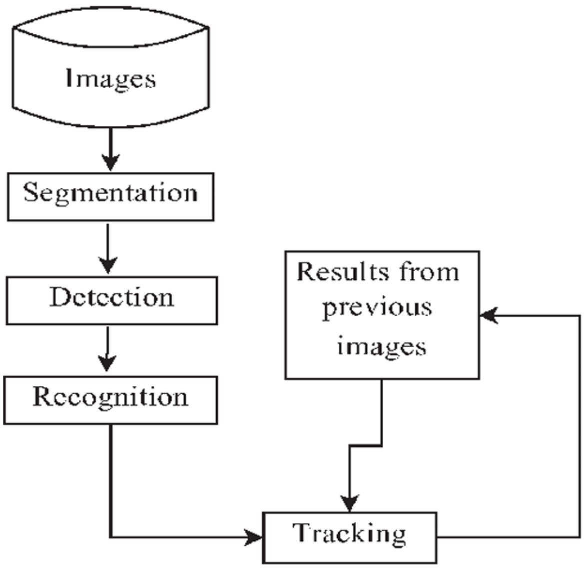

Fig.1. Block diagram of Traffic Sign Recognition

After division, there will be some turbulence in the picture.
This work uses math's morphological activity to eliminate unnecessary impedance data during image division. visual morphology can improve visual information by preserving its essential condition and eliminating unnecessary design elements. After HSV space division, the image employs open activity due to minor impedance differences. As previously said, open activity can effectively eradicate these little things. with dividing the picture, erosion occurs with the development of handling.
As shown in the figure below.

II. LITERATURE REVIEW

In this section, Ciresan, D. C., Meier, U., Masci, J., Gambardella, L. M., & Schmidhuber, J. (2012). Multi-column deep neural network for traffic sign classification. Neural Networks, 32, 333-338. Introduced a multi-column deep neural network achieving high accuracy on the German Traffic Sign Recognition Benchmark (GTSRB)[1].

Sermanet, P., & LeCun, Y. (2011). Traffic sign recognition with multi-scale Convolutional Networks. IJCNN 2011, 2809-2813.Developed a multi-scale CNN that recognizes traffic signs in varying sizes and resolutions [2]. Stallkamp, J., Schlipsing, M., Salmen, J., & Igel, C. (2011). The German Traffic Sign Recognition Benchmark: A multi-class classification competition. IJCNN 2011, 1453-1460. Established a benchmark dataset for traffic sign recognition, spurring research in this area[3].

SJIF Impact Factor (2024): 8.675| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 9 | Issue: 9 | September 2024 - Peer Reviewed Journal

In Goodfellow, I. J., Bulatov, Y., Ibarz, J., Arnoud, S., & Shet, V. (2013). Multi-digit number recognition from street view imagery using deep convolutional neural networks. arXiv preprint arXiv:1312.6082. Applied CNNs to recognize multi-digit numbers from street view images, relevant for traffic sign recognition [4]. Hoang, T., & Vu, H. (2017). Real-time traffic sign detection and recognition using deep convolutional neural networks. ICIST 2017, 321-326. Proposed a real-time traffic sign detection and recognition system using deep CNNs [5]. Houben, S., Stallkamp, J., Salmen, J., Schlipsing, M., & Igel, C. (2013). Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark. IJCNN 2013, 1-8. Introduced a detection benchmark complementing the classification benchmark for traffic signs[6].

Cireşan, D., Meier, U., Masci, J., Gambardella, L. M., & Schmidhuber, J. (2011). Flexible, high performance convolutional neural networks for image classification. IJCAI 2011, 1237-1242. Demonstrated the flexibility and high performance of CNNs for various image classification tasks, including traffic signs [7]. Yadav, A. R., & Shukla, N. (2018). Traffic sign recognition using deep learning. ICICCS 2018, 193-198.Utilized deep learning techniques to achieve significant improvements in traffic sign recognition accuracy [8]. Basu, S., Sinha, P., Kar, A., & Dey, N. (2017). Traffic sign detection and recognition using deep learning. In Intelligent Vehicles and Materials Transportation in Traffic Engineering, 123-145.Explored deep learning methods for both detection and recognition of traffic signs [9]. Yang, S., Sun, Z., Liu, H., & Zhao, H. (2016). Towards real-time traffic sign detection and recognition. ICARCV 2016, 1-6. Focused on developing a system capable of real-time traffic sign detection and recognition using CNNs [10].

Zhang, L., & Zhang, L. (2015). Robust and efficient traffic sign recognition based on a CNN model. ICCIA 2015, 243-246. Developed a robust and efficient CNN model for traffic sign recognition [11]. Bahl, A., & Bahl, P. (2017). Traffic sign recognition using convolutional neural networks. I2C2 2017, 1-6. Presented a CNN-based approach for accurate traffic sign recognition [12]. Zhu, Z., Liang, D., Zhang, S., Huang, X., Li, B., & Hu, S. (2016). Traffic-Sign Detection and Classification in the Wild. CVPR 2016, 2110-2118.Addressed traffic sign detection and classification in challenging real-world conditions using CNNs [13].

Pitz, G., & Hartmann, U. (2017). Traffic sign recognition in real time using deep convolutional networks. TELFOR 2017, 1-4. Developed a real-time traffic sign recognition system leveraging deep convolutional networks [14].

Li, Y., Li, Y., & Sun, M. (2017). Traffic sign detection using a multi-task convolutional neural network. QR2MSE 2017, 244-247.Implemented a multi-task CNN for efficient traffic sign detection [15]. Chen, W., Xie, S., Huang, Y., & Huang, Z. (2015). A deep learning-based approach for traffic sign recognition. CYBER 2015, 127-131.Proposed a deep learning approach specifically tailored for traffic sign recognition [16].

III. METHODOLOGY

To capture images of traffic signs, use a high-quality camera. There may be some noise in the captured image.

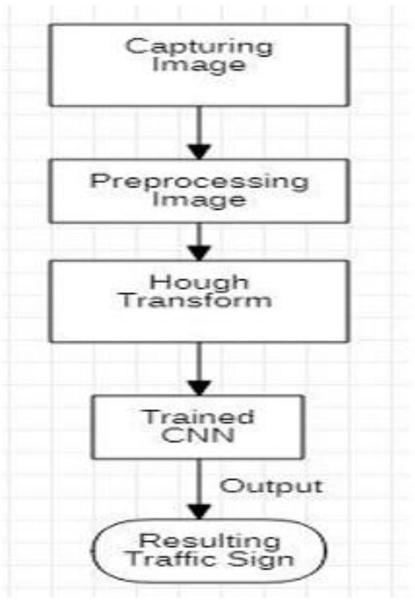

Fig.2. Content Diagram of Traffic Sign Recognition

SJIF Impact Factor (2024): 8.675| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 9 | Issue: 9 | September 2024 - Peer Reviewed Journal

To remove noise and disruptions, images should be preprocessed using many filters. Finally, Hough Transform is utilized to determine roundabout sign positions. Hough Transform uses global image elements to correlate edge pixels with structural territorial bounds. Hough change refers to the relationship between a picture and its surrounding surroundings. Using Hough, a difficult-to-resolve global location issue can be transformed into an easy-to-resolve local location issue, resulting in a clearer and more understandable result. It has the advantage of having minimal influence from disturbance and intermittent bends.

ER/UML Diagram
The ER/UML diagrams provide a clear picture of how the work is going on.

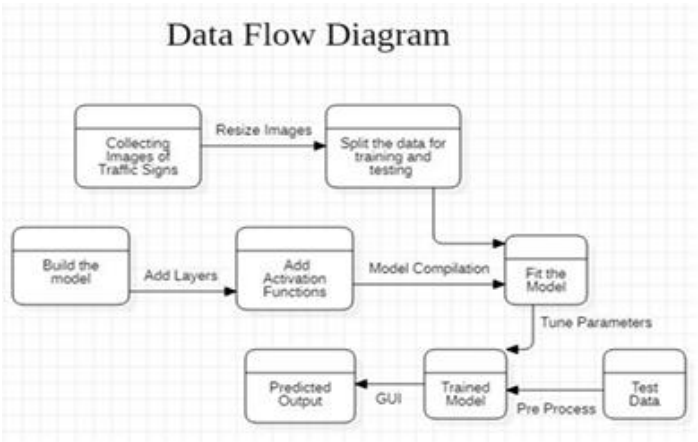

Fig.3. Data Flow Diagram of Traffic Sign Recognition

In addition to using CNN to define the distinct indications, a lightweight CNN classifier is also envisaged for this research. Two pooling layers, two full association layers, and two convolutional layers make up the lightweight CNN. This paragraph sets the convolution layer's section size to 5x5, the convolution part's amount to 32, and the step size to 1. The primary convolution layer has sixteen stored away layer hubs, whereas the secondary convolution layer has thirty-two. Highlight charts come in two sizes: 32x32 and 16x16. The pooling layer's piece size is 2x2, the full association layer's secret hubs are 512 and 128; and the final result layer has 43 stowed-away hubs. The initial value of the learning rate can be set at a higher value to improve preparation time or a lower value to speed up the combination process. The text's learning rate has an underlying value of 0.0001. Dropout (regularization) management is the covert layer of the entire association that prevents the peculiarity of overfitting in the organization. To avoid over-fitting, information on some hubs is randomly removed during the preparation phase. To eliminate some eigenvalues, Dropout set the hub information to 0. Figure 7 illustrates the CNN process of extracting elements and arranging them.

Model Design

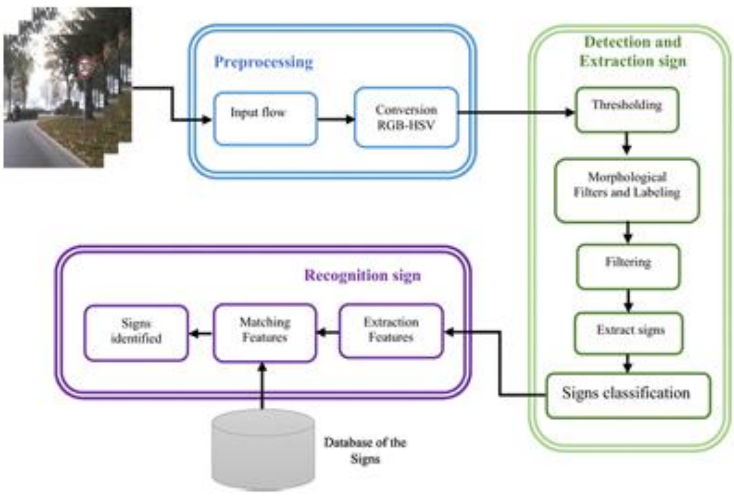

Fig.4. Flow Chart of Traffic Sign Recognition

SJIF Impact Factor (2024): 8.675| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 9 | Issue: 9 | September 2024 - Peer Reviewed Journal

In this paper, the neural network is trained on the training set to ensure recognition accuracy on the validation set. The validation set's results are used to continue training on the training set. Finally, the network's accuracy on the test set is evaluated.

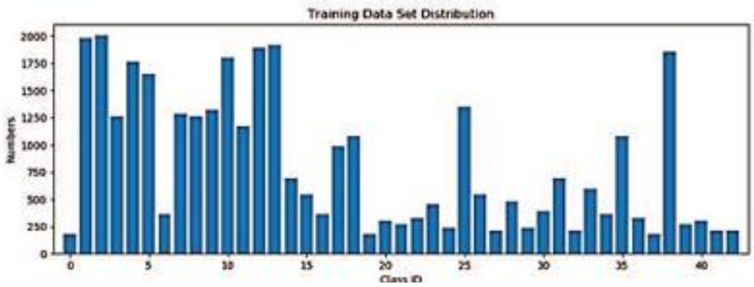

Fig.5. Dataset Distribution

Figure 1 depicts the 43 classes GTSRB that have been appropriated. Class amount is the vertical coordinate, and there are 43 classes in the level direction. It is evident that the picture dataset is disproportionately used. In order to address this, this paper employs information improvement strategies to expand the dataset. While it is relatively easy to accurately order certain classes (with more information), the order impact for other classifications (with less information) is incorrect. Both the organization's capacity for speculating and the numerous shooting points' capacity for order are advanced.

IV. DISCUSSION AND RESULTS

The calculation enhancement makes use of imgaug, an AI package for image processing. Various upgrade tactics exist, such as grayscale, revolution, and obscure, among others. As a result, this study uses imagaug to expand the GTSRB data and divide it into small chunks for network preparation, which not only increases the organization's capacity for speculation but also lowers the PC's registering heap.

One commonly used picture expansion technique to boost network speculating capacity is information increase. Accordingly, in order to increase the size of datasets and improve viability, this research uses information upgrade [5], [8] to carry out half picture hiding on the preparation set, arbitrary editing and filling of specified pixels, and half picture variety transformation.

Our approach to network development involves implementing Dropout innovation. By randomly deactivating neurons with a particular probability P during the forward growth period, this strategy reduces boundary size and improves the model's capacity for speculation. The graphs before and after are shown in Fig. 3.

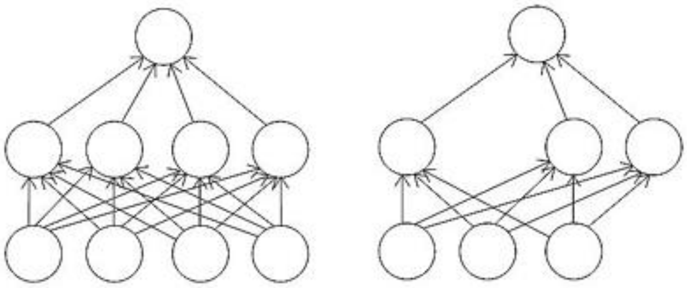

Fig.6. Before and after using Dropout

In the image above, the right picture uses Dropout while the left picture does not. It is clear that the complexity of the organization. Reduced structure after using Dropout is helpful in helping the business prepare for increased productivity and speculative capacity.

This article focuses on ELU work rather than traditional ReLU. This capacity combines the benefits of ReLU and Soft-Max capacities. The capacity's articulation and figure are as follows:

SJIF Impact Factor (2024): 8.675| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 9 | Issue: 9 | September 2024 - Peer Reviewed Journal

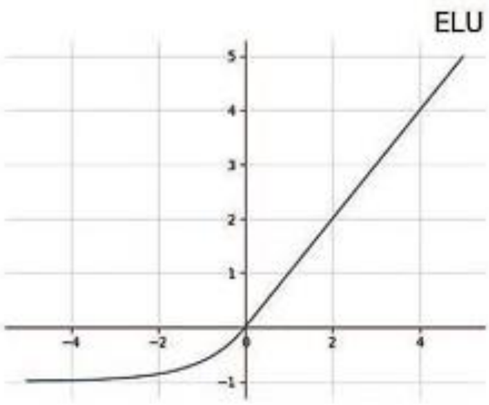

Fig. 7. ELU function.

Where is a nonzero constant? When t > 0, the output equals the input, resulting in linear growth of the function.
The ReLU function can help reduce the gradient vanishing problem. The left side exhibits soft saturation and is more adaptable to changes in the input image, unlike the ReLU function.

As shown in Fig. 7, here is -1.
Implementation of Key Functions

- Predict ()
- train_test_split ()
- length ()
- DWT ()
- Fit ()
- to_categorical ()
- Sequential ()
- Compile ()
- Predict_classes ()
- subplot ()
- plot ()

VI. CONCLUSION

This article proposes a technique for recognizing traffic signs via deep learning, with a focus on roundabouts. Using image preprocessing, traffic sign position, recognition, and arrangement, this technique can recognize and distinguish traffic signs, according to the International Research Journal of Engineering and Technology (IRJET). The test results indicate that this method is 98.2% accurate.

This study introduces a lightweight convolutional network for traffic sign recognition and grouping. The organization recognizes traffic signs using simple convolution and pooling jobs, ensures calculation productivity, and checks against GTSRB information.
This organization's handling time is faster than existing calculations, and it has a clear design with key areas of strength. Future research will focus on recognizing traffic signs under extreme weather conditions and analyzing larger datasets. We intend to use this model to identify traffic signs.

Essentially, the goal of this project is to improve the evaluation process by making it more effective, equitable, and perceptive. Through the reduction of grading duties for teachers and the provision of insightful student feedback, our application facilitates more tailored and efficient learning experiences, which in turn leads to better learning outcomes.

VII. REFERENCES

1. *Chaiyakhan, K., Hirunyawanakul, A., Chanklan, R., Kerdprasop, K. and Kerdprasop, N., 2015. Traffic Sign Classification using Support Vector Machine and Image Segmentation.*
2. *Aghdam, H.H., Heravi, E.J. and Puig, D., 2016. A*

SJIF Impact Factor (2024): 8.675| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 9 | Issue: 9 | September 2024 - Peer Reviewed Journal

3. *practical approach for detection and classification of traffic signs using convolutional neural networks. Robotics and autonomous systems, 84, pp.97-112.*
4. *Bouti, A., Mahraz, M.A., Riffi, J. and Tairi, H., 2019. A*
5. *robust system for road sign detection and classification using LeNet architecture based on convolutional neural network. Soft Computing, pp.1-13.*
6. *Stallkamp, J., Schlipsing, M., Salmen, J. and Igel, C.,*
7. *2011, July. The German traffic sign recognition benchmark: a multi-class classification competition. In The 2011 international joint conference on neural networks (pp. 1453-1460). IEEE.*
8. *Jin, J., Fu, K. and Zhang, C., 2014. Traffic sign recognition with hinge loss trained convolutional neural networks. IEEE Transactions on Intelligent Transportation Systems, 15(5), pp.1991-2000.*
9. *Krizhevsky, A., Sutskever, I. and Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).*
10. *Ciresan, D. C., Meier, U., Masci, J., Gambardella, L. M., & Schmidhuber, J. (2012). Multi-column deep neural network for traffic sign classification. Neural Networks, 32, 333-338.*
11. *Sermanet, P., & LeCun, Y. (2011). Traffic sign recognition with multi-scale Convolutional Networks. The 2011 International Joint Conference on Neural Networks (IJCNN), 2809-2813.*
12. *Stallkamp, J., Schlipsing, M., Salmen, J., & Igel, C. (2011). The German Traffic Sign Recognition Benchmark: A multi-class classification competition. The 2011 International Joint Conference on Neural Networks (IJCNN), 1453-1460.*
13. *Goodfellow, I. J., Bulatov, Y., Ibarz, J., Arnoud, S., & Shet, V. (2013). Multi-digit number recognition from street view imagery using deep convolutional neural networks. arXiv preprint arXiv:1312.6082.*
14. *Bahl, A., & Bahl, P. (2017). Traffic sign recognition using convolutional neural networks. I2C2 2017, 1-6.*
15. *Pitz, G., & Hartmann, U. (2017). Traffic sign recognition in real time using deep convolutional networks. TELFOR 2017, 1-4.*
16. *Li, Y., Li, Y., & Sun, M. (2017). Traffic sign detection using a multi-task convolutional neural network. QR2MSE 2017, 244-247.*
17. *Chen, W., Xie, S., Huang, Y., & Huang, Z. (2015). A deep learning based approach for traffic sign recognition. CYBER 2015, 127-131.*
18. *Menze, M., & Geiger, A. (2015). Object scene flow for autonomous vehicles. In CVPR 2015, 3061-3070.*
19. *[16]. Jaderberg, M., Simonyan, K., Zisserman, A., & Kavukcuoglu, K. (2015). Spatial Transformer Networks. In NIPS 2015, 2017-2025.*
20. *Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. In NIPS 2015, 91-99.*
21. *Girshick, R. (2015). Fast R-CNN. In ICCV 2015, 1440-1448*
22. *Zhang, L., & Zhang, L. (2015). Robust and efficient traffic sign recognition based on a CNN model. ICCIA 2015, 243-246.*
23. *Mohanty, S. P., & Sahoo, S. K. (2016). Real-time traffic sign recognition using deep learning. FiCloudW 2016, 158-163*
24. *Lee, H. J., & Wang, J. Y. (2017). Traffic sign recognition using deep convolutional neural networks. ICASI 2017, 1-4*
25. *Mu, Y., & Su, H. (2016). Traffic sign detection using region-based fully convolutional networks. ICIA 2016, 1-6*
26. *Liu, S., Gao, Y., & Yao, Y. (2016). Traffic sign detection using a selective search algorithm and CNNs. ICNC-FSKD 2016, 833-837.*
27. *Zhu, Z., Liang, D., Zhang, S., Huang, X., & Hu, S. (2017). Deep learning for traffic sign detection and recognition. Neurocomputing, 214, 430-438.*
28. *Jin, X., & Yin, Y. (2017). Real-time traffic sign detection based on YOLO and CNN. CIS 2017, 609-613.*