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Traffic Sign Recognition and Classification Using Deep Convolution Neural Network

Purva Firodia[1], Tanvi Chouhan[2], Shraddha Jadhav[3]

[1]*Computer Engineering, PES Modern College Of Engineering*
[2] *Computer Engineering, PES Modern College Of Engineering*
[3] *Computer Engineering, PES Modern College Of Engineering*

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Abstract - Traffic signs classification is that the process of identifying which class a traffic sign belongs to. There are several differing kinds of traffic signs like speed limits, no entry, turn left or right, etc. A neural network model based on deep learning is utilized to explore the traffic sign recognition (TSR) and expand the application of deep intelligent learning technology in the field of virtual reality (VR) image recognition, thereby assessing the road traffic safety risks and promoting the construction of intelligent transportation networks Firstly, a dual-path deep CNN (TDCNN) TSR model is constructed supported CNN, and recognition accuracy is calculated to research the training results of the model. Secondly, we assess the road traffic safety risks, and also the prediction and evaluation effects. Finally, the changes in safety risks of road traffic accidents are analyzed based on the two key influencing factors of the number of road intersections and the speed of vehicles traveling. The results show that the learning rate of the network model and the number of hidden neurons in the fully-connected layer directly affect the training results, and there are differences in the choices between the early and late training periods. It instantly assists drivers or automatic driving systems in detecting and recognizing traffic signs effectively.

***Key Words*:** Deep Convolutional Neural Network CNN, TensorFlow, Image Processing, ReLU Activation Function.

1.INTRODUCTION

In this era of computer science, humans have become more enthusiastic about technology. With the improved technology, multinational companies like Google, Tesla, Uber, Ford, Audi, Toyota, Mercedes-Benz, and plenty of more are acting on automating vehicles, they're trying to form more accurate autonomous or driverless vehicles. We all might have idea about self-driving cars, where the vehicle itself behaves like a driver and doesn't need any human guidance to run on the road. This is often not wrong to consider the protection aspects—a chance of serious accidents from machines. But no machines are more accurate than humans. Researchers are running many algorithms to make sure 100% road safety and accuracy. One such algorithm is Traffic Sign Recognition that we have used during this project. After you last the road, you see various traffic signs like traffic signals, turn left or right, speed limits, no passing of heavy vehicles, no entry, children crossing, etc., that you simply must follow for a safe drive. Likewise, autonomous vehicles even have to interpret these signs and make decisions to attain accuracy. The methodology of recognizing which class a traffic sign belongs to is termed Traffic Signs Classification. In this Deep Learning project, we are going to build a model for the classification of traffic signs available within the image into many categories employing a Convolutional Neural Network (CNN) and Keras library.

2. CNN Model

Here we are able to convert the traffic signs into text and further we are able to add the feature of speech module where a driver doesn't must read the sign. – Traffic signs have some constant characteristics that may be used for detection and classification, among them, color and shape are important attributes which will help drivers obtain road information that's why Tensor flow is employed to implement CNN. – the colour employed in traffic signs in each country are almost similar, usually consisting of straightforward colors (red, blue, yellow, etc.) and glued shapes (circles, triangles, rectangles, etc.). There might occur some problem like reflection on the sign which impacts its color or in the dead of night times when light is dim. Similarly, if the sign is chipped or bring to an end, the shape of the sign is impaired, thus leading to no detection of the sign. – the general performance could even be improved and customised with the assistance of more datasets from different countries

Dataset Used: Imported GTSRB – German Traffic Sign Recognition Benchmark dataset by web scraping.

Fig -1: Dataset

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System Architecture: For training the model we provide input as traffic sign image from the dataset. From the data we extract important parameters. The feature scaled data is passed to algorithm, and the resulted text format of the image is generated.

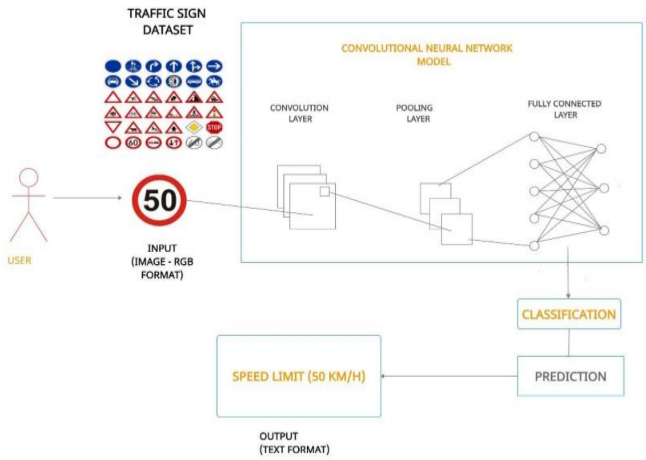

Fig -2: Architecture

Convolution Neural Network :

CNN Model consists of two convolution-pooling layers and three full connected layers. The input of CNN is image (the pixel matrix), and the output is the image feature obtained by the convolution calculation. The convolution layer is the first layer that separates and identifies the various features of the image for analysis and the output is termed as the Feature map which gives us information about the image such as the corners and edges. The Pooling Layer decreases the size of the convolved feature map to reduce the computational costs. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer. The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. It utilizes the output from the convolution process and predicts the class of the image based on the features extracted in previous stages.

Fig.3 is a classical AlexNet structure, consists of five convolutional layers, three max-pooling layers, two normalization layers, two fully connected layers, and one softmax layer. AlexNet was the first convolutional network which used GPU to boost performance

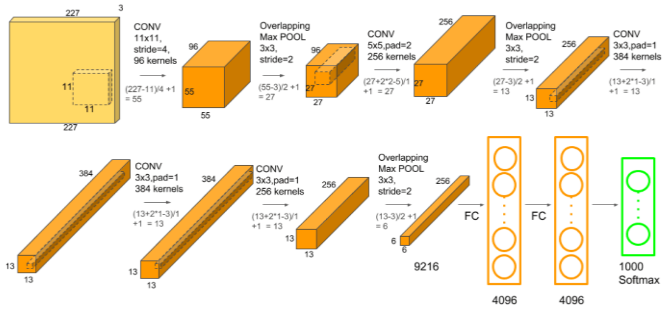

Fig -3: The AlexNet structure

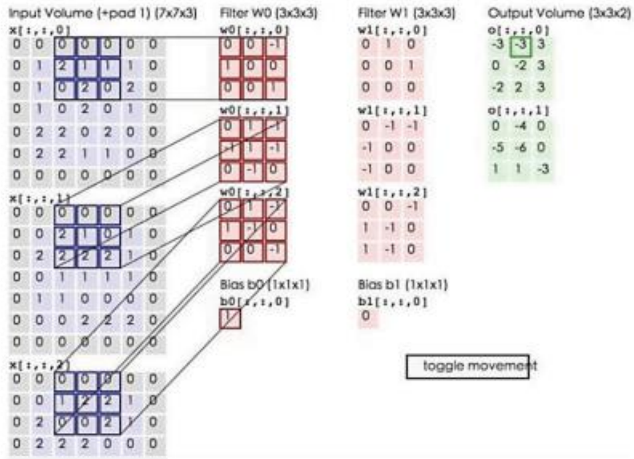

Fig -4: The Convolution process

In the CNN, the convolution kernel is the most important part, which is also the origin of the name "convolution neural network". The convolution kernel is a two-dimensional matrix with size n ∗ n, in which each point has a corresponding weight. A convolution kernel corresponds to a neuron, and the size of convolution kernel is called the receptive field of the neuron. When an image is input into the CNN, one calculation process starts: k convolution kernels in the system carry out convolution calculation on the image, that is, the weight values in the convolution kernel and the pixel values at the corresponding position of the image are summed within the receptive field. Then, the convolution kernels slide to the next position of the image according to the step size and repeat the above process until all the pixels in the image are counted. At this point, the output pixel matrix is the feature map of the original image, and k convolution kernels output k feature maps.

$$o_w = [\frac{i_w - n + 2p}{s}] + 1 \qquad (1)$$

$$o_h = [\frac{i_h - n + 2p}{s}] + 1 \qquad (2)$$

Fig -5: Figure 1

where, o_w and o_h are the size of the output feature graph, i_w and i_h are the size of the input image, s is the sliding step of the convolution kernel, and p is the number of pixels filled. The pooling layer can further reduce the size of image and retains important information. The pooling methods mainly include maximum pooling, average pooling, etc. Here, we select the maximum pooling method, and its calculation process is shown in Fig.4. A filter with size 2 ∗ 2 selects the pixel point with the largest value in the range of 2 ∗ 2 on the image, which is retained as the feature point of this region. Then, the filter slides down to the next range and repeats this process, a feature map is formed.

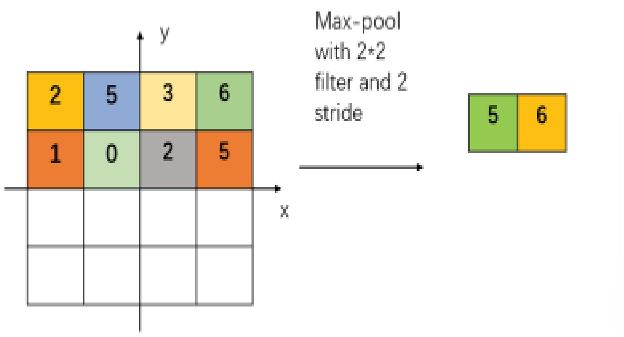

Fig -6: The Pooling process

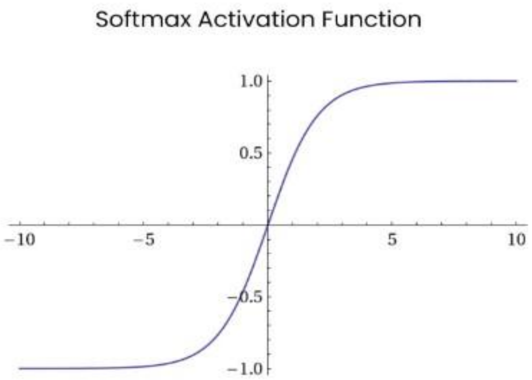

Fig -7: The Softmax Activation function

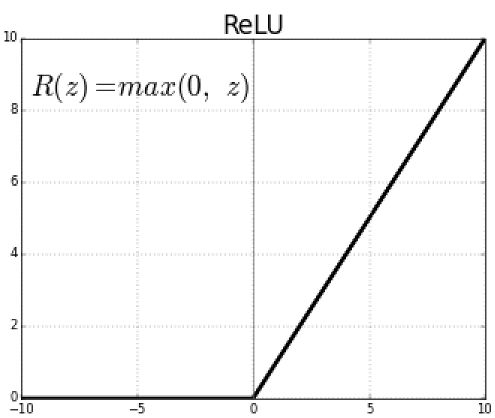

Fig -8: The ReLU Activation function

To improve the fitting ability of CNN, the nonlinear factors need to be added. Therefore, the nonlinear activation function is adopted to map the output characteristic graph of CNN. The commonly used nonlinear activation functions include tanh, sigmiod, ReLU, etc. Among them, the ReLU function (shown in Fig.7) is the most common one in the CNN because it can better simulate the brain environment, the Softmax function (Softmax(x) = log(1 + e x)) is a smooth ReLU function. The ReLU activation function is expressed as:

$$f(x) = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases} \qquad (3)$$

Fig -9: Figure 3

3. CONCLUSIONS

By using Deep CNN, Image Preprocessing, Traffic sign recognition and classification, this method can effectively detect and identify traffic signs. Reasonable regulation of the number of road intersections and vehicles' speed is of vital importance in promoting the improvement of road traffic safety and smooth passage. As an important part of intelligent transportation system, the detection and recognition of traffic signs in active warning system for safe driving of automobiles has very important research value and application prospects. Aiming at the problem that traffic sign classification is greatly influenced by uncontrollable factors, our algorithm is adopted to realize accurate classification of multiple traffic signs and it has good adaptability to environmental and weather changes. The experimental results show that the proposed method can achieve high detection rate and classification accuracy in traffic sign detection and recognition, ensuring the detection and recognition efficiency simultaneously

Epoch	Training Accuracy	Training Loss
1	0.9209	1.86
2	0.9579	0.52
3	0.9814	0.21

.Table 1 – CNN AlexNet model Accuracy

The overall testing accuracy for the model is 95%.

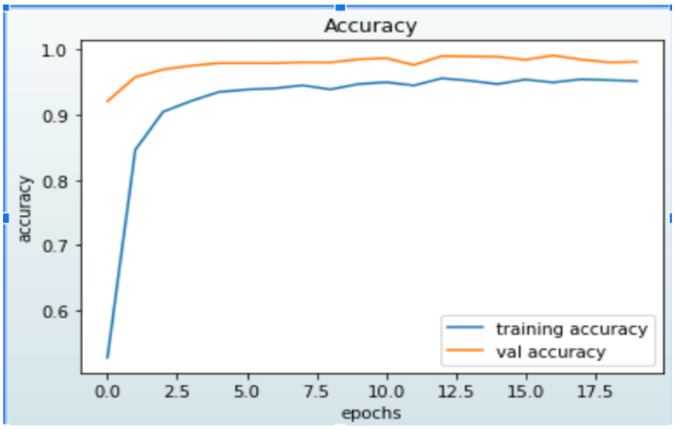

Fig -10: The Accuracy Graph

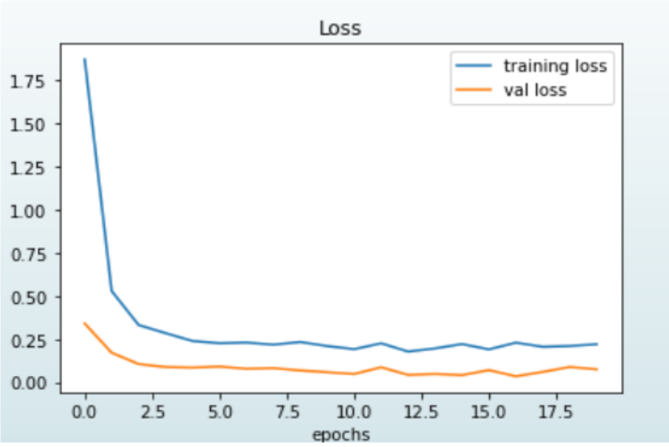

Fig -10: The Loss Graph

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REFERENCES

1. K. He, X. Zhang, S. Ren, and J. Sun, ''Delving deep into rectifiers: Surpassing human-level performance on imagenet classification,'' in Proc. IEEE Int. Conf. Comput. Vis., vol. 1, Dec. 2015, pp. 1026–1034.
2. K. He, X. Zhang, S. Ren, and J. Sun, ''Deep residual learning for image recognition,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., vol. 1, Jun. 2016, pp. 770–778.
3. A. Krizhevsky, I. Sutskever, and G. E. Hinton, ''ImageNet classification with deep convolutional neural networks,'' in Proc. Adv. Neural Inf. Process. Syst., 2012, pp. 1097–1105.
4. K. Simonyan and A. Zisserman, ''Very deep convolutional networks for large-scale image recognition,'' in Computer Science, 2014.
5. J. Long, E. Shelhamer, and T. Darrell, ''Fully convolutional networks for semantic segmentation,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2015, pp. 3431–3440.
6. J. Lafferty, A. McCallum, and F. C. N. Pereira, ''Conditional random fields: Probabilistic models for segmenting and labeling sequence data,'' in Proc. 18th Int. Conf. Mach. Learn., 2001, pp. 282–289.
7. Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, ''Gradient-based learning applied to document recognition,'' Proc. IEEE, vol. 86, no. 11, pp. 2278–2324, Nov. 1998
8. Y. LeCun, B. Boser, and J. S. Denker, ''Handwritten digit recognition with a back-propagation network,'' in Proc. Neural Inf. Process. Syst., 1990, pp. 396–404.
9. S. Pang, A. Du, M. A. Orgun, and Z. Yu, ''A novel fused convolutional neural network for biomedical image classification,'' Med. Biol. Eng. Comput., vol. 57, no. 1, pp. 107–121, 2018.