















half axis of  $x$ , but it is easy to "kill" some neurons in the negative half axis. Compared with Tanh, Sigmoid improves the network training speed, but does not fundamentally solve the gradient dispersion problem of saturated activation function. However, because its derivative meets the characteristics of "first large and then small", it can ensure the convergence speed and make the convergence stable at the same time. Therefore, the combination of the two can accelerate the convergence speed and reduce the occurrence of gradient dispersion.

(2) In the positive half axis of  $x$ , the denominator term of sigmoid model is linearly combined with  $X$ , which can meet the requirement of "first large and then small" of the gradient of activation function in the positive half axis.

(3) At the first negative half axis of  $x$ , the sigmoid is multiplied by the first to ensure the non-zero output of the negative half axis. At the same time, the gradient of the activation function tends to zero at the negative infinity, which also meets the gradient requirements, improves the convergence speed and nonlinear expression ability of the network, and ensures the convergence stability at the same time. Compared with ReLU, in the negative half axis,  $x$  and  $1/(1+e^{-x})$  are combined to make the function value gradually converge to 0 after reaching the minimum at a certain point, which increases the nonlinearity of the activation function and the nonlinear mapping ability of neurons; In the positive half axis of  $X$ , the sub term  $0.5(x-1)$  is used to ensure the gradient of the positive half axis, and then added with  $1/(1+e^{-x})$  to enhance the nonlinearity of the function. Compared with Sigmoid and Tanh functions, the model meets the gradient requirements while increasing nonlinearity.

In this paper, the function images of the activation function sigmoid ReLU and the activation functions of sigmoid, Tanh and ReLU are shown in Figure 5.

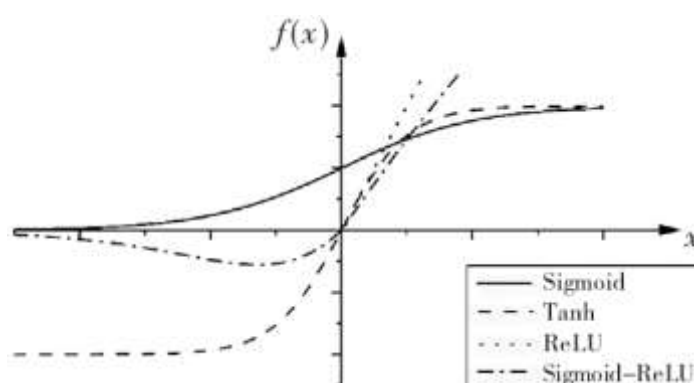


Fig 5: ReLU, LReLU and activation function curves

## V. EXPERIMENTAL RESULTS AND ANALYSIS

### 5.1 Simulation Environment

The experimental platform is based on Win10 (64 bit) operating system and (GPU) Geforce GTX



1050ti hardware platform, and the algorithm is programmed and developed through tensor flow deep learning framework. This experiment uses the zhengxin expressway data set of the University of Berkeley. There are 69863 pictures belonging to 15 sub categories. The original resolution of the pictures is 1280x720. In order to reduce the computational cost, the pictures are uniformly scaled to 128 x 128[11-13].

### 5.2 Data Set

Remove the invalid labeled images and blurred images in the data set. Figure 6 is some sample images, including 3 categories of weather, place and time, with a total of 15 categories.

### 5.3 Deep Learning Model

In this paper, convolutional neural network is used to classify and recognize road scenes with different activation functions. The super parameters of network structure are shown in TABLE I. Where k represents the number of output categories.



Fig 6: Sample data set  
(a) Weather conditions (b) scene location (c) time

**TABLE I Convolutional neural network structure**

Layer name	Kernel size	Step size	Pooling	Characteristic diagram
Input layer				132×132×4
Convolution layer 1	12×12×32	5×5		32×32×34
Standardization layer 1				32×32×34
Maximum pooling layer 1	4×4	2×2		16×16×3
Convolution layer 2	6×6×48	1×1	same	16×16×48
Standardization layer 2				16×16×48

Maximum pooling layer 2	4×4	2×2		6×6×48
Convolution layer 3	4×4×64	1×1	same	6×6×64
Maximum pooling layer 3	4×4	2×2		4×4×64
Global average pooling layer				4×4×64
Full connection layer				2×2×k
Output layer				2×2×k

#### 5.4 Performance Evaluation Index

In the experimental stage, we use the training recognition accuracy and kappa coefficient to evaluate the performance of the algorithm.

#### 5.5 Experimental Results and Analysis

In the experimental stage, the training accuracy of this activation function model is compared with Sigmoid, Tanh, ReLU, ELU and LReLU activation models. Taking the average value of three experimental results, it can be seen from the accuracy histogram that compared with other models, the algorithm in this paper has achieved the highest training and recognition accuracy in 12 subclasses (15 in total). The average accuracy is calculated for three categories: weather, location and driving time. The results show that the algorithm in this paper leads ReLU, ELU and LReLU by 8.58%, 7.94% and 16.55% respectively, as shown in TABLE II. Because every training of LReLU changes the super parameters of the activation function, the training is unstable[14-17].

Calculate the kappa coefficient on 15 sub categories for each model, which is an index that can reflect the classification performance of the model under the condition of unbalanced data. The closer the value is to 1, the better the performance is. It can be found that the recognition performance of the model in this paper is higher than that of other models. The data are shown in Table III.

**TABLE II. Average accuracy of each model category**

Model	Sigmoid	Tanh	ReLU	ELU	LReLU	DL
Correct recognition rate	60.84%	67.89%	75.22%	75.68%	67.21%	83.78%

**TABLE III. Kappa score of each model**

Model	Sigmoid	Tanh	ReLU	ELU	LReLU	DL
Correct recognition rate	66.56%	70.31%	77.15%	77.93%	72.50%	86.85%

The model in this paper is lower than the ReLU, ELU and ReLU models only in the three categories of snow, highway and night are 1.54%, 1.48%, 0.01%. Other categories have achieved the highest training recognition accuracy and the highest average accuracy. The average accuracy of ReLU is higher than that of LReLU, which reflects that LReLU is prone to oscillation and instability. Sigmoid and Tanh function

models are significantly different from ReLU model[18-23], so they are rarely used in deep networks. The experimental results show that the average accuracy of this model is 8.58% and 16.55% higher than that of ReLU and LReLU, which proves that this model can improve the recognition performance of deep learning model for road scene. In addition, by investigating the loss reduction of the three branch networks, it can also be found that the algorithm in this paper can effectively reduce the training loss of the model and have better convergence. The details are shown in Figure 7.

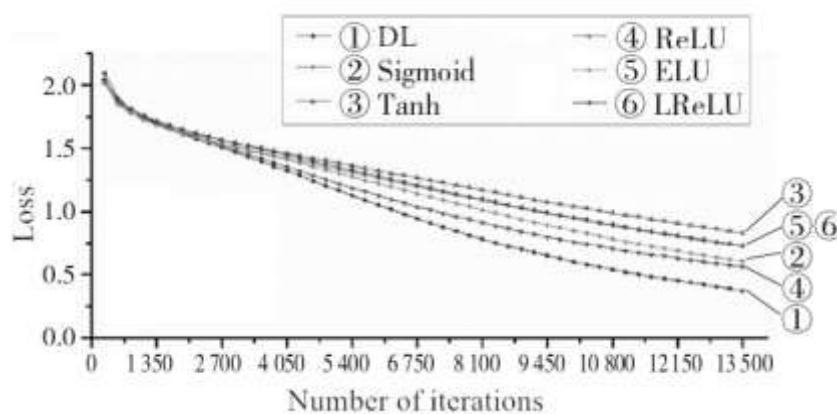


Fig 7: Training loss

## VI. CONCLUSION

This paper proposes an improved activation function combined with ReLU and sigmoid activation function. The experiment on the road scene data set of the University of Berkeley shows that the average recognition accuracy of this model is improved by 8.58% and 16.55% compared with ReLU and LReLU models, which proves that this algorithm can improve the recognition performance of deep learning model. Compared with sigmoid and Tanh functions, the recognition accuracy of large road data sets is significantly improved, which overcomes the shortcomings that ReLU function cannot extract features in the negative half axis and LReLU is easy to oscillate. At the same time, there is still room to improve the recognition accuracy of some road scene categories. In the next stage, the main research work is to enrich the data set and optimize the network structure super parameters to further improve the recognition accuracy of various road scene information.

## REFERENCES

- [1] Chen Xiaobo (2016) Challenges and prospects for developing self driving cars. Comprehensive transportation 38 (11): 9-13
- [2] Zhang Xiaoming, Yin Hongfeng (2018) Scene classification based on convolutional neural network and semantic information. Software 39 (1): 29-34
- [3] Kang Gaoqiang, Gao Shibin, Yu Long, et al. (2020) Fault detection of rotating double ear open pin missing of high speed railway catenary based on deep learning. Journal of railway (10): 45-51

- [4] Yang Lingyan, Zhang Hongyan, Chen Yufeng, et al. (2020) Research Progress on the application of machine learning in crop variety recognition. Chinese agronomy bulletin 36 (30): 158-164
- [5] Hu Weijian, Fan Jie, Du Yongxing, et al (2020) Tomato fine-grained disease recognition based on deep residual network. Journal of Inner Mongolia University of science and technology 39 (3): 251-256
- [6] Jiang Angbo, Wang Weiwei (2018) Study on Optimization of ReLU activation function. Sensors and Microsystems (2): 50-52
- [7] Guo Jinghua, he Zhifei, Luo Yugong, Li Keqiang (2022) Vehicle entry based on deep learning in man-machine mixed driving environment. Automotive Engineering 44 (02): 153-160 + 214 DOI:10.19562/j.chinasae. qcgc. 2022.02.001.
- [8] Huang Wei, Yuan Tingyi, Deng Baichuan, Zou Wenfeng, Zhang Feng, Cao Hui (2022) Autonomous Fault Detection System of robot circuit board based on deep learning. New technology of electrical energy 41 (02): 72-80
- [9] Guan Lintao, Huang Zhiqiang, Chen Yang (2022) A traffic accident prediction method based on spatiotemporal transformer. Computer and information technology 30 (01): 8-13.
- [10] Wen Haoyu, Zhao Lingjun, Wang Fan, Yu Jiangxia (2022) Prediction model of effective parking space based on deep learning. Journal of Chongqing Jiaotong University (NATURAL SCIENCE EDITION) 41 (02): 30-34 + 43
- [11] Wang Wei, Tang Xinyao, Tian Shangwei, Mei Zhantao (2022) Vehicle fine-grained recognition based on back projection space under monocular vision. Computer system application 31 (02): 22-30.
- [12] Yao Lihu (2022) Research on security interactive command system based on deep learning technology [J]. Scientific and technological innovation and application 12 (04): 94-96.
- [13] Zhang JD, Xu XB, Lu LB, Zhao YQ (2022) Research on traffic sign recognition method based on depth residual network. Computer simulation, 39 (01): 143-147
- [14] Xiong YZ (2022) Intelligent networked vehicle trajectory prediction based on LSTM deep neural network. Journal of Nanyang Normal University 21 (01): 32-36
- [15] Zhou Yu (2022) Research on intelligent traffic signal control based on deep learning network. Application of single chip microcomputer and embedded system 22 (01): 17-20
- [16] Cai Jun, Qiu huiran, Tan Jing, Yang Ping'an (2022) Research on traffic sign recognition algorithm based on multi-scale context fusion. Radio engineering 52 (01): 114-120
- [17] GUI xuhao, Zhang Junfeng, Tang Xinmin, Kang Bo (2021) Approach pattern recognition and prediction based on machine learning. Transactions of Nanjing University of Aeronautics and Astronautics 38(06):927-936.
- [18] Wu Xiang, shelf, Zhang Heng, Xu Binghao, Yi Menghua, Zhang Zhi (2021) Heavy load vehicle detection and recognition based on deep learning. Computer knowledge and technology 17 (35): 85-87.
- [19] Wang Hai, Xu Yansong, Cai Yingfeng, Chen long Overview of intelligent vehicle multi-target detection technology based on multi-sensor fusion. Journal of automotive safety and energy conservation (2021) 12 (04): 440-455
- [20] Xue Junjun, Chen Shuang (2021) Research on pavement roughness grade recognition based on deep learning Electromechanical engineering technology 50 (11): 66-69
- [21] Liang Zhengyou, Geng Jingbang, Sun Yu. (2021) Traffic sign detection algorithm based on improved SSD model. Modern computer 27 (32): 54-58 + 84
- [22] Dong Xinyu (2021) Pavement crack image recognition method based on depth learning. China Science and technology information (21): 91-94
- [23] Liu Lijing (2021) Research on traffic sign recognition based on deep learning. Application of single chip microcomputer and embedded system 21 (11): 14-17