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A NONLINEAR CONVOLUTIONAL NEURAL NETWORK ALGORITHM FOR AUTONOMOUS VEHICLE LANE LINE DETECTION

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Abstract. The traditional lane line detection algorithm relies on artificial design features, which has poor robustness and cannot cope with the complex urban street background. With the rise of deep learning technology, the algorithm model with convolutional neural network as the mainstream is widely used in the field of computer vision, which provides a new idea for lane line detection. In order to improve the disadvantages of traditional lane line detection methods that are vulnerable to environmental impact and poor robustness, a nonlinear convolution neural network algorithm for driverless lane line detection is proposed. Firstly, the pretreatment method of extracting the region of interest and enhancing the contrast of lane lines is used to reduce the unnecessary image background and enhance the feature details of the image. Existing deep learning-based lane line detection algorithms still have difficulties. First, accumulated wear and tear will cause lane line to fade and fade; roadside trees and buildings can interfere with the performance of lane line detection algorithm. In addition, compared with the pixels of the whole picture, the lane line pixels are too few, and the deep convolution neural network of layer convolution is easy to lead to the loss of details. In addition, when the traffic flow is large, the lane line is easily blocked, which makes it more difficult to detect the lane line. Then the model is built based on the lane line image features extracted by CNN, and the DBSCAN clustering algorithm is used to post-process the lane line segmentation model; Finally, the least square method is used to fit the quadratic curve of the pixel peak points of the lane line, and the fitting results are regressed to the original image. The experimental results show that the accuracy and recall of the lane line detection model verification set are 91.3% and 90.6%, respectively, indicating that the model has a good segmentation effect. It is proved that the lane line detection method based on CNN combined with post-processing can effectively reduce the defects of artificial experience, and has better robustness and accuracy than the traditional lane line detection method.

Key words: Lane line detection, Convolution neural network, Deep learning, clustering algorithm

1. Introduction and examples. With the rapid development of urban traffic, traffic safety has become increasingly important. By the end of June 2017, the number of cars owned reached 205 million, and the number of car drivers reached 328 million, cars have become one of the most commonly used vehicles in our lives. Driving safety has become one of the hot issues that people are most concerned about. During the driving process, the road conditions and vehicle conditions are complex, and the driver is nervous and prone to fatigue. According to statistics, 66% of drivers are prone to drowsiness when driving alone for a long time. This shows the importance of lane line deviation warning [1].

As a key step in driverless technology, lane line detection is an important component of the sensing module. The study of lane line detection algorithm has important research value and application significance in the information exchange, traffic path planning and traffic safety accident avoidance. In the autonomous driving technology, more and more domestic and foreign researchers have carried out detailed and rich research on the lane line detection algorithm, and have achieved fruitful results. Therefore, there is a need for a lane line warning system to send out a danger warning to the driver to reduce the accident rate. This system designed to help the driver in the driving process is called the auxiliary driving system (ADAS).The goal of the system is to detect lane markings and alert the driver when he leaves the lane. In recent years, the semiconductor industry has developed and made great progress, small and powerful electronic devices are widely used in vehicles [2]. These devices can perform complex calculations and provide hardware environment protection for the auxiliary driving system. Gives the driver a safety warning at the right time.Intelligent transportation is included in the 13th Five-Year Plan, as one of the core functions of assisted driving and automatic driving, lane line detection is of self-evident importance. Lane line detection is not only related to our daily travel safety, but also an important part of development planning [3].

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Lane line detection algorithm can be roughly divided into two categories: detection algorithm based on traditional digital image processing method, such as Hove transform, and lane line detection algorithm based on deep learning. Starting from the focus of the detection algorithm, the traditional lane line detection algorithm can be divided into two categories: one is the model-based detection algorithm based on the mathematical model such as curve or straight line, and the lane line detection algorithm based on the color, texture, shape and direction of the lane line.

2. Literature review. Convolution neural networks have been offered for over 20 years. The original neural network solution was also developed as a different type of neural network solution to solve problems in different research fields. It is used for image classification and image recognition in image processing. Lane line detection as one of the core functions of auxiliary driving and autopilot, the technology can in the process of driving real-time, accurate detection lane line, when the vehicle deviates from the current lane, warning, the driver operation error can be corrected, can effectively reduce the accident rate caused by the operation error and fatigue driving, so as to ensure the driver's personal and property safety. Therefore, lane line detection is crucial for the safety of drivers while driving. Neural networks are the first to be used to understand the environment of a self-driving car, such as recognizing traffic lanes captured by cameras, recognizing driving zones, and recognizing problems around the area take pictures from the face and the connection between the camera and the cap.In recent decades, many countries have invested in the direction of inquiry and the direction of research questions has become very good. Traditional line detection algorithms capture and filter the image and then use changes in line brightness to divide the lines [4].

Computer computing power and massive amounts of data have driven the development of deep learning technology, which has been applied to various fields, such as speech and images. Among them, the application of deep convolutional neural network to images is a negligible branch.

The line detection method based on neural network solution is to draw the lines of multi-dimensional scene image according to the data set, input them into the design of neural network solution, and train the neural network solution to make it clear.

The main purpose of lane line detection is to identify the lane lines from the original images. More specifically, the algorithm is used to extract the coordinates of the pixels belonging to the lane lines in the image, and then post-processing the pixels to finally obtain the actual position of the lane line in the original image.

Some assumptions about the lines on the road map. As an important part of raising environmental awareness, discovery line has been studied by researchers at home and abroad and has achieved a lot of results. The traditional line detection system can detect the line quickly and in real time, but the stability is poor, different lines of the line detection accuracy is low.

Lane lines have innate structural features, which are long and thin in shape. For a high-resolution RGB image, the proportion of lane line pixels in the whole image element tends to be small. After the deep convolutional neural network, the details of lane lines are easy to lose, resulting in the detection of lane lines.

In recent years, the rapid development of computer algorithm, gradually applied to the detection line. However, because the neural network scheme has more parameters and a large amount of calculation, the hardware cost of the detection line using the neural network scheme is high [5]. Haris, M improved line detection in complex environments, a method combined with visual data with wide distribution [6]. Ghazal, T. M proposed handwritten text recognition techniques based on neural network technology [7]. Dong, Y proposed a weighted fusion of convolutional neural network and graph attention network (WFCG) for HSI classification based on the characteristics of super-pixel-based GAT and pixel-based CNN, which proved to be successful [8].

Semantic segmentation network based on convolutional neural network for each pixel image detection, can be applied to different forms of target detection task, detection of details is more fine, so in dealing with different road scene also has advantages, such as in the car to change lanes or turn, lane line shape and structure has changed, for semantic segmentation network, can be very well processed, achieve better detection effect.

In order to improve the disadvantages of traditional lane line detection methods on environmental impact and poor robustness, a nonlinear convolutional neural network algorithm for unmanned lane line detection is proposed.

Considering that traditional line detection is easily affected by the environment and needs manual extraction, a line detection method based on CNN is proposed. Plus the post-treatment process, it has the advantages of no manual adjustment, multiple applications and good effects.

3. Research methods.

3.1. Convolution neural network. Machine learning is an important part of the field of artificial intelligence, through the theory of probability, statistics, biology and artificial intelligence problems abstract into mathematical models, so that the model has similar to human learning ability, iteratively adjust the model parameters, to optimize the model effect, machine learning classical algorithms, including neural network, support vector machine, K mean clustering, DBSCAN and logical regression, etc. Among them, the neural network mimics the image process of the human visual system in processing pupil intake.

Compared with neural network, convolution neural network has changed the connection mode of neurons, using convolution operation and pooling operation. Convolution layer, activation layer and pooling layer are essential components of convolution neural network. The function of convolution layer is to convolution the input of convolution neural network to extract the features of the input image. The convolution process can be understood as a filtering process, a convolution kernel is a window filter, in the network training process, the convolution kernel of a user-defined size is used as a sliding window to convolution the input data [9].

The edge length of the image output by the convolution operation=(input image edge length – convolution core length+1)/step length, if it cannot be divided, the result will be rounded up. Sometimes in order to ensure that the side length of the output image of a convolution operation is the same as the side length of the input image, all-zero filling will be performed around the input image, and the side length of the output image is equal to the side length of the input image divided by the step length, if it is not possible to divide and take an integer up, assume that the input image is a three-channel image of 52 * 52 * 3, the convolution kernel size is 5 * 5, and the depth is 3, that is, a convolution kernel of 5 * 5 * 3, if the convolution step is 1, the characteristic image of 48 * 48 * 1 will be output[10]. The parameters in the convolution kernel are the weights in the network, these parameters are unchanged in a forward calculation process and will not change because of the position of the convolution kernel in the input data, this is the weight sharing property of convolutional neural network. Finally, the image features are recognized by combining different features. The activation layer compensates for the linear operation of convolution, adds nonlinear elements, and makes the convolution neural network have the ability to learn nonlinear.

3.2. Image data preprocessing. The purpose of lane line image data preprocessing is to enhance the features of the target in the image, so that deep learning can better learn the feature information and obtain a model with stronger generalization ability.

3.2.1. ROI extraction. In order to remove redundant image information and improve the speed and detection effect of network training, a fixed ROI region extraction method is adopted, through OpenCV, the original image with the resolution of 720×480 is clipped to the ROI area of 720×240.

3.2.2. Brightness contrast transformation. Contrast is the ratio of the whitest and darkest brightness units. Adjusting the contrast can make the image more vivid. Take a color channel of an RGB image as an example, take the current color depth value I of the pixel as the abscissa, and output the transformed color depth value O as the ordinate to establish the coordinate system, each pixel of the traditional RGB format image can use a value of 0∼255 to represent its color depth [11].

When the brightness and contrast of the image are modified at the same time, the transformation equation is as follows 3.1:

$$O = KI + J \tag{3.1}$$

where J is the increased value of image brightness, and K is the original color depth scale value. According to the actual situation, several attempts have been made to determine the added value of image contrast and brightness adjustment, and the original image has been adjusted by K=1 and J=20.

3.3. Lane line detection algorithm. The whole process of anchor-based lane line detection model can be compared to the process of region-based target detection algorithm. First, the feature extraction was performed

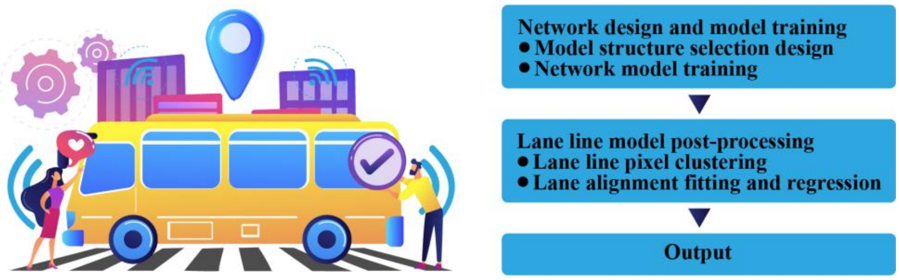

Fig. 3.1: Design steps of lane line detection algorithm

by placing anchor at each position of the feature graph to obtain the resulting feature vector. Finally, the feature vectors were regressed and classified separately.

The lane line detection algorithm established by the author is mainly divided into two steps, namely, network design and model training, and lane line model post-processing, as shown in Figure 3.1.

3.3.1. Model structure design. As a marker line on the road surface, it is a two-dimensional goal. Compared with the point cloud data of lidar, the model constructed by GPS and high-precision map, the images obtained by the visual sensor can express the two-dimensional features of the lane line more effectively. Moreover, compared with lidar and high-precision maps, visual sensors are low cost and cost-effective. Therefore, the lane line detection algorithm is mostly based on vision sensor, that is, the detection algorithm based on computer vision, which is also widely used in the industry to detect lane lines.

Fine-tune the VGG16 network, add a custom network on the VGG16 base network that has been trained on other classification issues, and then freeze the base network, re-train the previously added user-defined part and unfreeze some layers of the base network, and finally jointly train the unfrozen layer and the user-defined added part. The Softmax layer is added to the last layer of the network model output to modify the model framework, so as to achieve the probability distribution of multi-channel pixel points of the model output results, which is convenient for the clustering algorithm in the post-processing algorithm to cluster the lane lines [12].

3.3.2. Lane line pixel clustering. By clustering the core points and density reachable points, the area with enough high density is divided into one category. At the same time, DBSCAN can also recognize sparse noise data. The pixel distribution of the output image of the lane line segmentation model is clustered, and the image pixels belonging to the same lane line are classified into the same category. Convert the pixel probability distribution of lane line segmentation image into 3D visualization image. Sort the pixel probability distribution image output by lane line segmentation according to the axis value, and take the y item accuracy data corresponding to the image model position x=240, 250... 480, then extract the peak points with probability value greater than 0.5 and cluster them, the output image of the peak points with probability value greater than 0.5 is shown in Figure 3.2.

3.3.3. Lane line fitting and regression. Lane line fitting is a square theory of lane line curve according to a specific number of sampling points. Lane line fitting is to fit the pixel probability peak points of the reclassified lane line segmentation model, and then obtain the track parameter equation of the lane line[13].

Curve fitting refers to obtaining an approximate curve $y = \rho(x)$ for a given m data points $p_i(x_i, y_i), i = 1, 2, ..., m$, so as to minimize the deviation between the curve $y = \rho(x)$ and the real curve $y = f(x)$. The deviation δ_i of $y = \rho(x)$ at point p_i is calculated as follows 3.2:

$$\delta_i = \rho(x_i) - y_i \tag{3.2}$$

where δ_i is the deviation.

The deviation minimization calculation formula is as follows 3.3:

$$min \sum_{i=1}^{m} \delta_i^2 = \sum_{i=1}^{m} (\rho(x_i) - y_i)^2 \tag{3.3}$$

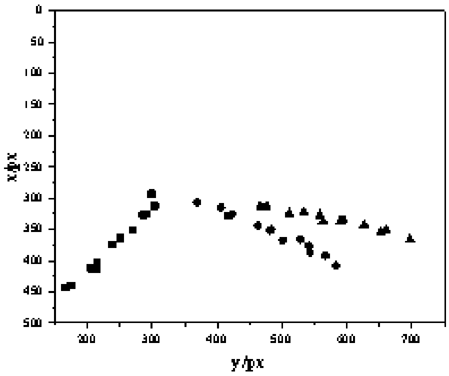

Fig. 3.2: Peak output image with probability value greater than 0.5

The least square method takes the quadratic equation as the fitting curve, and selects the fitting curve with the smallest sum of squares. The least square method is used to perform polynomial nonlinear fitting on the given m sample points, so that the approximate curve $\delta_i = \rho(x_i) - y_i$ of $y_i = f(x)$ passes through these sample points.

Assume that the polynomial of lane line to be fitted is the following equation 3.4:

$$p(x) = a_0 + a_1 x + ... + a_k x^k = \sum_{k=0}^{n} a_k x^k \tag{3.4}$$

The sum of squares of deviations of all pixel points reaching the approximate curve is as follows 3.5:

$$\begin{aligned} R &= \sum_{i=1}^{m} [y_i - (a_0 + a_1 x_i + ... + a_k x_i^k)]^2 \\ &= \sum_{i=1}^{m} (y_i - \sum_{k=0}^{m} a_k x^k)^2 \end{aligned} \tag{3.5}$$

Solve polynomial $a_i = (i = 1, 2, ..., k)$ to obtain the minimum value of equation 3.6, expressed as:

$$\begin{aligned} minR &= \sum_{i=1}^{m} [y_i - (a_0 + a_1 x_i + ... + a_k x_i^k)]^2 \\ &= \sum_{i=1}^{m} (y_i - \sum_{k=0}^{m} a_k x^k)^2 \end{aligned} \tag{3.6}$$

In order to solve the extreme value of the multivariate function of the parameter $a_1, a_1, ..., a_k$, the partial derivative formula of the variable $a_i = (i = 1, 2, ..., k)$ is obtained as follows 3.7:

$$\sum_{k=0}^{n} (\sum_{i=1}^{m} a_k x_i^{j+k}) = \sum_{i=1}^{m} x_i^j y_i, j = 0, 1, ..., n \tag{3.7}$$

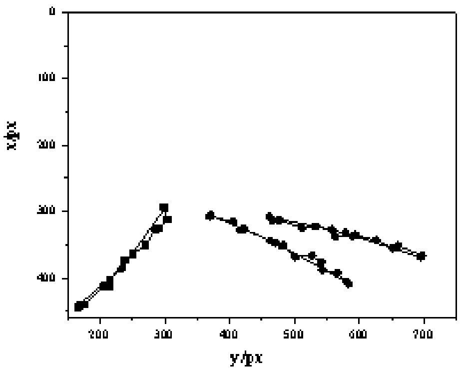

Fig. 3.3: Quadratic curve fitting image

Change the equation into matrix form as follows 3.8:

$$\begin{bmatrix} m & \sum_{i=1}^{m} x_i & \cdots & \sum_{i=1}^{m} x_i^n \\ \sum_{i=1}^{m} x_i & \sum_{i=1}^{m} x_i^2 & \cdots & \sum_{i=1}^{m} x_i^{n+1} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^{m} x_i^n & \sum_{i=1}^{m} x_i^{n+1} & \cdots & \sum_{i=1}^{m} x_i^{2n} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{m} y_i \\ \sum_{i=1}^{m} x_i y_i \\ \vdots \\ \sum_{i=1}^{m} x_i^n y_i \end{bmatrix} \tag{3.8}$$

The following formula 3.9 is obtained by simplifying the Vandermonde matrix:

$$\begin{bmatrix} 1 & x_1 & \cdots & x_1^k \\ 1 & x_2 & \cdots & x_2^k \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & \cdots & x_n^k \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \tag{3.9}$$

The solved coefficient matrix Q formula is 3.10:

$$Q = X^{-1}Y \tag{3.10}$$

Equation 3.10 is the relationship of the fitting curve, the least square method is used to fit the quadratic curve of the probability peak point of the lane line pixel after clustering classification, the fitting image is shown in Figure 3.3. Regression the fitting curve to the original lane line image [14].

4. Result analysis. The author's algorithm is based on the Keras deep learning framework, using Python language, OpenCV computer vision processing library, and tested on Ubuntu 18.04L TS system [15]. Keras is a deep learning framework based on theano / tensorflow. Is a high-level neural network API that supports fast experiments and can quickly translate your idea into results.

A random gradient is used to train a neural network model. The learning threshold was set to 0.01, the size was set to 16, and the learning period (Epoch) was set to 100. During the training process, introducing some obstacles during the training process indicates the state of the emerging model[16]. Based on the values of the output parameters of the training process, the OpenCV graphing function is used to plot the average accuracy and loss curves as a function of the number of iterations during training. The missing curve with 100 sampling iterations is shown in Figure 4.1, and the mean true curve with 100 sampling iterations is shown in Figure 4.2.

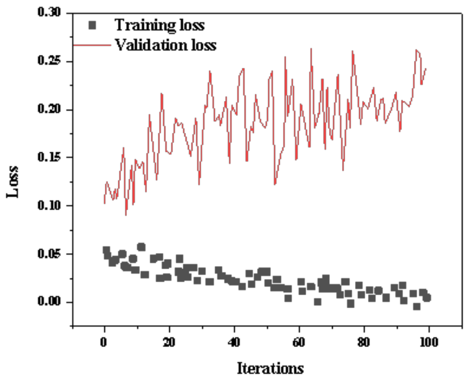

Fig. 4.1: Training loss change curve

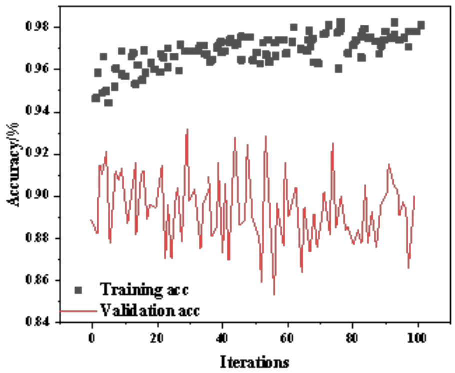

Fig. 4.2: Training accuracy change curve

The accuracy rate and recall rate of the model are defined as the basis for judging the segmentation effect of the model, that is, the greater the accuracy rate and recall value, the better the segmentation effect of the model. The calculation formula of average accuracy acc is:

$$acc = \frac{C_{img}}{T_{img}} \tag{4.1}$$

where, C_{img} is the correct number of pixels for segmentation, and T_{img} is the total number of pixels marked for the entire image[17].

All pixels labeled as lane line image areas are divided into lane line pixels and non-lane line pixels. The ratio of the two is the recall rate recall. The calculation formula is 4.1:

$$recall = \frac{TP}{TP + FN} \tag{4.2}$$

where, TP is the correctly predicted lane line pixel point, and FN is the incorrectly predicted lane line pixel point.

Table 4.1: Comparison between accuracy of different models and time consumption of single frame image

Model	Accuracy/%	Time consumption/ms
K-means	84.25	54
CNN+Hough	87.08	60
SegNet	90.06	50
VGG16	91.3	45

After calculation, the average accuracy rate and recall rate of the final model validation set are 91.3% and 90.6% respectively, indicating that the model has good segmentation effect. Then the lane lines in different scenes are detected and recognized[18].

For the same experimental sample, compare the detection accuracy and single frame image time of the author's model with other models, and the results are shown in Table 4.1.

The experimental results show that the accuracy of the traditional lane line detection method K-means is far less than that of other model methods combined with deep learning. Although the method of CNN combined with Hough transform improves the detection accuracy, it takes the longest average time to process a single frame image, compared with this method, the accuracy and average time of lane line detection of SegNet model have been greatly improved. Compared with the other three models, the VGG16 model has significantly improved in accuracy and single-frame image processing speed, achieving better image segmentation effect [19,20].

The features of the lines were studied using CNN in special image extraction operation and the DBSCAN clustering algorithm was used for line classification, which improves the accuracy of the model and the matching results. About this method. Experimental results show that the combination of CNN and post-processing algorithm is more accurate and reliable than conventional line detection methods.

5. Conclusion. Lane line detection is an important part of auxiliary driving and automatic driving. Lane line deviation alarm and lane line maintenance can correct the careless operation of drivers in time, reduce traffic accidents caused by wrong operation and fatigue driving, so as to effectively guarantee driving safety and reduce driving complexity. In complex road scenarios, lane line detection algorithms need to be robust and real-time.

In this paper, we take advantage of CNN in special image extraction operation to study the features of the line, and perform the post-line classification process using DBSCAN clustering algorithm, which improves the accuracy of the model and improves the matching results. about the method. The traditional lane line detection method K-means has much less precision than other model methods combining deep learning. Although the CNN method combined with Hough transformation improved the detection accuracy, the average time was the longest for processing single-frame images, and the lane line detection accuracy and average time of the SegNet model were significantly improved compared with this method. Compared with the other three models, the VGG 16 model showed a significant improvement in both accuracy and single-frame image processing speed, achieving better image segmentation.

Experimental results show that the combination of CNN and post-processing algorithm is more accurate and reliable than traditional line detection methods. The line of investigation suggested by the author is therefore of some value. However, the algorithm still has some disadvantages: on the one hand, due to the limitations of the image's own hardware during training, the training time increases, and the error resulting from training increases, which makes it impossible to learn all the network models. image features;On the other hand, when the output data of the lane-line segmentation model is postprocessed, a small amount of pixel data may be filtered out, leading to the failure to fit and missing part of the lane lines. The above questions are the key direction of the next research step. Because the input image resolution of the present network is not high enough, the localization information is not accurate enough. Moreover, when the network return is too deep, the speed of the network cannot meet the needs of real-time detection, so the results of both detection accuracy and speed cannot be realized. Next, we hope to innovate in the network input mode and network structure, so as to ensure the network detection speed and increase the resolution of the image, so as to better realize the lane line detection.

REFERENCES

[1] Alam, M. Z., Kelouwani, S., Boisclair, J., & Amamou, A. A. (2022). Learning Light fields for improved lane detection. IEEE Access, 11(3), 271-283.

[2] Dong, Y., Patil, S., van Arem, B., & Farah, H. (2023). A hybrid spatial–temporal deep learning architecture for lane detection. Computer-Aided Civil and Infrastructure Engineering, 38(1), 67-86.

[3] Gopal, K. V., Rohith, C., Siddhartha, D., & Mahule, S. (2022). Lane detection on roads using computer vision. International journal of engineering technology and management sciences, 6(4), 8-15.

[4] Dewangan, D. K., & Sahu, S. P. (2023). Lane detection in intelligent vehicle system using optimal 2-tier deep convolutional neural network. Multimedia Tools and Applications, 82(5), 7293-7317.

[5] Shirke, S., & Udayakumar, R. (2022). Hybrid optimisation dependent deep belief network for lane detection. Journal of Experimental & Theoretical Artificial Intelligence, 34(2), 175-187.

[6] Haris, M., Hou, J., & Wang, X. (2022). Lane lines detection under complex environment by fusion of detection and prediction models. Transportation research record, 2676(3), 342-359.

[7] Ghazal, T. M. (2022). Convolutional neural network based intelligent handwritten document recognition. Computers, Materials & Continua, 70(3), 4563-4581.

[8] Dong, Y., Liu, Q., Du, B., & Zhang, L. (2022). Weighted feature fusion of convolutional neural network and graph attention network for hyperspectral image classification. IEEE Transactions on Image Processing, 31(9), 1559-1572.

[9] Poliak, M., Jurecki, R., & Buckner, K. (2022). Autonomous vehicle routing and navigation, mobility simulation and traffic flow prediction tools, and deep learning object detection technology in smart sustainable urban transport systems. Contemporary Readings in Law and Social Justice, 14(1), 25-40.

[10] Ali, A., Zhu, Y., & Zakarya, M. (2022). Exploiting dynamic spatio-temporal graph convolutional neural networks for citywide traffic flows prediction. Neural networks, 145(11), 233-247.

[11] Tian, C., Yuan, Y., Zhang, S., Lin, C. W., Zuo, W., & Zhang, D. (2022). Image super-resolution with an enhanced group convolutional neural network. Neural Networks, 153(15), 373-385.

[12] Hassan, S. M., & Maji, A. K. (2022). Plant disease identification using a novel convolutional neural network. IEEE Access, 10(3), 5390-5401.

[13] Sharma, A. K., Tiwari, S., Aggarwal, G., Goenka, N., Kumar, A., Chakrabarti, P., ... & Jasiński, M. (2022). Dermatologist-level classification of skin cancer using cascaded ensembling of convolutional neural network and handcrafted features based deep neural network. IEEE Access, 10(8), 17920-17932.

[14] Torres, M., & Cantú, F. (2022). Learning to see: Convolutional neural networks for the analysis of social science data. Political Analysis, 30(1), 113-131.

[15] Tulbure, A. A., Tulbure, A. A., & Dulf, E. H. (2022). A review on modern defect detection models using DCNNs–Deep convolutional neural networks. Journal of Advanced Research, 35(6), 33-48.

[16] Shlezinger, N., Eldar, Y. C., & Boyd, S. P. (2022). Model-based deep learning: On the intersection of deep learning and optimization. IEEE Access, 10(8), 115384-115398.

[17] Aggarwal, K., Mijwil, M. M., Al-Mistarehi, A. H., Alomari, S., Gök, M., Alaabdin, A. M. Z., & Abdulrhman, S. H. (2022).Has the future started? The current growth of artificial intelligence, machine learning, and deep learning. Iraqi Journal for Computer Science and Mathematics, 3(1), 115-123.

[18] Lauriola, I., Lavelli, A., & Aiolli, F. (2022).An introduction to deep learning in natural language processing: Models, techniques, and tools.Neurocomputing, 470(9), 443-456.

[19] Zhan, Z. H., Li, J. Y., & Zhang, J. (2022). Evolutionary deep learning: A survey. Neurocomputing, 483(8), 42-58.

[20] Mo, Y., Wu, Y., Yang, X., Liu, F., & Liao, Y. (2022). Review the state-of-the-art technologies of semantic segmentation based on deep learning.Neurocomputing, 493(9), 626-646.

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