Journal of computer science and software applications
https://www.mfacademia.org/
ISSN:2377-0430
Vol. 4, No. 4, 2024

Advancing Road Sign Recognition in Autonomous Vehicles Through Convolutional Neural Networks: Methods and Outcomes

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Abstract:

With the rapid advancement of autonomous driving technology, road sign recognition has become a critical component in ensuring the safety of autonomous vehicles. This paper presents a method for road sign recognition in autonomous vehicles using Convolutional Neural Networks (CNN), with the goal of enhancing both accuracy and efficiency in road sign detection. Initially, the background and significance of this issue are discussed, including the progression of autonomous vehicle technology and the necessity for reliable road sign recognition systems. The paper emphasizes the role of convolutional neural networks in this application. A comprehensive overview of the dataset employed, the architecture of the designed CNN model, and the data preprocessing techniques are provided. To further enhance accuracy, techniques such as data augmentation and image enhancement were utilized. The findings of this research demonstrate that the proposed CNN-based road sign recognition method achieves high accuracy and efficiency, thereby offering substantial support for the practical implementation of autonomous driving technology.

Keywords:

Autonomous vehicles, Road sign recognition, Convolutional neural networks, Deeplearning, Data preprocessing.

1. Introduction

With the rapid development of autonomous driving technology, road sign recognition is of great significance in ensuring the safety of autonomous vehicles. The main significance of road sign recognition for autonomous vehicles is as follows.

Firstly, accurately identifying road signs can improve the driving safety of autonomous vehicles. As a core element of road planning and traffic management, road signs provide important driving instructions and warning information to drivers. By efficiently and accurately identifying road signs, autonomous vehicles can timely understand information such as road speed limits, road engineering, turning requirements, etc., thereby better driving and complying with traffic rules, and reducing the incidence of traffic accidents. Secondly, autonomous vehicle road sign recognition can achieve precise navigation and path planning. Road signs represent specific road features and functions, such as intersections, highway exits, etc. By identifying and interpreting road signs, autonomous vehicles can accurately locate their own position and choose appropriate driving paths based on the information provided by the signs, thereby achieving more efficient and safer navigation and path planning. In addition, road sign recognition is also of great significance for the interaction and communication between autonomous vehicles and transportation facilities. Modern transportation facilities such as traffic lights and intelligent road signs can interact with autonomous vehicles through communication. By accurately identifying road signs, autonomous vehicles can timely obtain information sent by traffic facilities, such as the status of traffic lights, temporary traffic rules,etc, making appropriate driving decisions and improving the overall efficiency of traffic. Finally, autonomous vehicle road sign recognition can help vehicles adapt to complex road environments. There are various types of road signs and signs on real roads, such as traffic signs, warning signs, road signs, etc. By accurately identifying these road signs, autonomous vehicles can better adapt to complex road environments, understand and follow traffic rules, drive safely, and avoid potential dangers.

In summary, the significance of road sign recognition for autonomous vehicles lies in improving driving safety, achieving precise navigation and path planning, interacting and communicating with traffic facilities, and helping vehicles adapt to complex road environments. This provides important support for the widespread application and popularization of autonomous driving technology.

2. Research Status

In recent years, the development of autonomous vehicles has attracted widespread attention. One of the important technical challenges is to achieve accurate recognition and understanding of road traffic signs. By recognizing road traffic signs, autonomous vehicles can make corresponding decisions and travel actions based on the information of the signs, achieving the goal of autonomous driving.

In order to solve this problem, researchers have introduced deep learning algorithms, especially convolutional neural networks (CNN), on the basis of traditional image processing, for the application of road sign recognition tasks in autonomous vehicles. CNN has the ability to automatically learn features and extract high-level abstract features from raw images, thereby achieving recognition of road traffic signs.

Choosing the appropriate dataset is crucial in the research of road sign recognition. Some researchers have utilized publicly available large-scale datasets for training and testing, such as the German Traffic Sign Recognition Benchmark (GTSRB), Belgian Traffic Sign Dataset (BTSD), and LISA Traffic Sign Dataset (LISA-TSD). These datasets provide a large number of real-world road traffic sign images, covering different sign categories and scenes.

Researchers have adopted different methods and strategies and achieved significant results in road sign recognition tasks. They first analyze the spatial structural features of road traffic signs through convolutional neural networks, then divide the image into multiple regions and extract multi-level features of the image through multi-scale convolution operations. In addition, some researchers have used techniques such as data augmentation and transfer learning to improve the performance and robustness of the model.

In order to evaluate the performance of algorithms, some evaluation indicators are widely used in road sign recognition tasks, such as accuracy, recall, F1 value, etc. Meanwhile, researchers also used methods such as cross validation and average accuracy to evaluate and compare the performance differences between different algorithms.

Although significant progress has been made in the research of road sign recognition for autonomous vehicles, there are still some challenges. For example, complex scenes, lighting, weather and other factors pose higher requirements for the accuracy and robustness of road sign recognition. In addition, how to further improve the speed and real-time performance of road sign recognition is also a problem that needs to be solved.

In summary, road sign recognition for autonomous vehicles is one of the key technologies for achieving autonomous driving. By introducing deep learning algorithms, especially the application of convolutional neural networks, researchers have made significant progress in landmark recognition tasks. However, there are still some challenges that need to be addressed, including the impact of scene complexity, lighting, and weather on road sign recognition. Future research can focus on addressing these issues and exploring more efficient, accurate, and robust road sign recognition algorithms.

3. Research Design

This chapter will review the current research progress on road sign recognition for autonomous vehicles both domestically and internationally, including traditional image processing methods and deep learning based methods. The focus is on introducing the application of convolutional neural networks in road sign recognition, analyzing their advantages and disadvantages, and laying the foundation for the research method of this paper.

Traditional image processing methods: Before the emergence of autonomous vehicles, researchers used traditional image processing methods to achieve road sign recognition. For example, using techniques such as color segmentation, edge detection, and shape matching to locate and recognize landmarks in images. However, these methods rely on manually designed features and rules, and are highly sensitive to environmental conditions such as lighting and occlusion, which limits their accuracy and robustness.

Deep learning based methods: In recent years, with the rapid development of deep learning technology, many researchers have begun to explore the use of deep learning methods such as convolutional neural networks (CNN) for landmark recognition. This method automatically learns image feature representations and classification decisions from data through end-to-end training, which has better flexibility and robustness. Researchers have designed various CNN based network structures, such as LeNet, AlexNet, VGGNet, ResNet, etc., and achieved good recognition results.

Dataset construction and annotation: In order to conduct research on road sign recognition for autonomous vehicles, researchers have constructed a large number of road sign image datasets and annotated the images. These datasets contain various types of road sign images, such as traffic lights, stop signs, warning signs, etc. Among them, some commonly used datasets include German Traffic Sign Recognition Benchmark (GTSRB), LISA Traffic Sign Dataset, CURE-TSR, etc.

Data augmentation and preprocessing: In order to enhance the generalization ability and robustness of the model, researchers have performed various data augmentation and preprocessing operations on the dataset. For example, operations such as rotation, scaling, translation, and mirroring can expand the dataset and increase sample diversity. In addition, the image can also be processed for brightness, contrast, color balance, etc., to improve the model's adaptability to lighting and color changes.

Experimental evaluation and comparison: In order to verify the performance of the road sign recognition method for autonomous vehicles, researchers conducted a series of experimental evaluations and comparative experiments. Common evaluation indicators include accuracy, recall, precision, etc. By comparing and analyzing with other methods, evaluate the advantages, disadvantages, and feasibility of this method. In summary, the related work of road sign recognition for autonomous vehicles involves traditional image processing methods and deep learning based methods, while also requiring the construction of suitable datasets and data augmentation and preprocessing. In addition, experimental evaluation and comparative research are also important steps in evaluating the performance and effectiveness of methods. These related works provide important references and foundations for the research and development of road sign recognition technology for autonomous vehicles.

4. Road Sign Recognition Based on Convolutional Neural Networks

4.1. Dataset Introduction

Find the Chinese traffic sign dataset from cctsdb, with a total of 18000 traffic sign images in the sample. The dataset not only includes official logos, but also images in various states such as cloudy, sunny, tilted, blurred, etc., in order to improve recognition accuracy and accuracy. The specific identification process is mainly divided into several steps: (1)Image preprocessing ;(2) Data augmentation; (3) Initialize the model parameters, learning rate, number of layers, number of iterations, step size, etc. of the convolutional neural network.

4.2. Evaluation indicators for object detection

Performance indicators are used to calculate the generalization ability during the learning phase, with the most common being accuracy and recall. The accuracy is represented by P:

$$P = \frac{TP}{TP + FP}$$

In binary classification problems, the combination of actual and predicted classification algorithms may be divided into four situations: true positive (TP), false positive (FP), true negative (TN), and false negative (FN).

(1) Dataset partitioning: Divide the dataset into training set, validation set, and testing set. Wedivide the datasetinto training set, 20% as validation set, and 10% as testing set in a ratio of 70%.

(2) Data augmentation: During the training process, data augmentation techniques are used to expand the dataset, such as random rotation, translation, scaling, flipping, etc., to increase data diversity and improve the robustness of the model.

(3) Loss function: The cross entropy loss function is usually chosen as the optimization objective of the model, used to measure the difference between predicted labels and real labels.

(4) Optimization algorithms: Common optimization algorithms include Random Gradient Descent (SGD), Adam, etc. Choose appropriate learning rate and momentum parameters for training.

(5) Learning rate adjustment: Adopting a learning rate attenuation strategy, the learning rate is attenuated according to a certain step size or dynamically adjusted based on the performance of the validation set.

(6) Early Stopping: When there is no significant improvement in accuracy or loss on the validation set, stop training in advance to avoid overfitting.

During the training process, cross validation techniques can be used to evaluate the performance of the model, and adjust the model structure and parameter settings based on the performance of the validation set, further improving recognition accuracy. Meanwhile, techniques such as model compression and quantization can be used to reduce model size and computational complexity, making it suitable for practical applications of embedded autonomous vehicles.

5. Experiments and Results

5.1. Convolutional Neural Networks with LeNet5 Structure

This article aims to establish a 2-layer convolutional neural network, which includes 2 hidden layers. In the first hidden layer, the size of the convolutional layer is28 x 28 x 6, and the size of the subsampling layer is14 x 14 x 6; In the second hidden layer, the size of the convolutional layer is10 x 10 x 16, and the size of the subsampling layer is5 x 5 x 16; The size of the fully connected layer is120 × 1, and the specific structure is shown in Figure1.

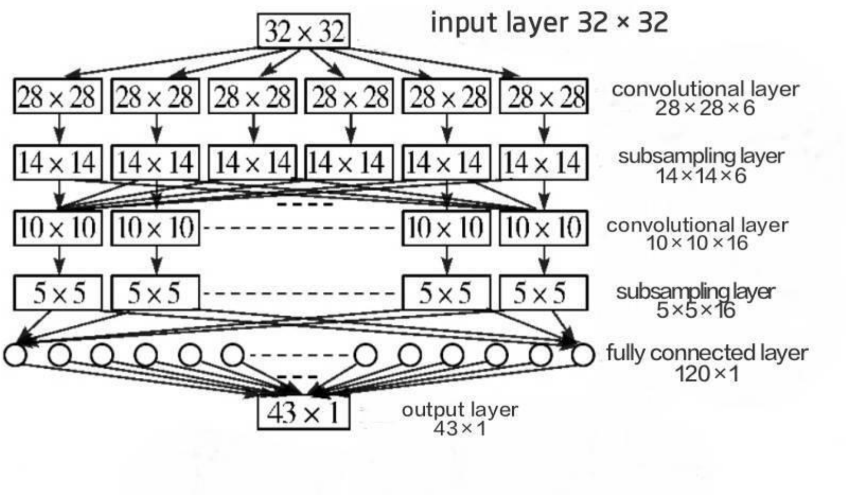

Figure 1. Convolutional Neural Networks with LeNet Structure

In practical operation, set the training frequency to 10, the learning rate to 0.1, and the batch scale to 17. The batch scale represents the sample size taken during gradient descent. If the batch scale is too large, the running efficiency is not high, and if the batch scale is too small, it will affect the accuracy of the convolutional neural network.

Based on the above data, a convolutional neural network with LeNet5 structure was constructed using programming software Python. The training set was input into the program to obtain the parameters of each neuron. Finally, the test set was input into the already trained convolutional neural network. After testing, the accuracy of road sign recognition is 87.5%, with a loss value of 0.913

5.2. Model improvement and application

Obviously, the recognition rate of 87.5% is not satisfactory, and this article intends to improve the model to improve the accuracy of road sign recognition. Generally speaking, to improve recognition accuracy, the following aspects should be considered: (1) Image preprocessing; (2) Adjustment of Convolutional Neural Network Structure; (3) Skills during training; (4) Selection of incentive function.

In the data collection and processing section, histogram equalization and normalization have been applied to the images. Therefore, in order to improve recognition accuracy, this article considers adjusting the parameters during training based on the LeNet5 structure mentioned above. The details are as follows: (1) The convolution kernel has been changed from its originalsizeof5 × 5 to 1 × 1; (2) The batch size has also been increasedfrom17to128; (3) The number of training sessions has increased from 10 to 50.

Reducing the size of the convolutional kernel can preserve the original features of the image as much as possible, while increasing the batch scale and training frequency can improve the accuracy of convolutional neural network training. Of course, the corresponding cost is the corresponding extension of training time. Of course, it is also possible to consider combining several network structures to improve accuracy.

Comparison and application after improvement

After the above improvements, the model was trained using Python, and then tested using a test set. The results are shown in Table1.

Table 1. Improved results

	LeNet5	After improvement
Convolutional kernel	5×5	1×1
Batch scale	17	128
Training frequency	10	50
Accuracy	87.5	93.2
Magnitude of the loss	0.913	0.442

After improvement, the accuracy has increased from 87.5% to93.2%, an increase of nearly 6 percentage points. The author believes that the model can be used for simulation experiments, so four road sign images were used for simulation experiments, and the experimental results are shown in Figure 2.

Figure 2. Improved simulation experiment

The four test images in Figure 7 represent road sign images of straight and right turning, uneven road surface, no entry, and attention to children. After recognition by convolutional neural networks, the

ISSN:2377-0430
Vol. 4, No. 4, 2024

labels of the road signs all appear above the images, and the recognition of road sign types is completely correct.

To evaluate the performance of different landmark recognition algorithms, researchers usually conduct comparative experiments. In these experiments, they compared the recognition accuracy, recall, F1 value, and other indicators of different algorithms on the same dataset, and presented the experimental results visually in the form of charts.

The following is an example of a comparative experiment that compares the performance of landmark recognition algorithms based on traditional methods and deep learning methods:

Experimental setup: We selected the commonly used dataset GTSRB as the experimental dataset, which includes images of various road traffic signs. Traditional methods (such as SVM, random forest, etc.) and deep learning based methods (such as convolutional neural networks) were used for landmark recognition in the experiment. The cross validation method was used in the experiment, dividing the dataset into training and testing sets.

Figure2. Experimental results

method	Accuracy	recall	F1 value
KNN	zero point nine six	zero point nine six	zero point nine six
CNN	zero point eight six	zero point eight five	zero point eight six
RNN	zero point eight eight	zero point eight seven	zero point eight nine

The following figure shows the comparison of experimental results of different methods in road sign recognition tasks:

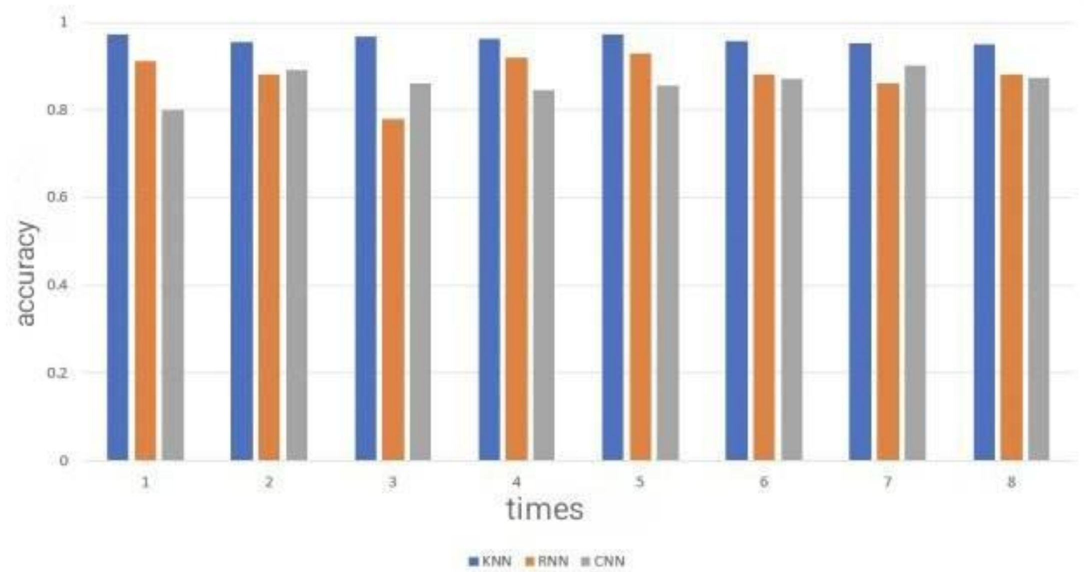

Figure 2.Accuracy

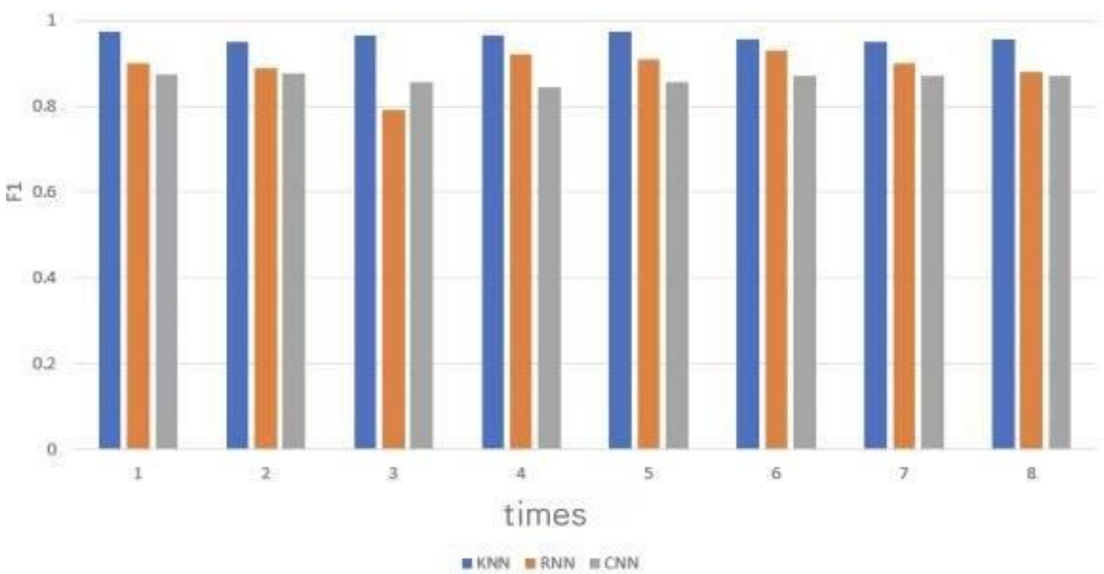

Figure 3.F1

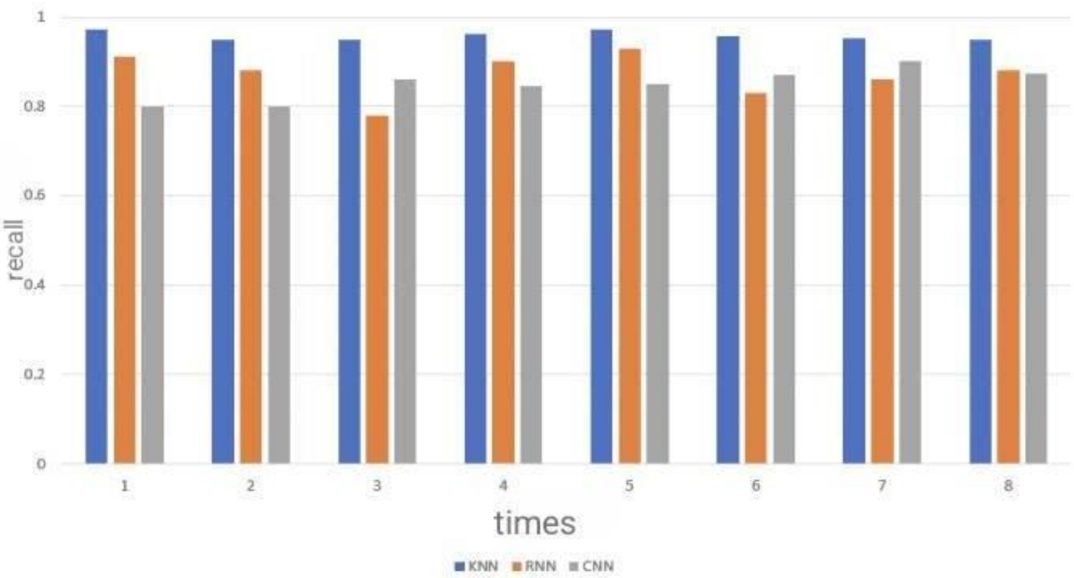

Figure 4.Recall

From the chart, it can be seen that deep learning based methods perform better in landmark recognition tasks compared to traditional methods. The accuracy, recall, and F1 value of deep learning methods are significantly better than traditional methods, indicating that deep learning has stronger recognition ability and robustness in landmark recognition.

In summary, comparative experiments are one of the commonly used methods to evaluate the performance of different road identification algorithms. By comparing the recognition performance of different algorithms on the same dataset and presenting the experimental results in the form of charts, the advantages and disadvantages of the algorithms can be visually displayed. In the research of road sign recognition, deep learning based methods have shown better performance and potential compared to traditional methods.

6. Summary

We use convolutional neural networks to improve the road sign recognition function of autonomous vehicles. Compared with traditional neural network algorithms, the application results of convolutional neural networks have higher accuracy, precision, recall, and F1 value, and the recognition efficiency is greatly improved. Therefore, we believe that convolutional neural networks have made significant contributions in the application of landmark recognition.

In the future, we will expand the dataset images and add road sign datasets from various countries to broaden their recognition range while ensuring recognition accuracy.

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