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Design of Intelligent Traffic Sign Image Recognition System Based on Machine Learning Algorithms

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While automobiles offer a convenient mode of transport, autonomous driving and unmanned driving have also begun to enter the commercial stage, but they have also given rise to an increasing number of vehicle safety issues. The image recognition of traffic signs (TS) is crucial for road safety. Therefore, research on automatic recognition of TS images is essential. However, changes in weather, shadows, and light intensity can easily affect the recognition of TS, which poses significant safety risks to autonomous driving. In this paper, the function and problems of TS detection method were studied by analyzing the methods of TS identification and detection; also, corresponding system design analysis was conducted based on machine learning. The purpose of this study is to develop a high-precision and real-time TS detection system based on the interference problems in complex environments. The relevant experimental analysis of the intelligent recognition system was carried out. The analysis showed that the recognition accuracy and anti-interference performance of TS image recognition system based on a machine learning algorithm were higher than those of traditional image recognition systems; the recognition accuracy was improved by 6.8%, and the anti-interference ability was improved by 0.24. These results suggest that machine learning algorithms can definitely improve the performance of TS image recognition systems.

Keywords: Traffic signs, image recognition systems, machine learning, traffic sign detection

1. INTRODUCTION

With the progress of social science and technology, the transportation industry has also been further developed, and road vehicles have become the main means used for travel. However, as a result of increased road traffic, road safety has become an increasingly urgent issue that needs to be addressed. The rapid detection and identification of TS is crucial for the safety and speed of vehicles. It not only provides driving guidance for drivers, but is also the key to developing intelligent vehicles. Only when intelligent vehicles can obtain accurate information from TS can they make correct decisions and engage in good driving behavior. Due to various factors affecting TS detection and recognition, the collected TS images cannot be accurately identified. Therefore, the research on TS recognition content has certain research value.

The recognition of TS includes two stages: sign detection and recognition. Its main purpose is to provide real-time feedback of the recognition results to road users. Therefore, many scholars have conducted relevant analysis on the recognition of TS. Tabernik conducted research on massive TS classifications applicable to TS inventory management, and conducted in-depth research on TS classifications with significant apparent differences in classification [1]. Yuan proposed a multi-resolution feature fusion network architecture. This structure uses a high-density deconvolution layer with jump connections to better identify small targets [2]. Neelakandan proposed an efficient traffic prediction method based on the Internet of Things, and used a microprocessor based traffic signal control system for smart cities [3]. Chu stabilized the learning process by improving observability and reducing the learning difficulty of each local agent. He

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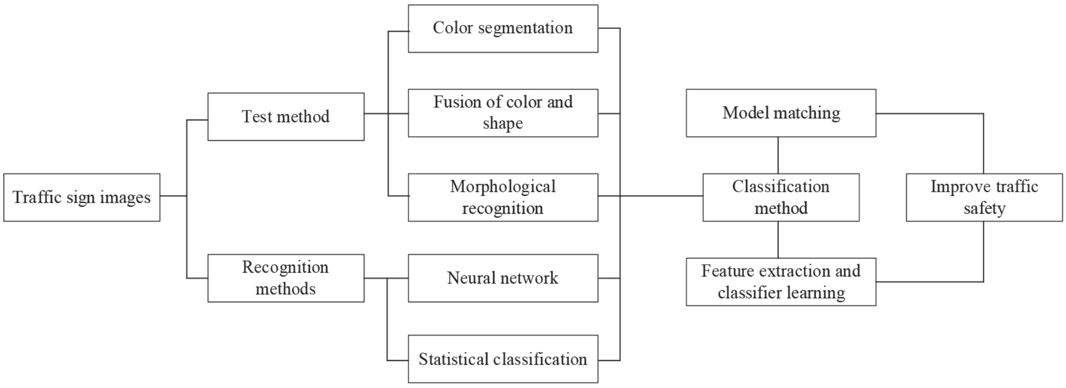


Figure 1 Analysis of TS detection and recognition methods.

compared multi-agent and independent learning algorithms in Monaco's large synthetic traffic grid and in a large real-world traffic network [4]. Tan decomposed previously complex reinforcement learning tasks into several subclasses with relatively simple reinforcement learning objectives, providing a common deep learning system to solve traffic congestion problems [5]. Jaseem proposed a robust and novel spatiotemporal relationship model for urban road TS detection and recognition of moving vehicles [6]. Liang proposed a deep reinforcement learning model to control the traffic light cycle. By collecting traffic data and dividing the entire intersection into small grids, complex traffic scenes were quantified into states [7]. All of these studies described the content and role of TS image recognition, but they have not combined machine learning algorithms for relevant system design.

Machine learning algorithms are widely used in image recognition systems, which can comprehensively analyze the stability and detection accuracy of the system. Therefore, many scholars have used machine learning to design and analyze TS recognition systems. Jacob performed deep learning methods through feature extraction to improve the accuracy of processing. In terms of image registration on the Internet of Things, the usefulness of deep learning methods has been evaluated [8]. Ahmed studied TS detection and recognition issues under different challenging conditions, focusing on the performance degradation associated with them. To this end, he proposed an improved system for detecting and identifying TS problems based on convolutional neural networks [9]. Lin introduced a TS recognition and classification method based on transfer learning, and used the model to decrease the amount of training data significantly, and reduce computing costs. The Belgian TS database was selected and enhanced through data preprocessing technology [10]. Chen believed that the recognition ability of depth features would be limited if there were insufficient training samples. To solve this problem, an improved deep fusion convolutional neural network was devised [11]. In order to improve the accuracy of visual inspection, He developed a directional gradient histogram method for image detection [12]. In summary, machine learning algorithms play a significant role in TS image recognition systems, and corresponding optimization should also be carried out in TS recognition.

In order to study the specific practical effects of TS image recognition systems based on machine learning algorithms, this paper verified the proposed machine learning algorithm recognition system by studying the recognition accuracy and anti-interference performance of the image recognition system based on machine learning algorithms. It also studied the performance of the recognition system based on machine learning through comparative analysis of image detection quality and recognition speed. Through experimental analysis, it was found that the recognition accuracy and recognition speed of the TS recognition system based on machine learning algorithm proposed in this paper were higher than those of traditional TS recognition systems. Unlike previous research, this study focused on analyzing the anti-interference and recognition accuracy of TS recognition systems.

2. DETECTION AND IDENTIFICATION METHODS AND FUNCTION OF TS

2.1 Detection and Identification Methods of TS

An efficient TS detection system may help minimize event response time, thereby strengthening situational awareness and reducing the duration of traffic congestion [13]. TS image recognition involves the accurate recognition of TS in traffic images. Existing TS recognition methods are based on the colors and shapes of signs as the starting point for research. The most commonly-used TS recognition techniques include color segmentation, shape recognition, and classification design based on specific image characteristics. Various detection and recognition methods are shown in Figure 1.

2.1.1 Detection Method of TS

The main feature of TS images is color, which includes red, yellow, blue, white, and black. Color characteristics include size, scale, rotational invariance, and separability. Therefore, the main method used to identify TS is based on color features. Color space can be directly distinguished from colors with better real-time performance, but it is sensitive to light and is not adaptable to changing real-time lighting conditions in the natural environment.

The second method is based on morphological recognition. Due to different image acquisition angles, the shape of the TS in the image may vary depending on the acquisition angle, making it difficult for the TS to recognize the sign. The Hough transform method facilitates the recognition of specific images in a region by setting the appearance of a circular image and inputting local features, thereby improving recognition accuracy.

The third method is based on color and shape fusion detection. Due to the shortcomings of both color separation and shape recognition techniques, the combination of color separation and shape recognition can improve recognition accuracy. Hence, the two methods are combined to segment objects using their color characteristics. The combination of morphological features and two detection methods exploits their respective strengths. In addition, color and shape are invariant features of TS and can be detected by existing means and methods.

2.1.2 Identification Method of TS

After TS detection, the TS image must be further identified to determine the type of road sign, and then sent to the driver or driver assistance system for appropriate control. Currently, image recognition algorithms include neural network classification methods, statistical classification methods, and so on.

The first is neural networks. This method is widely used in the research focusing on the identification of TS and other images through advanced computer computing capabilities and software development. A two-level classifier is developed through neural network group, which completes the coarse classification and then fine classification of TS. Firstly, a rough preliminary classification of TS is done, and then it is more accurately classified using a subdivision classifier. On this basis, the image is recognized using a self-organizing neural network classification method. By combining it with the color mode and morphological mode, the classification of TS and effective region recognition are achieved.

The second type is statistical classification which is widely used and applies class probability density functions and initial probabilities to identify different distribution features. Support Vector Machine (SVM) is a method based on the structural risk minimization principle of existing database design. It has the characteristics of simple design and strong universal ability for character recognition, and achieves good results in applications such as face recognition. Using support vector classification and taking TS image pixels as features can assist nonlinear support vectors to achieve good TS classification results.

2.1.3 Classification Method of TS

There are two traditional TS classification methods. One is model matching, and the other is a classification method that combines feature extraction and classifier learning. Pattern matching uses the feature vectors extracted from identifiable objects and the distance between the feature vectors of each model in the pattern library to calculate the corresponding relationship between patterns; that is, the smaller the distance between models, the closer are the models. Using the original pixel values in the image directly for matching not only takes longer computation time, but also requires more matching time. Currently, the multi-source data fusion method is widely used in the field of image classification to organically integrate feature extraction and classifier training, by first extracting appropriate features from the image, and then using these features to train it.

2.2 Role of TS Detection and Identification

TS offers users specific traffic management and safety information by providing graphics, colors, text, and other features. TS contains a large amount of traffic information, and its characteristics are simple and clear, allowing users to quickly and accurately obtain traffic information, thereby achieving fast and efficient transportation. Of course, it can also provide drivers with various road warnings, instructions, and other auxiliary information. If the correct driving behavior is completely determined by the driver's observation of the TS, there is no doubt that it would increase the burden on the driver and accelerate driver fatigue. This would make traffic accidents more likely to occur, and traffic flow may be significantly impaired. Therefore, it is necessary to study a road traffic safety detection method in complex traffic environments, which uses cameras to collect images of natural environment information in the road traffic environment, and identify and analyze them. The image processing module in the system can transmit images to achieve recognition and detection of TS. It can also send the identification results to the driver and assist the driver to make correct driving decisions, thereby reducing road congestion and improving road safety. Therefore, the research on TS recognition is also necessary for future development.

2.3 Problems Identified by TS Detection

The problems of TS detection and recognition are associated mainly with the following issues. Firstly, there is the issue of environmental interference. The complexity and variability of the actual road environment have significant impacts and obstacles on traffic signal recognition. However, in the process of achieving the goal of TS identification, there are still many obstacles. Among them, there are several issues related to environmental disturbances associated with TS identification, including the following.

One is the issue of color changes. Under natural conditions, the color of TS may change due to long-term use, resulting in changes to its color characteristics (such as decreased image saturation, etc.), which affects the accuracy of image recognition. The second is the issue of lighting. TS can appear in all real-world environments, including time zones, lighting angles, reflections, and shadows that may affect image quality. The third is the problem of occlusion. In a real road environment, the optical path between the TS and image acquisition sensors may be blocked by obstacles such as moving vehicles, pedestrians on the road, and trees on both sides of the road. The fourth is motion blur. The driving assistance system is an on-board system. During

Table 1 Changes in environmental interference, recognition accuracy, and algorithm real-time before and after improvement.

	Traditional TS Recognition System		New TS Recognition System	
	Before improvement	After improvement	Before improvement	After improvement
Environmental interference	0.75	0.42	0.55	0.26
Identification accuracy	0.42	0.55	0.55	0.72
Algorithm real-time performance	0.46	0.53	0.53	0.69

the image acquisition process, the vehicle is maintaining motion. According to video imaging principles, in order to meet the visual standards of image brightness, the shutter must be maintained for a period of time. During this period, vehicle motion can cause motion blur of the image. The fifth is the issue of background interference. The light and color of the background in an urban environment are so complex that the human eye can quickly recognize signs through persistent knowledge learning, but computers have difficulty accurately recognizing TS under complex conditions.

Secondly, there is the issue of recognition accuracy. In the detection of TS recognition systems, traditional TS recognition methods capture graphics, colors, and so on. By using a combination of basic pattern matching and machine learning, TS can be quickly and easily recognized. However, existing TS identification methods generally have problems such as low identification accuracy and low disturbance safety. Using machine learning methods, TS recognition algorithms with high recognition accuracy and high interference safety can be developed.

Finally, there is the real-time problem of the algorithm. TS recognition is a typical image recognition problem. Image processing on computer platforms requires higher performance than existing linear data problems, and vehicles also require embedded systems with real-time feedback results. Machine learning methods require a large amount of data, and after a long period of learning and training, their detection process becomes more complex. Therefore, it is necessary to optimize the structure and algorithm of the network model in multiple respects, and improve the training speed of the network model to execute the algorithm in real time.

Addressing the problems existing in TS recognition systems, this study made improvements to traditional TS recognition systems and TS recognition systems based on machine learning algorithms, and analyzed the changes in environmental interference, recognition accuracy, and real-time performance of the algorithm before and after the improvements. Each system was tested with 10 TS images. The specific investigation is shown in Table 1.

According to the data in Table 1, the recognition accuracy and real-time performance of the two TS recognition systems were significantly improved, while their environmental interference was significantly reduced after the improvement. However, the recognition accuracy and real-time performance of the TS recognition system based on machine learning algorithms are significantly higher than those of traditional TS recognition systems. Under machine learning, TS recognition systems can reduce the interference problems caused by the environment and therefore reduce the noise caused by environmental interference. Moreover, it is possible to quickly calculate the relevant image data of the recognition samples, and improve the recognition accuracy of the TS recognition system through multiple learning and training. In addition, the TS recognition system based on machine learning algorithms has faster processing speed and higher execution efficiency in terms of image recognition.

3. KEY TECHNOLOGIES FOR TS DETECTION AND IDENTIFICATION

3.1 Image Preprocessing Technology

The original captured TS image is affected by many environmental factors. Images contain a large amount of noise and interference, which greatly reduces the quality and efficiency of image recognition and detection. Therefore, before image processing, noise cancellation and description processing should be performed. It is necessary to delete or reduce irrelevant information and provide useful information, which can significantly reduce the complexity and workload of subsequent image processing. In addition, local random noise caused by certain factors can also reduce image quality. Therefore, extracting feature vectors from images and using machine learning methods to identify images can effectively improve the quality of image processing [14]. For image preprocessing, the two main methods are: image enhancement and filtering. Image enhancement not only highlights the objects in the image, but also strengthens the contrasts in the image. It also converts the image into a data format suitable for computer analysis and processing. Image filters eliminate isolated noise points and reduce interference points during image digitization. This article investigated the road TS in a certain area, and added noise to its image. The image was preprocessed using mean filtering and median filtering as shown in Figure 2.

As shown in Figure 2, after adding salt and pepper noise, the overall image quality has decreased, and there are many more noise points. However, after the image undergoes median filtering and mean filtering, the noise points have significantly decreased, reducing the interference points generated by image processing. Both mean filtering and median filtering can smooth images and filter noise, although mean filtering can destroy image details when suppressing noise, which can blur the image and cannot remove noise points well. Therefore, the processing outcome of mean filtering is poor.

3.2 Image Detection Technology

Image detection is determined based on the specific features of the image, while TS image recognition is accomplished based on the color, shape, and other characteristics of the

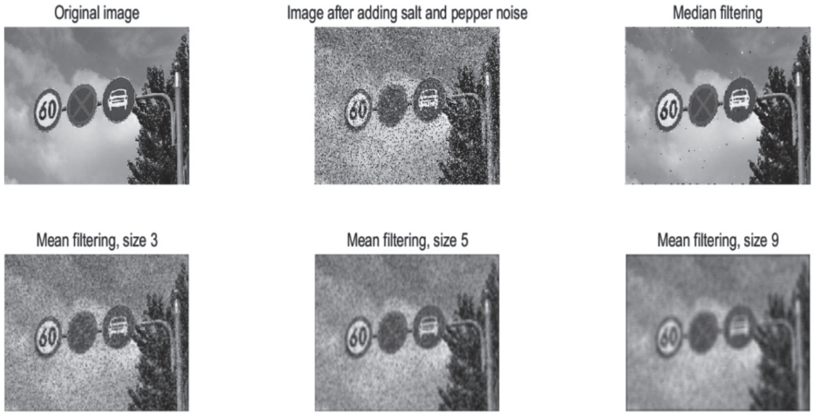


Figure 2 Image denoising process using different methods.

image. First, based on the recognition of color features, a color model is selected. Each color model has advantages and disadvantages, so the correct color model is selected based on the search object. In order to solve the problem of light intensity changes caused by this, HSV (Hue, Saturation, Value, HSV) color models that can be extracted from luminance components are selected to identify colors. The shapes of TS are generally circular, triangular, rectangular, or octagonal. According to the geometric characteristics of polygons, a geometric feature-based detection method can be used for corresponding image detection.

3.3 Image Recognition Technology

Recognition of TS in images is the main task of TS detection and recognition, which requires accurate real-time and robustness. TS image recognition is intended to extract certain characteristics of TS from an image and compare the characteristics of the sample with the data in the feature library. The functions of TS images can be divided into pixel functions and shape functions. After extracting the characteristics of the image, an appropriate recognition algorithm is required to recognize the TS image. Conventional models are used to search for data repository-based algorithms that search for new values without restricting the information database. If there is no need to complete this model, the database is searched for valid values for which the model can continue to be run.

4. TS IMAGE RECOGNITION SYSTEM UNDER MACHINE LEARNING

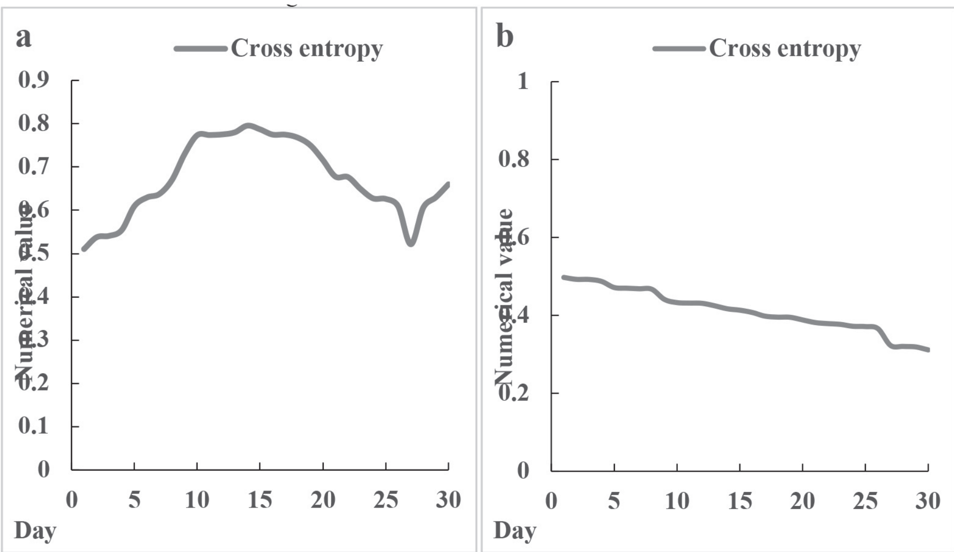
4.1 Overall Design of TS Recognition Image System

The TS identification system has two stages: detection and identification. The TS detection stage detects the presence of marked regions in an image, and filters their TS regions by separating color thresholds and shape recognition operations to improve image quality. The TS recognition step performs initial classification based on the shape and image characteristics of the original TS, and uses SVM algorithms for classification and recognition. In order to correctly recognize TS images, it is necessary to select the most appropriate threshold value, and then first separate the target area from the background area. The selection of threshold values requires continuous checking of the degree of separation in color domain values. Therefore, photo data collection is divided into a training group and a test group. The training group selects the optimal threshold value, and the training group verifies the effectiveness of image analysis to prevent randomness in data selection. Therefore, it is necessary to select an appropriate number of TS images, so that real-time management and control measures can be implemented to improve system performance [15]. The planned software implementation includes the main aspects of client implementation: taking photos, selecting pre-identified images in folders, viewing selected images, uploading images to the server, searching for results on the server, and viewing identification results. The server receives images, runs analysis programs, and returns results. The image recognition system achieves better image detection and recognition under better light conditions. The natural environment in which TS are located is relatively complex, so it is necessary to conduct tests under insufficient lighting conditions, including weak light, too bright light, shadows, and so on. In this case, the contrast is strengthened by improving the brightness processing [16].

4.2 Application of Machine Learning Algorithms in TS Recognition

TS recognition requires processing the image, and then performing corresponding TS recognition based on the image processing results [17]. Therefore, TS recognition requires corresponding optimal solution analysis, and then calculates its separation hyperplane based on its optimal solution. After that, the classification decision function of TS recognition is studied, and the activation function and cross-entropy function of TS recognition are calculated. Firstly, the recognition training dataset in TS recognition is calculated as:

$$C = \{(a_1, b_1), (a_2, b_2), \cdots, (a_n, b_n)\} \quad (1)$$



a: Cross entropy changes in traditional TS recognition systems
b: Cross-entropy change of TS recognition system based on machine learning algorithm

Figure 3 Cross-entropy change of TS recognition systems under different algorithms.

where a_n, b_n are planar vectors and hyperplane vectors in the TS recognition image, respectively. Next, the constraint conditions for TS image recognition are constructed and calculated as:

$$\begin{cases} V = \min \frac{1}{2}\|\delta\|^2 \\ s.t. \qquad b_n(\delta \bullet a_n + t) - 1 \geq 0 \end{cases} \tag{2}$$

where δ is the constrained optimal solution for TS identification, and t is the constraint factor for the constraint condition. The separation hyperplane for TS recognition is then constructed based on its constraints as:

$$\delta \cdot a_n + t = K \tag{3}$$

where K is a separation constraint. Then, based on its separation hyperplane, the classification decision function for TS recognition can be obtained as:

$$f(a) = sign(\delta \cdot a_n + t) \tag{4}$$

where $sign()$ is the classification decision factor. According to its classification decision function, it can be obtained that the activation function of the image recognition system is:

$$\eta(a) = \frac{1}{1 + e^{-a}} \tag{5}$$

Finally, according to the activation function, the cross-entropy function for TS recognition can be obtained as:

$$Y = -\frac{1}{n}\sum_{a}[b\ln x - (1-b)\ln(1-x)] \tag{6}$$

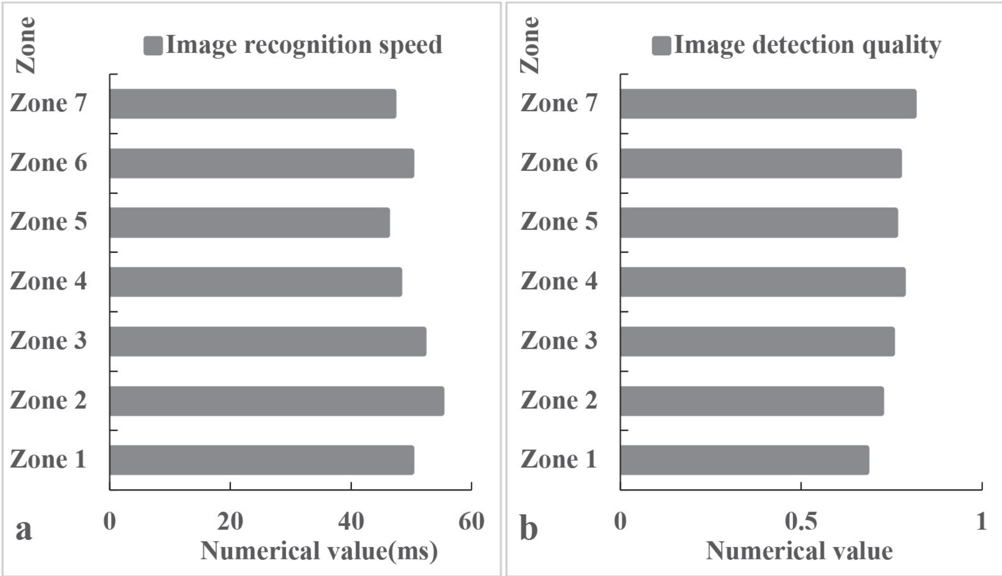
Among them, x is the cross-entropy weight in the TS recognition system. This study investigated the cross-entropy changes of ten sets of TS images after recognition using different algorithms. After 30 days of investigation, the average cross entropy of these ten sets of TS image recognition was taken as experimental data. The investigation results are shown in Figure 3.

Figure 3a shows the cross entropy change of a traditional TS recognition system. During this process, the cross entropy under the system was gradually increasing, gradually decreasing from the 14th day, and finally slowly increasing and stabilizing to 0.66. This indicated that the TS image recognition under the system was not accurate enough, and the recognized TS image was quite different from the original image. At the same time, it also indicated the system's poor recognition of images.

Figure 3b shows the cross entropy change of a TS recognition system based on a machine learning algorithm. During this process, the cross entropy of the system gradually decreased to 0.31, and the cross entropy under machine learning was always lower than that of traditional TS recognition systems, which also proved that the machine learning algorithm was superior to traditional TS recognition systems. With the support of machine learning algorithms, the TS recognition system is more accurate for road TS recognition. Moreover, the system can be used in complex and volatile road environments.

4.3 Performance of TS Recognition Systems Based on Machine Learning Algorithms

The practical effectiveness of TS recognition systems based on machine learning algorithms needs to be studied by testing the specific performance of the system. Therefore, this study determined the image recognition speed and image detection quality of the TS recognition system. A total of seven areas of road TS were investigated and specific identification conditions under the system were studied. Each area was surveyed for one day, and its average value was taken as the data for this experimental analysis. According to the survey, the image recognition speed under the traditional TS recognition system was 200ms, and the image detection quality was 0.65. The results of the investigation are shown in Figure 4.



a: Image recognition speed b: Image detection quality

Figure 4 Changes in image recognition speed and image detection quality of the TS recognition system.

Table 2 Image recognition accuracy and anti-interference performance of machine learning algorithms and traditional algorithms.

	Identification accuracy		Immunity	
	General identification system	Machine Learning Algorithms	General identification system	Machine Learning Algorithms
Test 1	88.3%	93.5%	0.42	0.76
Test 2	86.4%	94.6%	0.53	0.75
Test 3	85.5%	92.5%	0.55	0.72
Mean value	86.7%	93.5%	0.50	0.74

Figure 4a shows the image recognition speed of the TS recognition system. In the seven regions surveyed, the average image recognition speed was 49.7 ms, which was 150.3 ms less than that of traditional TS recognition systems. This indicated that traffic recognition systems based on machine learning can overcome problems such as brightness, illumination, and obstructions, and can also improve the contrast of images, thereby rapidly improving image recognition speed. Conversely, traffic image recognition systems based on traditional TS recognition systems were susceptible to environmental interference, which can increase image noise and reduce recognition speed. Figure 4b shows the image detection quality of the TS recognition system. The image detection quality of each region in this system was greater than that of traditional TS recognition systems, and the image detection quality was 0.1 higher than that of traditional TS recognition systems. The TS recognition system under machine learning can collect the data set of TS through continuous learning and training, and improve the contrast of the image through image enhancement and median filtering, thereby improving the detection of the image.

In order to further understand the effectiveness of TS image recognition under machine learning, this article tested three sets of image recognition through investigating the accuracy and interference resistance of machine learning algorithms and traditional TS recognition systems. Each set of images was tested with 10 images. The specific investigation results are shown in Table 2.

According to the data given in Table 2, the recognition accuracy and anti-interference performance of TS image recognition systems based on machine learning algorithms were higher than those of ordinary TS recognition systems; the recognition accuracy was improved by 6.8% and the anti-interference ability was improved by 0.24. The training speed of TS image recognition based on machine learning algorithms was faster and had stronger anti-interference ability. It can resist the interference problems caused by complex natural environments, especially in environments with poor light conditions. This can greatly reduce the recognition error rate of TS images, and can also avoid image interference caused by environmental issues, thereby improving the recognition quality of images, in order to meet the needs of TS image recognition. In addition, machine learning algorithms are more targeted, allowing for corresponding sample training for TS images, and reducing the time required for image classification. At the same time, they also improve the recognition accuracy of TS images, thereby strengthening the validity of the recognition data of the system.

5. CONCLUSIONS

The detection and recognition of TS is vital to the development of intelligent vehicles. It can detect in advance and can give feedback to drivers the road, thereby assisting drivers to achieve autonomous driving. At the same time, its research and development level also largely reflects the road conditions and the development level of technology. Therefore, in today's society, it is very important to master the detection and recognition technology of TS. Due to the emergence of a large number of TS datasets and the continuous improvement of the operational efficiency of computer systems, the advantages of machine learning have become increasingly evident. Based on the analysis of existing TS image recognition methods, machine learning algorithms were used to determine the image recognition quality and recognition accuracy of the traffic recognition system, thereby reducing the TS image recognition error rate and improving the TS image recognition speed. The results show that the machine learning approach can create a large TS database and then classify TS, achieving high-precision TS recognition in complex environments, and its recognition results are more stable and reliable. At the same time, it also provides a new direction for the research on TS recognition.

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