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COGNITION OF ROAD TRAFFIC SIGNS: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

As a research hotspot in computer vision, traffic sign recognition has made remarkable progress in the past few years. This study provides a systematic review of the field of traffic sign recognition. Thirty-nine papers relevant to this study were manually selected for exploration from four well-known databases (IEEE Xplore, ScienceDirect, Scopus, and Google Scholar). Five questions were proposed to describe general trends in traffic sign recognition. These questions are answered by the literature review. Specifically, first, determine the literature review method and select the papers to be analyzed. Next, various algorithms and commonly used data sets for traffic sign recognition are analyzed in detail. Then, the advantages and disadvantages of various algorithms are compared, and the challenges faced in traffic sign recognition are discussed in depth. Finally, the application fields of traffic sign recognition were deeply explored. This review helps provide guidance and comprehensive information to researchers in this field.

Keywords: *Traffic sign recognition; Deep learning; Classification; Localization; Datasets*

1. INTRODUCTION

Traffic sign recognition is a very challenging and important task in the field of computer vision, which aims to enable computers to automatically recognize various traffic signs on the road [1]. The wide application of this technology covers intelligent driving [2], traffic supervision [3], navigation system [4] and many other fields. This is important for improving traffic safety, reducing the risk of accidents, optimizing traffic flow, and realizing intelligent traffic systems.

As an important way of conveying road information, traffic signs convey various information, such as speed limit, prohibition of passage, road instructions and warnings, etc. Different types of signs have their own unique shapes, colors and patterns, which are easy to understand and recognize for human drivers, but a challenging problem for computers. Therefore, the traffic sign recognition task needs to solve two core problems which are classification and localization [5].

In the field of traffic sign recognition, researchers have proposed many different methods and techniques. Early methods are mainly based on traditional image processing techniques such as edge detection [6], color segmentation and shape matching [7]. These methods need to manually design features and classifiers to realize sign recognition. However, due to the diversity and complexity of traffic signs, these methods have certain limitations in generalization ability.

With the development of machine learning technology, methods based on feature engineering and machine learning have been gradually applied. Researchers try to classify by designing more effective feature representations and combining them with machine learning algorithms. Common feature extraction methods include Histogram of Oriented Gradients (HOG) [8] and Scale Invariant Feature Transform (SIFT) [9]. While these methods perform well in some situations, they may not perform well for complex traffic signs and diverse environments.

In recent years, the development of deep learning technology has brought breakthroughs in traffic sign recognition. Using deep convolutional neural networks (CNNs), computers are able to automatically learn feature representations in images, leading to more accurate classification and localization of traffic signs. Deep learning methods no longer need to manually design features, but allow computers to learn advanced abstract features by themselves through large-scale data sets and powerful computing capabilities. AlexNet [10],

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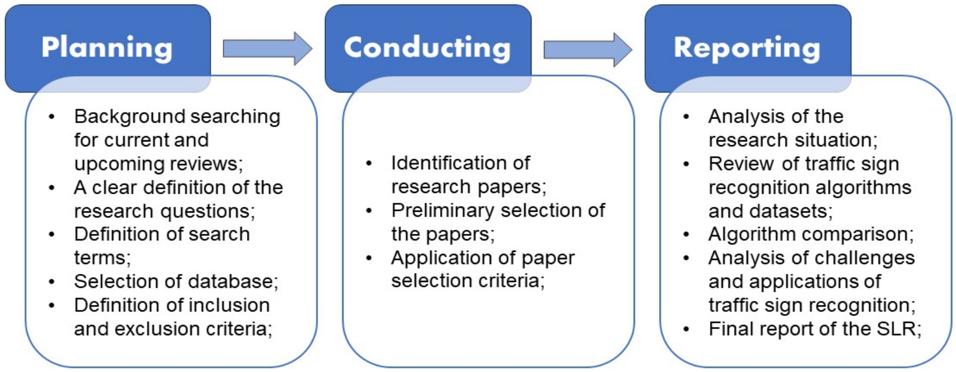

Figure 1: A systematic literature review process.

VGG [11], ResNet [12], MobileNet [13] and other network structures have achieved remarkable results in traffic sign recognition.

In the practical application of traffic sign recognition, object detection [14] and multi-task learning [15] are also involved. Sometimes, it is not enough to identify the category of the logo, but also need to precisely locate the location of the logo in the image. Object detection techniques, such as You Only Look Once (YOLO) [16] and Single Shot Multibox Detector (SSD) [17], can effectively solve this problem, achieving both classification and localization. Multi-task learning further improves the performance of traffic sign recognition. It combines traffic sign recognition with other related tasks, sharing feature representations to achieve complementary advantages in data utilization and model generalization performance. This approach has shown good results in real scenarios, improving the overall performance.

Datasets and data augmentation play a key role in traffic sign recognition. In order to train and evaluate traffic sign recognition algorithms, researchers have constructed multiple public datasets, such as German Traffic Sign Recognition Benchmark (GTSRB) [18], LISA Traffic Sign Dataset [19], etc. At the same time, data augmentation technology is also widely used. By performing transformations such as rotation, translation, scaling, and flipping on the original data, data samples are added to improve the robustness and generalization capabilities of the model.

Traffic sign recognition technology has been widely used in real scenes. With the continuous development of deep learning technology and the establishment of large-scale data sets, the accuracy and performance of traffic sign recognition can continue to improve.

The paper is structured as follows: Section 2 provides an in-depth analysis of the review methodology adopted. Section 3 discusses various algorithms for traffic sign recognition. Section 4 presents the dataset used in traffic sign recognition. Section 5 provides a comparative analysis of various algorithms, highlighting their advantages and disadvantages. Section 6 explores the challenges faced by traffic sign recognition algorithms. Section 7 discusses areas of practical application of these algorithms. Finally, Section 8 summarizes and answers the research questions.

2. REVIEW METHODOLOGY

This study extensively searched four authoritative databases, including IEEE Xplore, ScienceDirect, Scopus and Google Scholar. During the screening process, thirty-nine high-quality papers closely related to the research topic were finally selected. This paper proposes five in-depth research questions for traffic sign recognition to deepen the understanding of this field. Following the guidelines provided by Keele [20] (as shown in Figure 1), the three main steps of the literature review work were performed: planning, conducting and reporting. Each step covers a number of specific activities to ensure a comprehensive and in-depth understanding of the research area.

2.1 Research Questions

The main goal of this system evaluation is to delve into the field of traffic sign recognition. Based on this research background, the following research questions are proposed:

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RQ1: What traffic sign recognition algorithms are there?

Table 2: The description of the selected paper.

Author	Title	Year of publication
Ren et al. [21]	General traffic sign recognition by feature matching	2009
Creusen et al. [22]	Color exploitation in hog-based traffic sign detection	2010
Zhao et al. [23]	Real-time traffic sign detection using SURF features on FPGA	2013
Ardianto et al. [24]	Real-time traffic sign recognition using color segmentation and SVM	2017
Ellahyani et al. [25]	Traffic sign detection and recognition based on random forests	2016
Han et al. [26]	Robust traffic sign recognition with feature extraction and k-NN classification methods	2015
Meuter et al. [27]	A decision fusion and reasoning module for a traffic sign recognition system	2011
Perez-Perez et al. [28]	Principal component analysis for speed limit Traffic Sign Recognition	2013
Cao et al. [29]	Improved traffic sign detection and recognition algorithm for intelligent vehicles	2019
Niu [10]	Traffic light detection and recognition method based on YOLOv5s and AlexNet	2022
Zhou [11]	Improved VGG model for road traffic sign recognition	2018
Dubey [12]	Efficient traffic sign recognition using CLAHE-based image enhancement and ResNet CNN architectures	2021
Li et al. [30]	Traffic sign detection based on improved faster R-CNN for autonomous driving	2022
Lin et al. [31]	Transfer learning based traffic sign recognition using inception-v3 model	2019
Joze et al. [32]	MMTM: Multimodal transfer module for CNN fusion	2020
Lu et al. [33]	Traffic sign recognition via multi-modal tree-structure embedded multi-task learning	2016
Haque et al. [34]	DeepThin: A novel lightweight CNN architecture for traffic sign recognition without GPU requirements	2021
Ezzahra et al. [35]	Comparative Analysis of Transfer Learning-Based CNN Approaches for Recognition of Traffic Signs in Autonomous Vehicles	2023
Wang et al. [36]	Multiscale traffic sign detection method in complex environment based on YOLOv4	2022
Greenhalgh et al. [37]	Traffic sign recognition using MSER and random forests	2012
Xu et al. [38]	Traffic sign recognition based on weighted ELM and AdaBoost	2016
Aydin et al. [39]	Traffic sign recognition using scale invariant feature transform and bagging based ensemble	2016
Chen et al. [40]	Accurate and efficient traffic sign detection using discriminative adaboost and support vector regression	2015
Yildiz et al. [41]	Hybrid Image Improving and CNN (HIICNN) Stacking Ensemble Method for Traffic Sign Recognition	2023
Stallkamp [18]	The German traffic sign recognition benchmark: a multi-class classification competition	2011
Møgelmose [19]	Detection of US traffic signs	2015
Changzhen et al. [42]	A traffic sign detection algorithm based on deep convolutional neural network	2016
Temel et al. [43]	CURE-TSR: Challenging unreal and real environments for traffic sign recognition	2017
Noh et al. [44]	Better to follow, follow to be better: Towards precise supervision of feature super-resolution for small object detection	2019
Singla et al. [45]	Improved deterministic l2 robustness on CIFAR-10 and CIFAR-100	2021
Batool et al. [46]	iELMNet: integrating novel improved extreme learning machine and convolutional neural network model for traffic sign detection	2022
Ahmed et al. [47]	DFR-TSD: A deep learning based framework for robust traffic sign detection under challenging weather conditions	2021
Rehman et al. [48]	D-patches: effective traffic sign detection with occlusion handling	2017
Wang et al. [49]	Improved YOLOv5 network for real-time multi-scale traffic sign detection	2023
Ellahyani et al. [50]	Traffic sign detection for intelligent transportation systems: a survey	2021
Mogelmose et al. [51]	Vision-based traffic sign detection and analysis for intelligent driver assistance systems: Perspectives and survey	2012
Modi et al. [52]	A comprehensive review on intelligent traffic management using machine learning algorithms	2022
Arcos-García et al. [53]	Evaluation of deep neural networks for traffic sign detection systems	2018
Kim et al. [54]	Deep Learning-Based Real-Time Traffic Sign Recognition System for Urban Environments	2023

RQ2: What are the data sets used in traffic recognition algorithms?

RQ3: What are the advantages and disadvantages of each category of traffic recognition algorithms?

RQ4: What are the challenges faced by traffic sign recognition algorithms?

RQ5: What are the application areas of traffic sign recognition?

2.2 Study Identification and Selection

The search for this article used the phrase "traffic sign recognition" or "road sign recognition" or "traffic sign detection" or "traffic sign classification". EZAccess Portal (University Putra Malaysia Library database) and Google Scholar

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were chosen as search platforms. EZAccess Portal includes many well-known databases, such as IEEE Xplore, ScienceDirect, and Scopus, while Google

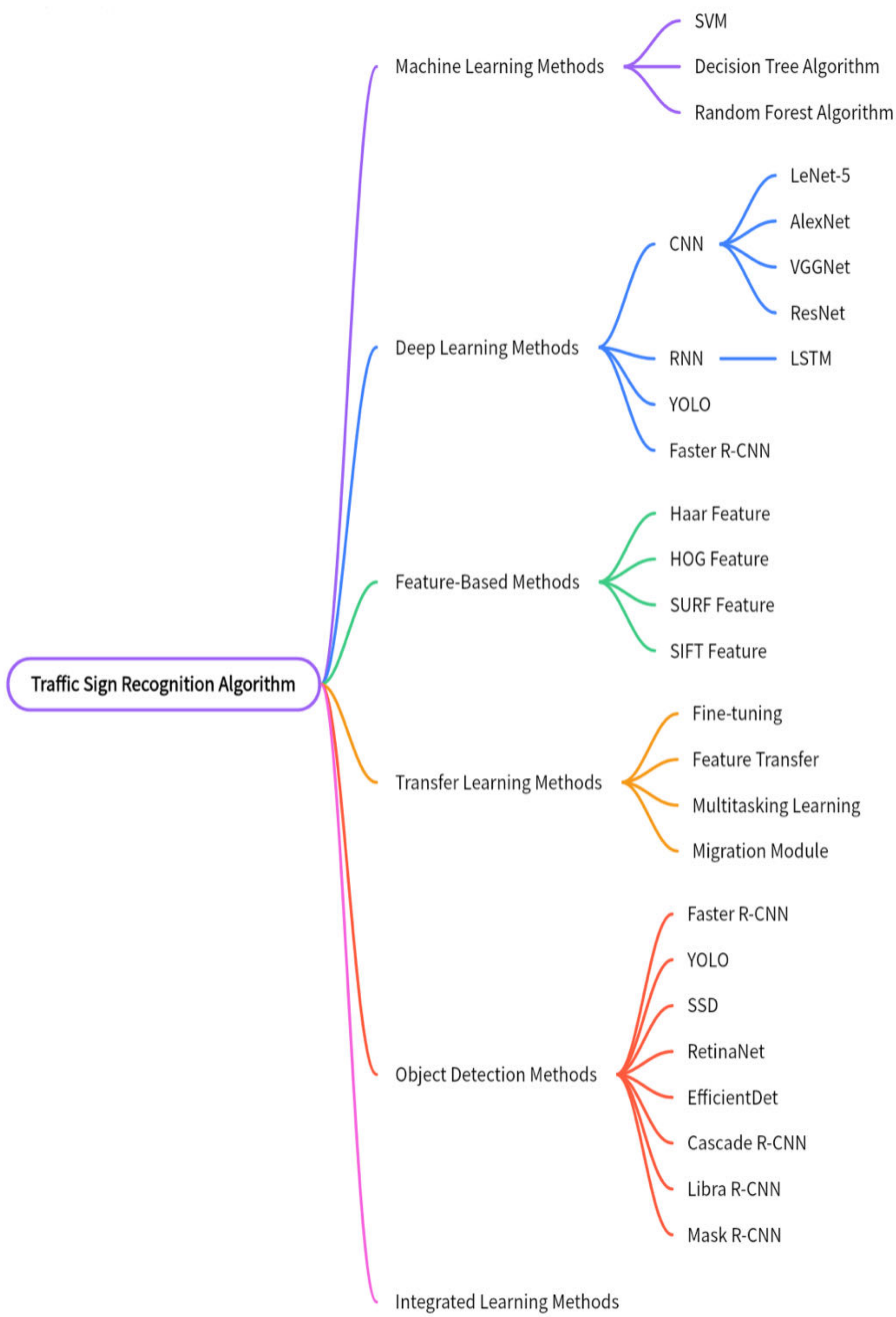

Figure 2: The FigureThe classification of traffic sign recognition algorithms.

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Scholar has a wide range of academic literature, making searching more convenient. Based on the search for the above phrases, a total of 36,769 papers were obtained. Table 1 shows the distribution of papers in each database. After excluding duplicate, irrelevant, low-quality, and non-English-written papers, 39 papers were selected for detailed review. The selected papers are shown in Table 2.

Table 1: The number of papers retrieved from each database.

Database	Number of papers
IEEE Xplore	1255
Science Direct	14792
Scopus	2722
Google Scholar	18000

3. TRAFFIC SIGN RECOGNITION ALGORITHM

As shown in Figure 2, traffic sign recognition algorithms cover a wide range of technical means, including machine learning algorithms, deep learning algorithms, feature-based methods, transfer learning methods, target detection methods, and integrated learning methods. To answer RQ1, the next few sections will provide an in-depth review of these algorithms to fully understand their application and performance in the field of traffic sign recognition.

3.1 Feature-Based Methods

Feature-based traffic sign recognition is a traditional computer vision method that relies on pre-defined image features to detect and recognize traffic signs. These characteristics can be attributes such as shape, color, texture, etc. that distinguish different signs. The following are the main features and steps of this method:

1. Feature Extraction: First, discriminative features are extracted from the input image. This can include edge detection, color histograms, texture features, etc. These features are used to describe different aspects of traffic signs in images.

2. Feature matching: The extracted features are compared and matched with known traffic sign features. Classifiers or similarity measures are often used to determine whether a feature in an image matches a certain traffic sign.

3. Decision-making: Based on the result of feature matching, the system can make a decision, i.e. identify the type of traffic sign in the image.

4. Post-processing: Some post-processing steps can be applied, such as removing noise or correcting the orientation of landmarks, to improve the accuracy of recognition.

Traffic signs usually have a specific color. The method based on color features is to use image processing technology to extract the color features of traffic signs, and then classify the signs according to the color features [55].

Traffic signs usually have specific shapes, such as circles, triangles, rectangles, etc. Shape features can be extracted by edge detection and shape matching techniques. This approach usually requires traffic signs to have distinct edges and shapes in the image. In addition, patterns and textures on traffic signs can be used for identification. These features can be extracted by techniques such as Local Binary Patterns (LBP) [56]. LBP analyzes the gray level variation around the pixels, so it can capture the texture information. Ren [21] proposed a traffic sign recognition method, using a feature matching strategy. Based on feature extraction and matching, the method first extracts key feature points of traffic sign images, and then uses these feature points to match sign images in a sign library. By feature matching the image with candidate signs in the sign library, this method can realize the recognition of universal traffic signs.

Haar feature is a method for image feature extraction, especially suitable for target detection tasks, originally used for face detection [57]. It extracts local features of the image by sliding a series of rectangular filters of different sizes and shapes on the image. Haar features are often used in strong classifiers such as Adaboost to distinguish objects from background or different object categories. Histogram of Oriented Gradients (HOG) feature is a feature extraction method widely used in object detection and image recognition in the field of computer vision [58]. The HOG feature is to describe the texture and shape features of the image by analyzing the local gradient direction of the image. It outperforms conventional color and texture features in some scenarios. In traffic sign recognition, HOG features can be used to help detect and identify traffic signs. Creusen [22] proposed HOG based traffic sign detection method that focuses on utilizing color information to enhance detection performance. This method improves the accuracy of traffic sign detection by combining HOG features and color information.

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The main contribution is the introduction of color features based on HOG features, thereby enhancing the robustness and efficiency of traffic sign detection.

Traffic sign recognition based on the Speeded-Up Robust Features (SURF Feature) method [59] is a computer vision application that uses SURF technology to quickly and robustly extract key feature points from road images, and then compares the descriptors of these feature points with existing Traffic sign templates are matched to achieve automatic detection and recognition of traffic signs. Zhao [23] proposed a real-time traffic sign detection method based on SURF features and implemented it on the FPGA hardware platform. This method uses SURF technology to quickly extract key feature points in the image, and matches the descriptors of the feature points with the traffic sign template to achieve instant detection of traffic signs. By transplanting the algorithm to FPGA hardware, high-performance real-time processing is realized, which is suitable for traffic monitoring and automatic driving applications requiring low latency.

Table 3: Comparison of traffic sign recognition algorithms based on feature methods.

Method	Feature	Technique
Color feature [55]	Color histogram, color space	Detect and classify based on color information.
Texture feature [60]	Texture descriptor, LBP	Matching and classification based on shape features.
Shape feature [61]	Edge and contour features	Recognition based on the characteristics of the surface texture of the sign.
Haar Feature [62]	Brightness change	Slide a series of rectangular filters of different sizes and shapes on the image to extract local features of the image.
HOG Feature [22]	Gradient Orientation Histogram	Calculate the gradient orientation histogram of the pixels in each cell.
SURF Feature [59]	Feature descriptor	Image matching using feature descriptors.
SIFT Feature [63]	Feature descriptor	Image matching using feature descriptors.

Feature-based methods usually require careful design and tuning of feature extractors, and are sensitive to factors such as lighting conditions, rotation, and scale changes. However, they are still effective in some cases, especially when training data is limited or computing resources are limited. Table 3 compares several common traffic sign recognition algorithms based on feature methods. However, with the development of deep learning technology, the application of feature-based methods in traffic sign recognition is gradually replaced by deep learning methods, because deep learning can automatically learn image features and perform well in a wider range of conditions.

3.2 Machine Learning Methods

Support Vector Machine (SVM) is a binary classification algorithm that separates data points of different classes by finding a hyperplane in the feature space. In traffic sign recognition, SVM can be used to learn the features of signs and perform classification based on these features [64]. Ardianto [24] proposed a real-time traffic sign recognition method that combines color segmentation and SVM. First, rely on color segmentation technology to separate the traffic sign area in the image from the background for more accurate recognition. Then, use the support vector machine as a classifier to classify and recognize the extracted traffic sign images. This method enables fast and accurate recognition of traffic signs in real-time situations, which can be applied in traffic management and driver assistance systems.

Random forest is an ensemble learning method that classifies by building multiple decision trees and voting [65]. Each tree is trained on randomly selected training data and feature subsets to improve the generalization ability of the model. Ellahyani [25] proposed a random forest based traffic sign detection and recognition method. By applying the random forest algorithm, this method achieves efficient detection and accurate recognition of traffic signs. The researchers distinguished traffic sign regions in images from the background, enabling efficient sign detection. Subsequently, the random forest model is used to identify the signs, which can handle a variety of sign types and has strong generalization ability. The innovation of this method is that it combines the advantages of random forest and provides an effective solution for traffic sign processing.

The k-Nearest Neighbors (k-NN) algorithm selects the k nearest neighbor training samples according to the distance between the samples to be classified and the training samples, and then predicts the category of the samples to be classified according to the categories of these neighbors [66].

Han [26] proposes a robust traffic sign recognition method that combines feature extraction and k-NN classification techniques. Researchers first perform feature extraction to extract key information from traffic sign images to represent the characteristics of different signs. Then, the extracted features are classified by k-NN classification method, and the category of traffic signs is determined by comparing with the nearest neighbor samples. This method can achieve robust sign recognition in complex scenes, and has certain adaptability and generalization ability.

Table 4: Comparison of traffic sign recognition algorithms based on machine learning.

Method	Data Set	Feature	Accuracy	Precision	Recall	Test Time
SVM [24]	GTSRB	HOG	97.4%	—	—	1.26ms
	GTSRB	Gabor	94.9%	—	—	0.79ms
Random forest [25]	GTSDB	HSI-HOG+LSS	—	90.13%	91.07%	—
	STS	HSI-HOG+LSS	—	90.27%	93.27%	—

Decision tree is a method of classification by a series of feature tests [67]. Each node represents a feature test, and different branches are selected according to the result of the feature test until a leaf node is reached and a category is assigned. Meuter [27] proposes a decision fusion and reasoning module for a traffic sign recognition system. This module aims to improve the accuracy and reliability of traffic sign recognition systems. Researchers achieve more credible recognition results by fusing different recognition decision results. This method also introduces an inference mechanism to perform inference based on the outputs of different recognition modules, thereby further improving the recognition performance of signs in complex traffic environments.

Principal Component Analysis (PCA) is a dimensionality reduction technique that reduces high-dimensional image data to a low-dimensional space, thereby reducing the number of features while retaining the most important information [68]. Perez-Perez [28] proposed use of PCA technology to perform dimensionality reduction and feature extraction on traffic sign images to reduce the dimensionality of features and capture key information. Traffic signs can be recognized more effectively through the features after dimensionality reduction. This method aims to improve the performance of speed limit traffic sign recognition.

Table 5: Running time of two machine learning algorithms with different features.

Feature	Run time (ms)	
	SVM	Random forest
HOG	46.18	21.24
HSI-HOG	51.96	28.51
HSI-HOG+LBP	53.87	29.75
HSI-HOG+LSS	53.12	28.93

In this section, a traffic sign recognition algorithm based on machine learning is introduced. Table 4 compares traffic identification algorithms based on SVM and random forest. In addition, as shown in Table 5: Ellahyani [25] compares the running time of SVM and random forest under different characteristics. This can provide a reference for future researchers.

3.3 Deep Learning Methods

CNN is one of the earliest and most successful deep learning methods applied to image recognition. Relying on convolution and pooling operations, CNN can extract abstract features from images, thereby realizing the distinction of different traffic signs. LeNet-5-based traffic sign recognition is a classic method that uses the LeNet-5 architecture for the classification of traffic sign images. LeNet-5 is an early convolutional neural network, first designed by LeCun et al. [69] in 1998 for handwritten digit recognition, but it can also be applied to traffic sign recognition. Cao [29] proposed an improved intelligent vehicle traffic sign detection and recognition algorithm, aiming to deal with the problems that traditional detection methods are susceptible to environmental interference and deep learning methods have poor real-time performance. This method effectively detects the shape features of traffic signs by using HSV color space for spatial threshold segmentation. At the same time, the LeNet-5 convolutional neural network model is improved, using Gabor kernel, batch normalization and Adam optimization algorithm to improve performance. The experiment was conducted based on the German traffic sign recognition benchmark. The results showed that the traffic sign recognition rate of this algorithm reached 99.75%, and the processing time of each frame was 5.4 milliseconds. Compared with other methods, this algorithm performs well in terms of accuracy, real-time performance, generalization ability and training efficiency.

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AlexNet is a deep convolutional neural network designed by Krizhevsky et al. [70] in 2012. AlexNet's architecture employs multiple layers of convolution and pooling layers, and introduces a rectified linear unit (ReLU), enabling the network to learn rich image features. Through techniques such as data parallel training and dropout, AlexNet successfully reduces the error rate of large-scale image classification tasks. YOLO (You Only Look Once) is an advanced real-time object detection algorithm that simultaneously completes object location and classification in a single feedforward neural network, which is faster and more accurate than traditional methods [71]. YOLO divides an image into grids and predicts bounding boxes and class probabilities for each grid, making it suitable for multi-object detection. Its speed and performance make it widely used in autonomous driving, video surveillance, object recognition, and other fields. Different versions of YOLO (such as YOLOv3 [72], and YOLOv4 [73]) have continuously improved accuracy and speed, making it an important tool in the field of object detection. Niu [10] proposed a traffic light detection and recognition method based on the combination of YOLOv5s and AlexNet. This method uses YOLOv5s for real-time traffic light detection, and then classifies and recognizes the detected traffic lights through the AlexNet deep learning model to achieve accurate detection and recognition of different types of traffic lights. Experimental results show that this method has efficient performance and can detect and recognize traffic lights quickly and accurately in complex traffic scenes.

Visual Geometry Group (VGG) is a deep convolutional neural network architecture [74]. It uses multi-layer convolution and pooling layers to extract features in the image, and then classifies them through fully connected layers. VGG has achieved outstanding performance in image classification tasks due to its depth and scalability. Its different versions, such as VGG16 [75] and VGG19 [76], differ in the depth of the network, and the appropriate version can be selected according to the requirements of the task. Zhou [11] proposed an improved VGG model for road traffic sign recognition. This method improves the recognition performance of traffic signs by optimizing the VGG model, including adding convolutional layers and adjusting the network structure. In addition, data augmentation techniques are used to increase the training data, thereby further improving the robustness of the model. Experimental results show that this improved VGG model exhibits higher accuracy and robustness in the task of traffic sign recognition.

Residual Neural Network (ResNet) [77] is a deep convolutional neural network architecture. Its innovation lies in the introduction of the concept of residual learning, which allows the network to train very deep layers more easily. ResNet transfers information by adding shortcut connections in the network, which allow the gradient to backpropagate more easily, effectively solving the problem of gradient disappearance in deep networks. With this innovation, ResNet can train a deeper neural network than before, further improving the performance in computer vision tasks such as image classification and target detection. Dubey [12] proposed an efficient traffic sign recognition method using CLAHE (Contrast Limited Adaptive Histogram Equalization) image enhancement technology and ResNet deep convolutional neural network structure. This method first enhances the contrast of the input image through CLAHE, and then uses the ResNet deep convolutional neural network to classify and recognize traffic signs. This approach improves the accuracy and robustness of traffic sign recognition.

Recurrent neural network (RNN) is a deep learning neural network architecture with memory and context awareness capabilities [78]. The neurons of the RNN can accept the input information of the previous time step and pass its hidden state to the next time step through the recurrent connection. This loop structure endows RNN with the ability to process time series data, but there are also problems such as gradient disappearance and gradient explosion. Therefore, improved RNN variants, such as long short-term memory network (LSTM) [79] and gated recurrent unit (GRU) [80], have emerged to solve these problems. Faster R-CNN is an efficient object detection algorithm, which is a convolutional neural network architecture for detecting objects in images and locating their locations [81]. Compared with the traditional R-CNN method, Faster R-CNN introduces a mechanism called Region Proposal Network (RPN), which can efficiently generate candidate object regions and then classify these candidate regions and position regression. The main advantage of Faster R-CNN is its speed and accuracy. With RPN, it is able to perform object detection end-to-end without multiple stages of processing. Li [30] proposed an improved Faster R-CNN algorithm aimed at improving traffic sign detection performance in autonomous driving. The researchers optimized Faster R-CNN to more

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accurately detect and recognize traffic signs on the road, especially for autonomous driving scenarios. This improved approach is expected to enhance the visual perception capabilities of autonomous driving systems, improving the accuracy and robustness to traffic signs. Table 6 compares several common traffic sign recognition algorithms based on deep learning.

Table 6: Comparison of traffic sign recognition algorithms based on deep learning.

Method	Network Structure	Data Set	Accuracy	Precision	Advantage
LeNet-5 [29]	CNN	GTSRB	99.75%	—	It has fewer parameters and good feature extraction capabilities.
AlexNet [10]	CNN	—	87.8%	—	Use multi-layer convolution, pooling layer, and dropout regularization.
VGG [11]	CNN	GTSRB	—	99.0%	Simple and deep CNN architecture.
ResNet [12]	Residual network	GTSRB	98.6%	—	The deep network degradation problem is solved.

3.4 Transfer Learning Methods

Transfer Learning is a machine learning method that uses the knowledge or model that has been learned and the parameters and features of the model trained on one task (source task) to improve another related task (target task) performance [82]. The goal of transfer learning is to transfer the knowledge of the source task to the target task in order to obtain better performance on the target task, reduce data requirements, and improve the generalization ability of the model. Transfer learning has wide applications in traffic sign recognition tasks and can improve the performance and robustness of models, especially when data is limited. Fine-tuning is a common strategy in transfer learning, where the weights of a pre-trained model are loaded into the model and then supervised fine-tuning is performed on the target task data [83]. Fine-tuning can help the model adapt to specific characteristics of traffic sign data. Lin [31] proposed a traffic sign recognition method based on transfer learning, using the Inception-v3 model. The method first uses Inception-v3 to pre-train on large-scale image data, and then transfers it to the traffic sign recognition task. By fine-tuning the model, the weights of the pre-trained model are adapted to traffic sign data to improve recognition performance. Experimental results show that this method shows good performance in traffic sign recognition.

Feature transfer is a common transfer learning method in traffic sign recognition. It can improve traffic sign recognition performance by applying feature knowledge extracted from the source task to the target task. The advantage of feature transfer is that it can reduce the need for large amounts of labeled data for the target task, because feature extraction usually requires a smaller amount of source task data, and these features are shared between different tasks [84]. This enables traffic sign recognition to achieve good results even with limited data, and helps the model converge faster on new tasks. The traffic sign recognition method proposed by Joze [32] uses transfer learning and CNN models. This method uses pre-trained CNN models and applies these models to traffic sign recognition tasks through fine-tuning or feature extraction. Experimental results show that this method based on transfer learning shows good performance in traffic sign recognition.

Multi-task learning can be used to handle multiple related tasks, improving the performance and efficiency of the model [85]. The advantage of multi-task learning is that it can improve the generalization performance of the model and improve the accuracy of traffic sign recognition while reducing data requirements because knowledge can be shared between different tasks. In addition, it also helps the model to better handle complex traffic sign scenarios, such as recognizing sign type and location at the same time. Lu [33] proposed a traffic sign recognition method that uses Multi-Modal Tree-Structure Embedded Multi-Task Learning. The method utilizes multimodal data (images and videos) for training, and simultaneously processes multiple related traffic sign recognition tasks through tree-structured nested multi-task learning, thereby improving the performance of traffic sign recognition. This method effectively utilizes the correlation between multi-modal information and tasks to improve the accuracy and robustness of the model through shared features and knowledge transfer.

Transfer modules can be combined and adjusted according to specific task requirements and transfer learning strategies to build an efficient transfer learning system [32]. This helps the model better utilize existing knowledge in new tasks or domains, improving performance, generalization capabilities, and data efficiency. Haque [34] proposed a

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lightweight CNN architecture called DeepThin for traffic sign recognition, which is characterized by not requiring a GPU for inference. DeepThin aims to solve the challenge of traffic sign recognition in resource-limited environments. Through carefully designed network structure and parameter optimization, it achieves efficient and accurate sign recognition and is suitable for application scenarios with limited computing resources. As shown in Table 7, Ezzahra [35] compares different migration models. This comparison uses two commonly used metrics, accuracy training (Train-accuracy) and accuracy test (Val-Accuracy), to evaluate the performance of each model. This study can provide a reference for other researchers on traffic sign recognition based on transfer learning.

Table 7: Performance comparison of different migration models.

Model	Original Task	Target Data Set	Train-accuracy	Val-accuracy
VGGNet16	ImageNet	GTSRB	0.9426%	0.7132%
VGGNet19	ImageNet	GTSRB	0.9142%	0.6572%
ResNet50	ImageNet	GTSRB	0.5258%	0.4724%
ResNet101	ImageNet	GTSRB	0.6450%	0.4946%
MobileNetV2	ImageNet	GTSRB	0.9796%	0.7760%
MobileNetV3	ImageNet	GTSRB	0.5345%	0.3343%

3.5 Object Detection Methods

The target detection method achieves accurate detection and identification of the location and category of traffic signs in images or videos by training deep learning models. Li [30] proposed a traffic sign detection method based on improved Faster R-CNN for autonomous driving applications. The improved Faster R-CNN model adopts a series of optimization strategies, including introducing a more effective backbone network, adjusting the anchor box size and aspect ratio, and adopting an enhanced loss function design to improve traffic sign detection performance. Experimental results show that this method can detect traffic signs efficiently and accurately in autonomous driving scenarios. Wang [36] proposed a multi-scale traffic sign detection method based on YOLOv4, which aims to deal with the problem of traffic sign detection in complex environments. This method uses YOLOv4 as the basic target detection model, and improves the detection performance of traffic signs through a multi-scale strategy. First preprocess the input image, and then use the YOLOv4 model to detect traffic signs at different scales. To improve detection accuracy, a joint loss function is also introduced that combines classification loss and bounding box regression loss. Experimental results show that this method shows good traffic sign detection performance in complex environments.

3.6 Integrated Learning Methods

In traffic sign recognition, ensemble learning methods are widely used to improve classification performance and robustness. Random forest is an ensemble learning method based on decision trees, which can be used for traffic sign recognition in images [86]. Multiple decision trees are trained on different subsamples, and then their results are integrated to improve classification performance. For traffic sign recognition, each decision tree can focus specifically on a different type of sign. Greenhalgh [37] proposed a traffic sign recognition method, which uses Maximally Stable Extremal Regions (MSER) to detect traffic sign candidate areas in the image, and uses random forest as a classifier. Through the effective feature extraction of MSER and the ensemble learning of random forest, the method can efficiently detect and recognize traffic signs with robustness and accuracy, and is suitable for practical traffic sign recognition applications.

The adaptive boosting algorithm (Adaboost) is an iterative ensemble learning method that trains multiple weak classifiers by adjusting the weights of training samples and then combines them into a strong classifier [87]. In traffic sign recognition, Adaboost can be used to combine multiple features or classifiers to improve the accuracy of sign recognition. Xu [38] proposed a traffic sign recognition method that combines weighted extreme learning machine (ELM) and AdaBoost. It uses ELM as the base classifier and weights the output of different classifiers through AdaBoost to improve the recognition performance of traffic signs. This method effectively utilizes the high speed and high performance of ELM while enhancing the classification results through the trade-off mechanism of AdaBoost, making it suitable for robust and accurate recognition of traffic signs.

Bagging is a method of building multiple classifiers through bootstrap sampling and voting or

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averaging their results [88]. In traffic sign recognition, bagging can be used to train different classifiers, such as support vector machines (SVM) or neural networks, and then integrate their outputs to obtain more robust classification results. Aydin [39] proposed a traffic sign recognition method that uses Scale Invariant Feature Transform (SIFT) for feature extraction, and then applies a strategy based on Bagging ensemble learning to improve classification performance. SIFT is used to detect and describe feature points in traffic signs, and then Bagging integrates multiple classifiers to obtain more reliable traffic sign recognition results. This method achieves robust recognition of traffic signs at different scales and angles.

Table 8: Comparison of traffic sign recognition algorithms based on ensemble methods.

Method	Basic Classifier	Integration Method	Data Set	Accuracy	Precision	Recall	F1-Score
Random Forest Ensemble [37]	Decision tree	Random forest	GTSRB	83.33%	—	87.72%	0.85
AdaBoost Ensemble [40]	Decision tree	AdaBoost	STSD [91]	—	94.52%	80.85	—
Stacking Ensemble [41]	Various	Stack learning	GTSRB	—	99.63%	99.62%	99.62%

Boosting is a type of integrated learning method, including Adaboost [89]. They iteratively train a series of weak classifiers and adjust the weights of samples according to their performance. Boosting methods can improve performance in traffic sign recognition and pay more attention to misclassified samples to improve classification results. Chen [40] proposed an accurate and efficient traffic sign detection technique by combining AdaBoost and support vector regression (SVR) for discriminative detector learning. Different from previous traffic sign detection techniques, a novel saliency estimation method is proposed for the first time, in which a new saliency model is constructed based on the color, shape and spatial information of traffic signs. By introducing saliency information, an enhanced feature pyramid is constructed and used to learn an AdaBoost model to detect a set of traffic sign candidate regions from images. Then, a novel iterative codebook selection algorithm is designed to represent the sign candidate regions detected by AdaBoost, while an SVR model is learned to recognize real traffic signs. Experiments on three public datasets demonstrate that the proposed traffic sign detection technique is robust and achieves superior accuracy and efficiency. Gradient Boosting Ensemble is a method to build a powerful ensemble model by combining multiple weak learners.

Stacking Ensemble is a method that takes the output of different base classifiers as input and then trains a meta-classifier to combine them [90]. In traffic sign recognition, stacked ensembles can be used to combine different types of feature extractors or classifiers to get more accurate results. Yildiz [41] proposed a traffic sign recognition method named Hybrid Image Improving and CNN (HIICNN) Stacking Ensemble Method. This method employs a hybrid image enhancement strategy to improve the quality and clarity of traffic sign images, thereby enhancing the subsequent recognition performance. CNN is then used as the basic classifier to combine multiple CNN models into a stacked ensemble model to further improve the recognition performance. This ensemble method can effectively capture the diversity among different CNN models, thereby improving the overall recognition accuracy. Finally, the effectiveness of the HIICNN method in traffic sign recognition tasks is verified by experiments, showing that it has the potential to improve recognition performance and can be applied in actual traffic scenarios. Table 8 compares several common traffic sign recognition algorithms based on ensemble learning.

4. TRAFFIC SIGN RECOGNITION DATASET

The traffic sign recognition dataset is a collection of traffic sign recognition models used for training and evaluation, usually including traffic sign images of different types, shapes and scenes. These datasets are crucial for the research and development of traffic sign recognition algorithms, as they provide rich data samples that help models better understand and classify different traffic signs. To answer RQ2, Some common traffic sign recognition data sets are listed:

1. German Traffic Sign Recognition Benchmark (GTSRB) [18];
2. LISA Traffic Sign Dataset [19];
3. Belgium traffic signs dataset (BelgiumTS) [42];
4. CURE-TSR [43];
5. Tsinghua-Tencent 100K (TT100K) [44];
6. CIFAR-10 and CIFAR-100 [45];
7. Chinese Traffic Sign Database (CTSDB) [46].

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When performing traffic sign recognition tasks, you can choose from several different datasets, and determine the most suitable dataset according to task requirements and model design. The GTSRB datasets all provide a relatively large amount of data, but the number of sign categories is relatively small. In contrast, the LISA Traffic Sign Dataset and BelgiumTS cover more sign categories, but their data volume is relatively small.

It should be noted that the image resolution provided by the LISA Traffic Sign Dataset is 64x64, which may affect the performance of the model in some cases, because lower resolution may cause information loss. While the image resolution of other datasets may vary depending on the data source and purpose. All these datasets are derived from real-world traffic signs, so they can well reflect the situation in practical applications, thus contributing to the generalization ability of the model in the real environment.

Table 9: Comparison of commonly used traffic sign recognition datasets.

Name	The amount of data	Number of traffic sign categories	Image Resolution	Data Sources	The balance of data distribution
GTSRB	50000+	43	different	Actual road in Germany	unbalanced
LISA Traffic Sign Dataset	7000+	47	64×64	Real way	—
BelgiumTS	10000+	62	different	Belgium actual road	Balanced
CURE-TSR	1700000+	14	different	—	—
TT100K	100000+	128	32×32	China's actual road	—
CIFAR-10 and CIFAR-100	60000	10（CIFAR-10）, 100（CIFAR-100）	different	General Image Dataset	Balanced
CTSDB	4170	58	different	China's actual road	—

Table 10: Comparison of the advantages and disadvantages of different types of traffic sign recognition algorithms.

Algorithm type	Typical algorithm	Advantage	Disadvantages
Traditional method	Color feature [55] Texture feature [60] Shape feature [61] Haar Feature [62] HOG Feature [22] SURF Feature [59] SIFT Feature [63]	(1) The training speed is relatively fast. (2) Performs well on small-scale data sets.	(1) Sensitive to changes in lighting and viewing angle. (2) It requires manual design of features and is not adaptive enough.
Deep learning methods	LeNet-5 [29] AlexNet [10] VGG [11] ResNet [12]	(1) It can automatically learn feature representations, reducing the need for manual design. (2) Better performance can usually be obtained on large-scale data sets.	(1) Training time is relatively long, especially on large deep networks. (2) It relies heavily on a large amount of annotated data.
Fusion method	Random Forest Ensemble [37] AdaBoost Ensemble [40] Stacking Ensemble [41]	(1) The advantages of the two methods can be combined to improve performance. (2) Still performs well on relatively small data sets.	Algorithm complexity is high

In addition, the balance of data distribution is also one of the factors that need to be considered when selecting a data set. An unbalanced data distribution can cause a model to favor classes that occur more frequently, ignoring others. GTSRB has unbalanced data distribution, which may require special handling methods, such as sample resampling or using loss functions for unbalanced data. In contrast, BelgiumTS and CIFAR-10 and CIFAR-100 are more balanced in the signature categories. Table 9 compares the traffic sign recognition data sets mentioned above.

Therefore, when selecting a data set suitable for traffic sign recognition tasks, it is necessary to comprehensively consider factors such as data volume, number of sign categories, image resolution, and data distribution balance. According to the specific requirements of the task and the

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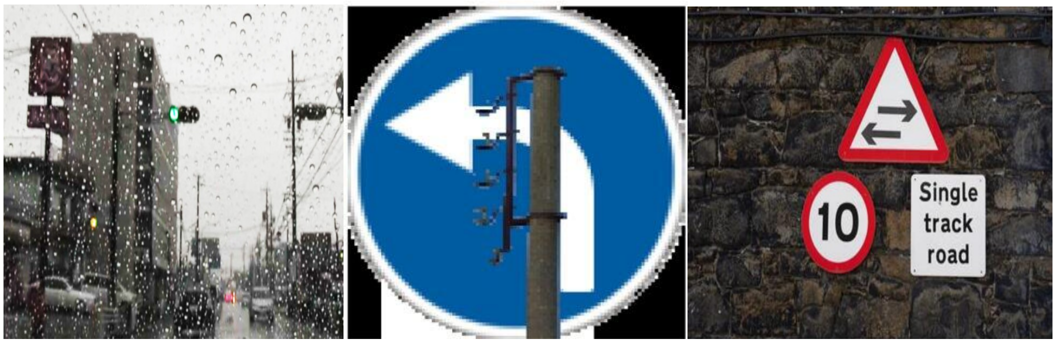
model design adopted, a reasonable choice is made to achieve the best recognition effect.

5. COMPARISON OF DIFFERENT TYPES OF ALGORITHMS

Traffic sign recognition involves a variety of algorithms and methods, which can be based on traditional computer vision technology or use deep learning methods. To answer RQ3, Table 10 compares different types of traffic sign recognition algorithms and their advantages and disadvantages.

6. CHALLENGES OF TRAFFIC SIGN RECOGNITION ALGORITHMS

To answer RQ4, Figure 3 shows that traffic sign recognition algorithms face many challenges.



(a) *(b)* *(c)*

Figure 3: Factors affecting traffic sign recognition algorithms. (a) weather, (b) occlusion, (c) multi sign.

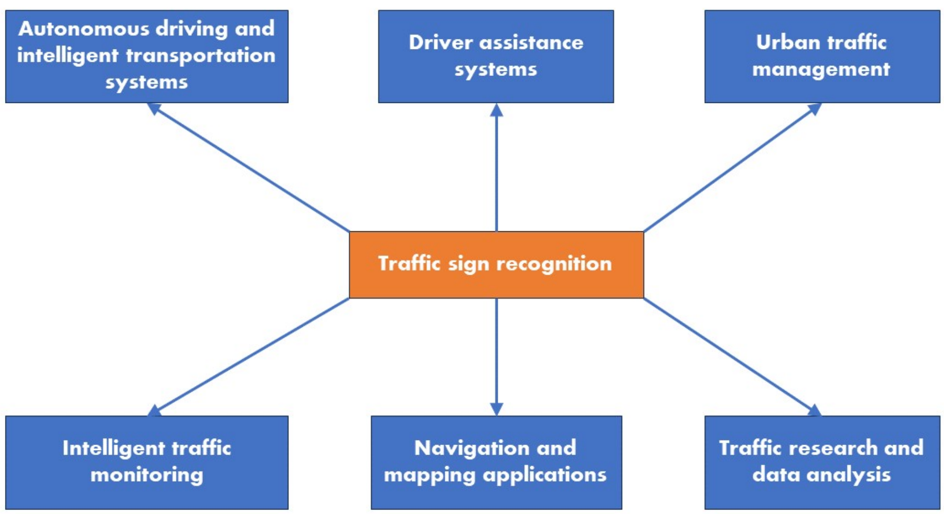


Figure 4: Application areas of traffic sign recognition.

Changes in weather, time of day, and location can cause traffic signs to appear differently in images. Strong sunlight, shadows, or low-light conditions at night may affect the performance of the algorithm, so the algorithm needs to be adaptable to different lighting conditions. Ahmed [47] proposes a TSDR framework based on prior-augmented convolutional neural networks. The framework includes a CNN-based challenge classifier, Enhance-Net, and two independent CNN architectures for symbol detection and classification. This method can handle challenging meteorological conditions, such as rainy and snowy days. Experimental results show that this method has improved the overall precision and recall rate by 7.58% and 35.90% respectively, which has significant advantages over other methods.

In actual traffic scenarios, traffic signs may be partially obscured by other vehicles, buildings or road facilities, or only part of the sign may be visible. It is quite a challenging task for algorithms to accurately identify signs when they are partially visible or occluded. Rehman [48] proposes a new traffic sign detection framework called discriminative patches (d-patches), which utilizes the most discriminative feature areas of objects for training and classification to improve performance.

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Experimental results show that this method improves the detection accuracy by 4.0% compared to other well-known methods on the Korean traffic sign data set.

In traffic scenarios, fast and accurate recognition of traffic signs is crucial for real-time decision-making, especially in systems such as autonomous driving. Therefore, algorithms need to achieve real-time performance while processing images efficiently. Wang [49] proposed that traditional feature pyramids have difficulties in solving the problem of scale changes, because the diversity of traffic sign sizes leads to inaccuracy in feature map extraction, affecting the feature consistency between traffic signs. An improved feature pyramid model AF-FPN is proposed, which adopts adaptive attention module (AAM) and feature enhancement module (FEM) to reduce information loss and enhance the representation ability of feature pyramid. Experimental results show that on the TT100K data set, this method is more versatile and superior than several state-of-the-art methods. It not only improves the detection performance of multi-scale targets, but also ensures the real-time performance of detection.

In addition, in some scenes, multiple traffic signs may exist in the image at the same time, or even overlap. Therefore, the algorithm needs to have an effective ability to accurately distinguish and identify multiple signs in an image to ensure a correct understanding of the combination of traffic signs in the image. It is worth noting that different countries and regions adopt unique logo design standards, including differences in shape, color, symbols and text. This diversity requires the algorithm to be able to adapt to a variety of logo appearances and structures, not just logos targeting a single design standard.

7. APPLICATION FIELD

To answer RQ5, Figure 4 shows the wide range of application areas for traffic sign recognition. In terms of autonomous driving, traffic sign recognition can help vehicles recognize traffic signs, thereby achieving the purpose of convenient and standardized driving [50]. Traffic sign recognition can also be embedded in the driver's assistance system to provide the driver with real-time information during vehicle driving, thereby reducing the rate of traffic accidents [51]. In addition, traffic sign recognition plays a huge role in urban traffic management, helping traffic management departments to control traffic flow and improve traffic efficiency. Traffic sign recognition technology is often used in traffic surveillance cameras in intelligent traffic monitoring to help law enforcers monitor traffic violations [50]. Traffic sign recognition technology can also be used to improve navigation and map applications, making it easier for users to find the correct route and obey traffic rules [53]. Collecting and analyzing traffic sign data can help urban planners better understand traffic patterns and trends to better plan urban infrastructure and transportation policies [54].

8. CONCLUSIONS

This study conducts an in-depth analysis of 39 papers related to traffic sign recognition, and comprehensively reviews various algorithms and popular data sets. At the same time, the advantages and disadvantages of these algorithms are compared in detail. After examining various challenges faced in the field of traffic sign recognition, this study further summarizes the wide range of practical application scenarios of traffic sign recognition.

8.1 Answer of Five Research Questions

After concluding the review of this article, the five research questions raised in Part 2 are answered.

RQ1: What traffic sign recognition algorithms are there?

Traffic sign recognition algorithms cover a variety of methods. Machine learning methods rely on traditional techniques such as support vector machines and decision trees, which are trained by manually designing features. Deep learning methods use deep models such as convolutional neural networks to automatically learn image features and significantly improve recognition performance. Feature-based methods focus on pre-defined image features, such as shape and color, to achieve traffic sign classification. Transfer learning uses knowledge learned on one task to improve performance on another related task. The target detection method can not only identify the sign category, but also calibrate its location, using algorithms such as R-CNN, Fast R-CNN and SSD. Finally, ensemble learning improves overall performance, reduces errors, and enhances algorithm robustness and accuracy by integrating the output of multiple classifiers. These methods together constitute a rich and diverse traffic sign recognition technology system.

RQ2: What are the data sets used in traffic recognition algorithms?

The traffic sign recognition algorithm uses multiple data sets during its research and evaluation process, including GTSRB, LISA Traffic Sign

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Dataset, BelgiumTS, CURE-TSR, TT100K, CIFAR-10 and CIFAR-100, and CTSDB. These datasets cover a rich set of traffic sign images with different scenarios and variations, thereby effectively testing and validating the performance of the algorithm. GTSRB is a German traffic sign recognition benchmark dataset, while the LISA Traffic Sign Dataset provides images of signs on US roads. BelgiumTS contains Belgian traffic sign images, CURE-TSR focuses on Chinese urban roads, and TT100K is a large-scale multi-task data set. CIFAR-10 and CIFAR-100 are general image classification datasets, while CTSDB focuses on Chinese urban traffic signs. These diverse datasets provide researchers with rich experimental conditions to evaluate the robustness and accuracy of algorithms in different environments and scenarios.

RQ3: What are the advantages and disadvantages of each category of traffic recognition algorithms?

Various traffic sign recognition algorithms have their own advantages and disadvantages. Traditional methods, such as machine learning methods and feature-based methods, rely on hand-designed features, which although perform reliably in simple scenarios, may be limited in complex environments. Deep learning methods automatically learn image features through deep models such as convolutional neural networks and have excellent performance, especially when training on large-scale data sets, but their training requires large computing resources. The fusion method effectively deals with the advantages and disadvantages of different algorithms, but it also requires comprehensive consideration of the selection and integration strategies of each algorithm, which increases the complexity of the system.

RQ4: What are the challenges faced by traffic sign recognition algorithms?

Traffic sign recognition algorithms face many challenges, including weather and environmental changes that lead to diversity in sign appearance, requiring algorithms to adapt to different lighting conditions. In traffic scenarios, especially in autonomous driving systems, real-time performance is crucial, and algorithms need to efficiently process images while maintaining real-time performance. At the same time, multiple signs or overlaps are common, and the algorithm needs to accurately distinguish and identify them to ensure a correct understanding of the combination of signs. Differences in national standards increase algorithm complexity and adaptability challenges, requiring adaptation to various logo appearances and structures. To effectively address these challenges, algorithms need to remain robust, real-time, and accurate under different conditions.

RQ5: What are the application areas of traffic sign recognition?

Traffic sign recognition plays an important role in multiple application areas, including autonomous driving and intelligent transportation systems, driver assistance systems, urban traffic management, intelligent traffic monitoring, navigation and mapping applications, and transportation research and data analysis. These fields use traffic sign recognition technology to improve traffic safety, optimize traffic flow, realize intelligent navigation, and provide valuable data analysis support for traffic decision-making and research.

8.2 Final Remarks

This paper meticulously reviews the research status, method classification, and application domains of traffic sign recognition technology by thoroughly examining and analyzing pertinent literature. The discussion places particular emphasis on the application of deep learning technology in this context, highlighting its significant contribution to feature learning. This not only furnishes readers with a comprehensive comprehension of traffic sign recognition technology but also offers thorough theoretical insights and practical guidance for future research and applications within this domain.

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