Review

Review of Intelligent Road Defects Detection Technology

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Abstract: Road defects are important factors affecting traffic safety. In order to improve the identification efficiency of road diseases and the pertinence of maintenance and management, intelligent detection technologies of road diseases have been developed. The problems of high cost and low efficiency of artificial inspection of road diseases are solved efficiently, and the quality of road construction is improved availably. This is not only the guarantee of highway quality but also the guarantee of people's lives and safety. This study focuses on the intelligent detection of road disease and summarizes the commonly used detection equipment in the intelligent detection technology of road diseases, which include cameras, GPR, LiDAR, and IMU. It systematically describes the evolution and development of road disease detection technology. This study analyzes the common problems existing in road disease detection technology and proposes corresponding improvement suggestions. Finally, the development trend of road detection technology is discussed, which has practical significance for the future development of road detection technology.

Keywords: intelligent transportation; defects detection; deep learning; image processing

1. Introduction

The quality of roads can directly affect the development of the city. With the erosion of roads caused by rain and vehicles, various defects may appear on the road surface, such as cracks, ruts, grooves, and subsidence [1]. The common types of pavement defects are shown in Figure 1.

Cracks are one of the most common diseases on the pavement. It mainly has transverse cracks, longitudinal cracks, and reticular cracks. It is extremely harmful to the road surface. Especially in winter and spring, due to the infiltration of rain and snow water, the road disease that is already in a crack state is more serious under the action of driving load [2]. Ruts are the permanent grooves in the road surface under the repeated action of vehicle loads [3]. This is mainly due to the unreasonable design of the asphalt mixture gradation or insufficient compaction during construction. This can make the road surface drainage poorly on rainy days, and the driving vehicle is prone to drifting and affecting the safety of high-speed driving. The grooves [4] are mainly formed due to the lack of timely maintenance after the surface layer is cracked, which has the potential to cause a flat tire in a moving vehicle and cause a traffic accident. These defects can bring damage to the vehicles on the road. Uneven or irregular roads can lead to tire wear. What is more, it can lead to a flat tire and cause a traffic accident. To ensure driving safety, the funding for road maintenance is increasing every year [5]. Identifying road defects timely is important for pavement maintenance. Manual inspection is intuitive with the high cost and low efficiency. In order to solve this problem, various intelligent detection methods for road surface defects detection have been developed [6]. However, there is a lack of studies summarizing the advantage and disadvantages of those intelligent detection methods.
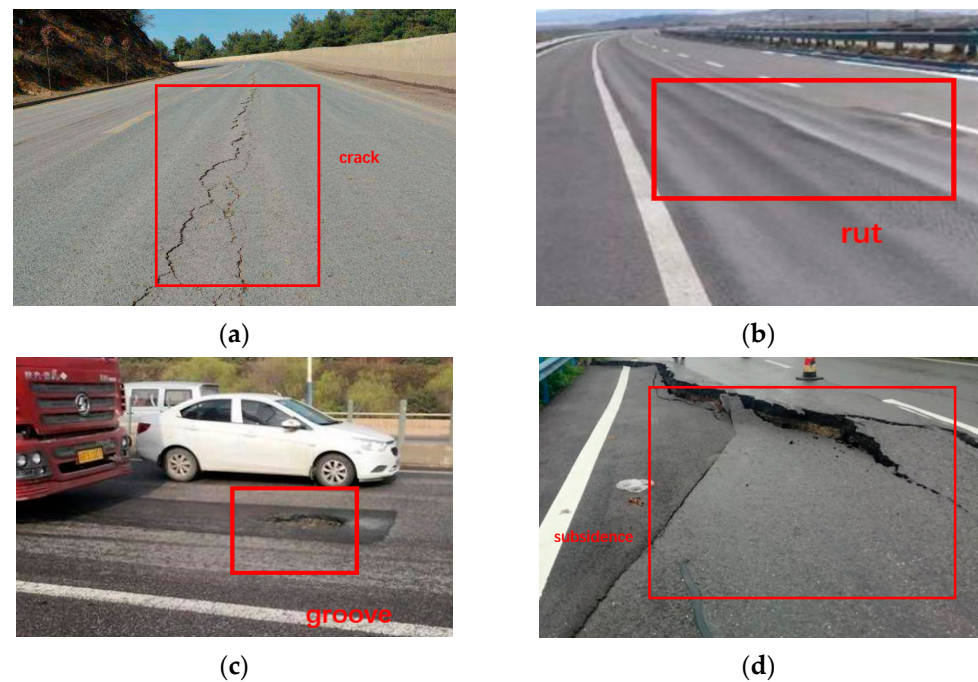
Figure 1. (**a**) The diagram of crack; (**b**) The diagram of rut; (**c**) The diagram of groove; (**d**) The diagram of subsidence.

Therefore, this paper conducted a comprehensive literature review on intelligent road defects detection technology. Firstly, the data collection methods of pavement defects, including cameras, ground-penetrating radar (GPR), Light Detection and Ranging (LiDAR), and an inertial measurement unit (IMU), were introduced. The data processing methods, including fitting, a support vector machine (SVM), convolutional neural network (CNN), and decision tree, were then discussed. Finally, it summarized and prospected the development of road defects detection technology.

2. Data Collection

Data collection is the first but important step for road defects detection. Road defects data can be obtained by different devices, such as cameras, ground-penetrating radar, LiDAR, IMU, etc. [7–10], as shown in Figure 2.
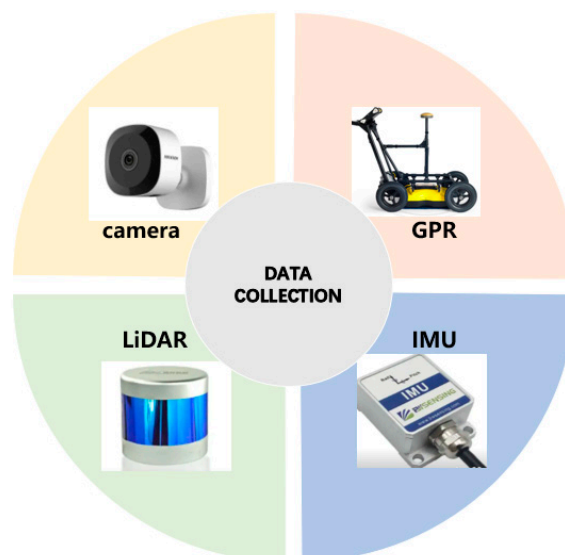

Figure 2. Data collection equipment for road disease.

2.1. Camera

Many researchers used cameras for pavement image collection [11–15]. The image can then be used for pavement texture analysis [16], pavement crack detection [17], and asphalt mixture crack detection [18]. Y. Du et al. [19] collected a large number of pavement defect images, including timestamp and location information, using car-mounted cameras. Repeated collection and overlapping of pavement defects images were found during the collection process. Therefore, a feature matching and image mosaic method for pavement disease detection based on multi-vehicle images was proposed. Tang [20] developed intelligent road inspection equipment with existing road inspection vehicles installed with cameras. The qualitative and quantitative assessment of road surface quality can be then achieved. Du et al. [21] used the high-resolution industrial cameras installed on vehicles to collect pavement images. The detection and classification method of pavement diseases based on the You Only Look Once (YOLO) network was combined. Grabowski, D. et al. [22] proposed a method for estimating pavement conditions based on images obtained from onboard cameras. A set of algorithms was created to process images from depth cameras and RGB (red, green, blue) cameras. The neural network model was trained by video samples from the camera for road defects classification. Studies showed that the processing accuracy of the application of digital image processing technology reached more than 80%. Jahanshahi, M. R. et al. [23] used RGB-D sensors to detect and quantify pavement defects. The sensor system consisted of an RGB color image, an infrared projector, and a camera as a depth sensor. Combined with the corresponding algorithm, the automatic detection of road diseases such as cracks and potholes can be completed. In addition, the global positioning system was combined with the proposed system to locate the detected defects. It can be used as an auxiliary sensor system for road surface assessment vehicles. Cui, X et al. [24] used profiling and digital image technology to achieve a three-dimensional reconstruction of asphalt pavement contours. Image processing technology helped to locate the precise coordinates of each point on the model. According to the contour method, a comprehensive calculation program for texture depth was established.

With the development of unmanned aerial vehicles (UAVs), more and more pavement engineers or researchers are starting to install cameras on UAVs for the detection of various road diseases [25–27], as shown in Figure 3. Junqing, Z. et al. [28] proposed that the road detects information were collected by drones using high-resolution cameras. A drone platform for road surface image acquisition was assembled, and the flight settings were studied to obtain optimal image quality. The acquired images were processed and annotated for model training. Combined with the YOLOv3 algorithm, the average accuracy (MAP) of data processing was 56.6%. Zhijian, M. et al. [29] analyzed the development technology of unmanned aerial vehicles in the field of intelligent transportation to improve the accuracy of road surface disease detection. A framework for road disease recognition and perception based on drones was constructed. The Yuneec H520 UAV was used to collect road surface image data, and the road surface disease image preprocessing technology based on wavelet threshold transformation was analyzed. Inzerillo, L. et al. [30] used data collected by drones to analyze structural self-motion (SfM) techniques at different heights. This technology was applied to old pavements on the campus of the University of Palermo. The technology accurately identified pavement diseases and developed an integrated approach to optimizing pavement management strategies.

Cameras are widely used in pavement disease detection technology. It has a high dynamic range and resolution, and it is inexpensive. However, the imaging of the camera is greatly affected by the lighting conditions of the road surface under test. The light intensity is too strong, too weak, or the light is uneven and is not conducive to imaging. In order to ensure that the system can work properly in any environment, auxiliary lighting equipment needs to be configured to provide uniform lighting conditions and ensure image quality. Moreover, the camera provides only 2D information and lacks depth information, which is not conducive to a more comprehensive analysis of the problem [29,31,32].
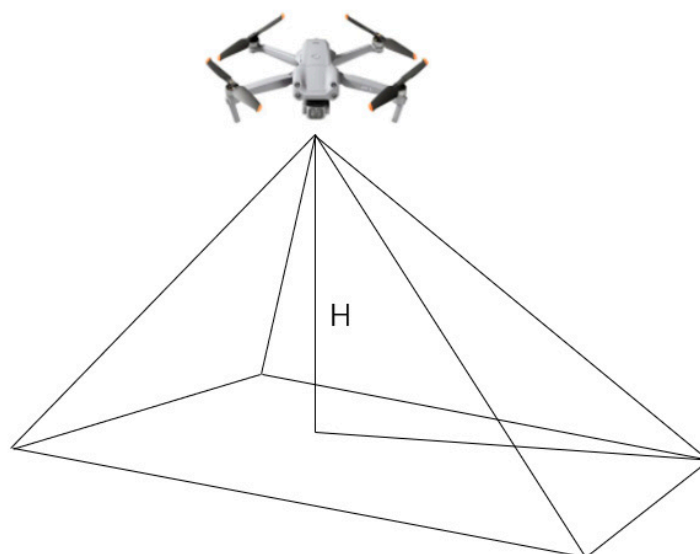
Figure 3. Aerial model of a drone.

2.2. GPR

Compared to the camera, GPR detection technology [33,34] is more efficient for identifying roadbed diseases. This method does not need to destroy or excavate road surfaces and can effectively overcome the concealment of roadbed diseases.

Road disease detection is an important basis for road maintenance and maintenance. Although the conventional drill core sampling method can achieve the purpose of pavement inspection, the detection results of this method are not comprehensive, and the damage to the pavement is large. As an efficient non-destructive testing technology, ground-penetrating radar offers the possibility of non-destructive testing of road diseases. Zhu et al. [35] discussed the effects of diseases such as road surface reflection cracks, subsidence, and uneven pavement on ground-penetrating radar image results, as shown in Figures 4 and 5. Based on the influence of diseases on the image results of ground-penetrating radar and the detection results of ground-penetrating radar, the types and causes of road lesions in a certain section of the highway were successfully analyzed. Gao, J. et al. [36] used ground-penetrating radar (GPR) for road surface damage detection. Data processing in conjunction with the faster R-ConvNet algorithm to complete the task. The results showed that the accuracy was 89.13%. The stability of this model was better under different road structures. One of the problems encountered when conducting non-destructive testing of the road surface with ground-penetrating radar is the detection of multi-layered reflectors in the echoes of ground-penetrating radar. Lahouar, S. et al. [37] solved this problem by iteratively detecting strong reflections in GPR signals by using threshold or match filter detectors. The detected pulses were then used in the reflection model to synthesize a signal that is "similar" to the measured ground-penetrating radar signal in the least-squares sense. The synthesized signal was then subtracted from the measured signal to show the faint reflections that were masked. Then these reflections were detected iteratively using the same method. After testing, the study can be successful in disease detection. To test and evaluate the field application effect of asphalt pavement ground-penetrating radar rapid detection technology, Zhang et al. [38] conducted on-site test research based on the key points and implementation process of on-site detection technology. They relied on physical engineering and analyzed the accuracy of the detection results. The results showed that the compaction of the asphalt surface layer detected by ground-penetrating radar on-site was relatively accurate. The relative error can be controlled by 1%. The on-site detection results of the pavement disease ground penetrating radar were consistent with the scoring results, and the scanning image of the ground-penetrating radar can clearly reflect the structural condition of the asphalt pavement. To study the defect detection and identification of the

road surface by ground-penetrating radar (GPR), Huang et al. [39] proposed a method with obvious effects on improving abnormal resolution and singular value decomposition by embedding metal plates at the interface of each layer in the surface of the road surface. It was applied to road field detection. The results showed that this can reduce the amount of work processing data and increase the accuracy of the detection.
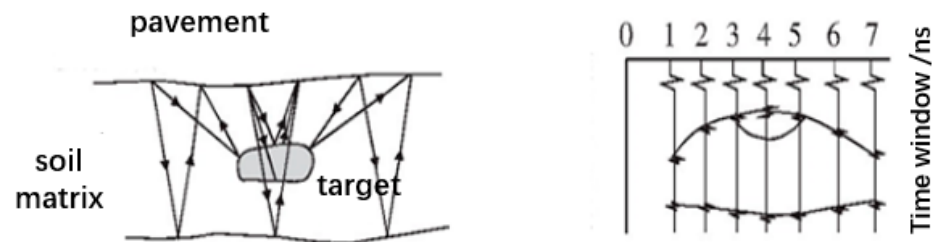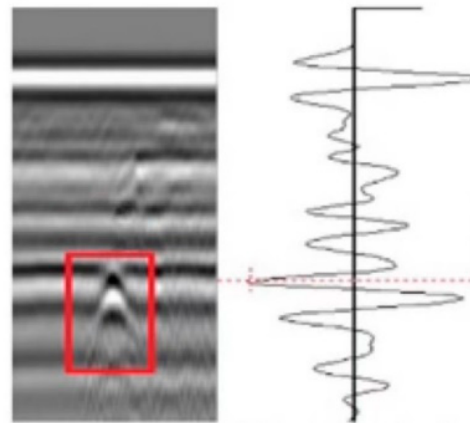

Figure 4. GPR detection process.

Figure 5. Image of flaw reflection echo on GPR.

Ground-penetrating radar is a non-destructive and fast method of pavement detection. It mainly has the following characteristics [40]. Its adaptability is strong. Geological radar can be safely applied to the city or construction site of the engineering site by the use of non-destructive testing technology. The working conditions are more relaxed. Its anti-interference ability is strong, and its anti-electromagnetic interference ability is strong [41]. It can work in various noise environments in the city and is less affected by the bad environment. Its positioning is fast and accurate. It has better inspection depth and resolution and can provide real-time cross-sectional views directly with clear and intuitive images [42]. It uses a laptop to control the acquisition, recording, storage, and processing of data for ease of portability. However, the big data obtained by the ground-penetrating radar delay the processing time, which leads to problems such as subjectivity in data interpretation [43,44].

2.3. LiDAR

LiDAR is an emerging device for road surface defects detection with the unique advantages of high precision, high resolution, high automation, and high efficiency [45,46], as shown in Figure 6.

Zhang et al. [47] conducted data comparison and analysis on the stability of the specified laser road condition detection equipment from three angles (flatness, surface section construction depth, and rut) in ordinary roads and special test roads. The applicability of laser detection was demonstrated. Suggestions and methods for improving the reliability of equipment detection were proposed. Zhao [48] proposed a change detection method based on a digital elevation model and density map by using point cloud data obtained by vehicle-mounted LiDAR scanning. After verification, the detection accuracy of this

method can reach 93.1%. M.Bellone et al. [49] detected the uneven position on the road by studying the driver warning system. LiDAR was used to generate the environment in the form of a three-dimensional (3D) point cloud, which was analyzed and processed based on a normal vector and presented to the driver in the form of a traversable grid. Li et al. [50] adopted line laser technology to construct a 3D data acquisition system for pavement and collected high-resolution (0.5 mm) 3D pavement depth data. Yan et al. [51] used LiDAR to detect road irregularity information. Road environmental information was extracted and segmented by the network structure of random sampling and local feature aggregation. In order to solve the problem of the loss of key features in the process of road environment information segmentation, a local feature aggregator was added to increase the acceptance domain of each 3D point cloud to retain geometric details. The results showed that the method could accurately identify the road environment information, and the recognition accuracy of the convex hull, pit, and drivable area can reach 71.87%, 82.71%, and 93.01%, respectively. Jiang et al. [52] took advantage of the three-dimensional data of the pavement to propose an enhanced dynamic optimization algorithm to improve crack segmentation. The four most common types of pavement cracks (longitudinal, transverse, block, and crocodile-like) were tested. Experimental results showed that the average calculation time of the algorithm was greatly shortened. At the same time, cracks in multiple directions were better handled, and the accuracy of crack segmentation was improved. Song [53] took the three-dimensional line laser technology as the research object and analyzed its system composition and working principle. Comprehensively engineering examples were introduced to discuss its application effect in road rutting detection and the factors affecting the detection results so as to provide a reference for road rutting detection. Guo et al. [54] applied the new three-dimensional laser detection technology with high precision and high density, and the indoor rutted pattern simulation equipment was developed to quantitatively evaluate the detection accuracy and reliability of the non-uniform 13-point laser rutting detection equipment for the problem of rut depth. The results showed that the detection error and dispersion of the 13-point laser detection equipment for the bump type rut were significantly higher than those for the detection of no bump rut, and the relative error exceeded 5%. Hu et al. [55] used a non-uniform 13-point laser detection device to obtain cross-sectional data from 110 sets of measured rutted vehicles. The effect of lateral offset of multi-point laser detection vehicles on the error of depth detection of rutted vehicles in different forms was studied. To evaluate the pavement quality completely and intuitively, Wang et al. [56] proposed a three-dimensional pavement detection method based on a laser displacement sensor and gyroscope. The results showed that the method can measure the pavement shape of the entire lane with high detection accuracy and fast detection speed.
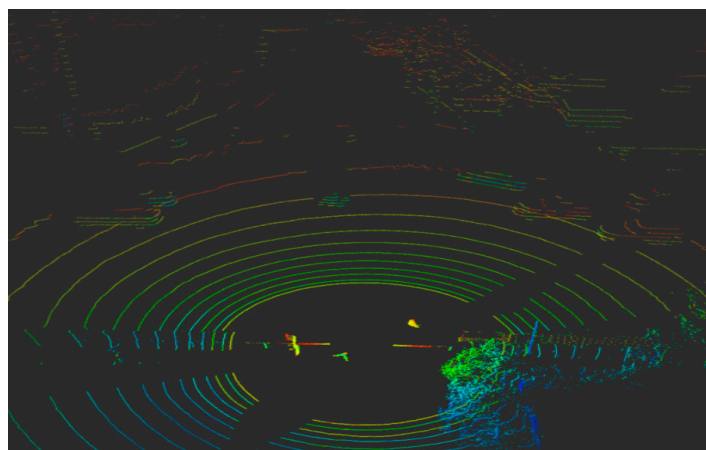

Figure 6. Point cloud data collected by LiDAR.

The detection distance of LiDAR is long, and the angle measurement accuracy is high. What is more, the resolution is high, and the viewing angle is wide. However, it is susceptible to natural light and thermal radiation, and it is greatly disturbed in weather such as rain and fog, wind and sand, etc. The working environment requirements are high, and the cost is high [57–59].

2.4. IMU

The IMU installed on the detection vehicle can detect whether the road surface is damaged by analyzing the data of the acceleration sensor, angular velocity sensor, and other components [60–62], as shown in Figure 7. Acceleration changes, angular velocity changes, and attitude changes in the process of vehicle movement can all be collected by IMU, which requires a small amount of calculation and can achieve high accuracy [63–65].
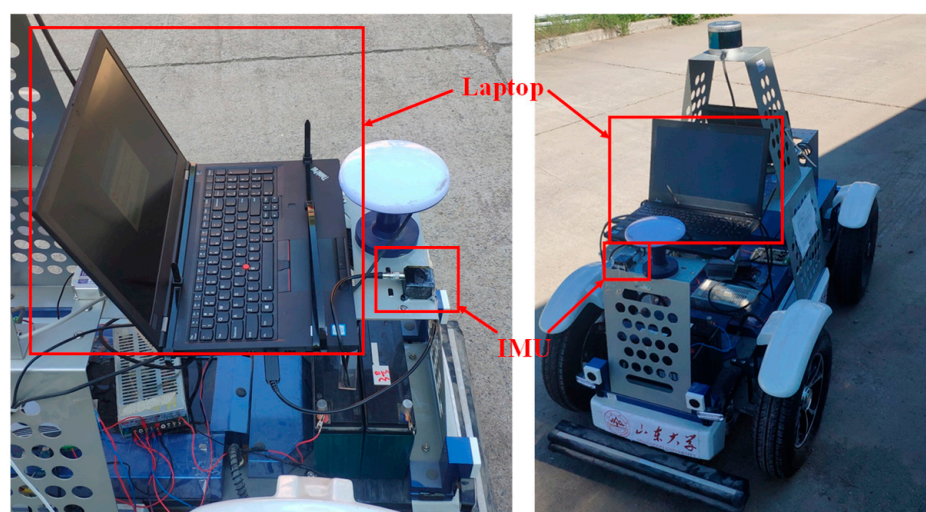

Figure 7. IMU fixed to the inspection vehicle.

M. et al. [66] presented a road surface defect identification system based on 3D accelerometers, a global positioning system (GPS), and video modules deployed on vehicles. Anthony et al. [67] applied IMU and laser to evaluate road roughness and generate road profile, improving the accuracy of vehicle-based longitudinal road profilometer in road roughness and large texture evaluation. Christodoulou et al. [68] inputted acceleration and angular velocity data into the designed artificial neural network to distinguish potholes on the road, and the detection accuracy was about 90%. In order to solve the drift problem of velocity and avoid affecting the accuracy of calculation and target positioning, a method for velocity and displacement calculation based on stable numerical integration was proposed by Kong et al. [69] The results showed that this method can reduce the drift error and improve the accuracy of the integral results.

IMU is an autonomous system that does not rely on any external information and does not radiate energy to the outside. It is well concealed and is not affected by external electromagnetic interference. Plus, it can work at all times. It has a high data update rate, short-term accuracy, and stability. However, because the navigation information is generated by integration, the positioning error increases with time, it requires a long initial alignment time before each use, and the price of the device is expensive [70–73].

2.5. Section Summary

The advantages and disadvantages of each device are summarized here, as shown in Table 1.

Table 1. Overview of data acquisition devices.

Device	Advantage	Disadvantage
Camera	1. It has high dynamic range and resolution. 2. The price is inexpensive.	1. It affects by the lighting conditions. 2. It lacks depth information.
GPR	1. Its anti-interference ability is strong and anti-electromagnetic interference ability is strong. 2. It less affected by the bad environment. 3. It has better inspection depth and resolution.	1. The big data obtained by the ground penetrating radar delay the processing time, which leads to problems such as subjectivity in data interpretation. 2. The detection depth needs to be improved.
LiDAR	1. The detection distance is long and the angle measurement accuracy is high. 2. The resolution is high and the viewing angle is wide.	1. It is susceptible to natural light and thermal radiation. 2. The working environment requirements are high. 3. The price is expensive.
IMU	1. It is not affected by external electromagnetic interference. 2. It can work all times. 3. It has a high data update rate, short-term accuracy and stability.	1. The positioning error increases with time. 2. It requires a long initial alignment time before each use. 3. The price is expensive.

3. Data Processing

Image processing technology is widely used in many research fields such as medicine [74,75], aerospace engineering [76,77], civil engineering [78,79], meteorology [80], biological science [81], transportation science [82]. The commonly used data processing methods in the field of road disease intelligent detection include digital image processes, fitting, support vector machines (SVM), neural networks, and so on.

3.1. Digital Image Process

Methods based on basic image analysis are the more common methods. This method generally does pretreatment work, such as enhancement of the image first. Then the targets are segmented and extracted by thresholds [83]. Finally, the targets are identified and classified. It enables a specific quantitative analysis of the differentiated disease targets, as shown in Figure 8.
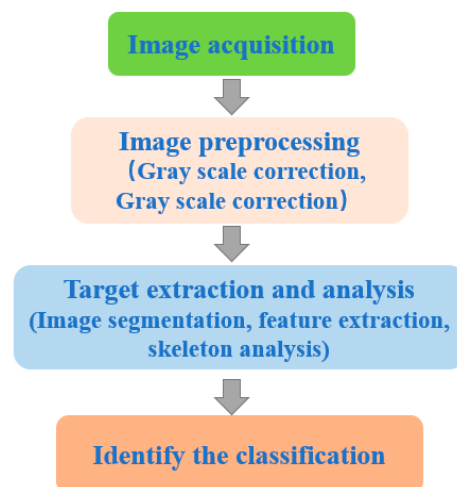
Figure 8. Digital image processing method.

The highway is an important meridian to complete the transportation and communication between the various regions. Road cracks are easily caused by natural factors

and external forces. Wang et al. [84] proposed a road crack automatic identification and evaluation system based on digital image processing so that the degree of road cracks can be more quickly and accurately determined. The appropriate treatment methods were developed. To improve the recognition speed and recognition rate of highway pavement crack automatic detection and recognition technology based on digital image processing technology, Xiao et al. [85] proposed an adaptive rapid denoising method for enhancing pavement crack images through equalization processing. It can improve the recognition speed. Xu et al. [86] achieved automatic identification of pavement diseases through image preprocessing, disease detection, morphological operations, disease localization, and classification. After comparing and analyzing various edge detection algorithms, the adaptive threshold obtained by the OTSU algorithm was proposed as a high threshold input into the collaborative operation method of Cany's algorithm. It improved the accuracy of disease detection by about 10% compared with traditional edge detection algorithms. This further improved the practicality of image-based pavement disease detection solutions.

However, due to the particularity of pavement images and the weak signal of disease targets, although researchers have proposed many different treatment methods, there has not been a common and effective method to detect crack diseases on various pavements. This is also a major problem that has plagued researchers. For example, the general disease crack boundary has a certain marginality, so the edge detection method can be used. Abrupt changes in grayscale are detected by using some suitable edge detection operators in the image, reinforcing the information of the crack target. What is more, the overall gray level of the image is corrected so that the light intensity of the entire image becomes uniform, and then use methods of thresholds to segment the target. However, the limitation of these methods is that the crack strength is uncertain. There are too many changes, and it is not easy to divide the target. Moreover, there are too many noise targets that are split, which has a great impact on the subsequent processing results [87–90].

3.2. Fitting

Road diseases are complex and diverse. There are often many thin and weak cracks in terms of cracks alone, and there are also a large number of reticulated cracks [91].

Detection has become difficult by simply taking thresholds to segment the general approach, and disease information must be extracted and identified by other special methods [92]. A single crack is linear. If its width is ignored, it can be thought of as a curve. From the curve fitting theory, it can be seen that the curve can be approximated by segmented straight line segments [93]. Therefore, the possible crack pixels can be considered extracted directly from the grayscale image. Then the cracks are fitted from these points by fitting the method. Finally, the fitted crack target is identified. The false target is discarded, leaving the real crack target [94], as shown in Figure 9.
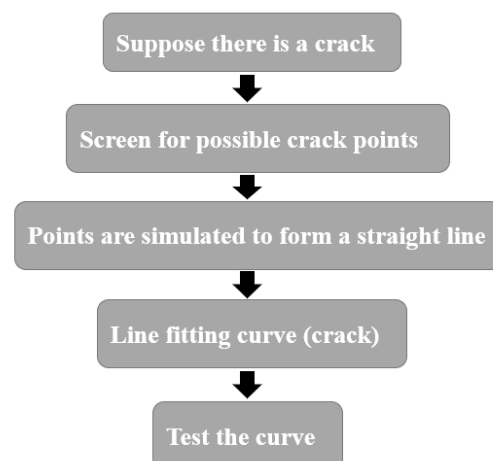

Figure 9. The process of fitting.

On the basis of the demonstration and analysis of the depression characteristics of the pavement, Wang et al. [95] proposed the depth, area, edge density factor, slope point identification factor, and other judgment indicators that describe the depression characteristics. By using the fitted datum method, a Matlab automatic identification program was prepared. The correct identification of known pits and subsidences in the 400 m test section was realized. Jianfeng Lu et al. [96] proposed an automatic detection and recognition method for road cracks based on a multi-level fitting mechanism. Firstly, the image was divided into small windows. It can be assumed that it is internal and contains a crack. The crack point was extracted, and then these points were synthesized into a straight line by using the method of fitting a straight line. In the process of fitting a straight line by moving the window continuously, these lines were continuously combined to form a composite curve (cracks) and form a multi-level fitting mechanism. A large number of experimental data showed that the reliability, stability, and universality of this method were satisfactory.

3.3. SVM

The support vector machine (SVM) is a binary classification model algorithm based on supervised learning [97,98]. The basic principle of operation of the algorithm is to find an optimal classification hyperplane that maximizes the distance between the two samples at the lower edge of this hyperplane. The greater the edge distance, the more the two types of samples are divided, and the results of the classification are better [99]. However, there are usually more than two types of diseases on the road surface, so it is necessary to construct a suitable multi-classifier. At present, the methods of constructing SVM multi-classifiers mainly include the direct method and indirect method [100].

(1)   Direct method

The direct method is to modify the objective function directly. Multiple classification questions are combined into one optimization problem. By solving the optimization problem, the multi-classification problem can be solved at once. Although this solution seems simple and easy to understand, it is difficult to implement. The calculation process is complex, and the generalization is poor.

(2)   Indirect method

The idea of the indirect method is to achieve the construction of multiple classifiers by combining a variety of binary classification methods. There are two commonly used methods: one-to-many and one-to-one. This is shown in Figure 10.
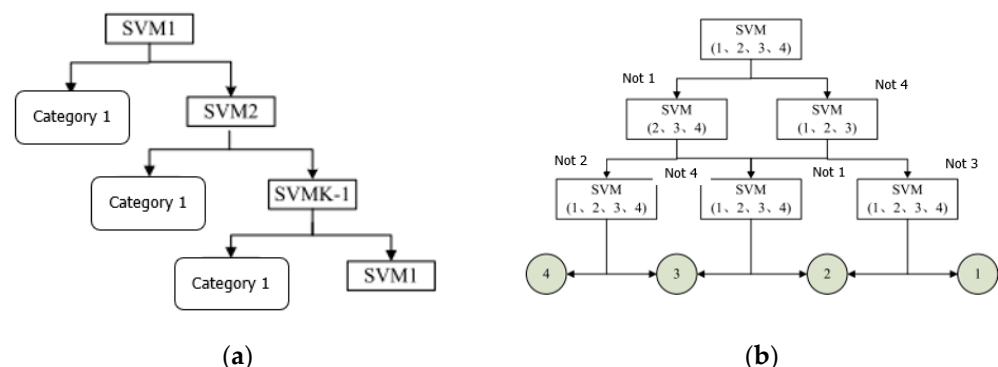
Figure 10. (**a**) One-to-many classification algorithm; (**b**) One-to-one classification algorithm.

Wang [101] used the support vector machine (SVM) classification algorithm to study the classification and identification of different diseases. In order to solve the optimization problem of c and g of the super parameters of the SVM algorithm, the mesh search method and the particle swarm optimization algorithm are used to optimize the parameters of the SVM. The classification prediction results of the SVM model obtained by using these

two optimization algorithms were 88.333% and 86.667%, respectively. It is found that although the grid search method can still meet the detection requirements, it runs slowly. Although the particle swarm algorithm increased speed, it was easy to fall into the local maximum. Thus, an adaptive variation particle swarm optimization (PSO) algorithm was proposed to improve the original algorithm. The classification prediction of the improved SVM model was 91.667%, which improved the disease recognition rate. To solve the problems of repeated acquisition and multiple overlaps of the same disease in the detection of pavement diseases by cameras, Y. Du et al. [19] proposed a feature matching and image Mosaic method for pavement disease detection based on multi-vehicle images. The mean Euclidean distance (MEUD) and matching rate (MCR) were constructed to identify the duplication between two images. Then support vector machines were used to determine the thresholds of MEUD and MCR. The algorithm solved the problem of road surface disease repetition effectively and provided a reliable method for road surface disease detection in a multi-vehicle cooperative environment.

3.4. Neural Network

In recent years, as deep learning has been recognized, neural networks as the basis of deep learning have become the hottest research direction. [102–104] At present, the computing power of neural networks is becoming stronger and stronger, prompting different fields and disciplines to try to use neural networks to solve some problems in this field [105–109]. Especially in the field of image processing [110,111], in view of its large amount of computation and a large amount of data, neural networks can easily solve some of the problems encountered. Neural networks are essentially simplified human brain neuronal systems, connecting many neurons through different connection methods to form a neural network similar to human brain nerves. This is shown in Figure 11 The neural network is an adaptive, nonlinear data processing system consisting mainly of a multitude of interconnected processing units [112,113]. It processes information obtained from the outside world in a way that is similar to the brain's neural thinking process, and it can process data faster and more accurately than traditional artificial intelligence. Therefore, it is particularly suitable for classification, recognition, and other issues in image processing. Many scholars use neural networks to determine whether road images are diseased. The diseased images are extracted from massive amounts of data, reducing the workload for the next disease detection. At the same time as liberating manpower, it is possible to accurately and quickly select pictures containing diseases, and the accuracy rate is almost close to the level of manpower [114–116].
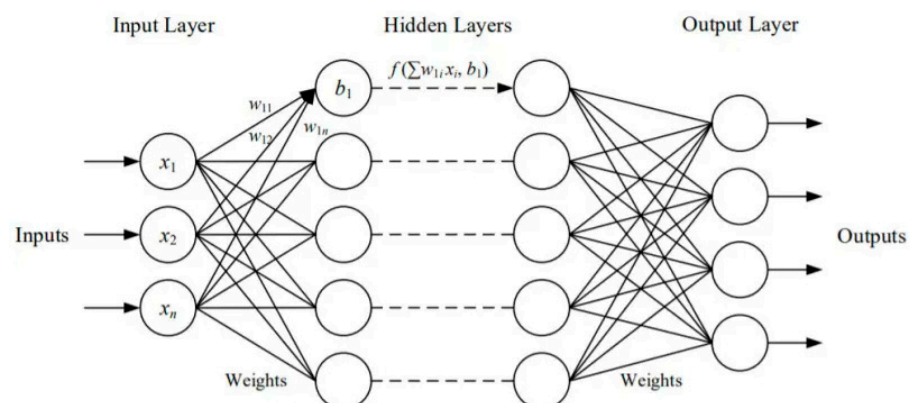
Figure 11. Neural network structure model.

A. Riid et al. [117] used a computer vision algorithm to automatically detect road surface diseases. Based on several existing image classifier structures, a deep learning convolutional neural network model was developed. In addition, a manual preprocessing step was introduced to train the carefully selected frame sets and manually digitize them to ensure adequate detector performance. The corresponding experimental results

showed that the implementation of the detector was successful. The software was easy to update, and hence it would soon be ready for deployment, further testing, and its eventual application for improving highway road pavement conditions. Chang Ying et al. [118] can detect road disease types and automatically identify road conditions through convolutional neural networks and intelligent algorithms, helping road maintenance departments carry out daily maintenance work efficiently. Based on a convolutional neural network, a multi-category road surface disease recognition method was proposed. This method can detect and recognize many kinds of road diseases, including cracks, potholes, and looseness. The performance of the proposed recognition method was evaluated through the pavement disease data set, and the recognition accuracy was confirmed to be up to 0.9438. However, this method had an obvious detection effect on large objects such as pits and ponds, while the detection accuracy of small cracks needed to be improved. D. Yuchuan et al. [21] proposed a pavement disease detection and classification method based on the YOLO network to solve the problem of pavement disease detection and classification. Target detection framework YOLO network based on deep learning was used to predict possible disease locations and disease categories. The comprehensive detection accuracy reached 73.64%. The processing speed reached 0.0347 s/PIC. The applicability of the model under various illumination conditions was also discussed. Under proper illumination conditions, the performance of the method was improved significantly. However, when the main information on the road surface was blocked by shadows, detection became more difficult. This aspect of work needs to be further improved. X. Lei et al. [119] proposed a deep learning method based on a pre-trained neural network structure for real-time identification and positioning of different diseases according to the interactive panorama of the urban road network. Eight types of diseases were recorded using Yolov3 deep learning architecture. A decision tree was designed to assess disease changes over time. Experimental results showed that the average accuracy of the proposed algorithm was 88.37%. Because street view maps provided a time-by-time view of disease conditions, they can help departments arrange repairs more efficiently and efficiently. In addition, street view images were inevitably obscured by obstacles such as trees and vehicles, which still needed to be improved. J. Gao et al. [36] proposed a deep learning method for faster R-Convnet. The optimal model was determined by training, verification, and testing with massive images. The accuracy of the faster R-Convnet was 89.13%. The stability of the model under different pavement structures was desirable. The performance of the faster R-Convnet was not obviously influenced by the pavement structures and materials. However, its performance was influenced by the transmitting frequencies of the GPR due to the detail loss of the pavement distresses in the GPR images. Tian Yang et al. [120] adopted the fast regional convolutional neural network (Fast-RCNN) method to organically combine image recognition technology, a global positioning system (GPS) position information, and vehicle-mounted signal information. Road pictures collected by road inspection vehicles were automatically identified. The Fast-RCNN model was established for training and testing based on disease characteristics, and the performance of the model was tested by an automatic partitioning algorithm. Experimental results showed that the recognition accuracy of the model could reach 84.9%. This can effectively improve the efficiency of road disease identification. The road disease model based on FastRCNN had the characteristics of high recognition accuracy, fast response speed, strong system portability, and low cost. It can be seamlessly deployed on mobile terminals and mobile phones. S. Liang et al. [121] adopted a detection method based on faster R-CNN to automatically identify and locate defects such as road cracks, potholes, oil stains, and spot surfaces. The optimal faster R-CNN was obtained through analysis and training. Finally, the stability and superiority of this method were verified by experiments and comparative studies. Compared with the CNN model, the faster R-CNN model was more efficient in identifying and locating road surface diseases. However, it was impossible to classify the types of cracks based on their cause just by using pavement images. In further works, other pavement data, such as infrared scanning and ground-penetrating radar, should be utilized to help the faster R-CNN classify the types

of cracks based on their cause. Guan. J.C. et al. [122] proposed an improved u-net deep learning structure to efficiently complete the segmentation of cracks and potholes in the actual environment and reduce the amount of calculation, which introduced the detachable depth convolution for the segmentation of cracks and potholes. This method was tested on asphalt pavement in different environments. The results showed that the accuracy of the 3D road image was up to millimeter level. The automatic detection of other pavement diseases based on this framework needs further development and improvement in future research, especially the automatic detection of three-dimensional pavement diseases such as rutting and spalling. Xianyan Tang [20] proposed that the convolutional neural network intelligent algorithm can be used to train the road video images collected by inspection vehicles, which can effectively identify various types of road diseases such as cracks, pits, cracks, crushing, and repair. Pavement diseases also successfully developed intelligent identification and maintenance management information system platform, using the information of road disease in maintenance management platform. It had positive data value for analyzing the cause of road disease and making road maintenance strategies. Yu Jun et al. [123] proposed an intelligent detection system of road surface disease based on deep learning for highway safety. In the abnormal detection stage, the convolution encoder was constructed to extract the disease map from a large number of road surface images. In the stage of anomaly extraction, the feature of road surface disease was extracted by the threshold segmentation method. In the stage of highway pavement disease classification, ResNet structural training model was used to determine the classification of highway pavement disease. The results showed that the method can train the model for about 3 min and the classification accuracy was above 90%. This greatly improved the efficiency of disease detection.

3.5. Case Introduction

As urbanization accelerates and urban populations proliferate, the number of urban roads and their ancillary facilities increases, which poses challenges to municipal road management. For the custody enforcement unit, the manual-based inspection method is not only inefficient, but also the safety of the staff during the inspection process is difficult to guarantee. For industry regulatory units, the manual-based inspection method is too inspection results are difficult to guarantee. The result of the inspection is unstructured data, which is difficult to use to promote the fine management of road facilities. Therefore, Heze City, Shandong Province, China, implemented the "Urban Municipal Road Rapid Inspection System". The system was based on artificial intelligence vision AI technology innovation and development, using artificial intelligence technology to automatically patrol municipal roads. Compared with the traditional inspection method, the work efficiency was increased by 70%, which not only saved labor but also ensured the safety of the staff. This system consisted of an onboard high-definition camera, an edge computing analysis all-in-one machine, and an artificial intelligence visual recognition platform. Roads can be inspected automatically. As long as the patrol vehicle is within 100 km per hour, it can automatically identify 12 road diseases in 3 lanes at the same time. The system currently supports the detection of 12 types of asphalt and cement pavement diseases, including transverse cracks, longitudinal cracks, strip repair, cracks, exposed bones, looseness, ruts, potholes, block repairs, subsidence, broken markings, and road area water. It can be further updated and iterated according to the actual use needs and road health characteristics of pavement disease types. The rapid inspection and identification of vehicles with problems such as sidewalk disasters, broken guardrails, damaged anti-collision barrels, and green plant lodging will be gradually realized.

3.6. Section Summary

This section described several approaches to image processing, including traditional digital image processing techniques, fitting, SVMs, and neural networks. Currently, image processing technology is characterized by high speed and high precision, which liberates human resources. However, there are still deficiencies. The current problems are mainly

incomplete identification of disease types, which needs to be further developed and improved in future research. In addition, street view images are inevitably obscured by obstacles such as trees and vehicles, and the impact of these obstacles on subsequent image processing still needs to be improved.

The advantages and disadvantages of each method are summarized here, as shown in Table 2.

Table 2. Overview of data processing.

Device	Advantage	Disadvantage
Digital image processing	1. It has high accuracy and is easy to operate. 2. Image quality will not be degraded because of image storage, forwarding, copy and other operations.	1. The processing speed is relatively slow
Fitting	1. It models quickly. 2. It works well for simple relationships.	1. It is difficult to model nonlinear data.
SVM	1. It does not need to rely on the entire data set. 2. It can solve higher dimensional problems.	1. It is not very efficient when you have a lot of samples.
Neural network	1. It has high accuracy of classification. 2. It has associative memory function.	1. It needs a lot of parameters.

4. Conclusions

The study summarized the content of intelligent pavement disease detection technology. From the perspective of research significance, the development history and significance of intelligent pavement disease detection were briefly described. Several methods of acquiring road disease image data and data processing methods in the field of intelligent disease detection were introduced. There was still one shortcoming in this article. This paper lacked a summary of pavement maintenance. The maintenance of roads is becoming increasingly heavy. The limited design life, increasing traffic flow, and overload state operation test the highway maintenance work. Once the security maintenance cannot be completed in time, it will cause huge economic loss and negative social impact. Therefore, the construction of a perfect maintenance system for traffic road development has far-reaching significance.

The research on intelligent detection of road diseases has been relatively mature for the identification of cracks, but other road disease detection methods are not mature. It is necessary to ensure the practicability and universality of the research. Existing technologies should be moved from the laboratory to practical engineering applications, and they need to be able to cover as many diseases as possible. Of course, with the increase in the types of diseases studied, the requirement for the corresponding technology also increases, which needs to overcome difficulties and actively solve the problem. Moreover, most of the studies are limited to urban roads, and subsequent studies need to take rural roads into account. In addition, a data management platform needs to be established to record disease types, disease locations, and detection times to provide a complete platform for big data collection, storage, sharing, and application.

In general, the basic theoretical framework related to the intelligent detection of road diseases has been relatively perfect, and various image processing technologies have also been relatively mature. However, considering the actual engineering demand, we still need to constantly absorb new methods of theory and technology to achieve the universality and high accuracy of road disease intelligent detection.

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