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Research Article

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Design of a Road Pothole Detection System Based on Monocular Vision

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Abstract: Road transportation is essential in daily life. The presence of potholes and other defects on the road significantly impacts people's travel safety. Therefore, detecting road surface potholes is an indispensable task. With advancements in road defect detection technology, deep learning has become increasingly developed and is widely used in road surface detection. The pothole detection system discussed in this paper is based on deep learning algorithms. Image processing technology is used for preprocessing captured images. MATLAB tools are utilized to classify annotated pothole images, creating a dataset for training the chosen YOLOv2 convolutional neural network algorithm. In summary, the deep learning-based road pothole detection system implemented in this paper has high accuracy and good reliability, addressing the problem of manual pothole identification and providing a better method for pothole detection.

Keywords: Pavement pothole detection, Vision sensors, Image processing, Deep learning, Distance detection

Introduction

Currently, China's economy continues to grow, infrastructure is being continuously improved, and significant progress has been made in public road construction, leading to enhanced road transportation services. This not only provides greater convenience for daily travel but also presents more challenges for road maintenance and upkeep. With increasing road traffic volumes, the rise in surface defects has a greater impact on traffic safety. Therefore, detecting and maintaining road defects has become crucial. In practical road usage, factors such as rain, snow, temperature fluctuations, weathering, and load-bearing gradually reduce the structural strength of the road surface, eventually leading to various types of defects (e.g., potholes, cracks, ruts). These issues persist throughout the road's service life, shorten its lifespan, and pose threats to vehicles and pedestrians, significantly increasing the incidence of road accidents. According to the road development experiences of developed countries like the U.S., Japan, and Germany, road construction and maintenance should be divided into three stages: construction-focused, equal emphasis on construction and maintenance, and maintenance-focused. Thus, maintenance work will become a critical direction for future road development in China. Figure 1 illustrates the development of total road mileage and road density over the past five years.

The detection methods for road surface defects must meet requirements for accuracy, efficiency, cost-effectiveness, and road integrity. Accuracy refers to the need for the pothole detection results to be precise, clearly indicating the types of road defects, their quantities, and the extent of damage on a specific road segment. As public transportation construction in China continues to improve and the use of public transport increases, issues such as climate warming, rain erosion, wind erosion, and increased load-bearing are gradually weakening the compressive strength of public roads, leading to problems like cracks, potholes, and ruts. The low durability of road surfaces and harsh weather conditions result in bowl-shaped depressions on the roads. Potholes significantly impact road traffic safety and cause disruptions to travel. These potholes greatly shorten the road's lifespan and increase the likelihood of traffic accidents due to vehicle tire blowouts and damage caused by driving over potholes. Therefore, the condition of the road directly affects travel safety. Integrating computer vision technology with artificial intelligence in intelligent driving can allow vehicles to sense changes in the surrounding environment. Some dangerous conditions can be detected early through these advanced driving assistance features, giving drivers more time to respond to various traffic situations and ensuring safety. With the rapid advancement of technology, machine vision is increasingly applied not only for object recognition and tracking but also for enhancing vehicle control. For instance, it can be used to identify a vehicle's appearance, shape, size, speed, and direction, thereby improving vehicle safety and reliability. Advanced object detection technologies can accurately locate depressions and protrusions on the road and use this data to support autonomous driving systems, ensuring vehicle safety. Pothole detection in road scenarios must consider robustness, accuracy, and real-time performance due to the complex and variable environment. Factors such as lighting changes, pothole shapes, and obstruction by other objects can affect detection accuracy. Therefore, applying road pothole detection tasks to intelligent driving systems has significant practical value and importance.

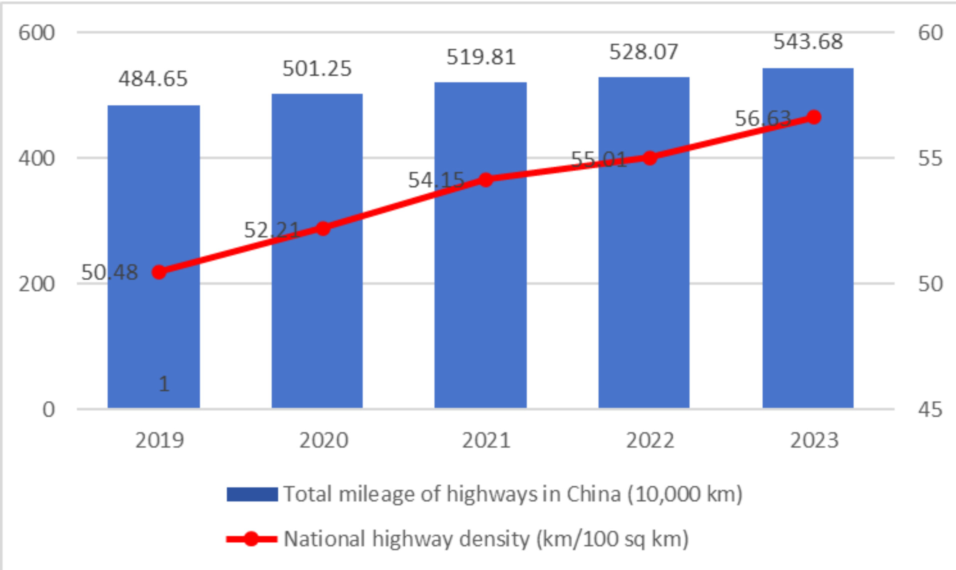

Figure 1: The total number of road kilometers and highway density in the country from 2019 to 2023

Image Preprocessing

In real-life image collection of road surface potholes, various external factors such as lighting conditions, road markings, and oil stains can cause image blurriness and make processing challenging. This often leads to difficulties in accurately identifying potholes or even missing them altogether. In cases where external factors are too significant, these images may be misclassified, necessitating manual removal of such images. To more accurately detect and identify potholes on roads, image preprocessing is required to minimize external interference. This step can significantly improve the performance of convolutional neural networks. An example reference image of road surface potholes is provided below, as shown in Figure 2.

Figure 2: Pavement pothole example reference diagram

Image characteristics of pavement potholes

In practical use, roads are affected by many environmental factors, including lighting intensity, surface moisture, and deformation caused by vehicle traffic, leading to various types of potholes. This poses a significant danger to travel safety, and if not promptly maintained, the repair costs will increase over time. Images of road potholes typically have several characteristics:

(1) Observing the grayscale values of pothole images reveals that the defect areas have significantly lower grayscale values than other areas, indicating that the defect areas are darker in color.
(2) In terms of pothole structure, road defects come in various forms, and generally, the pixel count in the defect areas is very low with relatively weak edge information.
(3) Some potholes are adjacent to or even overlap each other, displaying spatial continuity.
(4) During the collection of road surface images, the resulting images are often complex, with potholes possibly affected by boundaries, lighting, or tree shadows, leading to unclear images.

Pavement pothole image preprocessing

Figure 3 shows the results after applying various image processing methods. Itcan be observed that the processed images have significantly improved in quality, with more uniform pixel values and enhanced contrast. The features of theroad pothols have become clearer and smoother.

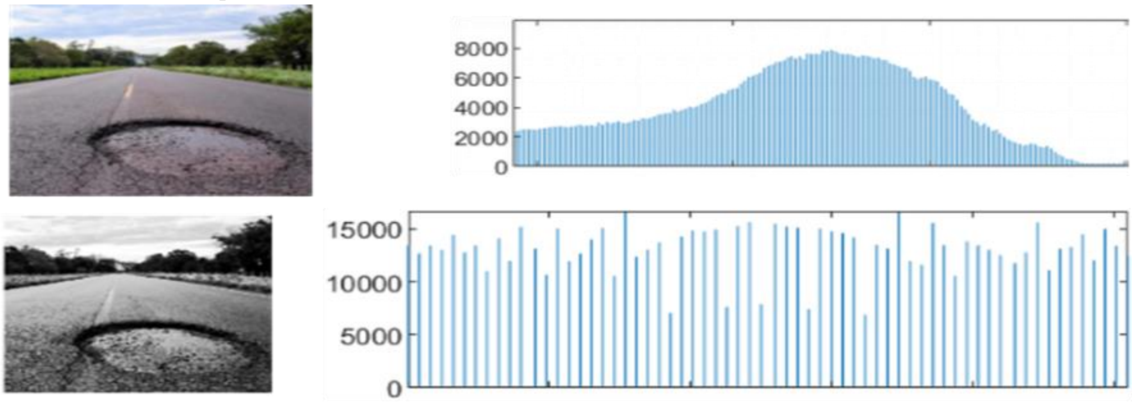

Figure 3: Image preprocessing plots

Build a dataset of road potholes

Before training with supervised learning methods, it is necessary to label the dataset to better understand and manage it during the training process. This involves marking the locations of road potholes in the images with bounding boxes, allowing the labeled data to be directly imported into the model for training. Prior to labeling, the original images are manually filtered to remove blurry and unusable ones, resulting in a preliminary set of 500 road pothole images. These are then annotated using MATLAB's internal tool, Image Label, producing 500.mat annotation files corresponding to each pothole image. The annotated dataset is converted into a format suitable for direct network training. This results in a dataset of 500 road defect images for object detection. The main objective of this work is to identify and detect road potholes. The annotated image display is shown in Figure 4.

Figure 4: Annotated Image

Convolutional Neural Networks and Methods

To effectively compare the detection of road potholes, two advanced network models were used: Faster R-CNN and YOLOv2. These algorithms were evaluated to identify the most suitable one for pothole detection.

Based on Fastra-Ken's pothole detection algorithm

For Faster R-CNN, various feature extraction networks are available, but this study selected the ResNet50 feature extraction network for pothole recognition experiments. The network model is illustrated in Figure 5.

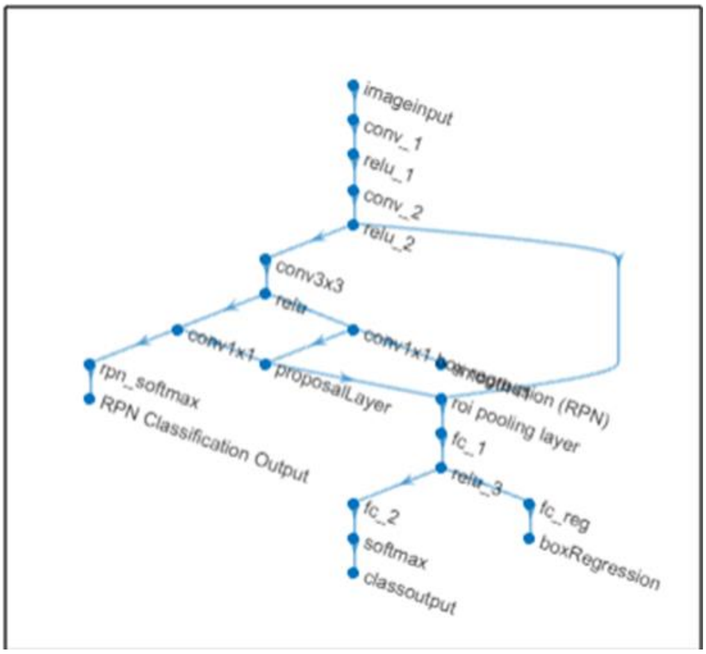

Figure 5: Network model diagram

The dataset used consists of MATLAB .mat files and original image files located in the Set(2) folder. The training was conducted for a total of 1 epoch with a learning rate of 0.001. The parameters of each network layer were adjusted to fit the training model, using the "sgdm" gradient descent optimization algorithm. The minimum batch size was 10 images per epoch, with the entire process running for 1 cycle. The detection results are shown in Figure 6.

Figure 6: Validation set test results

Pothole detection algorithm based on YOLOv2

The dataset used consists of the data1.mat file and the original images in the Set(2) folder. The training was conducted for a total of 100 epochs with a learning rate of 0.001. Each training batch included 16 images, and the entire process was run for 30 cycles. The training process and pothole detection results are shown in Figure 7, which displays the training loss after 100 epochs. The accuracy of this network is illustrated in Figure 8.

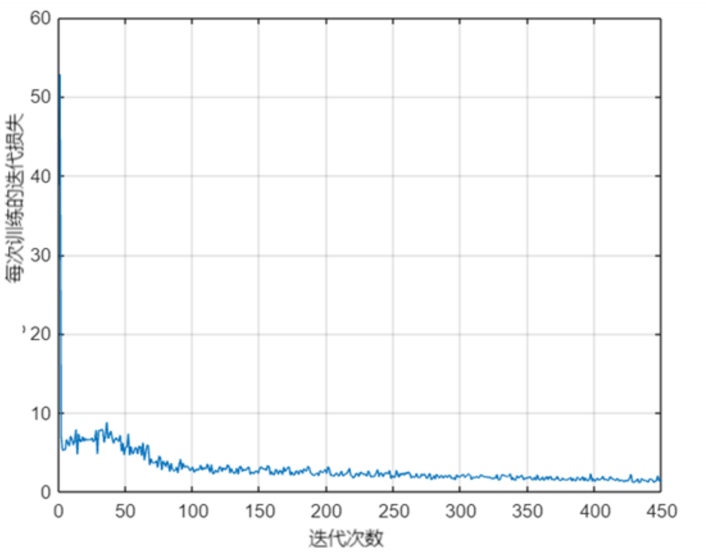

Figure 7: Iterative loss graph

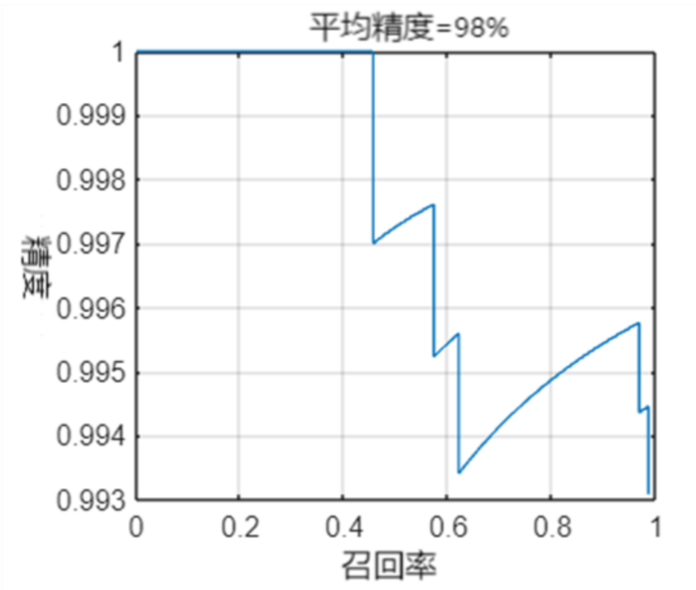

Figure 8: Average accuracy

To evaluate the network's accuracy in detecting potholes, a few images from the validation set were tested, and the results are shown in Figure 9.

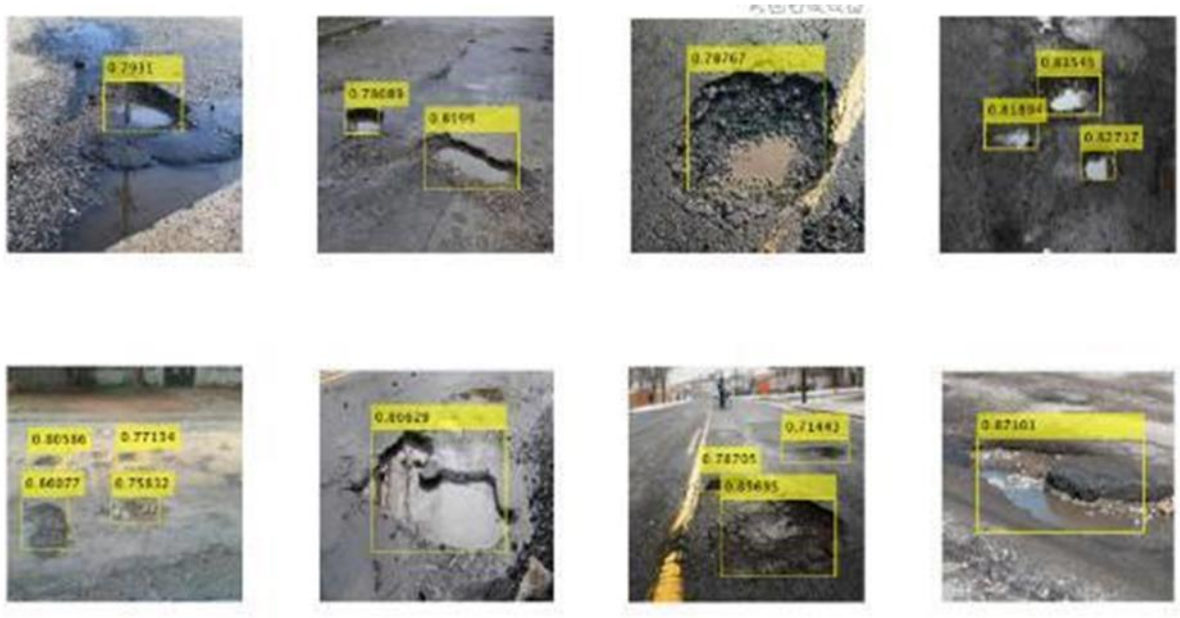

Figure 9: Validation set validation

Analysis of experimental results

Based on the results from experiments 3.1 and 3.2, Faster R-CNN exhibited a lower accuracy for pothole detection with an average precision of 43%, while the YOLOv2 network model achieved a high detection rate of 98%. Therefore, the YOLOv2 network model provides the best performance for pothole detection.

Real-World Vehicle Testing and Analysis

The acquisition equipment designed for the monocular vision-based road pothole detection system consists of two parts: a detection vehicle and an onboard camera. The camera is installed at the front of the vehicle to capture images of road potholes. Since it is challenging to find a large number of potholes on the road, artificial potholes were created for experimentation. The experimental vehicle is shown in Figure 10.

Figure 10: Experimental trolley

To apply the pothole detection system to a vehicle for practical use, the experiments were conducted in suburban and rural areas, focusing on detecting potholes ahead of the vehicle. The experiments covered various conditions: multiple potholes, single potholes, and low-light conditions (dusk). Figures 11 display the detection results across different scenarios, indicating that the system performs well in detecting potholes under diverse conditions.

Figure 11: Screenshot of the results of the pothole detection ahead

Due to experimental constraints and the lack of high-precision radar equipment, precise measurements of pothole and vehicle distances, as well as pothole dimensions, could not be obtained. Therefore, measurements were taken using a tape measure to determine the distance between the vehicle and the pothole, as well as the size of the pothole. This data was then compared with the distances and sizes detected by the system to demonstrate that the distance and size measurement functions meet practical application needs. To validate the accuracy of the detection system, a further analysis was conducted by comparing the number of potholes detected by the system with the actual number of potholes. The pothole detection accuracy is shown in Table 1, while Table 2 presents experimental results for measurements of distances and pothole sizes.

Table 1: Accuracy of pothole detection

Actual number of potholes	Number of potholes detected	Accuracy
50	46	0.92

Table 2: Results of the pit measurement experiment

Number	Actual distance/m	Measure distances/m	Actual size/m	Measure the size/m
1	3.2	3.0	0.3*0.3	0.3*0.2
2	1.3	1.0	0.4*0.4	0.5*0.5
3	1.0	0.7	0.4*0.2	0.3*0.2
4	1.0	0.75	0.2*0.2	0.2*0.2

Conclusion

In current road surface inspection processes, the task is typically performed manually, which is time-consuming and labor-intensive, with variable efficiency and significant uncertainty leading to considerable differences in manual inspections. To achieve real-time, effective detection of road potholes, improve road maintenance levels, and ensure safe and reliable transportation, there is a need for innovative and improved detection methods. This paper investigates pothole detection using convolutional neural network algorithms in deep learning. The trained model can automatically identify road potholes and detect them more effectively. Although the paper has achieved efficient pothole detection, several areas still require improvement due to time constraints and the need to identify other road defects:

(1) The paper used rectangular bounding boxes for image annotation, which included a lot of background information, leading to incorrect identifications. The next step will involve adopting polygonal annotation methods to minimize background information and improve training accuracy and performance.

(2) Due to the limited size of the dataset, the model's detection accuracy is not sufficiently high. The next step will involve expanding the dataset through further collection of samples.

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