Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 15, No. 3, 2024

Overview and optimization strategy of road crack detection based on YOLOv8 algorithm

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Abstract: This paper comprehensively reviews the YOLOv8 algorithm and its application in road crack detection, focusing on the advantages of the algorithm in real-time target detection and high accuracy. With the continuous expansion of road infrastructure around the world, road cracks have become a serious safety hazard, which not only poses a threat to drivers but also brings a huge economic burden. Traditional road crack detection methods, such as manual inspection and sensor technology, often face the problems of high labor intensity, low efficiency and high cost. With the development of computer vision and deep learning technology, YOLOv8, as an efficient target detection system, provides new possibilities for the automation and accuracy improvement of road crack detection. This paper reviews different application versions of YOLOv8 in road crack detection, evaluates their performance, and points out the challenges of small target detection, real-time processing and multi-scale feature fusion. This paper proposes a variety of optimization strategies, including model optimization, data enhancement, training strategy and hardware acceleration. In addition, this paper looks forward to the future development trends of deep learning in the field of road crack detection, such as multimodal fusion, cross-domain detection and automated system integration, to promote the improvement of road safety and maintenance efficiency.

Keywords: YOLOv8; Road crack detection; Deep learning; Model optimization; Real-time processing.

1. Introduction

With the rapid development of road construction around the world, the problem of road cracks has become increasingly serious. This not only threatens road safety [2 , 3] , but also leads to a huge economic burden. According to statistics, the global investment in road construction and maintenance is as high as US$400 billion per year . Among them, one-third of the major highways in the United States are rated as medium or lower, and drivers therefore have to pay an additional US$67 billion in vehicle maintenance costs each year. Faced with the challenges brought by urban expansion, increased traffic load and extreme climate, it is particularly urgent and important to develop technologies that can detect road cracks in real time and efficiently. Road crack detection technology based on deep learning has become a powerful tool to solve this problem due to its high efficiency and accuracy. Current detection methods mainly include manual visual inspection , sensor detection, and laser and infrared technology. These methods are usually labor-intensive, costly and inefficient. With the rapid development of computer vision technology, especially the widespread adoption of deep learning methods in various applications, crack detection technology based on convolutional neural networks has made significant progress in automation, accuracy and efficiency. This paper focuses on the application of YOLOv8 algorithm in road crack detection and explores its optimization strategy. As a real-time target detection algorithm with superior performance, YOLOv8 provides a new solution for road crack detection through its innovative architecture and optimization technology. This paper will analyze the performance of YOLOv8, evaluate its effect in practical applications, and propose improvement plans to further improve the accuracy and efficiency of detection.

2. Overview of YOLOv8 Algorithm

2.1. Algorithm Background

Since the YOLO (You Only Look Once) algorithm was first proposed in 2015, it has undergone multiple iterations and improvements, gradually optimizing the balance between speed and accuracy and reducing computing resource requirements . The proposal of YOLOv8 is based on further optimization of the performance of the previous version to adapt to the needs of dynamic environments and multi-scale object detection. This version emphasizes improvements in real-time performance and detection results, making it perform better in complex application scenarios such as video surveillance and autonomous driving.

2.2. Algorithm Structure

Input layer: YOLOv8 supports multiple input resolutions, the most common being 416x416 or higher. The input image is first preprocessed by normalization and color space adjustment to achieve the best performance during network training and inference.

Backbone: The backbone layer of YOLOv8 is used to extract basic features of the image. Usually, an efficient convolutional neural network architecture is used, such as CSPNet (Cross Stage Partial Networks) or a residual network similar to ResNet, to capture local and global information in the image. This layer generates multiple feature maps through deep convolution and downsampling operations, which will be used for subsequent detection tasks.

Neck: The Neck layer fuses multi-scale feature maps from the Backbone through feature fusion techniques such as FPN (Feature Pyramid Network) or PAN (Path Aggregation Network) to enhance the model's ability to detect objects of different scales. This part is mainly responsible for combining high-resolution and low-resolution feature maps to improve

the detection accuracy of small objects, while also enhancing the robustness of the model in complex backgrounds.

Head: The head of YOLOv8 is used for final object detection. It generates prediction boxes through multiple convolutional layers, predicting the category label, confidence score, and coordinate position of the bounding box. YOLOv8 optimizes the anchor box design in this part and combines clustering analysis technology to enable the model to better adapt to objects of different shapes and sizes. This part directly affects the accuracy and speed of the detection results .

2.3. Algorithm Advantages

YOLOv8 places special emphasis on processing speed in its design. By optimizing the network structure and simplifying the calculation operations, the processing speed is improved compared to the previous version to meet the needs of real-time applications. In addition, the improved loss function and deeper network structure improve the accuracy of the model on multiple standard data sets, especially in the detection of small objects and complex scenes. YOLOv8 also demonstrates excellent generalization capabilities by training in a variety of environments and conditions. The model can maintain stable performance under different lighting and weather conditions and adapt to various complex application scenarios.

3. A review of YOLOv8 applications in road crack detection

3.1. Application Status

In recent years, the application of YOLOv8 and its improved versions in road crack detection has gradually increased. Various research teams have achieved high accuracy and efficiency in crack detection by introducing different innovative methods. The following are several representative research cases:

YOLOv8-PD model: Based on YOLOv8n, this model significantly improves the detection accuracy by introducing the BOT (Bottleneck Transformer) module and LSKA (Large Separable Kernel Attention) mechanism . The BOT module combines the advantages of CNN and Transformer, enabling the model to better capture global features, while the LSKA mechanism enhances the ability to capture long crack features through large convolution kernels. Figure 1 shows the improved structure of YOLOv8-PD:

MRC-YOLOv8 model: This model proposes a multi-scale feature fusion strategy (Multi-Scale Feature Fusion), which enhances the detection capability of multi-scale cracks by improving the feature pyramid network (FPN) of YOLOv8. This model performs particularly well in crack detection on mountain roads. Figure 2 shows the network structure of MRC-YOLOv8.

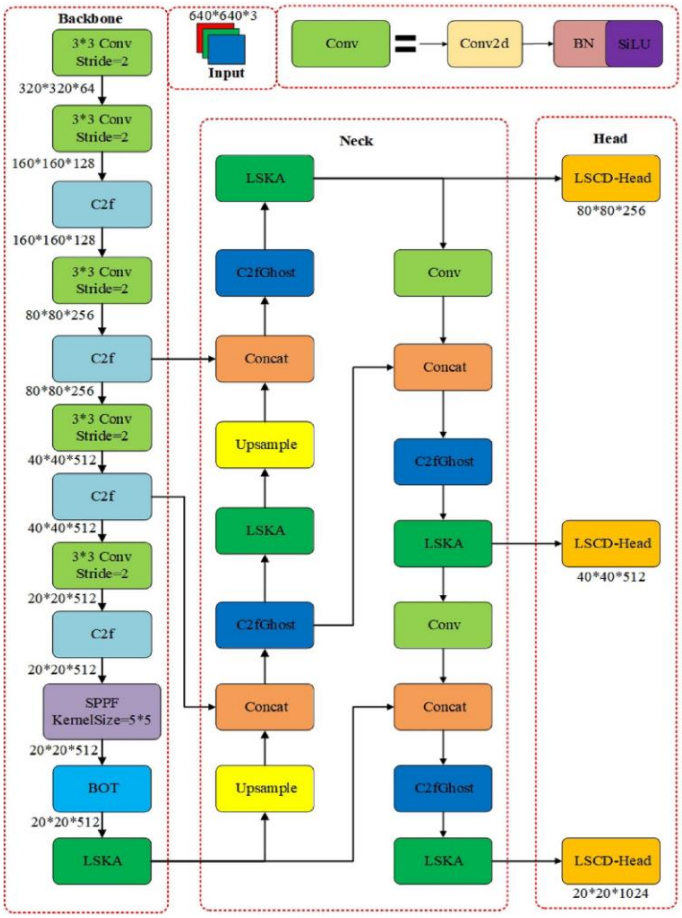


Figure 1. Network structure diagram of YOLOv8-PD (cited from reference)

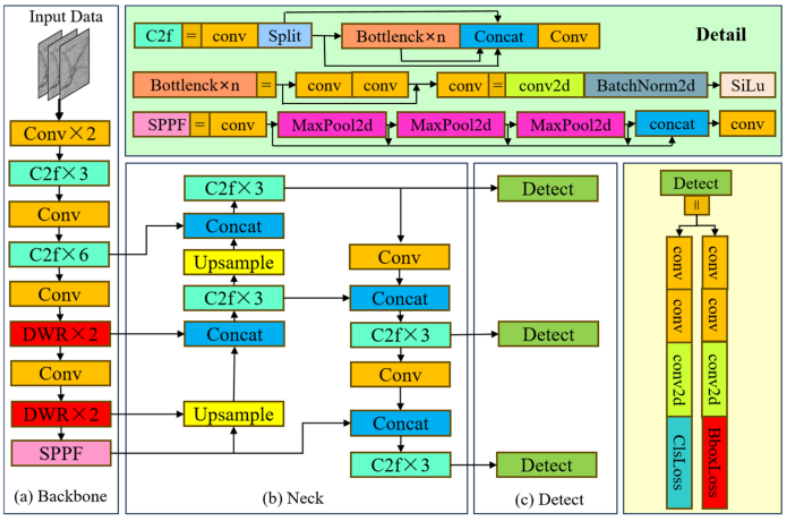


Figure 2. Network structure diagram of MRC-YOLOv8 (cited from reference).

YOLOv8-CD model: This model achieves efficient detection of small cracks by introducing the large convolution kernel spatial attention mechanism (LSK-Attention) and the improved SPPF module. Experiments show that the model

achieves an mAP of 93.5% on the RDD2022 dataset, and performs particularly well in small target detection . Figure 3 shows the structure of the YOLOv8-CD model.

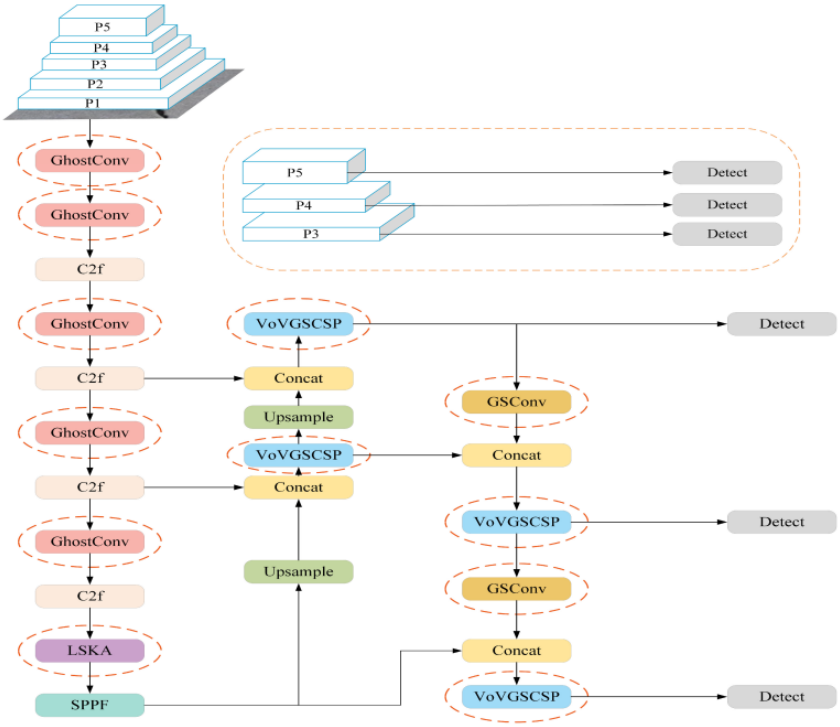


Figure 3. Network structure diagram of MRC-YOLOv8 (cited from reference [1 3]).

BL-YOLOv8s model : This model optimizes YOLOv8s through a series of key improvements. First, based on the concept of bidirectional feature pyramid network (BiFPN), the feature fusion component is reconstructed. BiFPN enhances the semantic information of the model through bidirectional cross-scale connection and weighted feature fusion, especially in small target detection tasks. Secondly, the model introduces the SimSPPF module to replace the original SPPF module, reducing the computational complexity and improving the inference speed. In addition, the LSK-Attention mechanism further improves the detection accuracy of the model, especially in complex scenarios. Finally, through the lightweight improvement of GhostNet and LSCD-Head modules, the computational burden is reduced, making the model more suitable for the needs of embedded devices . Figure 4 shows the final improved structure of the YOLOv8s model .

YOLOv8-L model: This model improves the performance of YOLOv8 through a series of lightweight improvements, especially for embedded devices. The introduction of the C2f-Faster-EMA module and the SimSPPF module reduces the computational complexity of the model and improves the inference speed, while the Detect-Dyhead module enhances the accuracy of the detection head. Ultimately, the YOLOv8-L model achieves efficient road crack detection on embedded devices, maintaining high detection accuracy and efficiency . Figure 5 shows the structure of the YOLOv8-L model.

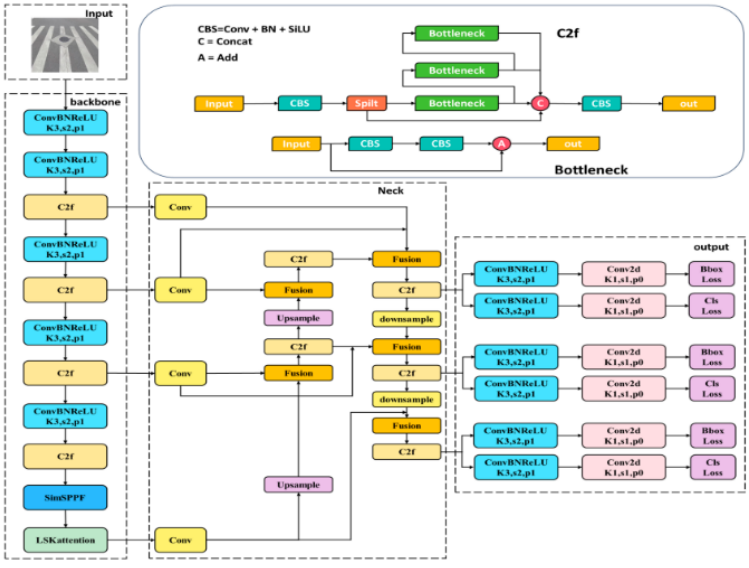


Figure 4. Network structure diagram of MRC-YOLOv8 (cited from reference [1 4]).

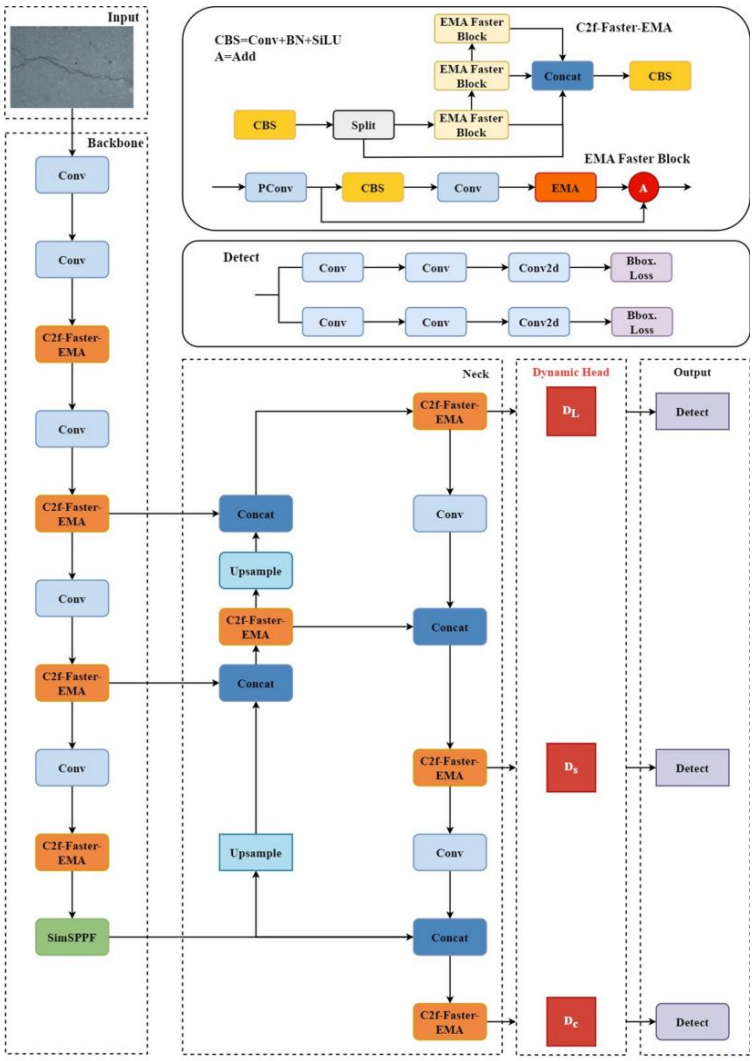


Figure 5. Network structure diagram of MRC-YOLOv8 (cited from reference [1 5]).

3.2. Performance Evaluation

To evaluate the performance of YOLOv8 and its improved versions in crack detection tasks in detail, multiple studies used different performance indicators, such as precision, recall, F1 score, and mAP. The following is a summary of the performance of these models on different datasets:

Table 1. Performance comparison of YOLOv8 and its improved models

Model	mAP50(%)	mAP50-95 (%)	F1(%)	Parameter quantity (M)	GFLOPs	FPS
YOLOv8n	69.9	38.6	67	2.36	6.5	89
YOLOv8-PD	70.5	39.5	68	2.36	6.5	111.9
YOLOv8-CD	93.5	71.4	93.2	7.9	8.2	88
MRC-YOLOv8	95.9	93.7	94.3	4.3	6.5	100
BL-YOLOv8	90.7	70	87	7.82	25.5	98
YOLOv8-L	71.5	57.7	78.4	8.59	22.4	136.7

YOLOv8n: As a baseline model, YOLOv8n achieved 69.9% on mAP50 and 38.6% on mAP50-95, showing good basic performance in crack detection tasks. Although it has a small number of parameters (2.36M) and low GFLOPs, its detection accuracy is relatively more basic.

YOLOv8-PD: By introducing the BOT module and LSKA mechanism, YOLOv8-PD has improved both accuracy and speed. The mAP50 has reached 70.5%, and the FPS has increased to 111.9, which is suitable for application scenarios with high real-time requirements.

YOLOv8-CD: This model achieves efficient detection of small cracks by introducing large convolution kernel spatial attention mechanism and SPPF module, with mAP50 up to 93.5%, which is particularly outstanding in small target detection, but its parameter amount is also increased to 7.9M accordingly.

MRC-YOLOv8: MRC-YOLOv8 adopts a multi-scale feature fusion strategy, which significantly improves the ability of multi-scale crack detection. The mAP50 reaches 95.9%, and its performance in different detection tasks is very outstanding.

BL-YOLOv8: Through a series of lightweight and optimized improvements, BL-YOLOv8 reduces the computational burden while maintaining a high detection

accuracy (mAP50 is 90.7%), which is particularly suitable for resource-constrained embedded device applications.

YOLOv8-L: This model has made a number of lightweight improvements to meet the needs of embedded devices. Although the computational complexity has been reduced, it still maintains a high detection performance, with an mAP50 of 71.5% and an FPS of 136.7, performing well under resource-constrained conditions.

3.3. Challenges and shortcomings

Although YOLOv8 and its improved versions perform well in crack detection tasks, they still face challenges and limitations in some aspects:

Detection in complex backgrounds: The YOLOv8 model is not good at dealing with complex backgrounds, especially in road scenes, where cracks often blend into the surrounding environment, making it difficult for the model to distinguish between cracks and background. Complex backgrounds such as vehicles, pedestrians, and other obstacles interfere with the detection results, resulting in reduced detection accuracy.

Challenges in small object detection: Although the BL-YOLOv8 model has improved in small object detection, it still faces challenges in detecting small cracks that are similar to the surrounding environment. The difficulty of small object detection is not only due to the size of the target, but also involves factors such as shooting distance and weather conditions, which will affect the detection effect.

Real-time and embedded application limitations: In resource-constrained embedded devices, although the lightweight YOLOv8-L model has improved computational efficiency, the model still has difficulty maintaining the trade-off between accuracy and speed. For real-time applications that require high accuracy and low latency, the complexity and computational requirements of the model are still a major limitation.

Efficiency of multi-scale feature fusion: Although the MRC-YOLOv8 model improves the crack detection capability through the multi-scale feature fusion strategy, this method also increases the computational overhead of the model, causing it to face certain performance bottlenecks in real-time applications.

In summary, although YOLOv8 and its improved versions perform well in road crack detection, there are still some challenges in complex background, small target detection, real-time and multi-scale feature fusion. These problems need to be further optimized and solved in future research to improve the robustness and adaptability of the model.

4. Optimization strategy of YOLOv8 algorithm

In order to improve the performance of YOLOv8 in road crack detection, improvements can be made in the following four aspects: model structure optimization, data enhancement, training strategy optimization, and hardware performance improvement. Through these strategies, the efficiency and generalization ability of the model can be significantly improved while maintaining the detection accuracy.

4.1. Model Optimization

BiFPN (Bidirectional Feature Pyramid Network) can improve the model's ability to capture multi-scale information through bidirectional connections and feature fusion. Integrating BiFPN into YOLOv8 can achieve better results in object detection at different scales, especially significantly improving detection performance in small object detection tasks. By transferring information between different levels, BiFPN ensures the effective use of features of different resolutions, thereby improving the model's adaptability to complex scenes.

Introducing attention mechanisms in YOLOv8 (such as LSK-Attention and CBAM) can help the model better focus on important areas and suppress interference from irrelevant backgrounds. These mechanisms dynamically adjust the feature maps to The importance of the same parts can improve the detection accuracy of the model in complex scenes.

The dynamic detection head can adjust its structure according to the needs of different tasks and maintain efficient detection results when facing targets of different sizes, shapes and positions. This method can significantly improve the stability and robustness of the model when dealing with diverse scenarios of road crack detection.

By applying lightweight convolutional networks such as GhostNet and MobileNetV3, the computational complexity of YOLOv8 can be reduced without significantly reducing model performance. GhostNet reduces the number of parameters by reducing redundant operations, while MobileNetV3 uses deep separable convolution technology to further optimize computational efficiency.

Combining the Transformer structure with the convolutional network can improve the ability to extract global information. Transformer is good at capturing long-distance dependencies, while CNN has an advantage in extracting local features. The combination of the two allows the model to maintain high resolution in complex scenarios while obtaining global features, thereby enhancing detection capabilities.

4.2. Data Augmentation

Mosaic technology enhances the generalization ability of the model by stitching multiple images together to generate training samples with diverse backgrounds. This technology can effectively improve the adaptability of the model, especially when dealing with different lighting conditions and weather changes.

Data augmentation methods such as CutMix and MixUp increase the diversity of training data by mixing multiple images to generate new samples, helping the model better cope with object detection tasks in complex scenes. CutMix generates new images by cropping and splicing, while MixUp mixes at the pixel level.

Self-supervised learning technology can significantly improve the pre-training effect of the model by mining information from unlabeled data. At the same time, optimizing data labeling strategies, such as using semi-supervised or active learning methods, can effectively reduce labeling costs and improve the generalization ability of the model.

4.3. Training Strategy

Reasonable loss function design can significantly improve the positioning accuracy of the model. Improved loss functions such as EIOU and GIoU optimize the training effect of the model by more accurately measuring the match between the predicted box and the true box.

Dynamic learning rate adjustment strategies, such as cosine annealing and learning rate restart, can adjust the learning rate during training to avoid falling into local optimality and speed

up convergence. This strategy helps the model reach optimal performance in fewer iterations.

To address the problem of data imbalance, using loss functions such as Focal Loss or weighted cross entropy can balance the contribution of different types of data. At the same time, data sampling strategies (such as Oversampling or Undersampling) can also help the model better handle unbalanced data distribution.

Regularization techniques (such as L2 regularization, Dropout, and Batch Normalization) can prevent the model from overfitting, thereby improving the model's ability to generalize to new data, especially when dealing with small-scale data sets or complex scenarios.

4.4. Hardware Acceleration

Using high-performance GPUs (such as NVIDIA RTX 3090 or A100) can significantly improve the inference speed of YOLOv8. By optimizing the CUDA and cuDNN libraries and combining mixed precision training, computing efficiency can be further improved and inference time can be reduced.

In embedded and edge computing scenarios, the application of TPU and FPGA hardware accelerators can significantly improve computing efficiency. TPU focuses on efficient matrix operations, while FPGA can be flexibly configured according to specific tasks to achieve optimal performance and energy efficiency.

Combining multiple computing devices for heterogeneous computing, such as using GPU and TPU at the same time, can further improve the reasoning speed. At the same time, using devices such as Edge TPU or Jetson Nano can achieve efficient edge computing.

Model quantization and pruning techniques can significantly reduce the amount of computation and memory usage of the model without significantly reducing the accuracy of the model. By converting floating-point operations to fixed-point operations, the model can run efficiently in an environment with limited resources, while pruning can further improve the computational efficiency of the model by removing unimportant parameters.

5. Future Outlook

With the continuous development of deep learning technology, YOLOv8 and its improved versions have great potential for application in road crack detection. The following is a detailed discussion of the future development trends, potential application scenarios and research directions of this technology.

5.1. Technology Trends

Improved algorithm efficiency: The rapid development of hardware technology will promote the further optimization of deep learning algorithms. Researchers are exploring how to reduce the consumption of computing resources and speed up the execution of models while improving detection accuracy through a lighter network architecture, such as optimizing the combination of Transformer and CNN. In the future, automated model architecture search (NAS) may become mainstream, helping to design more effective network structures for specific tasks, thereby greatly improving the efficiency and real-time performance of crack detection.

Dataset expansion: Data is one of the important factors driving the development of deep learning technology. With the continuous increase of crack detection datasets, especially those covering a variety of road types, climate conditions, and traffic environments, the generalization ability of the model will be further enhanced. In addition, technologies such as generative adversarial networks (GANs) may be used to generate synthetic crack data to make up for the lack of actual datasets and provide support for training more robust models.

Self-supervised learning and few-shot learning: In the future, self-supervised learning and few-shot learning will play an increasingly important role in crack detection. Self-supervised learning reduces the model's dependence on a large amount of labeled data by mining useful information from unlabeled data. Few-shot learning can help the model effectively learn features even when the labeled data is limited, thus enhancing its adaptability in different scenarios.

5.2. Application Prospects

Road maintenance and detection: With the continuous advancement of intelligent transportation systems, the application potential of YOLOv8 in road crack detection will continue to expand. This technology can not only effectively improve the efficiency of road maintenance and reduce the investment in manual detection, but also improve the accuracy of detection. By integrating YOLOv8 into drones or autonomous vehicles, real-time monitoring of road cracks can be achieved, helping to promptly identify and respond to potential safety hazards.

Optimization of intelligent transportation systems: In intelligent transportation systems, YOLOv8 can not only be used for road crack detection, but also for various tasks such as vehicle behavior monitoring and traffic flow analysis. By combining with traffic management systems, the algorithm can help predict road damage trends and provide recommendations for road maintenance. At the same time, real-time road detection data can also be used to optimize traffic flow and improve road utilization efficiency.

Application in driverless technology: YOLOv8 has broad application prospects in autonomous driving technology. The algorithm can help autonomous vehicles effectively detect road damage, thereby optimizing driving routes and improving driving safety. By integrating data from multiple sensors such as lidar and cameras, YOLOv8 can provide vehicles with more accurate environmental perception and decision support. Looking forward to the future, YOLOv8 will further enhance the autonomous decision-making capabilities of autonomous vehicles and enhance their overall safety performance.

5.3. Research Directions

Multimodal data fusion: In some complex scenes, a single visual information may not be able to provide sufficient detection accuracy. Therefore, multimodal data fusion will become one of the important research directions in the future. By combining multiple sensor information such as infrared images, lidar data, radar data, etc. with traditional visual data, the model can make more accurate detection decisions in more complex scenes.

Exploration of cross-domain detection: Cross-domain detection aims to ensure that the model can still maintain efficient detection performance in different environments or data distributions. Future research can focus on how to make YOLOv8 perform well on datasets trained under different geographical locations and climatic conditions. This may involve the application of domain adaptation technology and

transfer learning to improve the generalization ability of the model in cross-domain tasks.

Intelligent system integration and automated detection: Future research can also explore how to integrate the YOLOv8 algorithm into the intelligent transportation system to complete the fully automated process from detection to maintenance. By combining technologies such as the Internet of Things, edge computing, and cloud computing, the automated deployment of crack detection and real-time data upload can be ensured, thus providing a comprehensive road health monitoring solution.

6. Conclusion

This paper analyzes the YOLOv8 algorithm and its application in road crack detection in detail, and proposes optimization solutions for model optimization, data enhancement, training strategy and hardware acceleration. Through these methods, YOLOv8 can effectively improve the detection accuracy and generalization ability of the model, while meeting the real-time requirements in practical applications.

6.1. Summary

First, this paper explains the background and advantages of the YOLOv8 algorithm, focusing on its unique design in real-time object detection tasks. By combining different optimization strategies, such as BiFPN feature fusion, attention mechanism, data augmentation and self-supervised learning, the adaptability of the model in complex scenarios is significantly enhanced. Subsequently, this paper discusses in detail the practical application of YOLOv8 and its improved versions in road crack detection, and shows the performance and challenges of various improved models in different detection tasks. Finally, this paper proposes a series of optimization suggestions to further improve the efficiency and accuracy of YOLOv8 in future applications.

6.2. Emphasis on practical significance

Road crack detection technology based on YOLOv8 has important practical significance in practical applications. The efficiency and accuracy of this technology can not only greatly improve the efficiency of road maintenance, but also reduce the cost and error rate of manual detection. In the current context of intensified urban expansion, increased traffic load, and frequent extreme climate, intelligent systems with real-time detection and repair capabilities have become particularly critical. By introducing YOLOv8 and its improved versions, more accurate road health monitoring can be achieved, reducing traffic accidents and economic losses caused by road damage, thereby ensuring public safety and reducing infrastructure maintenance costs.

6.3. Future Work

Although the YOLOv8 algorithm has made important progress in road crack detection, there are still several research directions worth exploring in depth. First, by combining data from multiple sensors such as vision, lidar, and infrared, multimodal fusion technology can further improve the accuracy of detection and achieve more comprehensive road monitoring. Secondly, the research on cross-domain detection technology can enhance the generalization ability of the model, so that it can still maintain good performance in different geographical locations and climatic conditions. In addition, the integration of automated detection and intelligent systems is also one of the key directions in the future. Integrating YOLOv8 into the intelligent transportation system can realize the automation of the detection and maintenance process, greatly improving the efficiency and intelligence level of road health monitoring.

In general, the YOLOv8 algorithm and its improved versions show great potential and broad application prospects in the field of road crack detection. Future research will continue to promote the improvement of this technology so that it can play a greater role in intelligent transportation and infrastructure maintenance.

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