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A Review of Pavement Crack Detection Based on YOLO

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Abstract: As transportation infrastructure expands, pavement distresses have become more frequent. Cracks, as the most common early damage, directly affect road safety and service life. Traditional manual inspections are time-consuming and highly subjective, while conventional image-processing methods lack robustness under varying illumination, noise, and complex textures. Deep learning, especially the YOLO family, offers a feasible solution for large-scale, fast, and automated crack detection thanks to its real-time performance and end-to-end detection capability. Improving detection accuracy under complex conditions, enhancing small-target recognition, and boosting model generalization have become key issues in current road maintenance and intelligent inspection. With the continuous expansion of road infrastructure scale, the operational safety and service performance of pavements have become increasingly critical to transportation systems. Pavement cracks are one of the most common and representative forms of structural distress, and their timely and accurate detection is of great significance for pavement maintenance decision-making and lifecycle management. Traditional manual inspection and classical image processing–based methods suffer from limitations such as low efficiency, strong subjectivity, and poor robustness under complex environmental conditions. In recent years, deep learning–based object detection methods have shown remarkable advantages in feature representation and detection accuracy, among which the You Only Look Once (YOLO) series algorithms have attracted extensive attention due to their real-time performance and end-to-end detection framework. This paper systematically reviews the research progress of pavement crack detection based on YOLO algorithms. First, the basic principles of pavement crack detection and the evolution of YOLO models are introduced, including their network structures, detection mechanisms, and performance characteristics across different versions. Then, existing studies applying YOLO models to pavement crack detection are comprehensively summarized from aspects such as dataset construction, annotation strategies, model training schemes, and parameter optimization methods. Typical research results are comparatively analyzed in terms of detection accuracy, speed, and adaptability under complex backgrounds, and the advantages and limitations of different YOLO variants are discussed. Furthermore, this paper compares YOLO-based methods with other deep learning detection and segmentation approaches, highlighting their relative strengths in engineering applications. Finally, current challenges, including small crack detection, data imbalance, environmental interference, and model generalization, are analyzed, and future research directions such as lightweight model design, multi-scale feature enhancement, and intelligent inspection system integration are proposed. This review aims to provide a systematic reference for researchers and engineers engaged in pavement distress detection and to promote the practical application of YOLO-based crack detection technologies.

Keywords: YOLO; Pavement Crack Detection; Deep Learning; Object Detection; Intelligent Transportation.

1. Introduction

With the rapid economic development and accelerated urbanization, the scale of transportation networks has been continuously expanding. As a critical infrastructure supporting social and economic operations, the integrity of road pavements is directly tied to transportation efficiency, the safety of public travel, and the stable operation of the national economy. Subjected to the combined effects of long-term loading, climate change, material aging and other factors, road pavements are prone to various structural and functional distresses over time, such as rutting, settlement, potholes and, most commonly, cracks. Failure to detect and address these distresses in a timely manner will not only accelerate the deterioration of pavement performance and increase subsequent maintenance costs, but also trigger traffic accidents and jeopardize public safety. Therefore, establishing a scientific and systematic road health monitoring system to capture real-time pavement conditions and enable the early detection, diagnosis and repair of distresses has become an urgent requirement for road management and maintenance.

Pavement cracks are among the most prevalent and representative forms of road distresses, whose formation and propagation directly impair the load-bearing capacity, driving comfort and traffic safety of road pavements. Traditional manual inspection is characterized by high labor intensity and low operational efficiency; moreover, the detection results are highly susceptible to human experience and subjective judgment, making it difficult to ensure consistency and repeatability. With the expansion of highway networks and the increase in traffic volume, manual inspection can no longer meet the requirements of modern road maintenance in terms of timeliness and coverage, creating an urgent need for more scientific and efficient detection methods. Against this backdrop, automated detection technology has emerged as a viable solution. Through the synergy of sensors, imaging devices and intelligent algorithms, it enables the rapid identification, localization and quantitative analysis of pavement cracks, thus significantly improving detection efficiency and reducing labor costs. The early detection of pavement cracks is of great significance for extending pavement service life and cutting down on subsequent maintenance investments. Automated detection allows for frequent and large-scale data collection, supports the continuous monitoring of crack evolution, and helps transform maintenance decision-making from passive repair to active prevention. In addition, intelligent methods can provide standardized crack grading and distress statistics, facilitating the establishment of long-term databases and supporting the refined and scientific management of road networks. For emergency response and road maintenance under extreme climatic conditions, automated detection also demonstrates remarkable advantages: unmanned inspection equipment can operate in harsh environments or during periods with inconvenient traffic control, ensuring the continuity of detection work and the safety of personnel.

At the technical level, the advancement of computer vision and deep learning has provided a powerful impetus for the automated detection of pavement cracks. Detection systems based on these technologies exhibit high robustness and strong scene adaptability, capable of effectively identifying cracks on pavements with complex lighting conditions, cluttered backgrounds and different material properties. The results of automated detection can be easily integrated with geographic information systems and maintenance management platforms, enabling the visualization, traceability and decision support of crack information. The development and popularization of automated pavement crack detection is not only an inevitable requirement to improve the efficiency and quality of road maintenance, but also a crucial measure to realize the whole-life cycle management of roads, safeguard traffic safety and promote the sustainable development of the social economy.

This research conducts a systematic review and analysis of pavement crack detection based on the YOLO algorithm, aiming to comprehensively sort out existing research achievements, identify key issues and propose future research directions.

2. Overview of Pavement Crack Detection Technologies

2.1. Deep Learning-based Detection Methods

2.1.1. Application of Convolutional Neural Networks in Crack Detection

Convolutional Neural Networks (CNNs) are widely adopted in pavement crack detection, and their powerful feature extraction capability makes it feasible to identify tiny and morphologically diverse cracks from complex pavement images. In their 2023 study, Xiangcan Liao, Cailin Li, Yukai Yao and other researchers detected highway bridge cracks based on an improved YOLO V5 model, demonstrating the feasibility and advantages of combining CNNs with target detection frameworks for engineering distress identification [1]. The study pointed out that targeted improvements to the basic network structure and detection head can enhance the model's responsiveness to linear and slender targets, improve the positioning accuracy and recall rate of cracks in complex backgrounds, and maintain a high inference speed to meet the real-time requirements of engineering sites [1]. This finding reflects that CNNs can not only realize end-to-end learning in crack detection, but also effectively address challenges such as crack scale variation, morphological diversity and background interference through network structure design and loss function adjustment, providing a practical basis for subsequent YOLO-based improvement work.

2.1.2. Advantages and Limitations of Deep Learning Methods

Deep learning methods exhibit distinct advantages in pavement crack detection, yet there are several limitations that merit attention. In terms of advantages, first, they possess strong feature self-learning capability: CNN-based models can automatically learn multi-scale and complex texture features of cracks from a large number of annotated images, reducing the reliance on manual feature design and thus maintaining a high recognition rate even under complex backgrounds and varying lighting conditions. Second, they enable improved efficiency in end-to-end training and inference; in particular, one-stage detectors (e.g., the YOLO series) can achieve fast pixel-level or box-level localization while maintaining real-time performance, making them suitable for integration into mobile detection platforms for online inspection. Deep learning models can be easily combined with technologies such as data augmentation, transfer learning and semi-supervised learning, which can alleviate the problem of sample scarcity and enhance generalization ability. The progress in model visualization and interpretation technology helps engineers understand the model's attention regions, providing auxiliary evidence for subsequent maintenance decision-making.

In terms of limitations, first, there is a high dependence on annotated data: the acquisition of high-quality and diverse annotation sets is costly, and the variable morphologies of cracks lead to a significant long-tail problem in samples, which impairs the model's recognition performance for rare distress types. Tiny cracks and regions with texture similar to the background remain challenging; the model is prone to missing or false detection when identifying micro-cracks, especially in low-resolution or compressed images. Second, deep learning models suffer from insufficient transferability and robustness: model performance may fluctuate drastically under different pavement materials, acquisition equipment and environmental conditions, requiring extensive domain adaptation work. Third, computing resources and deployment costs are practical bottlenecks; although lightweight networks have been developed, a trade-off between accuracy and speed is still necessary in embedded real-time detection scenarios. Future research should focus on enhancing few-shot learning, multi-scale fine-grained feature extraction, cross-domain adaptation and model lightweighting to promote the widespread application of deep learning methods in engineering-level pavement crack detection.

2.2. Basic Principles of the YOLO Algorithm

2.2.1. YOLO Network Structure and Prediction Mechanism

As an end-to-end one-stage target detection method, YOLO emphasizes completing feature extraction and bounding box prediction simultaneously in a single forward propagation, thereby achieving efficient real-time detection capability. Its network structure typically consists of three components: a backbone feature extraction network, a feature fusion module and a detection head. The backbone network is responsible for extracting multi-scale semantic information layer by layer from input images; the feature fusion module fuses features of different levels to enhance the perception of small targets and fine-grained textures; and the detection head directly regresses the position and category of targets on the fused feature maps. In pavement crack detection tasks, cracks often exhibit characteristics of slenderness, discontinuity and large scale variation. Therefore, YOLO improves the positioning capability for cracks of different sizes through a multi-scale prediction mechanism and anchor box design, and maintains edge and detail information with high-resolution features to enhance detection accuracy. In their 2023 research on road surface crack detection, Xuwen Li and Qingzhe Zhang pointed out that a reasonable feature fusion strategy and multi-scale prediction have a significant effect on improving the recognition rate of tiny cracks, and the receptive field and feature resolution of the network need to be balanced between accuracy and computational efficiency [4]. In addition, Jiajia Guo, Zengshou Dong, Chunbo Chang and other researchers emphasized in their 2024 study on lightweight YOLO variants for bridge crack detection that the collaborative optimization of detection head design and lightweight backbones can maintain high detection performance while keeping the computational load low, which is of great significance for engineering deployment [3]. Overall, the YOLO network effectively captures the special target morphology of pavement cracks through structured multi-layer feature extraction and a direct regression prediction mechanism. However, when dealing with extremely tiny or occluded cracks, it is still necessary to combine more refined feature enhancement and post-processing strategies to improve robustness.

2.2.2. Evolution Characteristics of Different YOLO Model Versions

Since its first release in 2016, the YOLO series has undergone multiple evolutions in structure and performance, showing a trend from single-stage fast detection to a balanced focus on multi-scale refinement, lightweighting and modularization. The original YOLO transformed the target detection problem into the prediction of bounding boxes and categories in a single forward propagation based on the end-to-end regression idea, with the advantage of high speed but insufficient positioning accuracy for small targets. Subsequently, YOLOv2 improved positioning and recall capabilities by introducing the anchor mechanism and a deeper feature extraction network. YOLOv3 further adopted the multi-scale prediction idea, performing detection on feature layers of different scales, which significantly enhanced the recognition ability for small targets and slender cracks, and simultaneously used a residual network structure to strengthen feature expression. Entering the era of YOLOv4 and YOLOv5, the research focus has shifted to meeting actual engineering needs: feature fusion and information flow optimization are realized through modules such as CSP, SPP and PAN, and training techniques such as Mosaic data augmentation and CIoU loss are introduced to improve robustness and convergence speed. For engineering deployment, YOLOv5 proposed a model size classification (s/m/l/x), providing a trade-off scheme for different computing power platforms. YOLOv6 and YOLOv7 further improved inference efficiency and accuracy boundaries through operator optimization and network topology redesign. The latest YOLO series pays more attention to versatility and ease of use while maintaining real-time performance, adopts a more unified training and inference interface, and gradually introduces adaptive anchor boxes and more advanced loss functions to address the problems of unbalanced samples and scale variation. Reviewing the evolution path, the improvements of the YOLO series can be summarized into three main directions: first, the continuous optimization of multi-scale and feature fusion strategies to improve the detection capability for micro-cracks and complex texture backgrounds; second, network lightweighting and computing power adaptation, enabling deployment on mobile detection equipment or vehicle-mounted systems; third, the refinement of training and loss function design to enhance robustness in scenarios with lighting changes, noise interference and sample imbalance. For the pavement crack detection task, which requires both high accuracy and real-time performance, these evolutionary characteristics of the YOLO series provide a flexible and scalable technical foundation for engineering applications.

2.2.3. Performance Optimization and Improvement Strategies

When applying the YOLO series models to pavement crack detection, performance optimization and improvement strategies mainly focus on three aspects: accuracy improvement, speed maintenance and model generalization. At the network structure level, common practices include introducing multi-scale feature fusion modules (e.g., FPN, PAN) to enhance the recognition ability of tiny cracks, and improving the complementarity of position information and semantic information through the effective combination of deep and shallow features. Connecting higher-resolution feature maps with low-level detail features can improve the mAP index of small targets. In terms of loss functions and label assignment strategies, improving box regression loss (e.g., using CIoU, DIoU or GIoU) and adopting adaptive anchor boxes or anchor-free mechanisms can significantly reduce positioning errors and accelerate convergence. The loss function can usually be expressed as a weighted sum of multiple terms: $L = \lambda clsLcls + \lambda regLreg + \lambda objLobj$. Reasonably adjusting the weight coefficients is crucial for the accurate detection of cracks of different sizes. In terms of data augmentation and sample balance, augmentation strategies for lighting changes, noise, occlusion and crack morphologies (e.g., random cropping, color jitter, MixUp and CutMix) should be designed for pavement scenarios, and the insufficient recognition of small sample categories caused by long-tail distribution should be alleviated through resampling or online hard example mining (OHEM). In terms of model lightweighting and inference acceleration, technologies such as depthwise separable convolution, channel pruning, quantization and knowledge distillation can be adopted to reduce computational and storage overhead on the premise of maintaining accuracy, meeting the requirements of on-site real-time detection. To improve cross-domain generalization ability, common strategies include domain adaptive training, style transfer (e.g., synthetic data generation based on GAN) and multi-source data joint training, thus alleviating performance fluctuations under different road conditions, shooting equipment and environments.

3. Research Progress of Pavement Crack Detection Based on YOLO

3.1. Application Modes of YOLO in Pavement Crack Detection

3.1.1. Dataset Construction and Annotation Methods

The performance of pavement crack detection largely depends on the quality and annotation specifications of datasets. Therefore, data collection, preprocessing and annotation processes are the starting point of YOLO-based research. In the data collection stage, it is necessary to cover diverse pavement types, different lighting and weather conditions, and various crack morphologies to ensure that the data can represent the complexity of actual engineering scenarios. Meanwhile, the influence of camera viewing angle, resolution and driving speed on image quality should be considered, and the differences caused by scale and perspective should be reduced by fixing the shooting height or adopting a multi-height and multi-angle collection strategy. Image preprocessing includes denoising, brightness and contrast equalization, color correction and possible perspective distortion correction. These operations can improve the identifiability of crack textures and facilitate the consistency of subsequent automatic or manual annotation. In terms of annotation methods, for the one-stage detection framework of the YOLO series, the bounding box-based annotation method is often adopted. For slender cracks with complex trends, a strategy of multi-segment lines or subdivided small boxes can be combined to express the crack shape more accurately; at the same time, the definition of crack categories and the minimum annotation unit should be clarified to avoid annotation ambiguity. To improve annotation efficiency and quality, researchers have also explored semi-automatic annotation processes and interactive tools in recent years, accelerating the construction of large-scale datasets through initial model prediction results supplemented by manual correction. In their research on cracks on wet asphalt pavements, Enhua Zhang, Weijie Wang, Nan Duan and other researchers emphasized the importance of special collection and annotation for special pavement states (e.g., wet surfaces), and improved the model's detection robustness in complex environments through reasonable sampling and annotation strategies [5].

3.1.2. Model Training and Parameter Setting

In terms of model training and parameter setting, researchers generally emphasize the decisive influence of data preprocessing and training strategies on detection performance. Fangyuan Gong and other researchers pointed out that in view of the characteristics of pavement crack images such as large grayscale differences and complex backgrounds, preprocessing operations including image enhancement, balanced sampling and reasonable cropping must be carried out first to improve the visibility of small samples and small-scale cracks and alleviate the problem of category imbalance. Meanwhile, adopting phased learning rate scheduling and moderate regularization methods in the training process can significantly improve the convergence and stability of the model, thus enhancing detection accuracy while maintaining real-time performance [6]. In their research on rural highway scenarios, Changhong Lu, Fei Shan, Yi Zhao further emphasized the importance of hyperparameter selection and training details, suggesting adjusting the network input resolution, anchor box or prior box settings and batch size according to target size and scene complexity, and initializing the model through transfer learning to shorten training time and enhance generalization ability. For lightweight deployment needs, quantization awareness or distillation strategies can be added in the training stage to reduce the model's computational burden while maintaining accuracy, facilitating application on resource-constrained edge devices [7].

3.2. Typical Research Achievements and Comparative Analysis

3.2.1. Comparison of Detection Performance of Different YOLO Models

Different versions of the YOLO model exhibit obvious differences in performance in pavement crack detection tasks, mainly reflected in detection accuracy, inference speed and robustness in complex scenes. Taking recent research as an example, Zhaoyi He and other researchers proposed a tunnel lining crack detection method based on YOLO v5-IBX in their 2023 work [8]. Through the improvement of the YOLO v5 structure and the optimization of training strategies, this study achieved remarkable results in improving the recognition rate of small-scale cracks and suppressing false detection, showing that the improved YOLO model still has good adaptability and real-time performance under complex lighting and background interference conditions [8]. Earlier YOLO versions have advantages in speed but limited ability to detect tiny or blurry cracks. With the development of the YOLO series towards deeper and wider backbone networks, more scale feature fusion and attention mechanisms, detection accuracy has been improved, but the model complexity and computational overhead have also increased accordingly. In actual engineering applications, researchers usually need to balance model lightweighting and detection performance, and select appropriate YOLO variants or carry out customized improvements according to the scale distribution of cracks, shooting resolution and on-site computing resources to balance real-time performance and high recall rate. The above analysis is consistent with the experimental conclusions of Zhaoyi He and other researchers, indicating that targeted improvement of the YOLO structure is an effective way to enhance the performance of pavement crack detection [8].

3.2.2. Performance Comparison with Other Detection Methods

In comparative studies with traditional image processing and other deep learning detection methods, the YOLO series models demonstrate significant advantages in real-time performance and end-to-end detection efficiency. Guangliang Weng and other researchers carried out targeted optimization for concrete pavement cracks based on an improved YOLOv7 [9]. The experimental results show that the improved YOLO model significantly improves inference speed while ensuring detection accuracy, making it suitable for large-scale road inspection and mobile device deployment. This conclusion highlights the practical value of YOLO in engineering application scenarios [9]. In addition, Yanhua Shao and other researchers pointed out through a review of the comparison between different YOLO models and other deep learning target detection methods that the YOLO family maintains sustained competitiveness in lightweight design and real-time detection, but is still inferior to some methods based on multi-stage detection or semantic segmentation in small-scale crack recognition, as well as false and missing detection in complex backgrounds [10]. It is suggested to make up for these shortcomings through multi-scale feature fusion and special post-processing strategies [10]. Based on the above research, it can be seen that YOLO-based methods are superior to many traditional and complex models in detection speed and engineering deployment convenience, but still need to be combined with other technical means to improve the overall detection performance in terms of fine crack characterization and noise robustness.

4. Summary and Prospect

4.1. Analysis of Research Deficiencies and Existing Problems

Although pavement crack detection based on YOLO has made remarkable progress in accuracy and real-time performance, existing research still has several deficiencies and urgent problems to be solved. First, data-related issues restrict the further improvement of model performance. Most studies rely on datasets with limited scale or single scenarios, and the number of distress images of small cracks, hidden cracks and cracks under various lighting, humidity and contamination conditions is insufficient, leading to poor generalization ability of the trained models in real and complex working conditions. The inconsistency and subjectivity of sample annotation also affect the reliability of evaluation: fuzzy crack boundaries and differences in annotation methods for slender cracks will cause ambiguity in training targets, making it difficult for evaluation indicators to fully reflect the detection effect. Second, most studies focus on the improvement of algorithm performance indicators (e.g., mAP and FPS), but pay little attention to the connection between post-processing, crack connectivity analysis and engineering decision support, failing to fully consider the closed-loop demand from detection results to maintenance decision-making. Third, fine-grained crack detection remains a weak link. Although the YOLO series has advantages in speed, its perception ability for tiny targets is limited; especially in high-resolution images, when the crack width accounts for a very small proportion of pixels, the rate of false and missing detection increases significantly. Fourth, environmental interference and complex backgrounds pose challenges to model robustness: pavement textures, lane markings, shadows and oil stains can all be misidentified as cracks, and the degradation of image quality under conditions such as rain, snow and strong backlight will also lead to a decline in detection performance. Fifth, model lightweighting and deployment adaptation are still insufficient. Although some studies have proposed lightweight networks or pruning and quantization strategies, there is a lack of practical deployment experience and stability evaluation on embedded platforms or mobile inspection equipment, and real-time monitoring in energy and computing constrained scenarios still faces difficulties. Sixth, the lack of unified evaluation standards and comparison benchmarks makes it difficult to directly compare different research achievements, hindering the objective evaluation and rapid iteration of methods in this field. Future research needs to conduct in-depth work in terms of data diversity, annotation specifications, tiny target detection, robustness improvement and engineering deployment to promote the development of YOLO-based pavement crack detection to a higher level of practical application.

4.2. Future Research Directions

Promoting the transformation of YOLO-based pavement crack detection from laboratory research to engineering applications lies in algorithm improvement and model optimization at its core. First, it is necessary to enhance the detection capability for small-scale and slender cracks. In view of the characteristics of cracks being slender and their width much smaller than the image resolution, multi-scale feature fusion should be strengthened in the network, especially the expression ability of high-resolution layers. More refined context modeling mechanisms, such as atrous convolution, attention mechanisms or Transformer-style local self-attention modules, should be introduced to enhance the network's perception of fine textures and continuous features, thus reducing the probability of crack breakage and missing detection. Second, it is essential to solve the problems of data imbalance and few-shot learning. Through targeted self-supervised pre-training, Crack Generative Adversarial Networks (GAN) or synthetic data augmentation based on physical laws, the diversity of samples can be enriched without significantly increasing the cost of manual annotation. Category and difficulty-aware loss function design and online hard example mining strategies can be adopted to alleviate the imbalance between positive and negative samples and improve the model's response to hard-to-detect samples. Third, model lightweighting and acceleration are still inevitable requirements for engineering deployment. Technologies such as depth wise separable convolution, channel pruning, parameter sharing and knowledge distillation can be combined to significantly reduce computational and memory overhead on the premise of ensuring detection accuracy, facilitating real-time operation on vehicle-mounted, UAV or embedded equipment. Fourth, the robustness and generalization ability of the model should be improved. The same pavement exhibits great differences under different lighting, humidity, occlusion and pollution conditions; domain adaptation, adversarial training and multi-source data fusion should be adopted to reduce inter-domain performance fluctuations. The design of feature extractors and post-processing strategies with low noise sensitivity is conducive to maintaining stable output in complex scenes. Fifth, interpretability and maintainability should be emphasized. In response to the decision-making needs of maintenance engineering, the model should provide credible confidence estimation, quantifiable output of crack length and width, and visualization tools convenient for human-computer collaboration. Meanwhile, a continuous learning and online update mechanism should be established to enable the model to continuously adapt and optimize with the emergence of new scenarios and new distress types. Only by striking a balance among detection accuracy, real-time performance, robustness and engineering usability can YOLO-based crack detection technology truly become a reliable tool for road maintenance.

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