

Road Waterlogging Detection Based on YOLOv8n

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Abstract: With the increasing frequency of extreme weather events, road waterlogging has posed a serious threat to urban traffic safety and residents' daily travel. Traditional detection methods, such as manual inspection and sensor deployment, have limitations including high cost, limited coverage, and insufficient real-time performance. In recent years, deep learning-based object detection methods have shown advantages in complex environments. This study proposes an automatic road waterlogging detection method based on the YOLOv8n model. By training and testing on a self-constructed dataset, the model achieved 92.1% mAP@0.5, 91.4% Precision, and 80.3% Recall. The results indicate that YOLOv8n can achieve high detection accuracy and good real-time performance in waterlogging detection, providing a feasible technical solution for smart monitoring of urban waterlogging.

Keywords: YOLOv8n, Road Waterlogging, Object Detection, Deep Learning

1. Introduction

Urban waterlogging is a regional disaster caused by heavy or continuous rainfall that exceeds the urban drainage system's capacity, with road waterlogging being one of the most visible and frequent manifestations^[1]. Road waterlogging not only significantly reduces traffic efficiency, leading to congestion and delays, but also poses direct threats to public safety, such as traffic accidents, vehicle damage, and pedestrian hazards^[2]. Moreover, prolonged water accumulation can disrupt economic activities, damage infrastructure, and exacerbate urban flooding risks. Consequently, timely, accurate, and large-scale detection and early warning of road waterlogging have become essential components of modern urban management and disaster prevention strategies^[3-4].

Traditional detection methods primarily rely on manual inspection and water-level sensors. Manual patrols, while providing direct observation, are labor-intensive, time-consuming, and limited in spatial coverage, making them difficult to implement across extensive road networks^[5]. Water-level sensors can provide continuous measurements, but their deployment is constrained by high installation and maintenance costs, and they often struggle to adapt to the dynamic and complex conditions of urban roads, such as varying surface materials, slopes, and drainage capacities. In contrast, computer vision-based detection methods offer greater flexibility, scalability, and real-time monitoring capabilities^[6]. By leveraging visual information captured from cameras, these methods can dynamically detect water accumulation over large areas, enabling rapid response and mitigation measures.

In recent years, deep learning techniques—particularly object detection algorithms—have advanced significantly in the computer vision field. Among these, the YOLO (You Only Look Once) series stands out for its combination of high detection speed and accuracy. YOLOv8n^[7], as the latest lightweight version of this series, has been optimized for efficient feature extraction, multi-scale target recognition, and deployment on resource-constrained devices. This paper focuses on applying YOLOv8n to the detection of road waterlogging, aiming to evaluate its effectiveness and robustness in complex urban scenarios, such as varying lighting conditions, occlusions, and heterogeneous road surfaces, thereby providing a practical solution for intelligent urban waterlogging monitoring^[8-9].

2. Method and Dataset

2.1 YOLOv8n Method

YOLOv8n is an efficient and precise object detection model. It consists of three core components:

Backbone, Neck, and Head, each contributing to its high-speed and accurate detection capabilities. The Backbone acts as the primary feature extractor, employing an improved convolutional neural network optimized for multi-scale feature extraction. It integrates the C2f module, which enhances the network's capacity to capture rich semantic information, and the SPPF (Spatial Pyramid Pooling-Fast) module, which strengthens contextual awareness by aggregating features across multiple receptive fields^[10]. These improvements enable the Backbone to generate robust and discriminative feature maps, particularly beneficial for complex urban environments with waterlogging^[11].

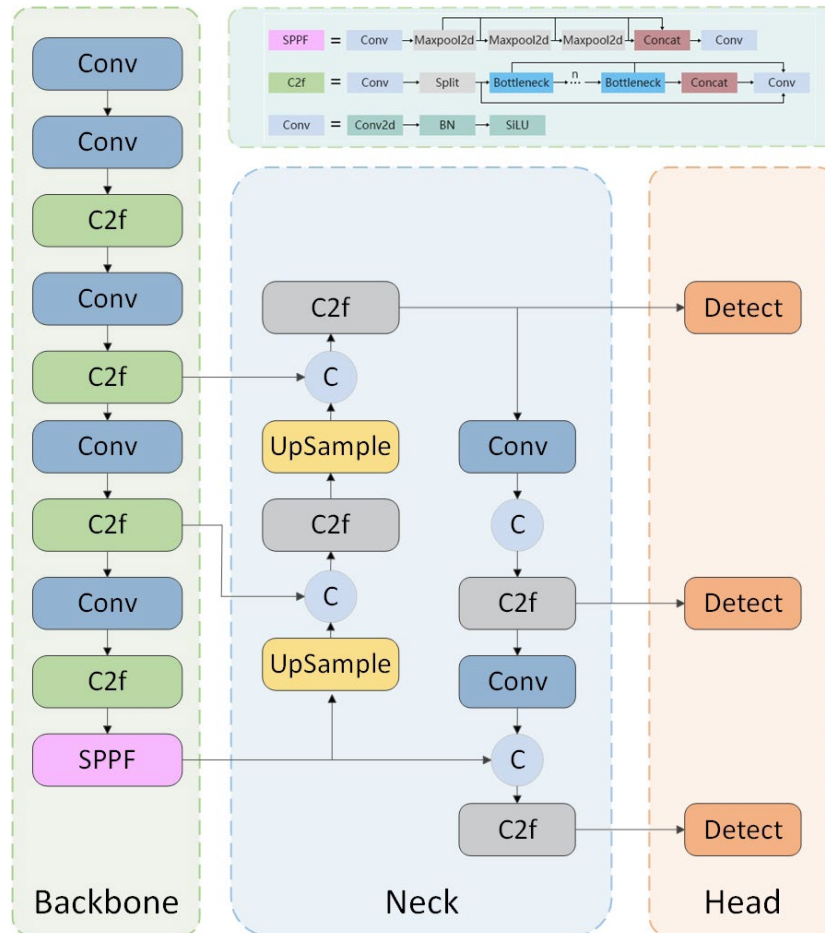


Figure 1 YOLOv8n architecture diagram.

The overall network structure of YOLOv8n is illustrated in Figure 1, providing a visual overview of the interactions between its main components. The Neck serves as a multi-scale feature aggregator, combining the strengths of FPN (Feature Pyramid Network) and PAN (Path Aggregation Network) structures^[12]. Through iterative up-sampling and down-sampling operations, the Neck fuses features from different scales, facilitating the detection of targets of varying sizes, from small puddles to extensive waterlogged areas. This multi-scale fusion is critical for addressing challenges in dynamic urban scenes, such as uneven road surfaces, varying lighting conditions, and occlusions^[13].

The Head employs a decoupled structure, separating classification and bounding box regression tasks, which allows more precise category prediction and localization of waterlogged regions. Additionally, YOLOv8n balances detection accuracy with computational efficiency. Its lightweight design, combined with an optimized loss function such as CIOU Loss^[14], enables accurate detection of small-scale targets and subtle water accumulation under complex backgrounds while maintaining low computational cost. This makes YOLOv8n highly suitable for real-time deployment on edge devices, providing a practical and efficient solution for intelligent road waterlogging monitoring and rapid disaster response^[15].

2.2 Dataset

A self-constructed dataset of 1,820 road waterlogging images was collected under diverse weather,

lighting, and road conditions. Annotations were made using labeling, marking waterlogging regions with bounding boxes. The dataset was split into 1,274 training images, 364 validation images, and 182 test images, following a 7:2:1 ratio. This diversity ensures reliable and generalizable experimental results. The dataset used in this study is illustrated in Figure 2.



Figure 2 The dataset of road waterlogging images

3. Experiments and Testing

3.1 Experimental Environment

Experiments were conducted on Windows 11 with an Intel i9-13900K CPU, NVIDIA RTX 3080 Ti GPU (12GB VRAM), and 32GB RAM. Software configuration included Python 3.8, PyTorch 2.1.0, and CUDA 12.1. Training parameters: input size 640×640, batch size 32, 250 epochs, initial learning rate 0.01, optimizer SGD.

3.2 Evaluation Metrics

The model was evaluated using several commonly adopted metrics in object detection: Precision, Recall, map@0.5, and map@0.5:0.95. These metrics together provide a comprehensive assessment of the model's detection performance under different conditions.

Precision (P) measures the accuracy of the model's positive predictions, indicating the proportion of predicted objects that are correctly identified. It reflects the reliability of the model in avoiding false positives. Mathematically, Precision is defined as:

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

Where TP (True Positives) denotes the number of correctly detected targets, and FPFPP (False Positives) represents the number of predicted targets that do not match any ground truth object. A higher Precision indicates fewer false alarms, which is particularly important in road waterlogging detection to avoid misidentifying dry areas as waterlogged.

Recall (R) quantifies the model's ability to detect all relevant objects in the dataset, reflecting target coverage. It is defined as:

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

Where FN (False Negatives) represents the number of ground truth objects that the model fails to

detect. Recall is critical in applications such as road waterlogging monitoring, where missing actual waterlogged regions can lead to unsafe conditions. A high Recall ensures that the majority of waterlogged areas are successfully detected.

The mean Average Precision (mAP) is calculated by averaging the Average Precision (AP) of all object classes, as expressed by the formula:

$$\sum_{i=1}^N AP_i mAP = \frac{i=1}{N} AP \quad (3)$$

3.3 Results and Analysis

This experiment provides a comprehensive evaluation of the YOLOv8n model's performance on the test set for road waterlogging detection. As shown in Figures 3 and 4, the results demonstrate the variation and stability of key evaluation metrics under complex urban conditions. Precision, which measures the proportion of correctly predicted waterlogged areas among all positive predictions, reached 91.4%, indicating that the model exhibits high reliability with a low false positive rate. Most predicted waterlogged regions correspond closely to actual accumulations, minimizing unnecessary alerts in urban traffic and disaster monitoring systems.

Recall, reflecting the model's ability to capture all actual waterlogged areas, achieved 80.3%, demonstrating that yolov8n effectively covers the majority of positive samples with a relatively low false negative rate. High Recall ensures that most waterlogged areas are detected, which is crucial for maintaining road safety and enabling timely emergency responses.

The Mean Average Precision metrics further validate the model's capability. Map@0.5 reached 92.1%, showing excellent detection performance under a relatively lenient iou threshold, while map@0.5:0.95 achieved 63.4%, reflecting the model's robustness in handling multi-scale waterlogged regions and complex scenarios with varying road materials, lighting conditions, and partial occlusions. Overall, these results indicate that YOLOv8n achieves high accuracy, strong sensitivity, and reliable generalization, making it suitable for real-time urban road waterlogging monitoring and intelligent flood management applications.

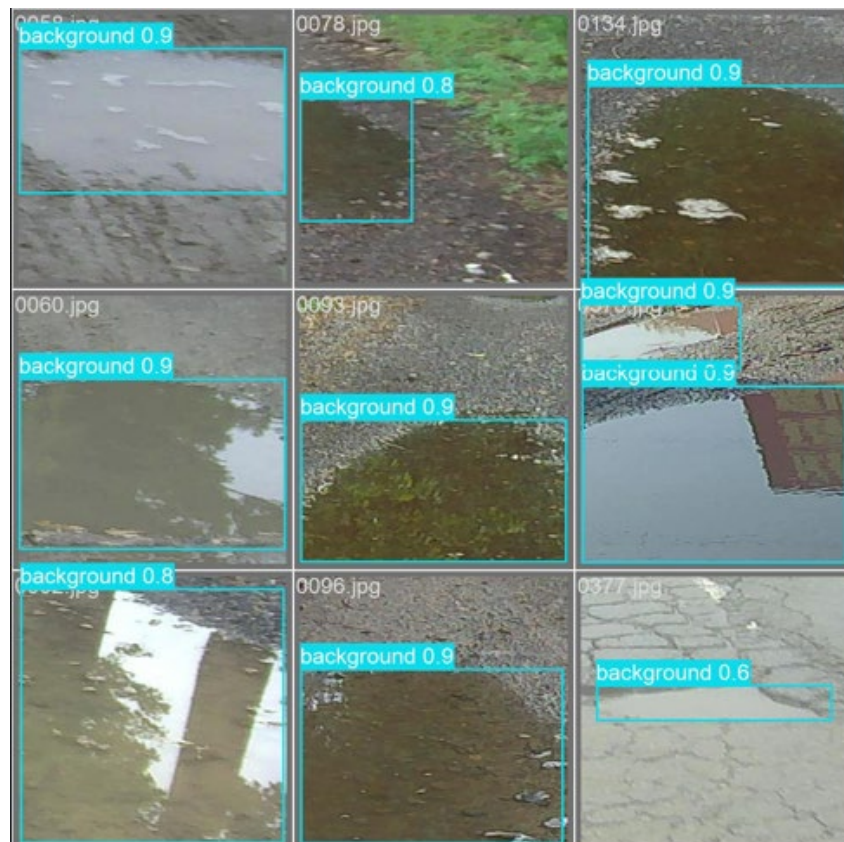


Figure 3 YOLOv8n Validation Set Road Waterlogging Detection Results

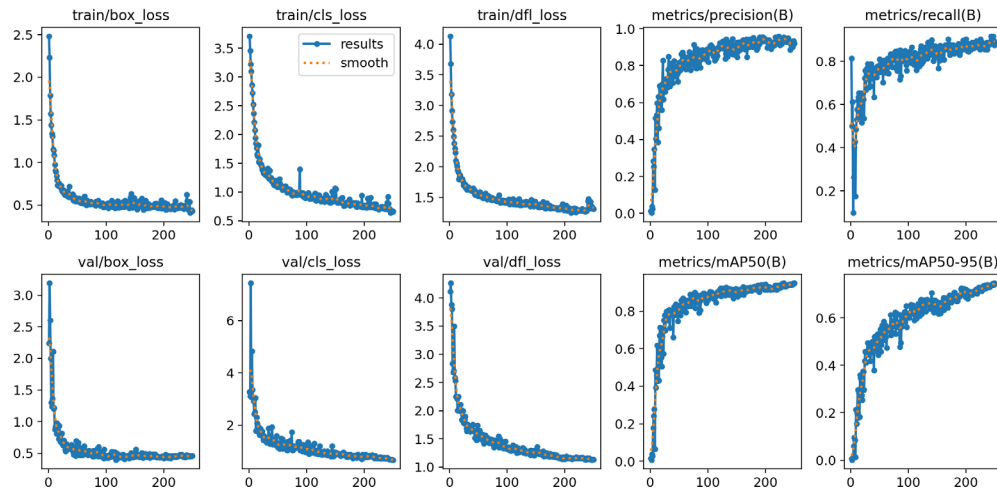


Figure 4 Experimental Results

4. Conclusion and Future Work

4.1 Conclusion

Road waterlogging is the most common phenomenon of urban flooding, directly affecting traffic safety. Traditional detection methods relying on manual inspection and sensors face limitations in efficiency and reliability. With the development of artificial intelligence and deep learning, object detection algorithms provide new solutions. This study implemented automatic detection of road waterlogging using YOLOv8n, achieving strong performance across precision, recall, and mAP. The results verify the potential of YOLOv8n for real-world deployment.

4.2 Future Work

Although the experimental results are promising, some limitations remain. The dataset size is relatively small with limited scene diversity, affecting generalization to complex road environments. Conventional data augmentation and basic optimization methods may not fully address challenges in small-scale waterlogging or extreme weather. Moreover, the model's computational requirements still pose challenges for real-time deployment. Future research should focus on expanding datasets, incorporating multimodal data (e.g., video and sensor data), optimizing feature extraction, and exploring lightweight or transfer learning strategies to enhance robustness and applicability in real-world scenarios.

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