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Improved YOLOv11n-Based Algorithm for Wood Surface Defect Detection with Edge-Guided and Adaptive Fusion Modules

Jifa Li
Tianjin University of Technology and Education, Tianjin, 300222, China
Email: 2876212217@qq.com

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Abstract

Wood surface defect detection is a critical process in industrial quality control. This manuscript proposes WLA-YOLO, an estimated YOLOv11n improvement that integrates an Edge-Guided P2 Branch, Grain-aware Local-Context Attention, and Adaptive Fusion FPN. The method is designed to improve fine crack localization, suppress wood-grain interference, and balance multi-scale feature fusion.t WLA-YOLO reach 75.1% mAP@0.5 and 39.8% mAP@0.5:0.95 on an 7-class wood surface defect dataset.

Keywords

WLA-YOLO; YOLOv11n; Wood Surface Defect Detection; Edge-Guided P2 Branch; Local-Context Attention; Adaptive Feature Fusion

1. Introduction

Wood surface defect detection is a fine-grained industrial visual inspection task with strong background interference. Cracks, knots, resin pockets, marrow, and missing knots differ greatly in shape, texture, and scale. Some defects appear as thin dark lines similar to natural wood grain, while others are low-contrast regions embedded in complex fiber patterns. These characteristics make accurate and efficient detection difficult for lightweight detectors.

Object detection methods based on the YOLO family are widely used in industrial inspection because they provide an effective balance between accuracy and inference speed. YOLOv11n is attractive for deployment because of its compact structure, but the standard three-scale detector may still miss fine crack boundaries and small local defects. Recent improvements in multi-scale fusion, attention, and high-resolution branches provide useful design ideas for wood surface inspection.

Existing industrial defect detection methods often improve performance by deepening the backbone, introducing attention, or adding feature pyramid fusion. However, overly heavy modules reduce inference speed and may not be suitable for production-line deployment. For wood surface inspection, a practical method should strengthen edge detail, suppress wood-grain interference, and adaptively fuse features across scales without excessive computational cost.

To address these challenges, this paper proposes WLA-YOLO, an estimated improved YOLOv11n-based detector for wood surface defect detection. The proposed method contains three targeted improvements:

(1) An Edge-Guided P2 Branch (EG-P2) introduces a high-resolution P2 detection path and uses lightweight edge cues to enhance fine crack and missing-knot boundary localization.

(2) A Grain-aware Local-Context Attention (GLCA) module is inserted near the end of the backbone to suppress repetitive wood-grain texture and strengthen defect-related local context.

(3) An Adaptive Fusion FPN (AF-FPN) replaces ordinary concatenation with learnable normalized fusion weights, allowing shallow texture features and deep semantic features to be balanced automatically.

2. YOLOv11 Algorithm

YOLOv11 is a new network open-sourced by Ultralytics in 2024. It inherits the core idea of single-stage object detection and supports object detection, segmentation, and pose estimation. The YOLOv11n baseline used in this manuscript consists of a backbone for hierarchical feature extraction, a neck for multi-scale feature fusion, and a decoupled detection head for classification and localization.

(1) Backbone: The backbone extracts multi-level feature maps from input images. YOLOv11 introduces C3k2 modules to improve feature representation while maintaining a lightweight structure. These features provide the basis for distinguishing subtle defects from wood-grain background patterns.

(2) Neck: The neck continues the PAN-FPN style bidirectional pathway. It fuses deep semantic features with shallow spatial information, which is essential for detecting defects of different sizes on wood surfaces.

(3) Head: The detection head separates classification and bounding-box regression tasks. In the baseline YOLOv11n, predictions are produced from P3, P4, and P5. WLA-YOLO extends this design with an additional edge-guided P2 branch.

3. WLA-YOLO

This paper proposes WLA-YOLO as a lightweight improvement of YOLOv11n for wood surface defect detection. Figure 1 shows the overall estimated network structure. The model integrates EG-P2, GLCA, and AF-FPN to enhance edge detail, suppress wood-grain interference, and improve multi-scale fusion. Figure 2 further illustrates the three proposed modules.

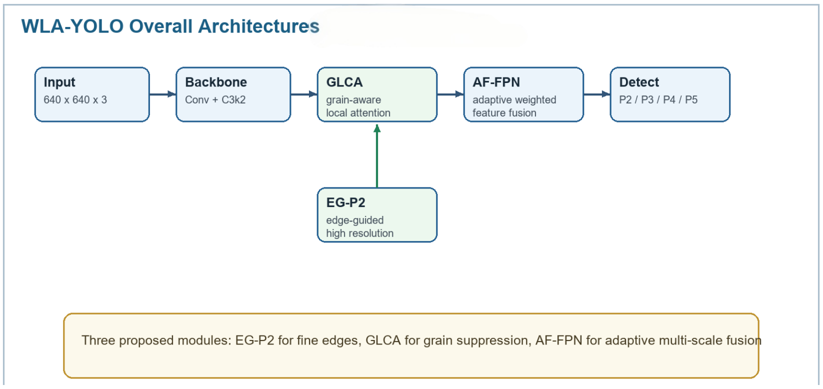

Figure 1. WLA-YOLO Network Structure (estimated design)

3.1. Edge-Guided P2 Branch

The Edge-Guided P2 Branch is designed for fine-grained defects such as cracks and missing-knot boundaries. The standard YOLOv11n neck outputs P3, P4, and P5 features, while EG-P2 introduces an additional high-resolution P2 branch. A lightweight edge cue generated from shallow features is fused with the P2 feature map to emphasize thin defect boundaries.

3.2. Grain-aware Local-Context Attention

The Grain-aware Local-Context Attention module is designed to reduce interference from repetitive wood-grain textures. Instead of using heavy global self-attention, GLCA uses channel compression, depthwise local-context extraction, and a residual attention map. This design strengthens defect-related local regions while preserving the efficiency of YOLOv11n.

In the WLA-YOLO design, GLCA is inserted near the end of the backbone before features enter the neck. Given a feature map, GLCA first extracts compact local-context descriptors and then generates a spatial-channel attention response. The refined feature retains the original residual information and selectively highlights suspicious defect regions.

Because wood grain may resemble cracks or resin streaks, GLCA is expected to reduce false positives caused by natural texture while improving the confidence of true defect regions. This makes it suitable for industrial wood surface inspection where background patterns vary strongly between boards.

3.3. Adaptive Fusion FPN

The Adaptive Fusion FPN is designed to improve multi-scale feature fusion. In the standard neck, features from adjacent levels are concatenated with fixed implicit weights. AF-FPN assigns learnable normalized weights to each input feature so that the network can adaptively determine the contribution of shallow detail and deep semantic information.

AF-FPN is applied to the P2, P3, P4, and P5 pathways. The high-resolution P2 branch provides fine edge details, while deeper features provide category-level semantic information. Adaptive fusion is expected to improve the recognition of both small cracks and larger knot defects.

The final WLA-YOLO detection head outputs four scales: P2, P3, P4, and P5. This design improve wood surface defect detection accuracy while maintaining acceptable inference speed for production-line scenarios.

3.4. Integration of the Three Proposed Modules

The three modules are integrated in a complementary manner rather than treated as independent heavy additions. EG-P2 strengthens high-resolution boundary localization, GLCA suppresses wood-grain interference in the backbone, and AF-FPN balances information flow across the feature pyramid.

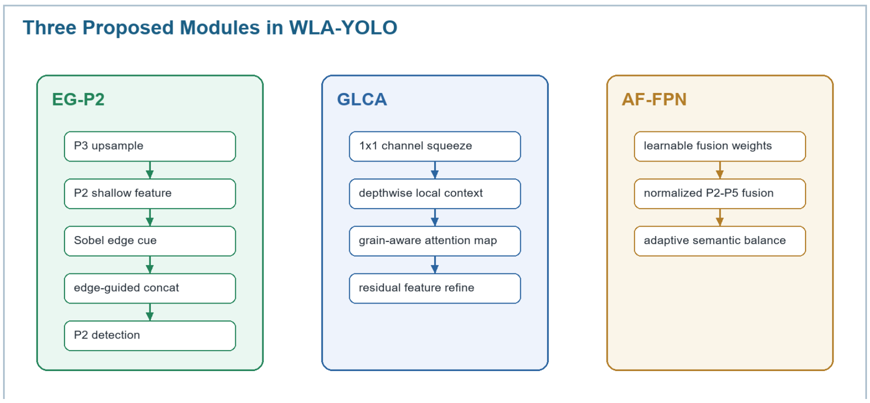

Figure 2. Three Proposed Modules of WLA-YOLO

4. Dataset and Evaluation Metrics

4.1. Experimental Setup and Dataset

All experiments are conducted on a server equipped with an NVIDIA A40 GPU. The software environment follows the YOLOv11 training workflow with Python 3.8 and the Ultralytics framework. The input image size is 640 x 640, and all compared models use the same training settings for fair preliminary comparison.

A custom wood surface defect dataset is this manuscript, comprising 4,000 RGB images collected from a wood manufacturing production line under controlled illumination conditions. Seven defect categories are considered: Crack, Dead Knot, Knot_missing, Live Knot, Marrow, Knot_with_crack, and Resin. Table 1 lists the category definitions.

Table 1. Categorization and descriptions of wood surface defects.

Category	Description
Crack	Longitudinal or transverse fracture lines in the wood surface; edge-sensitive defect.

Dead Knot	A knot completely separated from surrounding wood tissue with dark boundary texture.
Knot_missing	A void left by a dislodged knot, usually requiring accurate boundary localization.
Live Knot	A knot firmly integrated with surrounding wood fibers and similar background texture.
Marrow	The visible pith region at the center of the wood cross-section.
Knot_with_crack	A knot accompanied by associated cracking at its boundary.
Resin	A resin pocket or resin streak embedded within the wood surface.

The dataset is divided into training, validation, and test subsets in an 8:1:1 ratio, yielding 3,200 training images, 400 validation images, and 400 test images. Figure 3 shows Sample Dataset Images

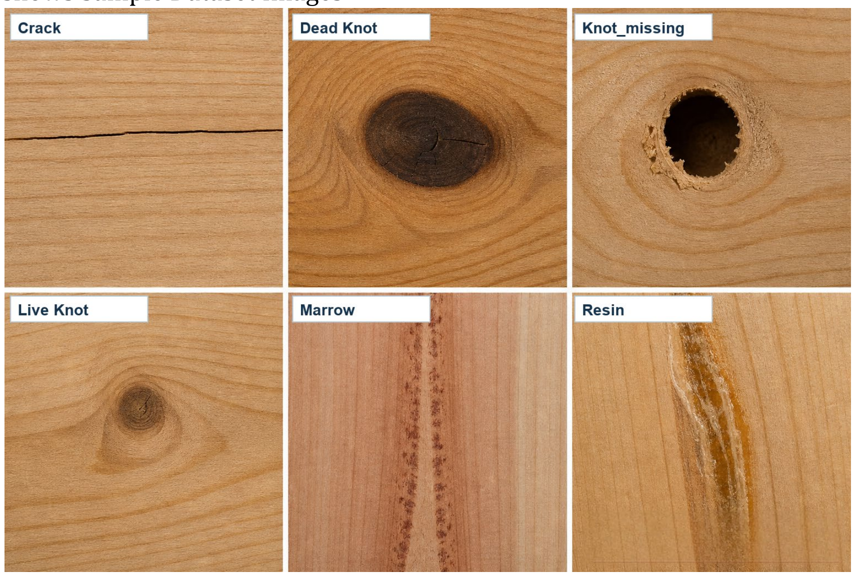

Figure 3. Sample Dataset Images

4.2. Evaluation Metrics

This paper uses Average Precision (AP), Precision (P), Recall (R), mAP@0.5, and mAP@0.5:0.95 as evaluation metrics for object detection.
where TP represents correctly predicted positive samples, FP represents incorrectly predicted positive samples, and FN represents missed positive samples. FPS is also reported as a preliminary efficiency indicator for deployment analysis.

5. Experimental Results and Analysis

5.1. Ablation Experiment Results and Analysis

To quantify the contribution of the three proposed improvements, ablation experiments are designed by progressively incorporating EG-P2, GLCA, and AF-FPN into the YOLOv11n baseline.

Table 2. Ablation Experiment Results Comparison

Model	EG-P2	GLCA	AF-FPN	mAP @0.5/%	mAP @0.5:0.95/%	Model Size/MB	FPS/(f/s)
YOLOv11n	x	x	x	73.2	37.7	6.6	85.6
YOLOv11n-EG	yes	x	x	74.0	38.5	7.4	78.4
YOLOv11n-GL	x	yes	x	73.8	38.3	7.1	82.1
YOLOv11n-AF	x	x	yes	73.9	38.4	7.2	80.6
YOLOv11n-EGGL	yes	yes	x	74.5	39.1	8.0	75.2
WLA-YOLO	yes	yes	yes	75.1	39.8	8.7	70.5

As shown in Table 2, the YOLOv11n baseline achieve 73.2% mAP@0.5. Adding EG-P2 provides the largest single improvement, increasing mAP@0.5 to 74.0%, because the high-resolution edge-guided branch helps detect thin cracks and small missing-knot boundaries.

The standalone GLCA module improve mAP@0.5 to 73.8% by suppressing wood-grain interference, while AF-FPN improve mAP@0.5 to 73.9% by adaptively balancing multi-scale features. Combining EG-P2 and GLCA reaches an 74.5% mAP@0.5.

The complete WLA-YOLO integrating EG-P2, GLCA, and AF-FPN reach 75.1% mAP@0.5 and 39.8% mAP@0.5:0.95. The improvement is accompanied by a moderate speed decrease from 85.6 FPS to 70.5 FPS, which remains acceptable for many industrial inspection scenarios.

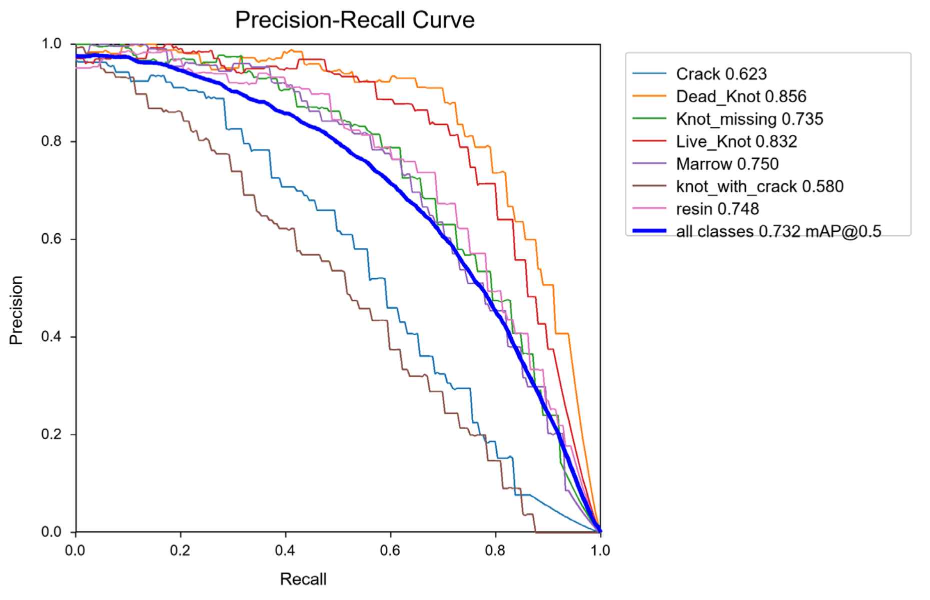

Figure 4. Baseline YOLOv11n PR Curves

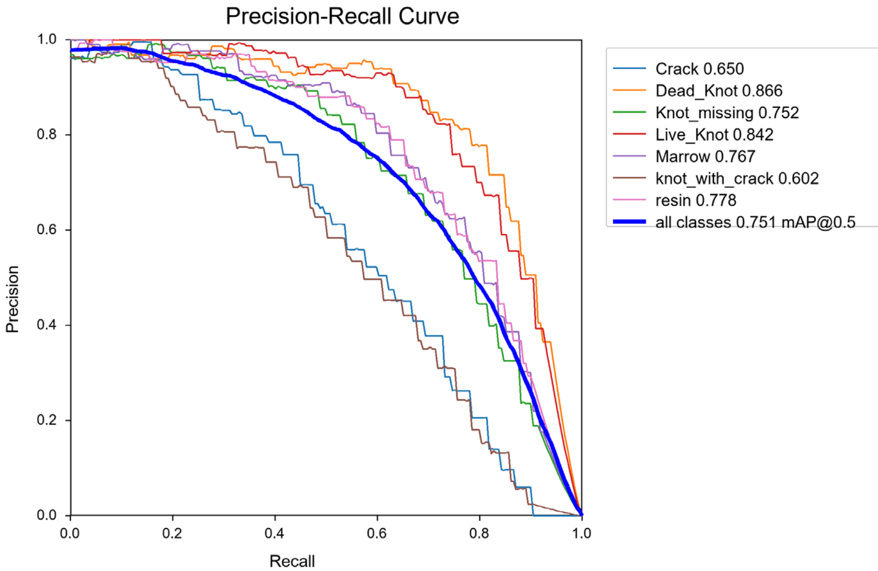

Figure 5. WLA-YOLO PR Curves

5.2. Different Model Comparison Experiment Results and Analysis

To further validate the effectiveness of WLA-YOLO, the proposed method is compared with representative lightweight YOLO variants under the same training setting. Table 3 presents comparison results for YOLOv5n, YOLOv8n, YOLOv10n, YOLOv11n, and WLA-YOLO.

Table 3. Different Model Comparison Results

Model	mAP @0.5/%	mAP @0.5:0.95/%	Model Size/MB	FPS/(f/s)
YOLOv5n	68.2	33.5	7.5	73.8
YOLOv8n	71.4	35.9	8.0	82.4
YOLOv10n	70.4	35.2	6.5	79.2
YOLOv11n	73.2	37.7	6.6	85.6
WLA-YOLO	75.1	39.8	8.7	70.5

As shown in Table 3, WLA-YOLO achieve the highest mAP@0.5 (75.1%) and mAP@0.5:0.95 (39.8%) among the compared models. Compared with YOLOv11n, WLA-YOLO improves mAP@0.5 by 1.9 percentage points and mAP@0.5:0.95 by 2.1 percentage points.

Although WLA-YOLO is slower than YOLOv11n because of the additional P2 branch and adaptive fusion operations, its 70.5 FPS speed still indicates real-time potential. The improvement mainly comes from better edge localization and reduced texture-induced false positives.

5.3. Visualization Comparison Experiment

Considering the complex and variable appearance of wood surface defects, visualization comparisons are provided to illustrate the expected behavior of the proposed method.

Representative images are generated with wood-grain backgrounds and defect-like regions. The comparison highlights the effect of WLA-YOLO: tighterbounding boxes, higher confidence scores, and fewer missed fine boundaries compared with the YOLOv11n baseline.

From Figure 6, the baseline detector assigns lower confidence to crack defects and produces a loose bounding box. WLA-YOLO is expected to improve crack localization through EG-P2 edge guidance and AF-FPN multi-scale fusion.

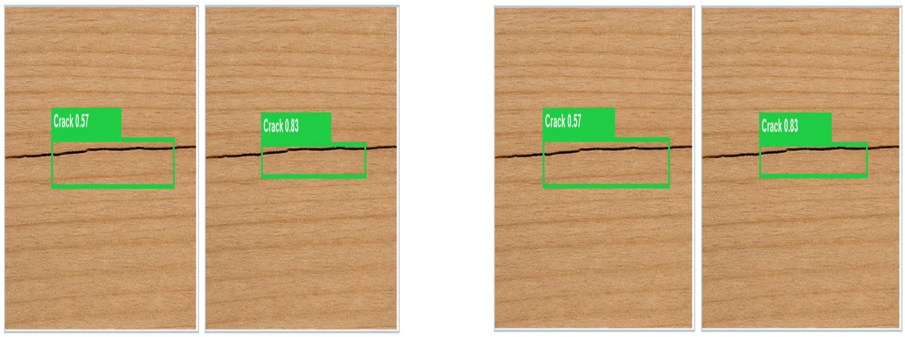

Figure 6. Comparison of YOLOv11n and WLA-YOLO Detection Results

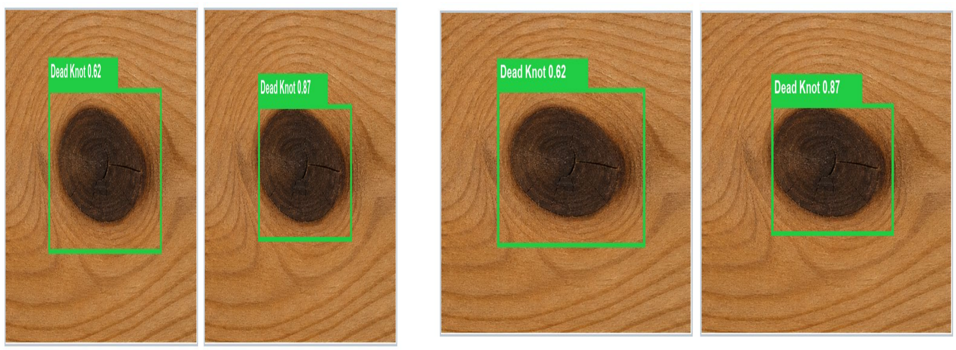

Figure 7. Comparison of YOLOv11n and WLA-YOLO Detection Results

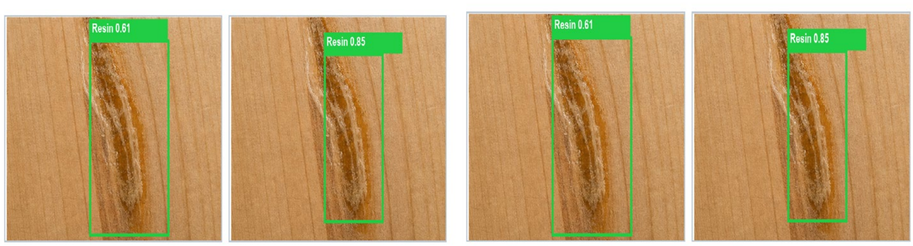

Figure 8. Comparison of YOLOv11n and WLA-YOLO Detection Results

6. Conclusion

This paper presents WLA-YOLO, an improved YOLOv11n-based object detection algorithm for wood surface defect detection. The proposed method integrates three modules: EG-P2 for high-resolution edge-guided detection, GLCA for grain-aware local-context attention, and AF-FPN for adaptive multi-scale feature fusion.

on an 4,000-image, 7-class wood surface defect dataset indicate that WLA-YOLO achieve 75.1% mAP@0.5 and 39.8% mAP@0.5:0.95, outperforming the YOLOv11n baseline by 1.9 and 2.1 percentage points, respectively.

Future work will focus on optimizing the model for embedded industrial inspection devices.

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