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CS-405 Deep Learning

Assignment 3

Efficient Timber Surface Defect Detection Using a Compact YOLO Architecture for Resource-Constrained Devices

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Abstract

Timber defect identification is a critical factor in the structural safety. Recent studies have explored a wide range of computer vision techniques, especially deep-learned object detectors, to address issues associated with the complex structures of the wood textures, defects morphology changes in irregular forms, and small surface disfiguration. Even though modern techniques have made significant gains in the accuracy of detection using sophisticated backbone designs, attention systems, and multiscale feature merging, many them have high computation costs, enormous parameter substances, and lower capability to execute on resource-constrained edge devices. On the other hand, lightweight solutions are often not able to maintain consistent performance between a wide range and fine-grained timber defects. This review summarizes the existing advances, identifies the common limitations in such research, and provides the outlines of critical research directions, insisting on the need to develop compact, efficient, and timber specific detection architectures, which can provide high accuracy under realistic deployment of the implementation limitations.

Introduction

Precise identification of timber faults is critical towards checking the safety of the structure, enhancing the use of the materials, and aiding automation in current wood-processing sectors. The conventional manual methods of inspection are subject to bias and inconsistency and there is need to have efficient computer-vision based processes that would perform uniformly without biases on different timber types and defects. The use of deep learning, and specifically convolutional and YOLO-like detectors has greatly promoted the use of visual inspection tasks because of the ability to detect defects at real time and with high accuracy.

There are however special challenges using these methods on timber. Timber has a high degree of variability in texture, interference of grains, uneven lighting effect, and pattern of defects which makes it hard to extract features.

Moreover, a significant number of those models that achieve high performance are computationally intensive, which restricts them in real life applications of real time or on the edge-based deployment (that is often necessary in the on-site grading setting).

There are lightweight models that usually cannot preserve consistent accuracy or are not very good at generalization during different timber surfaces.

The Project aims to design a lightweight, efficient and timber-oriented object detection model that maintains competitive accuracy while addressing computational limitations of existing models. The key question from this project are:

- How can lightweight YOLO based architecture be designed to give the practical results with minimum parameter.
- What are the best architectural elements (backbone, neck, feature modules) that represent the best trade-off of computational versus defect recognition performance?
- Which architectural trade-offs better accuracy, model sizes and computation can rest in some practical solutions for timber defect detection?

Related Work

3.1 A review of recent advances in data-driven computer vision methods for structural damage evaluation: algorithms, applications, challenges, and future opportunities (2025) [1]

Objective: Summarize progress in data-driven vision methods for structural damage assessment for different materials.

Method: Review multiple models CNN, attention models, transformer, hybrid architectures across structural head monitoring tasks..

Results: Highlights the timber structures are still a lot un explored and need of better models for edge deployment.

Relevance: Explores various model architectures and highlights the main research gap of the project.

3.2. SGN-YOLO: Detecting Wood Defects with Improved YOLOv5 Based on Semi-Global Network [2]

Objective: Enhance Detection using context sensitive efficient backbone.

Method: Substitute the backbone in YOLOv5 by a lightweight Semi Global Network (SGN) then add Extended Efficient Layer Aggregation (E -ELAN) and use the EIOU loss function for better convergence and localization.

Results: Obtained a mean average precision (mAP) of 86.4%.

Strengths: Strong level detection accuracy even on irregular defect geometries.

Limitations: Complex backbone incompatible with resource-constrained devices.

3.3. Wood defect detection based on the CWB-YOLOv8 algorithm [3]

Objective: Generalization in wood defect detection across various wood textures.

Method: Extend YOLOv8 with conditional parametric convolution (CondConv), an efficient loss (WiseIoU) and context-sensitive module (BiFormer) optimizing the learning of complex features.

Results: Higher performance results when compared to the vanilla YOLOv8 architecture.

Strengths: Robust Generalization across various wood types.

Limitations: Not ideal for edge devices because of complex module, inference latency not optimally tuned to edge cases. Not specialized for timber defects.

3.4. WDNET-YOLO: Enhanced Deep Learning for Structural Timber Defect Detection to Improve Building Safety and Reliability [4]

Objective: Detection of timber defects within high precision.

Method: Re-parameterized backbone (RepVGG) to learn multi-scale features, apply the ECA attention mechanism to reduce the interference of woodgrain, adaptive up-sampling (CARAFE) to learn finer and morphologically variate defects.

Results: +3.7% mAP@50 and +3.5% mAP@50-95 compared to base YOLOv8.

Strengths: Better detection of sophisticated defects, and a moderate growth in the size of the model (4.4% only).

Limitations: Model still not reliable for real world critical scenarios and requires high computational power.

3.5. FDD-YOLO: A Novel Detection Model for Detecting Surface Defects in Wood [5]

Objective: Detect small and multi-scale wood defects for industrial usage.

Method: Enhance feature extraction with a dedicated C2f-FA module, use a dual-branch spatial pyramid pooling module (DSPPF) for better local and contextual aggregation of features, and use an attention module (CSAM) to find long-distance contexts.

Results: Significant gains on small-defect AP.

Strengths: Detection of small-scale objects by using attention and pooling methods to establish strong features.

Limitations: High complexity impacting real-time inference and edge deployment.

3.6. SiM-YOLO: A Wood Surface Defect Detection Method Based on the Improved YOLOv8[6]

Objective: Detect subtle defects and overlapping defects with higher robustness.

Method: Add SPD-Conv to preserve micro-defect structures and SiAFF-PANet for better multi-scale fusion. Use multi-attention head and MPDIoU loss for overlapping bounding boxes.

Results: +4.3% mAP vs YOLOv8 baseline.

Strengths: Customized to small and irregular defects detection.

Limitations: Architecture not good for edge deployment due to increase complexity.

3.7. BPN-YOLO: A Novel Method for Wood Defect Detection Based on YOLOv7[7]

Objective: Minimize redundant computations while maintain detection accuracy.

Method: Replace traditional convolutions with partial convolutions reducing computation cost, add a BiFormer attention module for better content-aware features refinement. Use NWD loss to improve sensitivity in small-defect localization.

Results: +7.4% mAP@50 over the baseline YOLOv7.

Strengths: Excellent at overlapping anomalies.

Limitations: Heavier than ultra-light options, not good inference speed in edge devices.

3.8. Research Progress of Deep Learning-Based Wood Surface Defect Detection[8]

Objective: Summaries of advances in word defect detections

Method: From classical vision to modern detectors, it analyses the impacts of attention multi-scale fusion and other approaches in model performance.

Results: Identifies persistent issues, like small defects detection, overlapping defects, generalization and high computational requirements.

3.9. DAM-Faster RCNN: few-shot defect detection method for wood based on dual attention mechanism[9]

Objective: Improve detection by increasing candidate proposals and reducing texture noise.

Method: Modified architecture with dual-attention (cross and spatial), a wood RPN module followed by a feature reconstruction head.

Results: Better accuracy than baseline Faster R-CNN model.

Strength: Better localization even for rare types and robustness to texture noise.

Limitations: Two Stage Detector: high computational requirements.

3.10. A review of the automated timber defect identification approach [10]

Objective: Summarize various machine learning and deep learning techniques for detection of defects in timber

Method: Traces multiple classical ML to modern DL based solutions in detection.

Results: Shows the history of detection models with gaps and improvement strategies.

Gaps and Opportunities

Identified Gaps:

High Computational Requirements: Most of the high-performing models (e.g. SGN-YOLO, SiM-YOLO, CWB-YOLO) also use heavy backbones and high attention modules. They have too many parameters and would be too slow to use in a real-time system or on edges in timber inspection.

Weak Lightweight Models: Lightweight detector often compromises accuracy and struggle with small defects. Their performance is highly unstable making it unreliable for practical use.

Challenges in Edge deployment: Most reviewed model focus on maximizing the accuracy over computational cost which make it limited to be deployed on resource-constrained devices.

Limited Timber-Specific Research: Timber defect detection is still less explored. Existing models trained on mixed-species wood often fail to work for timber defects localization.

Opportunity:

There is a strong opportunity to create a **lightweight architecture** with comparable performance to large models with **timber-based dataset** rather than general wood defects optimized for usage in **resource-constrained environments** (edge devices).

Our work aims to develop a lightweight model specialized for timber defect detection with performance comparable to existing state-of-the-art models while remaining suitable for edge deployment.

We will design a custom YOLO-based architecture with compact backbone and neck modules to significantly reduce parameter count and computational overhead, enabling efficient real-time inference in resource constrained environments.

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