



Comparative Study of YOLO Architectures for Automated Wood Defect Detection

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ABSTRACT

The North American residential construction industry relies on wood as the principal material for structural framing, as well as for kitchen cabinets, decorative trim moldings, and door casings. In this regard, wood quality is a key determinant of structural integrity and aesthetics in construction. Traditional wood defect inspection during construction and furniture manufacture is time-consuming, inconsistent, and error prone. Machine-vision technology could solve these issues and improve wood quality assessment. The use of automated defect detection systems can improve inspection efficiency and accuracy while reducing manual labour. This paper presents and evaluates the performance of four advanced You Only Look Once (YOLO) object detection models: YOLOv5l-seg, YOLOv7-E6E, YOLOv8l, and YOLOv9e for automated wood defect identification. Each variant involves a balance between accuracy and computational efficiency. YOLOv5l-seg supports segmentation, YOLOv7-E6E improves feature extraction, YOLOv8l speeds up inference, and YOLOv9e uses transformer-based components for better detection. Using a dataset of 3,300 annotated images spanning ten defect types, it was found that YOLOv9e achieves the highest precision (90.15%), demonstrating strong potential for real-time wood inspection in construction and manufacturing workflows. The results are discussed in the context of their applicability to off-site construction systems for quality tracking and defect traceability.

KEYWORDS

Wood; Defects; Vision-based detection; YOLO; Quality

INTRODUCTION

Wood is a fundamental material across multiple industries and applications. In wood-based construction, it is the primary material for all above-grade elements, including walls, floors, and roofs. Wood is especially prevalent in North America's residential construction sector, forming the backbone of most single-detached homes, which dominate the residential market in North America. Defects compromise the structural strength and appearance of wood. As such, inspection and quality control to identify knots, cracks, resin pockets, marrow, and holes are critical functions. In this regard, though, rising wood demand and slow, inefficient visual assessment methods further challenge the construction industry. The importance of accurate wood defect detection is

increasingly recognized across both traditional and off-site construction domains, where production speed and material consistency are paramount. Manual inspection is prone to error and bottlenecks (Sobey & Semple, 1989; Lin et al., 2020). Prior models, such as SGN-YOLO (Meng & Yuan, 2023) and SiM-YOLO (Xi et al., 2024), have demonstrated the applicability of deep learning for wood defect detection, but direct comparisons across YOLO variants are limited in literature. Innovation in computer technology is needed to address these inefficiencies. Off-site construction (OSC) is drawing interest as a promising solution to address housing shortages. OSC typically employs a production line model to speed production, but disruptions due to material defects can stop the line, causing costly delays and lowering productivity. In order to avoid flow stoppages and rework, lumber fed to framing stations must be inspected for defects. Recent advances in machine vision, particularly the YOLO suite of models, have proven highly effective for real-time automated defect detection. YOLO differs from traditional algorithms in that it uses a single neural network to analyze the entire image, enabling simultaneous predictions of multiple bounding boxes and class probabilities. This approach ensures faster processing while maintaining high accuracy. In recent years, YOLO-based models have significantly advanced wood defect detection. For instance, SGN-YOLO (Meng & Yuan, 2023), which integrates the Semi-Global Network (SGN) and Efficient IOU (EIOU) loss function, has been found to achieve a 13.6% higher accuracy than Faster R-CNN, with an 86.4% mean average precision (mAP). SiM-YOLO (Xi et al., 2024), moreover, has been implemented in conjunction with SiAFF-PANet and a multi-attention detection head (MADH), to improve wood surface defect detection, resulting in a 9.3% mAP improvement over YOLOX. CWB-YOLO (An et al., 2024) introduced conditionally parameterized convolutions, dynamically adjusting to input features, enhancing performance in the case of complex wood textures. YOLOv4-Tiny (Lim et al., 2022), a lightweight version of YOLOv4, provides rapid real-time defect detection on wood surfaces while maintaining acceptable accuracy in an 88.32% mAP at 225.22 frames per second. YOLOv5 (Zhao et al., 2021) has been found to improve particle-board surface defect detection, achieving 89.3% mAP. SSD adaptations (Ding et al., 2020), meanwhile, have been found to represent a 13.6% improvement over YOLO in detecting solid wood panel defects. Lastly, BPN-YOLO (Wang et al., 2024), which is based on YOLOv7, has been found to increase wood defect detection accuracy by 7.4%, achieving 86.4% mAP and highlighting its potential for real-time timber production. These models represent continuous advancements in wood defect detection in terms of optimizing both accuracy and real-time performance while effectively managing complex wood textures. Table 1 summarizes these YOLO-based models and their contributions to wood defect detection.

RELATED WORK

In wood-based construction and wood furniture manufacture, knots, fractures, and deterioration must be identified to ensure product integrity and resource efficiency. Accurate defect identification is also crucial for meeting customer expectations, minimizing waste, and boosting competitiveness while satisfying industry standards amid rising demand. Manual detection techniques are prone to human error, inaccuracy, and inefficiency. These deficiencies may lead to defects being overlooked, resulting in decreased product quality and profitability. In this regard, automated detection systems can be adopted to improve reliability and efficiency.

Table 1. Summary of YOLO-based models for wood defect detection.

Work	Summary
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(Meng & Yuan, 2023)	SGN + EIOU, 13.6% accuracy boost over Faster R-CNN, 86.4% mAP.
(Xi et al., 2024)	SiAFF-PANet + MADH, 9.3% mAP improvement over YOLOX.
(An et al., 2024)	Conditional Conv Layers, better handling of textures, defects.
(Lim et al., 2022)	Lightweight YOLOv4, faster real-time detection, maintained accuracy.
(Zhao et al., 2021)	YOLOv5, real-time detection, 89.3% mAP.
(Ding et al., 2020)	SSD vs YOLO, 13.6% improvement over SSD.
(Wang et al., 2024)	YOLOv7, 7.4% accuracy improvement, 86.4% mAP in timber production.

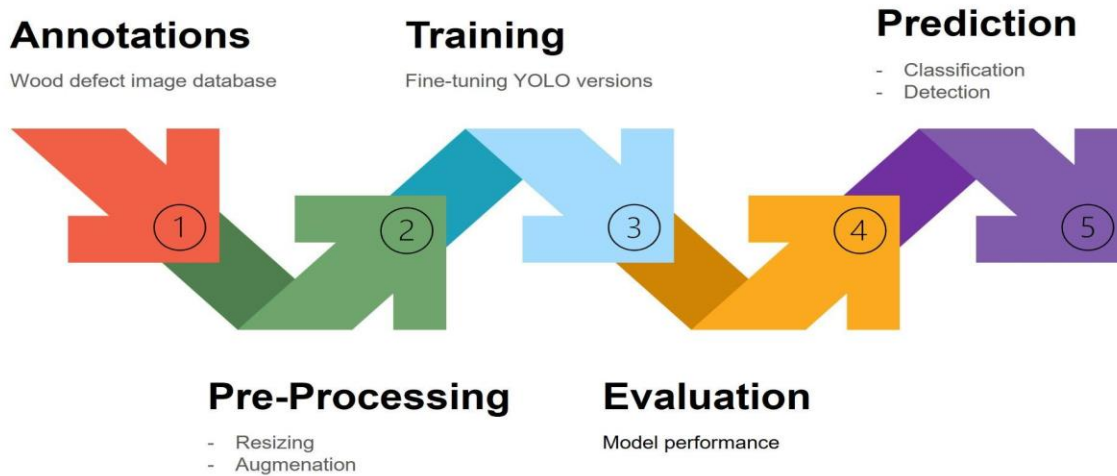
Defects in wood may be physiological (e.g., growth faults), pathological (e.g., pest damage), or human-caused (e.g., processing defects). The given wood use determines which defects are of interest to detect (Chen et al., 2023). Specific examples of natural wood defects include knots, twisted fibres, fissures, resin pockets, stains, rots, insect channels, waness, form anomalies, and sclerenchyma fibers (Wdowiak, 2017). There are many defect detection systems available for various uses. For instance, (Du et al. 2019) used X-ray-based deep learning to increase the accuracy of casting aluminum flaw detection. Infrared thermography (Kabouri et al., 2017) and laser systems (Zhang et al., 2018) have been used to enhance flaw identification and surface size estimations. Image processing and vision-based machine learning, meanwhile, are popular due to their low cost and high speed and accuracy (Tu et al., 2020). Surface defect detection in image processing can be broadly categorized into three paradigms (Chen et al., 2021): typical feature-based machine-vision algorithms (Lin et al., 2020, Wang et al., 2023), color feature-based methods (Kiratiratanapruk & Sinthupinyo, 2011), and shape feature-based methods (Bao et al., 2014). The unsupervised background reconstruction technique described by Lv et al. (2020) employs a deep autoencoder with a weighted SSIM-based loss function, unique DCT-based difference analysis, and fast online detection. There are also a number of defect detection techniques specific to wood. Connors et al. (1983) developed a grey-scale automatic vision system for hardwood timber fault identification, achieving 99.6% accuracy. Both Kauppinen et al. (1999) and Weidenhiller & Denzler (2014) effectively combined texture-based classification approaches with feature extraction techniques that concentrate on tonal, textural, and geometric properties and co-occurrence matrices. It should be noted at this juncture that segmentation is useful for determining wood grade (Cho et al., 1990; Hu et al., 2004), whereas non-segmenting methods identify defects more rapidly. Tonal measurements, meanwhile, have been found to provide 95% fault detection and 75–80% unambiguous wood identification (Sobey & Semple, 1989). (Butler et al. 1989) demonstrated that RGB color information improved pixel-based defect detection accuracy for some subtle defects by over 20% over gray-scale accuracy. Both (Kline et al. 2003) and (Rinnhofer et al., 2005) employed optical cameras, lasers, and X-rays to identify internal and exterior wood faults (achieving higher precision compared to single-sensor systems). In the present study, we compare the various YOLO deep-learning models to determine which is best suited to detecting defects in wood. Specifically, the objective is to find the fastest and most accurate model for real-time construction timber defect detection. In real-time detection and classification, the CNN-based object detection method, YOLO, is accurate and computationally light. Its applications include trading, autonomous driving, video surveillance, and facial recognition. In terms of the present context, YOLO has been widely used to automate industrial production quality inspection, particularly surface fault detection. Table 2 lists the major YOLO model algorithms, the studies describing them, and the advancements they represent. These advancements in machine vision lay the groundwork for the comparative analysis conducted in this study, where various YOLO architectures are benchmarked for their wood defect detection performance.

Table 2. Key features and improvements of YOLO models.

Studies	Key Features
(Qiu et al., 2022)	Spatial Pyramid Pooling, Mish activation, new loss function. Enhanced multi-scale feature extraction, better handling of challenging examples
(Yang et al., 2024)	Scaled-YOLOv4 approach, anchor boxes of various scales, image pyramids. Improved detection for small objects, enhanced accuracy across object sizes
(Li et al., 2022)	Anchor-free detection, EfficientRep backbone, RepBlocks/CSPStackRep neck, Task alignment. Higher accuracy, reduced overfitting, better parallelism, efficient label assignment
(Wang et al., 2023)	E-ELAN, model scaling, re-parameterized convolution, label assignments, EMA. Best speed and accuracy trade-off (5–160 FPS), superior learning efficiency
(Correia, 2023)	Anchor-free architecture, mosaic augmentation, streamlined NMS. Faster NMS, reduced box predictions, optimized final training epochs
(Wang et al., 2025)	Programmable Gradient Information (PGI), GELAN. New efficiency benchmarks, improved adaptability and detection performance across diverse datasets

METHODOLOGY

This section presents the methodology for evaluating YOLO models for wood defect detection. Figure 1 shows how images are preprocessed to meet the model input requirements in YOLO applications. The wood defect detection function is taught to a deep learning model. Then, after metric evaluation, the model is used for inference or “defect detection” on a set of test images.

**Figure 1.** Overview of a wood defect detection model's workflow.

Dataset, and Implementation Details

The database was chosen for its public accessibility, high-quality annotations, and extensive coverage of residential construction and manufacturing defect types. It supports automated wood quality assessment with 3,300 annotated images of Blue_Stain, Crack, Dead_Knot, Knot_missing, Live_Knot, Marrow, Quartzity, knot_with_crack, overgrown, and resin. The distribution of samples in each category is provided in Table 3 and Figure 2 shows examples of some of these wood defects.

Table 3. Distribution of wood defect categories.

ID	class	Train	Test	ID	Class	Train	Test
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0	Blue_Stain	26	57	5	Marrow	83	4
1	Crack	82	465	6	Quartzity	81	34
2	Dead_Knot	926	299	7	knot_with_crack	130	108
3	Knot_missing	48	73	8	overgrown	2	0
4	Live_Knot	2108	288	9	resin	313	236

Evaluation Metrics

The selected YOLO models were experimentally evaluated for wood defect detection using minimal parameters, with performance measured by precision and error on a common dataset to ensure consistent and unbiased comparison;

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

where precision refers to the percentage of true positive detections made by the model, TP = true positive and FP = false positive.

Error refers to the number of wrong predictions, which could be either false positives or false negatives. As expressed in Eq. (2), error is complementary to precision:

$$Error = 100 - Precision \quad (2)$$

It is assumed that the error metric indicates how often the model makes mistakes in identifying objects. With the dataset and evaluation criteria established, we now present the performance results of each YOLO model and discuss their implications.

RESULTS AND DISCUSSION

As noted above, several different YOLO architectures were compared. Table 4 shows the accuracy and error metrics for YOLOv5l-seg, YOLOv7-E6E, YOLOv8l, YOLOv9e, and Roboflow models (Roboflow, 2023). YOLOv9e was found to have the highest precision score (90.15%) and the lowest error rate (9.85%), indicating that it is highly effective in recognizing positive cases and limiting false positives.

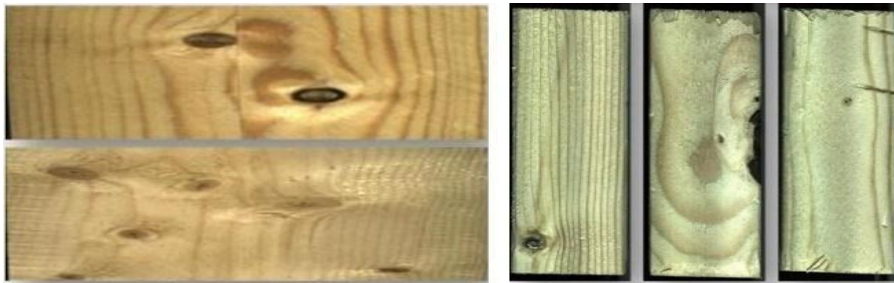


Figure 2. Example of wood defect.

With an accuracy of 81.5% and an error rate of 18.5%, the YOLOv7-E6E model can identify true positives while still producing some false positives. YOLOv7-E6E balances precision and error better than v8. YOLOv5l-seg has 72.21% precision and 27.79% error. YOLOv5 l-seg captures more positive instances than YOLOv8l, but with lower precision than YOLOv7-E6E and YOLOv9e. Its lower error rate makes it a good choice for tasks requiring recall and moderate error rates. YOLOv8l was found to have the lowest precision (65.33%) and highest error rate (34.67%) of the YOLO models, although it may be a suitable choice for applications in which computational

efficiency is a high priority. Because of wood surface lines that can be mistaken for lumber lines, all models were found to have trouble detecting finer cracks. Compared to the Roboflow dataset model (Roboflow, 2023), which reported 60% precision and 40% error rate, the YOLO models all had superior precision. In terms of training stability, YOLOv9e achieved stable losses and better detection performance than the other versions. Figure 3 presents the detection results achieved implementing the YOLOv9e model on the wood defect images. It successfully identified both small and dense wood defects (whereas earlier versions of the model struggled with incorrect detections and missed defects). These results show the strengths and weaknesses of each YOLO variant for wood defect detection.

Table 4. Comparative precision and error metrics for the selected YOLO models.

	Precision (%)	Error (%)
YOLOv5l-seg	72.21	27.79
YOLOv7-E6E	81.50	18.50
YOLOv8l	65.33	34.67
YOLOv9e	90.15	9.85
Roboflow	60.00	40.00

While YOLOv9e shows promise with its high precision, further optimizations are necessary to improve recall and achieve a more balanced performance. Moreover, it is crucial to consider the computational efficiency and resource requirements of these models in real-world deployment scenarios. While YOLOv9e may offer superior precision, its computational demands are high and require robust hardware resources. These findings demonstrate YOLOv9e's strong potential in practical applications, particularly in production environments demanding real-time, high-precision defect detection.

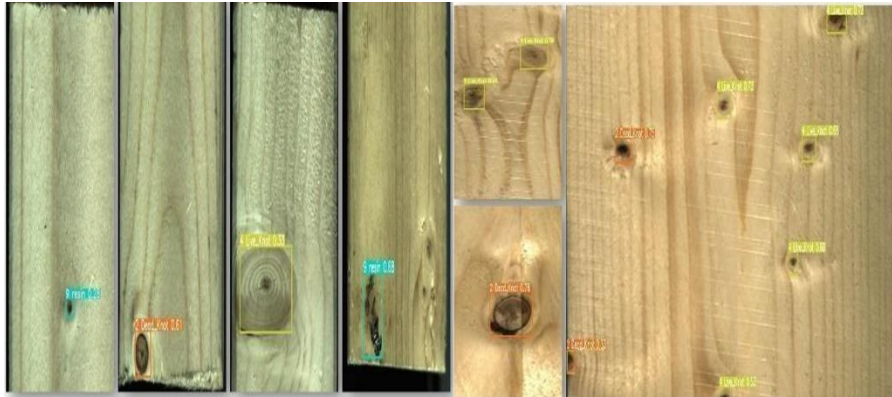


Figure 3. Examples of wood defect detection results.

CONCLUSION

The extensive comparative analysis shows that machine-vision technologies, particularly YOLO-based architectures (i.e., YOLOv5l-seg, YOLOv7-E6E, YOLOv8l, and YOLOv9e), have great potential in wood quality inspection processes. Each model's precision was tested, with YOLOv5 l-seg being found to achieve 72% precision, YOLOv7-E6E 81%, YOLOv8l 65%, and YOLOv9e 90%. YOLOv9e demonstrated the highest precision, while YOLOv7-E6E offered a balanced trade-off between performance and efficiency, indicating that YOLOv9e marks a notable

advancement in wood defect detection for real-time inspection applications. Future research may investigate attention mechanisms, dataset augmentation, or architectural enhancements to improve YOLO models for wood quality inspection in construction projects.

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