

Recent Advances in Wood Surface Defect Inspection using Deep Learning (2021-2025)

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Surface inspection plays a critical role in the wood industry, as it helps companies to enhance product quality, improves the utilization of wood resources, and increases the value of final products. In recent years, deep learning has emerged as a promising technique in this domain, offering significant advantages over traditional methods by enabling high-precision, real-time inspection. This paper presents a comprehensive review of advancements in the field from 2021 to 2025. It begins with a brief overview of three foundational aspects: common types of wood defects, publicly available datasets, and evaluation metrics. The core of the review then examines recent deep learning applications, organized according to three computer vision tasks—classification, detection, and segmentation. The paper concludes by discussing key challenges and proposing viable directions for future research, thereby offering a clear technical roadmap.

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INTRODUCTION

Wood remains an essential natural resource in human civilization and continues to be widely used despite technological advances and the emergence of alternative materials. However, it is prone to various defects, including knots, cracks, warping, twisting, decay, and insect damage (Ross *et al.* 2023). These imperfections not only compromise the aesthetic quality of wood but also adversely affect its mechanical properties, thereby reducing its practical utility and economic value. For instance, knots induce localized stress concentrations that undermine structural integrity. Such defects are also susceptible to splitting during processing, resulting in undesirable irregular fractures and surface imperfections in the final product (Fang *et al.* 2021). Against this backdrop, accurate detection of wood surface defects along with precise evaluation of their type, severity, and distribution can enable scientific wood grading, which in turn can greatly enhance wood utilization efficiency and economic benefits (Ehtisham *et al.* 2024).

Traditional defect inspection in wood primarily relies on manual methods, which are subjective and labor-intensive, failing to meet the demands of modern automated manufacturing (Chen *et al.* 2023b). Moreover, the reliability of manual inspection rarely exceeds 70%, as it is affected by human factors such as visual fatigue and lapses in concentration (Urbonas *et al.* 2019). Consequently, alternative inspection techniques have been developed, including acoustic, X-ray, and terahertz methods. Among these, vision-based systems integrated with machine learning have emerged as a promising solution for wood surface defect inspection due to their cost-effectiveness, efficiency, and adaptability to field conditions (Wang *et al.* 2021b).

Extensive research on this approach can be found in the literature, as exemplified by the comprehensive reviews of Kamal *et al.* (2017) and Urbonas *et al.* (2019). Although the types of input images vary across studies, most approaches follow two key steps: feature extraction and classification, as illustrated in Fig. 1a. For feature extraction, techniques such as Gray Level Co-occurrence Matrix (Savolainen 2023), Gabor filters (Hittawe *et al.* 2015), and Local Binary Pattern analysis (Li *et al.* 2019) have been employed to capture the distinctive color and texture characteristics of wood surface defects. Subsequently, classifiers including Artificial Neural Networks (Hwang *et al.* 2022) and Support Vector Machines (Gu *et al.* 2009) analyze these features and produce the final decision.

Alternative methods such as clustering (Silvén *et al.* 2003) and compressed sensing (Zhang *et al.* 2016) have also been explored. However, both feature extraction and classifier training are manually designed, making them dependent on human expertise. Furthermore, the performance of these methods degrades with changes in wood species, surface conditions, or lighting environments (He *et al.* 2019). Therefore, developing reliable techniques for wood surface defect inspection remains an ongoing challenge for the wood industry.

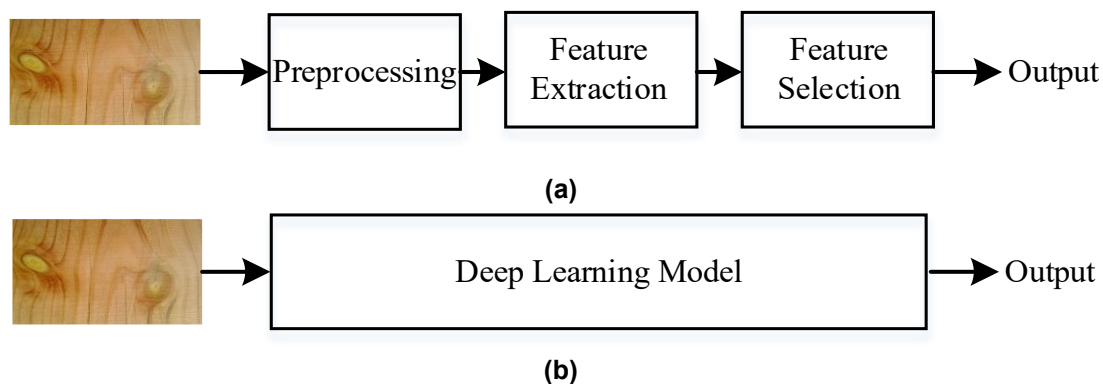


Fig. 1. The concepts of (a) traditional machine learning and (b) deep learning

Deep learning, an advanced subfield of machine learning, autonomously learns feature hierarchies from image datasets, as illustrated in Fig. 1b. Its capacity to extract discriminative features with minimal human intervention or specialized domain knowledge (Alzubaidi *et al.* 2021) has profoundly influenced wood surface defect inspection, positioning deep learning as a leading research trend. The number of related publications has grown substantially, with a marked acceleration during the period 2021 to 2025. This growth underscores the need for a dedicated review. Although previous reviews by An *et al.* (2022) and Yi *et al.* (2024) have discussed both traditional and deep learning methods, they did not focus specifically on the latter, thereby failing to provide a comprehensive overview of deep learning-centric research developments.

This paper summarizes advances in wood surface defect inspection, with particular emphasis on research conducted between 2021 and 2025. It covers key aspects including wood surface image datasets, network architectures, evaluation metrics, challenges, and alternative solutions. Researchers and students will gain a clear understanding of the topic, which will help identify promising directions for future work.

KEY ASPECTS IN WOOD SURFACE DEFECT INSPECTION

Main Wood Surface Defects

The categories of wood defects considered vary across industries, depending on their specific objectives. In the construction industry, defect inspection primarily focuses on assessing strength-related characteristics, with emphasis on insect damage, decay, and splits. In the furniture industry, inspections aim to eliminate both aesthetic imperfections and structural weaknesses, paying particular attention to knots, holes, and cracks. Table 1 summarizes the most frequently investigated wood surface defect types in the literature.

Table 1. The Types of Wood Surface Defects Concerned

Wood Product	Surface Defects Concerned
Building element (Haciefendioğlu <i>et al.</i> 2022)	Dry rot damage, wet rot damage, insect damage
Wood plate (Xia <i>et al.</i> 2022)	Rough shavings, watermark, sand marks, debris, glue spots, scratches
Sawn timber (Wang <i>et al.</i> 2023a)	Live knot, knot missing, marrow, quartzity, dead knot, knot with crack, crack, resin
Hardwood floor (Truong <i>et al.</i> 2023)	Boundary defects (crack), inside defects (stain and crack)
Particleboard (Zhang <i>et al.</i> 2025a)	Scratch, soft, mark of chalk, shaving, gluespot
Wood finish (Liu <i>et al.</i> 2025a)	Blister, crack, hole, scratch

Live knots, dead knots, and checks are consistently identified as critical defects in the literature due to their substantial impact on the quality of wood products. As shown in Fig. 2a, a live knot originates from a branch that was integrated into the trunk of a living tree. A high density of live knots complicates the wood grain pattern and reduces its ornamental value. In contrast, a dead knot (Fig. 2b) results from a deceased branch. Its fiber structure is often partially or completely detached from the surrounding wood tissue, significantly compromising the mechanical properties of solid wood panels. Checks (Fig. 2c) are fissures caused by the separation of wood fibers, typically due to external stresses. They reduce the wood's shear strength parallel to the grain and adversely affect its overall structural integrity. Moreover, checks are susceptible to fungal infection, which can lead to rot and progressive deterioration of the wood (Ding *et al.* 2020).

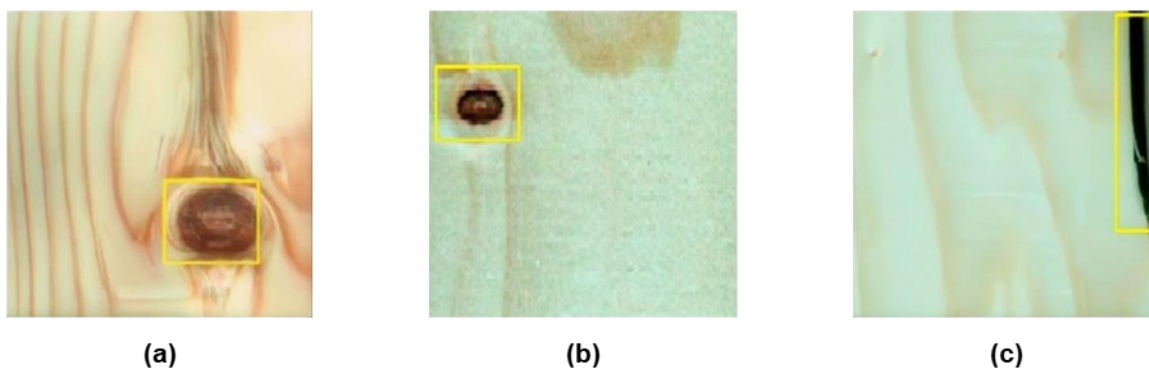


Fig. 2. Three common types of defect images (Ding *et al.* 2020): (a) live knot, b) dead knot, and (c) checking

Wood Image Datasets

The construction of high-quality datasets is a foundational step in deep learning research, as such data are essential for both training and evaluating models. However, data acquisition and annotation are inherently time-consuming and labor-intensive. Consequently, the availability of high-quality datasets remains limited, with public access being even more restricted. Table 2 summarizes typical open-access wood surface image datasets.

Table 2. Typical Open-access Datasets of Wood Surface Images.

Reference	Images	URL
Kodytek <i>et al.</i> 2021	43,000	http://doi.org/10.5281/zenodo.4694695
Tu <i>et al.</i> 2021	1,545	https://github.com/WenHe-Hnu/sawn-lumber-dataset
Zhong <i>et al.</i> 2024	4,4048	https://github.com/yumingzhong1/wood_dataset/tree/main
Li <i>et al.</i> 2025	950	https://github.com/humblefactos1/YOLOV8-CDC/tree/main
Tran <i>et al.</i> 2025	1,515	https://data.mendeley.com/datasets/vnst548g5n/1

In 2021, Kodytek *et al.* (2021) released a large-scale dataset of high-resolution sawn timber surface images collected in an industrial environment. This dataset contains 43,000 annotated images covering ten common types of wood defects. Each image is annotated with dual labels, enabling defect classification, localization, and semantic segmentation. Despite its relatively recent publication (approximately three years ago), this dataset has been widely adopted as a benchmark for validating numerous novel methodologies (Ehtisham *et al.* 2023; Meng and Yuan 2023; Wang *et al.* 2023a; Wang *et al.* 2023b; Zou *et al.* 2023; An *et al.* 2024; Ehtisham *et al.* 2024; Luo *et al.* 2024; Wang *et al.* 2024a; Wang *et al.* 2024b; Zheng *et al.* 2024b; Chen *et al.* 2025; Kılıç *et al.* 2025; Wang *et al.* 2025a; Wang *et al.* 2025b; Xi *et al.* 2024; Zou *et al.* 2025).

In addition, a limited number of research teams have shared their self-developed datasets *via* GitHub repositories. For instance, Tu *et al.* (2021) released a dataset of 1,545 sawn rubber wood images featuring four defect types: intergrown knots, dead knots, growth shakes, and inbark. Separately, Zhong *et al.* (2024) provided two distinct datasets: one for pine lumber and the other for rubberwood lumber. The pine dataset contains 2,686 annotated images with three typical defects (dead knots, sound knots, and missing edges), while the rubber dataset includes 1,362 annotated images with five typical defects (dead knots, sound knots, missing edges, tree cores, and cracks). All images in these datasets have a resolution of 658×492 pixels. Furthermore, Li *et al.* (2025) compiled a dataset of 950 wood panel images sourced from individual users on the Roboflow platform and shared it via a GitHub repository.

In contrast to these efforts, VNWoodKnot is a recently released publicly available image dataset comprising 1,515 high-resolution wood surface images. It includes three categories: live knots, dead knots, and knot-free surfaces. As such, it serves as a critical benchmark for developing learning models for industrial-grade wood defect inspection (Tran *et al.* 2025). Many researchers have also constructed proprietary datasets for their investigations. As summarized in Table 3, these self-developed datasets are typically small in scale. The largest among them comprises only about 5,000 images, which is far fewer than the dataset shared by Kodytek *et al.* (2021). The smallest contains merely 310 samples. Although studies using these datasets have reported satisfactory results, with average recognition rates exceeding 90%, their practical utility in real-world industrial settings remains significantly limited.

Table 3. Some Typical Self-developed Datasets

Reference	Wood Samples	Images	Resolution (pixels)	Defect types
Li <i>et al.</i> 2021	Wood of three species: birch, pine, poplar	1, 242	3369 × 2246	3
Wang <i>et al.</i> 2021a	Wood of three species: birch, pine, oak	1, 800	200 × 200	3
Yang <i>et al.</i> 2021	Wood panel	5, 000+	300 × 300	6
Haciefendioğlu <i>et al.</i> 2022	Wood elements in building	1, 068	/	3
Mohsin <i>et al.</i> 2023	Wood plank	5, 000	/	6
Han <i>et al.</i> 2023	/	3, 606	640 × 640	7
Zhang <i>et al.</i> 2024	Wood lumber	4, 000	2800 × 1024	8
Zhu <i>et al.</i> 2024	/	1, 100	512 × 512	2
Fan <i>et al.</i> 2024	dry, finished sawn timber	1, 500	200 × 200	5
Cui <i>et al.</i> 2024	Solid wood floor	3, 473	/	8
Ge <i>et al.</i> 2025	/	4, 321	/	8
Liu <i>et al.</i> 2025a; Liu <i>et al.</i> 2025b	Wood finish	310	2448 × 2048	4
Zhang <i>et al.</i> 2025a	Particleboard	1,000	2048 × 4300	5

Evaluation Metrics

Different applications impose distinct requirements on wood surface defect inspection methods, necessitating the use of diverse evaluation criteria. Existing research primarily focuses on two aspects: accuracy and efficiency.

Accuracy evaluation metrics

Accuracy metrics are used to quantify the predictive performance of algorithms in classifying, detecting, and segmenting wood surface defects. As summarized in Table 4, commonly adopted metrics include accuracy, precision, recall, F1-score, the receiver operating characteristic (ROC) curve, intersection over union (IoU), average precision (AP), and their derivatives such as mean average precision (mAP) and mean IoU (mIoU). Together, these metrics form a comprehensive evaluation framework that provides critical insights for algorithmic refinement and advancement.

Efficiency evaluation metrics

Efficiency metrics assess the processing speed and computational complexity of algorithms. As summarized in Table 5, commonly used efficiency metrics include the number of parameters, floating point operations (FLOPs), inference time, and frames per second (FPS). These indicators are vital for enabling fast and accurate identification of wood surface defects.

DEEP LEARNING MODELS FOR VISUAL INSPECTION OF WOOD SURFACE DEFECT

Similar to general computer vision tasks, deep learning techniques for wood surface defect inspection can be broadly classified into three categories: classification, detection, and segmentation. As illustrated in Fig. 3a, defect classification methods identify the

presence and type of defects in wood surface images. Defect detection methods extend beyond classification by localizing defects using rectangular bounding boxes. Current detection algorithms are mainly divided into one-stage and two-stage approaches. Representative one-stage algorithms include the You Only Look Once (YOLO) series and the Single Shot Multibox Detector (SSD). Over the years, the YOLO architecture has evolved significantly, with successive versions from YOLOv1 to YOLOv13 introducing consistent improvements in accuracy, speed, and efficiency. Representative two-stage algorithms belong to the region-based CNN (R-CNN) family, which includes R-CNN, Fast R-CNN, and Faster R-CNN. The developmental trajectories of these two model families are shown in Figs. 3b and 3c, respectively. Figure 3d illustrates defect segmentation methods, which perform pixel-level segmentation of defect regions from the background, thereby providing both geometric information and defect categorization.

Table 4. Common Accuracy Evaluation Metrics for Different Inspection Methods.

Metric	Description	References
Accuracy	Measures the overall classification accuracy. It performs well when the classes are balanced, but it may fail with imbalanced classes.	Ehtisham <i>et al.</i> 2023
Precision	The accuracy of the samples is predicted as defective	Liu <i>et al.</i> 2025b; An <i>et al.</i> 2024
Recall	The model's ability to cover defective samples	Liu <i>et al.</i> 2025b; An <i>et al.</i> 2024
F1-Score	The harmonic mean of precision and recall	Ehtisham <i>et al.</i> 2023; Chen <i>et al.</i> 2025
ROC curve	Depicts the trade-off between Sensitivity (or TPR) and Specificity (1 - FPR). Classifiers with curves closer to the upper-left corner are indicative of superior performance	Kılıç <i>et al.</i> 2025; Hacıfendioğlu <i>et al.</i> 2022
IoU	Measures overlap between predicted and actual bounding boxes	Musa <i>et al.</i> 2023; Urtans <i>et al.</i> 2022
AP	Average precision over IoU thresholds	Luo <i>et al.</i> 2024; Zheng <i>et al.</i> 2024b
mAP	Mean average precision across classes	Shi <i>et al.</i> 2020; Al-Zubi and Plapper 2022
mIoU	Mean IoU across classes	Mohsin <i>et al.</i> 2023; Zhong <i>et al.</i> 2024

Table 5. Common Efficiency Evaluation Metrics.

Metric	Description	References
Parameters	The number of weights that need to be stored. Fewer parameters indicate a more lightweight model for deployment.	Zheng <i>et al.</i> 2024b; Liu <i>et al.</i> 2025b
FLOPs	The number of floating-point operations per second. Fewer FLOPs mean lower computation resources requirements for model deployment.	Liu <i>et al.</i> 2025b; Chen <i>et al.</i> 2025
Inference Time	Time required for the model to process a single sample.	Xie and Ling 2023;
FPS	Evaluates whether the model is suitable for real-time defect detection application. Higher FPS indicates faster processing speed.	Lim <i>et al.</i> 2023; Luo <i>et al.</i> 2024

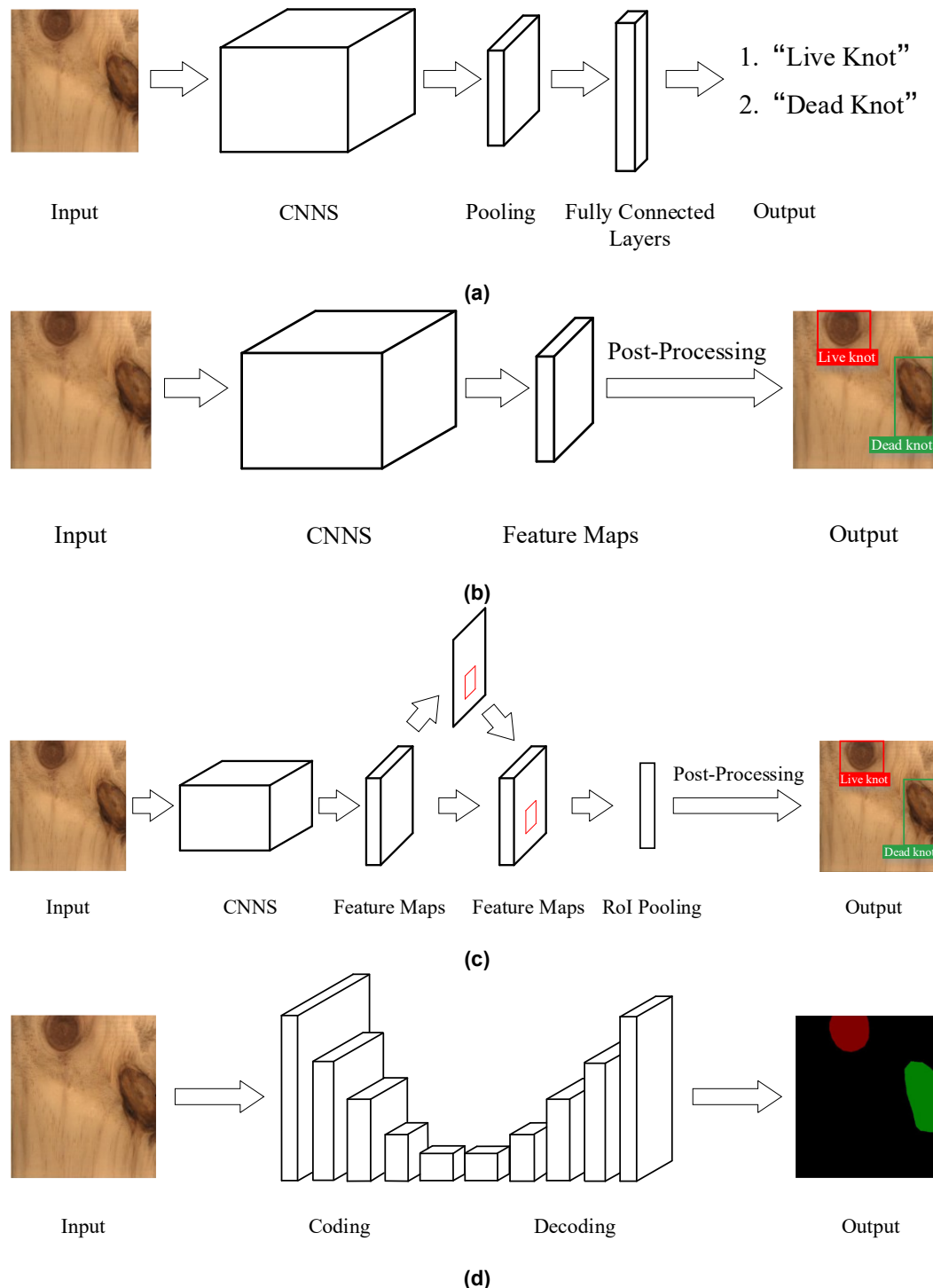


Fig. 3. Visual inspection of wood surface defects. Wood defect (a) classification, (b) detection using one-stage algorithm, (c) detection using two-stage algorithm, and (d) segmentation

Wood Surface Defect Classification

In the early stages of this field, several comparative studies were conducted on various wood surface image datasets. Hacıefendioğlu *et al.* (2022) reported that ResNet-50 and Xception achieved over 90% accuracy in classifying damage to wooden building elements, outperforming VGG-16, VGG-19, and Inception-V3. Chun *et al.* (2022) found that ResNet50 performed better than ShuffleNet, AlexNet, MobileNetV2, NASNetMobile,

and GoogLeNet, attaining a best accuracy of 94.59% in detecting timber defects across four Malaysian timber species. Ehtisham *et al.* (2023) evaluated ten pre-trained CNN models-ResNet18, ResNet50, ResNet101, GoogLeNet, ShuffleNet, Inception-V3, MobileNet-V2, Xception, Inception-ResNet-V2, and NASNetMobile-on a dataset of 9,000 wood surface images. Among these, Inception-V3 demonstrated superior performance in defect classification based on accuracy, processing speed, and overall efficacy.

Several researchers have improved classification accuracy by modifying existing deep learning architectures. Zou *et al.* (2023) integrated the Convolutional Block Attention Module (CBAM) and the Cross-Stage Partial Network (CSPNet) into ResNet-50, and replaced the Adam optimizer with the Ranger optimizer during training. These modifications significantly enhanced accuracy while reducing training time. Xie and Ling (2023) introduced two modifications to the RegNet architecture: incorporating an attention mechanism and adding the Ghost module into the bottleneck to replace some group convolution structures. The modified RegNet achieved a high classification accuracy of 96.58% with a smaller weight file. Wang modified the cross-entropy loss in a standard CNN classifier by adding Var Loss to the main loss function. The modified loss made the classifier more sensitive to hard samples regardless of batch size, while Var Loss reduced prediction confidence fluctuations, improving model robustness for practical use (Wang 2025). Yeh *et al.* (2025) proposed a Gabor Convolutional Network (GCN) that integrates CNNs with Gabor filters for wood defect recognition. Using the Taguchi method to optimize key hyperparameters, the optimized GCN achieved 98.92% accuracy on the MVTec wood dataset, outperforming a baseline Taguchi-optimized CNN by 2.73%.

The development of self-designed deep learning architectures has also been a focus of recent research. Wang (2022) proposed a novel dual-parallel network to classify light and dark wood defects, enhancing robustness against color diversity. Compared with complex CNN architectures, this design offered higher inference speeds, making it more suitable for industrial applications. Zhang *et al.* (2025a) introduced a novel network for particleboard defect detection based on a Densely Connected Dual Attention mechanism (DC-DACB). This architecture integrates three core modules-defect detection, classification, and feature enhancement-with the feature enhancement module embedded within the former two to synergistically boost overall performance.

Wood Surface Defect Detection

One-stage models

YOLO v3 and v4. The YOLO series is widely used in object detection due to its lightweight architecture, which entails a reduced number of parameters and lower computational complexity, thus achieving fast inference speed. However, a frequently cited limitation is its substantial computational demand, which hinders widespread deployment. Moreover, the conventional cross-entropy loss function often provides suboptimal guidance for model training. To address these issues, Wang *et al.* (2021a) replaced the backbone (*i.e.*, the core feature extraction network) of YOLOv3 with a Ghost module, a lightweight convolutional module that generates features through low-cost linear operations, creating a more lightweight architecture that increased online detection speed for wood surface defects to 28 FPS. Musa *et al.* (2023) introduced a large-scale dataset of 3,500 annotated wood surface images across seven defect categories and reported a mean Average Precision (mAP) of 67.3% using YOLOv4-tiny.

In a separate approach, Akhyar *et al.* (2022) simplified YOLOv4 by reducing residual block components, backbone channels, and the residual network within the Path

Aggregation Network (PAN). Experiments on pine and rubber lumber datasets showed that these modifications improved FPS by 10.8 compared to the original YOLOv4. Tu *et al.* (2021) proposed GC-YOLOv3 for accurate and fast detection of sawn lumber defects, using a Gaussian function to determine prediction box coordinates and localization uncertainty, and incorporating a focal IoU loss that considers overlap area, center points, and aspect ratio. These innovations effectively enhanced detection accuracy. Lim *et al.* (2023) integrated Efficient Channel Attention (ECA) modules into YOLOv4-Tiny to boost detection performance with minimal impact on model size, followed by an aggressive iterative channel pruning strategy that drastically reduced model size, achieving an 88% reduction in parameters.

YOLO v5, and X. As an enhanced iteration, YOLOv5 has demonstrated superior performance over YOLOv3-SPP in knot detection for sawn timbers in terms of detection accuracy, training speed, and model size (Fang *et al.* 2021). YOLOv5 also proved effective for automated inspection of small defects on hardwood flooring in production line settings (Truong *et al.* 2023). Several task-specific modifications have been made to YOLOv5 and YOLOX for wood surface defect detection. Yu *et al.* (2022) replaced the original PANet in YOLOv5 with a Bidirectional Feature Pyramid Network (BiFPN). Cheng *et al.* (2022) substituted the ReLU activation function with SiLU and incorporated a Squeeze-and-Excitation (SE) attention block to enhance inter-channel feature extraction. Meng and Yuan (2023) implemented three key changes: a Semi-Global Network (SGN) to replace the C3 module, an Extended Efficient Layer Aggregation Network (E-ELAN) embedded into the backbone, and the Efficient IoU (EIOU) loss function. Xu *et al.* (2023) developed YOLOv5-C3Ghost for detecting five wood defects, reporting a maximum improvement of 1.6% in mAP@0.5:0.95. Zheng *et al.* (2024b) proposed GBCD-YOLO, an enhanced YOLOv5s variant, achieving a 13.45% increase in mAP@0.5 (reaching 88.72%), an 11.95% increase in mAP@0.5:0.95, a 6.25% increase in FPS, and a 15.49% reduction in parameters.

Beyond YOLOv5, Li *et al.* (2022) adapted YOLOX for detecting four types of lumber defects by integrating an ECA attention mechanism and an ASSF module for multi-feature adaptive fusion into the feature fusion network, and replacing BCELoss and IoU loss with FocalLoss and EIoU loss. This model achieved 96.42% mAP@0.5 and a detection speed of 46.7 FPS. Han *et al.* (2023) introduced STC-YOLOv5 by integrating Coordinate Attention, a Transformer Encoder, and a Swin Transformer module into YOLOv5, resulting in a 3.1% mAP improvement over the baseline.

YOLO v7 and v8. YOLOv7 and YOLOv8 offer significant advancements in inference speed and detection accuracy. Afaf *et al.* (2024) evaluated YOLOv5, YOLOv5-tiny, and YOLOv7 on a wood image dataset, finding that YOLOv7 achieves higher accuracy in classifying defects including live knots, dead knots, knots with cracks, missing knots, cracks, resin, blue stain, and marrow. Fan *et al.* (2024) employed YOLOv7 to inspect lumber surfaces and used the detection results to guide a bilateral sawing strategy for targeted defect removal, reportedly increasing sawn timber volume yield by 12.3%. Fang *et al.* (2024) compared YOLOv8, Faster R-CNN, and Mask R-CNN for wood defect inspection, demonstrating that YOLOv8 excels in both detection speed and accuracy, with strong robustness on complex backgrounds and multiple defect types.

Recent research has focused on modifying YOLOv7 and YOLOv8 to further enhance speed, accuracy, and robustness. Table 6 summarizes the latest work, showing that YOLOv8 is most frequently selected as the baseline architecture, likely due to the short six-month interval between the releases of YOLOv7 and YOLOv8. Common enhancement strategies include integrating attention mechanisms, modifying feature extraction or fusion

networks, and optimizing loss functions. All enhanced models have demonstrated superior detection performance over their baselines, with reported mAP improvements ranging from at least 3.8% (Zhang *et al.* 2024) to as high as 9% (Wang *et al.* 2023b). Most optimized models also exhibit faster inference speeds; for example, Chen *et al.* (2025) reported a 21.6% reduction in parameter count and a 15.6% decrease in computational complexity.

Table 6. Improved Models Using YOLOv7 or YOLOv8

Reference	Base model	Improved model	Performance
Wang <i>et al.</i> 2023a	YOLOv8n	TSW-YOLO-v8n	Average detection accuracy: 5.1% increase; Detection time: 1ms reduction
Wang <i>et al.</i> 2023b	YOLOv7	ODCA-YOLO	mAP: 9% increase
An <i>et al.</i> 2024	YOLOv8	CWB-YOLOv8	mAP@0.5: 3.5% increase; mAP@0.5:0.95: 5.8% increase
Cui <i>et al.</i> 2024	YOLOv7	CCG-YOLOv7	Precision: 2.1% increase; Recall: 1.6% increase; mAP: 1.2% increase
Guo and Cao 2024	YOLOv8	FRCE-YOLO	mAP@0.5: 6.9% increase; mAP@0.5:0.95: 8.4% increase; Computational complexity: 1.2 GFLOPs reduction
Wang <i>et al.</i> 2024a	YOLOv7	BPN-YOLO	mAP: 7.4% increase
Wang <i>et al.</i> 2024b	YOLOv8	Improved YOLOv8	mAP: 5.5% increase
Xi <i>et al.</i> 2024	YOLOv8	SiM-YOLO	mAP: 4.3% increase; Reducing misdetection and omission issues
Zhang <i>et al.</i> 2024	YOLOv8	WLSD-YOLO	mAP: 3.8% increase; Frames per second (FPS): 3.8 increase
Chen <i>et al.</i> 2025	YOLOv8	YOLOv8-OCHD	mAP: 5.9% increase; Parameter count: 21.6% reduction; Computational load: 15.6% reduction
Ge <i>et al.</i> 2025	YOLOv8	Improved YOLOv8	Outperforming Faster R-CNN, YOLOv5s, and RT-DETR; Reducing missed detections and false positives; Robust in detecting small and complex defects
Dou and You 2025	YOLOv8	Improved YOLOv8	Outperforming Yolo variants(v5, v7,v9, v10, v11 and v12) in most defect categories
Li <i>et al.</i> 2025	YOLOv8	Improved YOLOv8	Precision: 3.6% increase; Recall: 8% increase; mAP: 6.1% increase
Wang <i>et al.</i> 2025a	YOLOv8	FDD-YOLO	mAP: 4.3% increase
Wang <i>et al.</i> 2025b	YOLOv8	DRR-YOLO	mAP: 5.2% increase
Long and Lin 2025	YOLOv8	Improved YOLOv8	mAP@0.5: 4.4% increase; number of model parameters: 61.1% reduction; floating-point operations: 62.7% reduction

Other recent YOLO versions. Since 2024, several new YOLO versions (YOLOv9 to v12) have been released. However, their application in wood surface defect detection remained limited by December 2025 due to their recency. Comparative studies have shown that these generic YOLO networks underperform relative to purpose-designed algorithms for this task (Guo *et al.* 2025; Hoang *et al.* 2025; Zhao *et al.* 2025). In contrast, modified versions based on these new models have demonstrated superior performance. Jiang *et al.*

(2025) proposed a lightweight enhanced model based on YOLOv11n to improve crack identification in wooden components under complex backgrounds. He *et al.* (2025) developed LE-YOLO, which optimizes YOLOv11n in terms of loss function, backbone, neck, and detection head. On the Chipboardv1.0 dataset, this algorithm achieved a 4–6% increase in mAP, a 12.69% improvement in inference speed, and an 18.6% reduction in parameters.

Other one-stage models. Beyond the YOLO series, the SSD framework has also been used for wood surface defect detection. Yang *et al.* (2021) replaced the VGG network in SSD with ResNet to refine input features for bounding box regression and classification, reporting an average detection time of 90 ms and 89.7% accuracy. Other customized architectures have shown considerable promise. Liu *et al.* (2025b) introduced MFWL-DETR, a lightweight framework with multi-scale feature fusion for detecting water-based paint defects (blisters, cracks, holes, scratches) on wooden surfaces. They also proposed MSIEGNet for identifying wood finish defects, achieving 90.8% mAP@50 and 97.4% accuracy (Liu *et al.* 2025a). Luo *et al.* (2024) developed two I2GF-Net variants: a deeper version (I2GF-Net-d) that outperforms 13 state-of-the-art methods with fewer false positives and missed detections, and a shallower version (I2GF-Net-s) prioritizing inference speed at 83.1 FPS.

Two-stage models

Two-stage object detection models have seen limited adoption for wood panel surface inspection compared to their success in other domains. Faster R-CNN has been applied in only a few instances. Fang *et al.* (2024) compared YOLOv8, Faster R-CNN, and Mask R-CNN for detecting knots, oil streaks, black dots, and cracks, finding that Faster R-CNN achieved the fastest convergence and best training results within the first 24 epochs.

Several modifications have been made to the Faster R-CNN framework to improve its performance in wood defect detection. Zou *et al.* (2025) refined three core components—the backbone network, the loss function, and soft non-maximum suppression (NMS), thereby achieving a higher mAP than classical networks. In a study on timber knot detection, Chen *et al.* (2023a) observed that the standard Faster R-CNN occasionally generated multiple detections for a single knot, leading to a high false-positive rate. To address this, they introduced an overlapping bounding box filter, which increased detection precision from 90.9% to 97.5%. An improved Faster R-CNN model incorporating a ResNet-50 backbone, focal loss, and soft NMS elevated mAP by 4.38% and reduced mean detection time by 3.6% compared to the baseline (Zou *et al.* 2025). Tong *et al.* (2025) proposed an enhanced Faster R-CNN with a dual attention mechanism to tackle challenges including few-shot sample scarcity, defect diversity, and complex background interference. Key enhancements include a Wood-Region Proposal Network (WRPN) and a Wood-Feature Reconstruction Head (WFRH), which improve candidate box quality and feature reconstruction. Experimental results demonstrate state-of-the-art performance on benchmark datasets, with significant gains in AP50 and AP75 for 17 wood defect types under few-shot conditions.

In a distinct approach, Pan *et al.* (2021) developed an elliptical detection and localization method by integrating Faster R-CNN with a Gaussian Proposal Network (GPN). This framework outputs detected ellipses parameterized by (cx, cy, rx, ry, θ) , representing the center coordinates, semi-diameters, and counterclockwise rotation angle of each ellipse. Experimental results on sawn lumber images showed that the proposed method improved the mean IoU by 10%.

Wood Surface Defect Segmentation

In the domain of computer vision, image segmentation techniques are predominantly categorized into two paradigms: semantic segmentation and instance segmentation. Semantic segmentation operates at the pixel level, assigning each pixel to a predefined defect category, such as live knots, dead knots, or resin pockets. Instance segmentation extends this capability by not only performing pixel-wise classification but also differentiating between distinct individual instances within the same category (Urtans *et al.* 2022).

Semantic segmentation

Mohsin *et al.* (2023) introduced a novel framework for real-time detection of wood planks on a high-speed conveyor system, integrating a CNN network for simultaneous surface defect segmentation. The proposed architecture comprises three core components: a backbone network for feature extraction, a detection algorithm for plank identification, and a segmentation module for real-time defect analysis. Zhong *et al.* (2024) proposed a deep Gaussian attention segmentation network for lumber surface defect detection. The network first employs a self-attention mechanism-incorporating both position and channel attention modules-to aggregate contextual information. It then integrates two Gaussian modules into these attention mechanisms to facilitate the fusion of enhanced and salient features. Additionally, Gaussian attention modules (GAMs) are incorporated into the Deeplabv3+ architecture, operating in parallel with the Atrous Spatial Pyramid Pooling (ASPP) module, to effectively merge multiscale, minor, and highly discriminative features. Zhao *et al.* (2022) proposed the YOLOv5-Seg-Lab-4 model, which integrates object detection with semantic segmentation to ensure real-time performance while enhancing detection accuracy. Deployed in a particleboard factory, the model successfully automated the classification and grading of boards containing defects such as sand leakage, big shavings, glue spots, oil pollution, and soft areas. The system achieved an accuracy of 98.2%, with processing times ranging from 183 to 208 ms per image.

Luo *et al.* (2025) proposed a layer-wise adapter module (LAM) to adapt visual foundation models for wood surface defect segmentation. The LAM integrates three key components: an instance-linking token module (ILTM) to enhance sensitivity to ambiguous boundaries and improve instance-level feature representation; a feature disentanglement module (FDM) to reduce feature redundancy and increase inter-class feature independence; and a layer switch module (LSM) to dynamically activate feature refinement for optimal layer-specific adaptation. By addressing challenges such as high inter-class similarity and fuzzy boundaries, LAM significantly improved segmentation performance on both Rubber Wood and Pine Wood datasets. Zhu *et al.* (2024) proposed a U-Net-based multi-source data fusion network for wood break detection. Their approach employs an improved ResNet34 backbone to extract multi-level features from image and depth data using depthwise separable convolutions (DSC) and dilated convolutions (DC), which reduce computational cost and feature redundancy. Features from the two modalities are then optimally integrated through an adaptive interacting fusion module (AIF), generating accurate feature representations for broken defects. Based on Attention U-Net, Dong *et al.* (2025) proposed a new model called IECAU-Net. This was achieved by incorporating CBAM and ECA modules, replacing the optimizer with AdamW, and using a weighted fusion multi-loss function. The resulting IECAU-Net outperformed other models in semantic segmentation of sawn wood surface cracks. Based on U-Net,

DBDFCNet incorporates several key innovations. It introduces a multiscale atrous spatial pyramid pooling (MSASPP) module for enhanced multiscale feature extraction, a dual-branch decoder (DBD) with binary and semantic branches, and a discriminative feature cross-attention module (DFCAM) to increase inter-class distances. Together, these improvements effectively address the challenges of defect variety, obscure boundaries, and size and shape variations in lumber surface defect segmentation (Zhang *et al.* 2025b).

Beyond fully supervised methods, researchers have also addressed the challenge of acquiring costly, high-quality datasets for training deep segmentation models by introducing generators capable of synthesizing pixel-level annotations. Tsai *et al.* (2021) proposed a two-stage deep learning method for pixel-wise defect detection on textured surfaces without manual annotations. Their approach employs two Cycle-Consistent Adversarial Networks (CycleGANs) to automatically synthesize defective images and generate corresponding pixel-wise annotations. The output from this synthesis stage is used to create a large-scale synthetic dataset, which subsequently trains a U-Net model for precise defect detection. This framework requires only a small set of real defect samples and eliminates labor-intensive human labeling, offering both practical implementability and computational efficiency in manufacturing environments. Zheng *et al.* (2024a) proposed a semi-supervised defect detection approach based on generative adversarial networks, comprising a generator and a discriminator. The generator produces pixel-level segmentation results for wood defect images. To improve segmentation performance, the discriminator is trained adversarially against the generator by assessing prediction quality and providing supervised signals for unlabeled images.

Instance segmentation

To detect defects on wood surfaces, researchers have adopted Mask R-CNN, an instance segmentation framework that simultaneously predicts a pixel-level mask and the corresponding class label for each defective region. Al-Zubi and Plapper (2022) provided a proof-of-concept by applying Mask R-CNN to synthetic images of wood panels to detect and segment drilled holes. Despite pronounced variations in color, texture, and hole appearance, the model yielded satisfactory results.

To address the challenges of modeling irregular defects and extracting contextual information, Li *et al.* (2021) proposed a layered deformable Mask R-CNN. By establishing layered connections between residual modules, a larger receptive field was achieved at each network layer, and deformable convolution was employed to better fit defect shapes.

Some researchers have argued that Mask R-CNN does not address the problem of calculating defect size (*e.g.*, area and diameter). In response, Zhong *et al.* (2025) proposed a parallel structure fusion approach. This method incorporates two dedicated branches: one for identifying veneer knot defect types using the Inception V3 network, and the other leveraging an improved K-means clustering algorithm from traditional computer vision to localize defects and determine their real-world dimensions. Ehtisham *et al.* (2024) presented a similar work, where Inception-ResNet-V2 is first used to classify images into three categories: knots, cracks, and undamaged sections. Subsequently, image processing techniques are employed to determine key morphological characteristics of the defects, such as width, length, angle, and spatial extent. Luo *et al.* (2025) proposed a layer-wise adapter module (LAM) built upon large-scale visual foundation models, which integrates an instance-linking token module (ILTM), a feature disentanglement module (FDM), and a layer switch module (LSM). This approach achieved significant improvements in both segmentation accuracy and efficiency over ten state-of-the-art methods on rubber wood

and pine wood datasets, while also demonstrating robust zero-shot transferability on unseen datasets.

CHALLENGES

Deep learning has yielded significant results in the visual inspection of wood surface defects, with some laboratory studies reporting accuracy rates approaching 100%. However, numerous challenges persist in practical applications.

Small Sample Problem

The small sample problem is a common challenge in applying deep learning algorithms, as it can easily lead to overfitting during training. An overfitted model exhibits poor generalization and struggles to recognize targets in unseen data. A primary cause of this issue is the scarcity of accurately labeled wood images. Raw wood images typically lack annotations and thus cannot be used directly for supervised training. The labeling process relies on domain experts and is often tedious and time-consuming; consequently, only a limited number of experts are available for such tasks. According to Kryl *et al.* (2021), most research on wood surface defect inspection utilizes datasets ranging from only 250 to 5,200 images.

To address data scarcity, researchers have increasingly adopted data augmentation (Gao *et al.* 2021a,c; Li *et al.* 2021; Chun *et al.* 2022; Wang 2023; Sujatha *et al.* 2024) and transfer learning (Gao *et al.* 2021a,b; Chun *et al.* 2022; Hacıfendioğlu *et al.* 2022; Ehtisham *et al.* 2023). However, these methods cannot guarantee capturing the full variability of real-world defects, particularly when such variability is potentially limitless (Kodytek *et al.* 2021). Therefore, the introduction and adaptation of more advanced techniques-such as self-supervised, semi-supervised, and weakly supervised learning-are anticipated to address various practical challenges in wood defect inspection under limited data conditions (Safonova *et al.* 2023).

Class Imbalance

Due to the differing causes of defect formation, the prevalence of various wood surface defect types varies significantly, and this imbalance is consistently observed in related datasets. For instance, Li *et al.* (2021) reported that knots constitute approximately 60% of all defects, with other categories collectively accounting for the remaining 40%. A more extreme example is provided by Cheng *et al.* (2022), whose dataset contained over 18,000 samples of live knots but nearly zero instances of blue stain, as illustrated in Fig. 4.

Such imbalanced sample distribution can bias deep learning models toward features from the majority classes, thereby compromising the reliability of the outcomes (Bai *et al.* 2024). To address this issue, data augmentation techniques have been widely employed to enrich existing datasets (Urbonas *et al.* 2019; Li *et al.* 2021; Riana *et al.* 2021; Chun *et al.* 2022). As another prominent generative approach, generative adversarial networks (GANs) have been extensively used to synthesize defect samples and alleviate data imbalance (Hu *et al.* 2020; Tsai *et al.* 2021; Deng *et al.* 2024; Zheng *et al.* 2024a). These methods, which can be categorized as data-level approaches, mitigate the effects of class imbalance to some extent. Furthermore, a range of algorithm-level and feature-level methods have recently emerged in other industrial domains. Such techniques also hold significant potential for application in wood surface defect inspection (Bai *et al.* 2024).

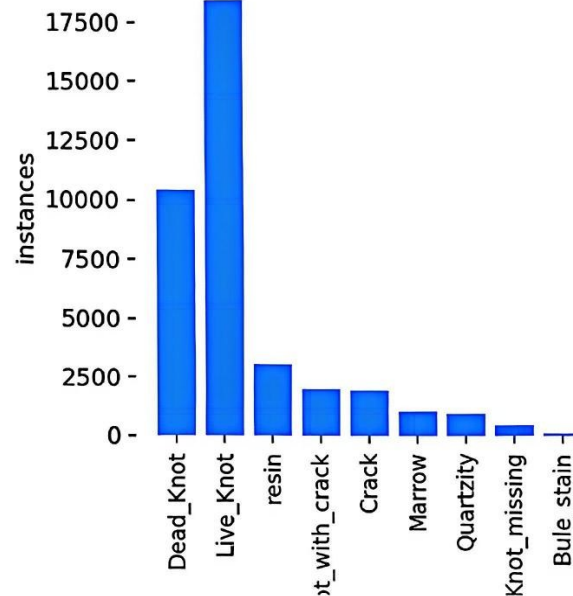


Fig. 4. The number of defects in various types of wood (Cheng *et al.* 2022)

Real-time Capabilities

For real-time operation, the inspection process must keep pace with manufacturing or image acquisition speeds. This is often challenging for deep learning-based models, as their complex and deep architectures frequently lead to reduced inference speeds. In industrial applications, however, both high accuracy and real-time performance are indispensable. Consequently, enhancing real-time capability remains a critical issue for wood surface defect inspection models, even when high accuracy has been achieved (Tu *et al.* 2021).

Lightweight models have been extensively employed to effectively balance accuracy and computational efficiency. Various techniques – such as factorized convolutions, group convolution, depthwise separable convolution, bottleneck design, and neural architecture search – have been explored to simplify model structures and reduce complexity. Representative models, including MFWL-DETR (Liu *et al.* 2025b), GBCD-YOLO (Zheng *et al.* 2024b), and YOLOv8-OCHD (Chen *et al.* 2025), have been reported to effectively inspect wood surface images with fewer parameters and lower computational demands. A typical case is MFWL-DETR, which, when applied to detect defects on water-based wood paint surfaces, achieved a 40.5% decrease in computation, a 40.2% reduction in parameters, and a 36.1% reduction in model size compared to the baseline (Liu *et al.* 2025b).

Quantization and pruning represent alternative approaches, although their adoption in this field has remained relatively limited to date. Lim *et al.* (2023) introduced a pruned model in which YOLOv4-Tiny was substantially compressed *via* an iterative pruning and recovery procedure. This process reduced model parameters by 88%, thereby enabling near-real-time wood defect detection on a general-purpose embedded processor without external hardware accelerators. Similarly, Mohsin *et al.* (2023) refined a non-quantized deep learning model through quantization-aware training, wherein both activations and weights are quantized to lower precision. This approach reduced the number of parameters by 40% and increased inference speed by approximately threefold without sacrificing overall accuracy.

FUTURE DIRECTIONS

More Efficient Algorithms

Despite the remarkable progress reported in existing research, most developed methods still face barriers to real-world practical deployment. Fortunately, wood surface defect inspection remains a relatively specialized subdomain within the broader deep learning research landscape. Advances in surface defect detection for other materials can offer valuable insights and methodological references for wood defect inspection, and it is foreseeable that emerging innovative algorithms will further narrow the gap between academic research and industrial application.

First, a continuous stream of novel CNN architectures has been proposed, such as EfficientNetV2, ConvNeXt, and MobileNetV3 (Rakesh *et al.* 2026). Incorporating these advanced lightweight and high-performance models is expected to facilitate low-cost, high-accuracy inspection of wood surface defects.

Second, transfer learning has evolved from a conventional technique merely targeting accuracy enhancement into an integrated methodological framework that simultaneously optimizes computational efficiency, model trustworthiness, data privacy, and interpretability. In the context of wood surface defect inspection, privacy-preserving mechanisms embedded in trustworthy transfer learning and the multi-task paradigm of cascaded transfer learning are particularly promising, as they can provide viable solutions for the industrial deployment of inspection models (Plested *et al.* 2026).

Finally, Vision Transformer (ViT)-based approaches have gained widespread attention in image processing tasks. Different from standard CNNs, ViT frameworks leverage the self-attention mechanism to adaptively assess the importance of individual image patches, thereby offering innovative perspectives for visual detection research. Although the application of ViT in wood surface defect detection is still in its early stage (Xie and Ling 2023), such methods have yielded encouraging results in other forestry image processing scenarios (Kılıç 2025; Zhang *et al.* 2023). Furthermore, hybrid architectures that combine Transformer and classic CNN structures, represented by Rep-MobileViT (Duanmu *et al.* 2025) and MFWL-DETR (Liu *et al.* 2025b), have been widely acknowledged as a promising direction to achieve superior detection performance.

Real Image Inspection

Most existing deep learning models require input images to be standardized to a fixed size with an aspect ratio of 1:1. Consequently, in current studies on wood surface defect detection, the images employed are often not of entire wood products but rather square patches extracted from authentic images, as illustrated in Fig. 2. In practical settings, however, wood products typically exhibit elongated and narrow dimensions, resulting in surface images with high width-to-height ratios. Therefore, to facilitate the application of these research findings in real-world scenarios, it is imperative to address the discrepancy between the characteristics of authentic wood surface images and the input requirements of deep learning models.

Three primary approaches have been explored to mitigate this issue. The first involves designing feature maps of varying sizes tailored to different product dimensions. While this method appears to offer an ideal solution, it significantly increases model complexity and lacks generalizability across products of differing sizes. The second method incorporates padding to transform images into a square aspect ratio by adding background regions. However, this increases computational overhead and substantially

slows inspection speed, thereby rendering real-time online inspection unfeasible. The third approach involves resizing non-conforming image regions into square dimensions, which leads to pixel loss. This compromises the integrity of image details and exacerbates the difficulty of detecting small defects.

New Applications

With the advancement of research, the application of deep learning has expanded beyond its initial focus on sawn timber and wooden boards to a broader range of wood products, including glued panels (Chen *et al.* 2022), wooden flooring (Truong *et al.* 2023), wood paint (Liu *et al.* 2025a,b), and particleboard (Zhao *et al.* 2022; Zhang *et al.* 2025a). Furthermore, a greater variety of imaging approaches – such as spectral and thermal imaging – are being employed for the surface characterization of wood products. In these emerging applications, defects exhibit diverse colors, textures, and geometric characteristics, necessitating substantial further efforts in areas such as dataset construction, specialized model design, and extensive testing.

Second, a growing number of previously challenging application scenarios are expected to become technically feasible. A typical representative is automated wood grading, which categorizes timber into distinct quality grades according to the severity and distribution of surface defects (Sarnaghi and Kuilen 2019). Such grading enables rational allocation of timber resources to their most suitable end applications, thereby minimizing material waste and overall resource utilization efficiency. Another promising scenario is intelligent wood sawing. By preplanning cutting strategies based on the spatial distribution of wood defects, production processes can effectively avoid defective regions and substantially improve the yield of high-grade timber (Fan *et al.* 2024).

CONCLUSIONS

Accurate and efficient defect inspection is critical for maximizing the utilization and economic value of wood products. This review has presented a comprehensive survey of state-of-the-art deep learning-based methods for wood surface inspection. It began with a concise introduction to the foundational components of an effective inspection system, including common wood surface defects, publicly available image datasets, and standard evaluation metrics. The review then provided a taxonomy of research advances during 2021-2025, categorizing them into classification, object detection, and segmentation tasks. Finally, it outlined persistent challenges and promising future research directions. This work is expected to serve as a valuable reference and guide for researchers in the field.

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