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Review

A comprehensive review of automatic defect detection in wooden surface inspection

Himat Shah[1,*], **Elisa Saarela**[2], **Teemu Korkeakangas**[2] **and Tomi Pitkäaho**[1]

[1] Robotics and Artificial Intelligence, Centria University of Applied Sciences, Vierimaantie 7, 84100 Ylivieska, Finland

[2] Industrial Wood, Centria University of Applied Sciences, Joutsentie 11, 84100 Ylivieska, Finland

* **Correspondence:** Email: himat.shah@centria.fi.

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Abstract: This review focused on automated detection and classification of wood surface defects, such as knots, cracks, and resin pockets. Machine learning and deep learning methods are increasingly replacing traditional inspection techniques, such as manual checks and imaging tools like X-rays and ultrasound. However, these conventional approaches suffer from significant limitations in accuracy and efficiency. We reviewed both single-stage models, such as you only look once (YOLO) and its variants, and two-stage models like faster region-based convolutional neural networks (R-CNN), and examined their strengths, limitations, and relevance in real industrial applications. We further investigated emerging zero-shot learning approaches that use vision-language models and NLP techniques to detect previously unseen wood defects. Zero-shot models do not rely on annotated training data. These methods offer scalable and flexible solutions, especially in scenarios where collecting labelled samples for all defect types is impractical. The paper also discussed publicly available labelled datasets used to train and test these models, and discussed standard performance metrics such as precision, recall, and mean average precision. This review aimed to support further research and practical improvements in automated wood surface quality assessment by analyzing defect types, detection methods, and evaluation techniques.

Keywords: wood defect detection; deep learning; machine learning; YOLO model; single-stage model; two-stage model

1. Introduction

Detecting wood surface defects is critical to the wood industry. When defects like knots and cracks are identified early, we produce better wood products that are more valuable. Defect detection is a vital process in wood processing, as defects such as knots, cracks, stains, and resin pockets can significantly impact the quality, usability, and market value of wood products [1].

Visual quality inspections are still primarily carried out by trained personnel in the wood processing industry [2]. Traditionally, wood-based industries rely on manual inspections or conventional methods like ultrasonic and X-ray imaging to identify defects [3]. Manual wood inspection methods are error-prone and require high labour costs [4]. Moreover, these methods face challenges such as low efficiency, scalability, and limited accuracy. Consequently, manual inspection is unsuitable for modern, high-speed industrial process environments [5].

In recent years, deep learning has substantially improved the accuracy and robustness of object detection, enabling new opportunities to automate defect detection in wood processing [6]. Unlike traditional methods, deep learning offers enhanced efficiency, scalability, and accuracy, addressing the limitations of manual inspection. Deep learning methods, particularly convolutional neural networks (CNNs), excel at analyzing image data to identify and classify objects, including various types of wood surface defects.

Among these methods, object detection models like YOLO (you only look once) [7], and faster R-CNN [8] models have gained attention for their ability to combine high accuracy with speed, making them suitable for real-time industrial applications. Some methods even use zero-shot NLP [9], enabling the detection of defects without prior examples.

Zero-shot learning using NLP has recently emerged as a promising approach for defect detection, as it does not require large amounts of annotated training data. Zero-shot methods can recognize previously unseen defects by leveraging textual descriptions rather than labelled examples. This capability is enabled by vision-language models such as contrastive language-image pre-training (CLIP), which learn a shared embedding space by aligning image features with corresponding text descriptions. As a result, a model can identify defects such as a "small resin crack" even if no labelled training images for that specific defect type are available. This approach is particularly advantageous in industrial settings where collecting labelled data for all possible defect categories is impractical or costly.

This survey aims to provide a comprehensive overview of the current research landscape in wood defect detection. Specifically, we focus on:

- Categorizing state-of-the-art deep learning methods into single-stage and two-stage object detection algorithms.
- Reviewing key models, including YOLO and its variants, and two-stage methods like faster R-CNN.
- A new way of finding wood defects in research, zero-shot NLP and vision-language models for flexible and scalable defect detection.
- Analyzing the datasets commonly used for wood defect detection, highlighting their strengths, limitations, and relevance to real-world scenarios.
- Exploring evaluation metrics, such as mean average precision (mAP), precision, recall, and frames per second (FPS), to assess model performance.

Regardless of the many studies on wood defect detection using deep learning, existing reviews often focus on either traditional methods or practical applications and limitations within industrial settings. They primarily evaluate models based on accuracy, computational cost, and suitability for deployment.

This review paper bridges that gap by systematically analyzing both established and new detection methods. It compares single-stage and two-stage deep learning models, including emerging zero-shot learning approaches from NLP.

Furthermore, this paper provides a detailed comparative analysis of key models like YOLO variants and faster R-CNN, also discusses their performance, data needs, and how well they scale for real-world use. It also highlights the limitations of current datasets and suggests future research directions for scalable, real-time industrial applications.

The structure of the paper is as follows: Section 2 provides detail about traditional wood surface defects, including common types and defect categories. Section 3 reviews both manual and automated wood inspection methods along with their limitations. Section 4 discusses machine learning and deep learning approaches, focusing on single-stage, two-stage, and zero-shot NLP models. Section 5 analyzes different types of model evaluation metrics used in wood defect detection. Finally, Section 6 concludes the paper with a summary of key findings and recommendations.

2. Wood surface problems

This section builds on the introduction by exploring common wood surface problems in more detail. Various defects negatively impact the quality and usability of wood surfaces. The most common wood defects include knots, cracks, resin exudation, and surface damage, each with distinct causes and implications. Understanding these defects is crucial for effective wood processing and maintaining product quality. We discuss these issues in Subsection 2.1, which are key aspects of common wood surface problems.

2.1. Defect categories

Wood defects appear in many forms, including knots (live, dead, cracked, or missing) [10–12], cracks and discolouration [13], insect damage [13], mineral inclusions such as quartzite [11], overgrowth [11], resin pockets [12], marrow [10], and blue stains [11].

Different types of wood defects require different levels of processing. Table 1 describes the datasets used and the types of faults shown in the images. It also shows how many images were used for classification or model training. Table 2 categorizes the defect types according to common characteristics.

Table 1. Specifications of wood defect datasets used in recent research studies with extended metadata.

Dataset	Defect	Image count	Tree species	Image resolution	Setting
F1000 research [14]	Live knot, dead knot, crack, resin, marrow	4000	Spruce, Pine	1024×768; RGB camera under controlled lighting	Laboratory
Industrial panel [15]	Knot, dead knot, crack	9000	Mixed hardwood	1280×720; Line-scan camera on production line	Industrial
Custom lumber [3]	Live knot, resin pocket, knot with crack	3600	Radiata Pine, Eucalyptus	1920×1080; DSLR under natural light	Laboratory
Mixed species [11]	Knot, crack, resin, overgrowth, blue stain	4588	Pine, Birch	1280×960; RGB camera with variable lighting	Industrial
WLSD-YOLO [10]	Small cracks, knots, resin	4350	Toon, Pine	1024×768; Controlled lighting	Laboratory

Table 2. Classification of wood defects and corresponding references.

Defect	References	Defect	References
knot	[16]	live knot	[3, 10–13]
dead knot	[3, 10–13]	knot with crack	[3, 10–13]
knot missing	[10–13]	marrow	[3, 10–13]
crack	[3, 10–13]	resin	[3, 11–13]
overgrown	[11]	blue stain	[11]
discolouration	[13]	insect damage	[13]
quartzite	[11]		

2.2. *Knot family*

Knots are common and critical defects on wood surfaces that significantly reduce mechanical strength and increase the risk of cracking or failure near the affected area [17]. Additionally, their hardness complicates cutting and sanding processes.

In many cases, especially for high-grade lumber or wood used for decorative purposes, knots are viewed as imperfections that diminish visual quality. The knot family includes several types, such as live knots, dead knots, and knots with cracks. Recent research [18] shows that the YOLOv5 detector effectively identifies knot defects. As shown in Figure 1, various types of knot defects appear on wood surfaces. However, the effects of knots on bending strength are not fully understood [19].

Live knots [20] are areas in wood where the knot remains connected to the tree. Because the wood fibres remain intact and actively grow, these knots are typically more solid and dense compared to dead knots. Consequently, live knots can significantly affect the physical and mechanical properties of the wood, as well as its aesthetic characteristics. The live knot is shown in Figure 1.

Live knots exhibit lower density compared to dead knots but are denser than clear wood, and thus affects overall wood strength. Live knots appear in softwood and hardwood species; they vary in size and contribute to the wood's distinct character and aesthetic appeal. However, they can also introduce specific challenges and require careful consideration during woodworking and processing.

Dead knots, in contrast, are sections of wood where branches were once attached to the tree but have since died and become separated from it. This is a characteristic that distinguishes them from live knots, where the branch is still connected. Over time, the wood fibres in dead knots may deteriorate or break away, leaving empty spaces or holes behind. Figure 1 shows a dead knot on the wood surface.

These gaps can be filled with resin or other materials during processing to enhance the wood's look and structural integrity. Because dead knots are often seen in reclaimed or salvaged wood, processors will often fill them in in some types of softwood.

Knots with a crack are another issue found on the wood surface. Cracked knots are a visible issue in wood, as shown in Figure 1. Knots create stress, which changes how we predict wood failure by up to 23% [21]. Cracks form around knots because of tension and shear failures. Understanding these failures helps us understand how wood breaks [22]. Figure 1, illustrate knots with cracks and missing knots, respectively.

Wood surface defects include *missing knots*, which may affect the aesthetic appeal of the surface. If a knot falls out and is lost, glue may be used for the remaining knots, and missing knots can be filled with epoxy [14].

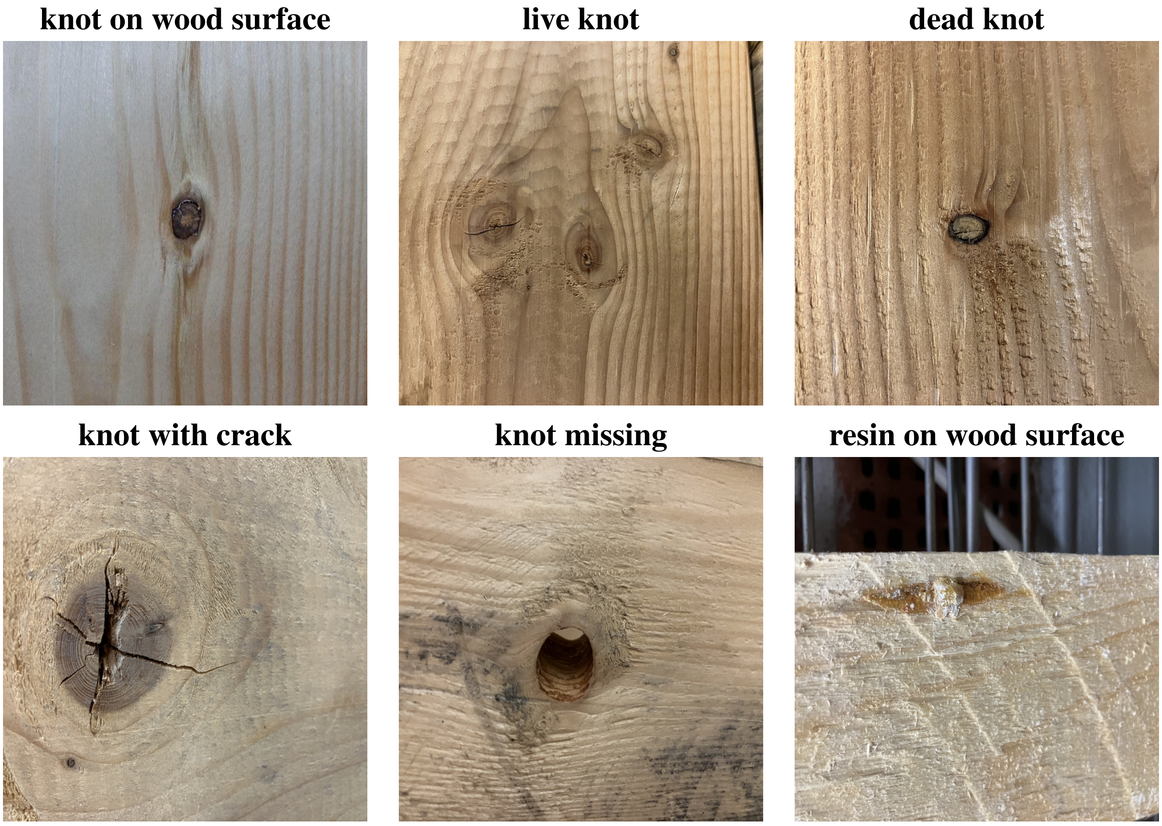

Figure 1. Examples of typical wood surface defects.

2.3. *Resin*

Resin is another significant defect found on wood surfaces. It refers to wood that holds an uncommonly high amount of resin, making it darker than normal wood material. To understand how much extra resin is in a piece of wood, we look at its surface. We then figure out what percentage of that total surface area shows this resin. Figure 1 illustrates a resin defect on the wood surface.

For example, if resin covers a quarter of the surface, we say it has 25% resin. Sometimes, one find a long, narrow space, like a small channel, inside the wood. This space usually appears between two of the tree's growth rings (the circles you see on a tree stump). This space is a *resin pocket*, and it often fills up with resin. We measure the length of the resin pocket in millimetres along the length of the wood piece where the pocket appears.

2.4. *Cracks and their types*

Drying cracks refers to cracks that form in wood when drying causes internal stresses. These cracks can appear straight or at an angle, depending on the wood's grain structure. Typically, the length of a drying crack is proportional to its depth and width.

Heart cracks are radial cracks that start from the tree's centre, caused by stresses inside the heartwood. The measurement and classification of heart cracks follow similar methods to those used for drying cracks.

Ring cracks appear as fissures that follow the tree's growth rings, especially in freshly cut wood. These cracks are measured and classified similarly to drying cracks, using methods that assess their length relative to the total timber size and their impact on the piece's overall quality. For example, longer or more numerous cracks can significantly reduce the timber's grade. These assessments are crucial for determining the suitability of the wood for different applications.

Measurement of crack length is the length of each crack expressed as a percentage of the total length of the timber piece. In assessing the wood's quality grade, the total length of any crack, or consecutive cracks, is expressed as a percentage of the piece's total length. Cracks shorter than 100 millimetres are generally excluded from this assessment. When adjacent parallel drying cracks, or cracks angled towards the piece's edge, are observed, the quality grade is based on the length of the cracked part or the combined length of all cracks.

2.5. Wane

Wane is another type of wood surface defect. Unlike other defects, such as knots, cracks, or resin pockets, wane refers to the portion of a sawn wood surface that remains uncut by the saw, retaining some of the tree's original, rounded surface. Its length and depth are expressed as a percentage of the wood's nominal size, while its width is measured in millimetres.

3. Wood inspection methods

In this section, we explain how people typically identify these wood problems, either by inspecting them directly or by using machines. Identifying these problems correctly helps maintain high quality. We now examine the two primary inspection approaches: manual and automatic inspection. We discuss the advantages and limitations of these techniques below.

Manual inspection has historically been used to detect issues like knots, cracks, and resin pockets (see Section 2). Manual inspection commonly involves trained personnel visually examining wood for quality, similar to how construction workers inspect lumber on site [3]. This method depends on experts' judgment to decide if the wood meets quality standards [13]. It is inexpensive and simple. However, it lacks the accuracy and efficiency required for modern automated production.

Automatic inspection replaces manual labour with machines to detect surface and internal defects. Technologies such as ultrasonic testing, X-ray imaging, and acoustic emission are commonly applied in industrial settings. These techniques enhance repeatability and minimize human error when assessing defects such as internal cracks, resin pockets, and stress-related flaws. However, while these methods provide better consistency than manual inspection, they still face limitations in scalability and versatility.

The emergence of data-driven techniques, such as machine learning and deep learning, builds upon these methods to offer even higher accuracy and adaptability, topics discussed in detail in Section 4. Table 3 compares manual and automatic inspection methods.

Ultrasonic testing, X-ray imaging, and acoustic emission are common automatic inspection methods. We describe each in detail below.

Table 3. Comparison of manual and automatic wood inspection methods.

Criterion	**Manual inspection**	**Automatic inspection**
Automation suitability	Not suitable for automation	Suitable for automation
Cost	Low initial cost	High initial investment
Operational efficiency	Low; slow and labor-intensive	High; fast and scalable
Consistency	Subjective; depends on operator experience	High repeatability and consistency
Accuracy	Limited, especially for subtle defects	High, particularly with advanced sensors
Industrial scalability	Poor	Well suited for industrial production lines

3.1. Ultrasonic methods

Ultrasonic methods use high-frequency sound waves to identify internal flaws in wood. A device transmits these waves into the wood; internal defects cause the waves to reflect or attenuate (weaken). The system detects and locates discontinuities by analyzing changes in the returning or passing sound waves. Ultrasonic methods have been widely studied for internal defect detection [23, 24]. Although effective, these methods require good acoustic coupling (e.g., a strong transmission interface between the sensor and material). This often requires a liquid or gel couplant to transmit waves between the sensor and the wood, making the method less practical for some situations.

3.2. X-ray methods

X-ray detection analyzes the attenuation to detect internal defects with high accuracy. X-ray imaging provides high accuracy but raises safety concerns due to harmful radiation exposure [25, 26]. These limitations restrict its widespread use in industrial environments.

3.3. Acoustic emission methods

Acoustic emission methods detect defects by capturing transient elastic waves caused by sudden stress in wood. This technique works well for identifying structural defects but cannot detect non-structural issues. Acoustic emission methods detect transient elastic waves efficiently and have been applied in wood quality assessment [27, 28]. Although other methods exist, they often face similar challenges, such as complexity, limited scalability, or operational constraints. These issues make them less practical for industrial applications.

3.4. Limitations of methods

Manual and automatic inspection methods help identify wood defects, but both approaches face significant limitations in industrial applications. Manual methods rely on human judgment and are not suitable for large-scale operations, while automatic techniques, though more precise, still encounter technical and operational challenges. Table 4 summarizes the advantages and limitations of these methods, highlighting their practical strengths and shortcomings.

Table 4. Comparison of detection techniques for wood defects: advantages and disadvantages.

Manual methods		
Technique	**Advantages**	**Disadvantages**
Manual detection	Simple and inexpensive method	Highly inefficient and arbitrary; not suitable for automation; inefficient for industrial-scale operations
Automatic methods		
Ultrasonic methods	Effective at detecting internal defects; non-invasive	Requires a transmission medium; limited flexibility; dependence on coupling medium reduces adaptability in different environments
X-ray methods	High accuracy in detecting internal defects	Exposure to harmful radiation; safety concerns; health risks limit prolonged or widespread use
Acoustic emission	Detects transient elastic waves due to wood deformation; non-invasive and efficient	Can not detect non-structural defects; limited to certain defect types; restricted applicability due to inability to detect non-structural defects
Other methods	May offer tailored alternatives	Often require complex setups; face similar challenges as above methods; lack adaptability and scalability for broad industrial adoption

Ultrasonic and X-ray methods detect defects well but face issues such as the need for a transmission medium or safety concerns. Acoustic emission detects structural defects efficiently, but cannot identify non-structural issues. These challenges show the need for better methods that improve adaptability, scalability, and safety. Table 5 shows the advantages and limitations of different inspection methods. This overview highlights key challenges and opportunities, setting the stage for exploring advanced methods like deep learning, machine learning, and computer vision in the subsequent discussion.

Recent advances in computer-based methods are improving how we detect wood defects. A critical application of these technologies is object detection, which combines machine learning with computer vision to identify and classify objects in images. In wood defect detection, these deep learning approaches transform traditional methods by enabling automated, fast, and accurate defect identification. Two primary types of algorithms drive this transformation: single-stage and two-stage object detection models.

Single-stage algorithms, such as YOLO, prioritize speed by performing object localization and classification simultaneously, making them well-suited for real-time applications. In contrast, two-stage algorithms, such as faster R-CNN, first generate region proposals and then classify the detected regions, offering superior accuracy at the cost of reduced processing speed. These deep learning approaches form a foundation to solve complex defect detection challenges, balancing efficiency and precision in industrial environments.

Table 5. Qualitative comparison of wood inspection methods.

Method	Efficiency	Adaptability	Key strengths	Main limitations
Manual inspection	Low	High	Flexible judgment; minimal equipment; handles rare cases	Subjective; inconsistent; slow; high labor demand; not scalable
Ultrasonic testing	High	Medium	Internal defect sensing; non-destructive; repeatable; suitable for many internal flaws	Requires good sensor contact; sensitive to wood grain; limited for surface-only defects
X-ray imaging	High	Low medium	High-resolution internal visualization; strong performance for hidden defects	Radiation safety and shielding; high cost; operational constraints
Other methods	Medium	Low medium	Useful for specific defect mechanisms; complements other sensors	Setup-dependent; limited defect coverage; integration complexity

4. Machine learning and deep learning methods

Following our examination of inspection methods, this section now looks at deep learning-based object detection methods. We will explore how these methods are categorized into one-stage and two-stage algorithms and examine what makes them useful, where they excel, and their potential drawbacks. The key differences between the one-stage and two-stage models are their operational efficiency and accuracy.

One-stage models, like YOLOv8, are designed for end-to-end detection, allowing faster processing times. This speed is vital in industrial applications where rapid decision-making is essential [15]. These models have been successfully used to identify various wood defects, such as colour variations, bug eyes, cracks, knots, and scars [15].

4.1. One-stage object detection methods

One-stage object detection methods perform classification and localisation in a single step, making them faster and more suitable for real-time applications. YOLO is one such model known for its speed and efficiency. Other examples of one-stage detection models include single shot detector (SSD) and RetinaNet. These models are particularly useful in applications like wood defect detection, where rapid processing is essential. In this survey, we only focus on YOLO-based models, and we discuss this as follows.

4.1.1. Overview of YOLO-based models

SiM-YOLO [13] method enhances the YOLOv8 algorithm for wood surface defect detection through several innovative modifications aimed at improving accuracy and efficiency. During the training, 3600 images of seven types of wood defects were used (for more details, see Table 1).

SiM-YOLO method improves defect classification accuracy using several key components that enhance feature extraction, feature fusion, localisation, and loss optimisation. It begins with a custom feature extraction module called SPD-Conv, which preserves fine-grained defect details. This module captures subtle variations and complex patterns on wood surfaces, reducing the loss of important features within and across defect types.

SiM-YOLO method also includes a scale-invariant attention fusion feature-path aggregation network (SiAFF-PANet) feature fusion module to address scale and semantic differences between defect types. It merges features from multiple levels while maintaining semantic consistency. As a result, the model better understands local context better and pinpoints defect locations more accurately.

The model integrates a *multi-attention detection head* (MADH) that focuses on cross-channel interactions and sharp spatial details. This design helps the model detect overlapping defects and clearly separate their boundaries, improving classification and localisation.

To improve localization, SiM-YOLO replaces the standard *complete intersection over union* (CIOU) loss with the *minimum point distance intersection over union* (MPDIOU) loss. This modification reduces distorted bounding boxes under strong overlap, improving boundary separation and localization accuracy.

Tests show that SiM-YOLO outperforms earlier models, achieving a 9.3% increase in *mean average precision* (mAP) over YOLOX model and a 4.3% increase over YOLOv8, confirming its effectiveness in wood surface defect detection.

SiM-YOLO method combines advanced feature extraction, effective fusion, focused attention, and optimized loss design to detect wood defects with high precision. However, it still faces challenges such as reliance on high-quality datasets, increased computational demands, and the need for fine-tuning in real-time applications. Future research should address these limitations to support wider industrial use.

FRCE-YOLO [11] method is a lightweight model based on YOLOv8 that improves the detection of wood surface defects. It increases mAP@0.5 by 6.9%, reaching 80.7%, and boosts mAP@0.5:0.95 by 8.4%, while reducing computational complexity by 1.2 GFLOPs. The model targets ten distinct defect types, including live knots, dead knots, quartzite, knots with cracks, missing knots, cracks, overgrowth, resin, marrow, and stains (see Table 1). Its lightweight structure and ability to manage noisy or inconsistent data make it a practical choice for industrial use.

Several architectural improvements enhance the model's efficiency. The C2f-fast module, a lightweight variant of the C2f block, simplifies the YOLOv8 backbone by reducing network complexity without sacrificing accuracy. The RG-C2f module further improves feature extraction by replacing computationally expensive operations with more efficient alternatives. The convolutional block attention module (CBAM) directs the network's focus toward defect-relevant spatial and channel features, while the efficient intersection over union (EIOU) loss improves localization accuracy for defects with varying shapes and sizes. Together, these modifications make FRCE-YOLO effective for identifying a wide range of defects under challenging conditions.

The model is evaluated on a specialized dataset designed for wood defect detection and demonstrates faster and more accurate performance than YOLOv8. The dataset includes defects of varying sizes, orientations, and lighting conditions, reflecting realistic industrial scenarios. Table 2 summarizes the defect categories included in the dataset. FRCE-YOLO also uses standard evaluation metrics such as precision, recall, mAP, and F1-score to validate its performance (Table 6). These results confirm its effectiveness for quality control in industrial environments with limited computational resources.

Table 6. Evaluation metrics used in wood defect detection and corresponding references.

Metric(s)	References
Precision	[3, 10–13, 29–32]
Recall	[3, 10–13, 29–32]
F1-score	[10, 11, 29–32]
Mean average precision (mAP)	[3, 10–13]
Parameters, GFLOPs	[11]

Although FRCE-YOLO performs well for wood surface defects, its effectiveness in other industries remains untested. The model may also require further optimisation for use on low-power hardware. Despite these limitations, it offers a strong balance of accuracy, efficiency, and practicality, making it a valuable tool for automated wood processing.

The WLSD-YOLO [10] model presents a novel approach to detecting surface defects in wood lumber. The model integrates a *squeeze-and-excitation* (SE) attention mechanism, a *GVC-neck* layer structure, and advanced loss functions to improve the detection accuracy of small wood defects. The experimental results show that the WLSD-YOLO model achieves a recognition accuracy of 76.5%, outperforms the YOLOv8 model in *mean average precision* (mAP) by 2.9%, and enhances processing. YOLO brought accuracy, efficiency, and speed at stage one, which were difficult and complex issues earlier.

CWB-YOLOv8 [3] improves wood defect detection by enhancing the YOLOv8 algorithm with three key modules: *conditional parametric convolution* (CondConv), Wise-IoU, and BiFormer. The model dynamically adjusts convolution kernel weights with CondConv to better identify complex defect features. BiFormer, a multi-scale attention mechanism, enhances the model's ability to detect both small and large defects. Wise-IoU replaces the standard loss function, improving anchor box quality and handling low- and medium-quality samples effectively.

The authors created a custom dataset of 6134 images, including defects from diverse tree species like radiata pine, eucalyptus, and toon trees. They addressed the scarcity of rare defect types, such as cracks and resin, through data augmentation. This dataset provides a strong foundation for training and testing the improved model.

CWB-YOLOv8 outperforms standard YOLOv8, achieving a 3.5% improvement in mAP@0.5 and a 5.8% improvement in mAP@0.5:0.95. It also detects challenging defect types like cracks and resin with high accuracy (96% and 93%, respectively). These enhancements make CWB-YOLOv8 a reliable and efficient solution for wood defect detection in industrial applications.

By addressing limitations of traditional methods and improving upon other YOLO-based models, CWB-YOLOv8 offers a practical approach for real-time wood processing. Its integration with other advances in one-stage object detection, such as SiM-YOLO and FRCE-YOLO, highlights the growing potential of automated defect detection systems in the timber industry.

R. Wang et al. [33] used a model that enhances the YOLOv7 algorithm by incorporating dynamic convolution and a full-dimensional dynamic coordinate attention mechanism to improve wood defect detection in a public dataset. However, these enhancements render the algorithm unsuitable for deployment on edge devices [34].

4.1.2. Limitations of YOLO-based models

The YOLO model has several limitations in accurately detecting and classifying wood surface defects such as knots, cracks, resin, and marrow. Researchers frequently highlight these challenges in multiple studies [22, 34]. One key challenge is the model's struggle to identify rare or complex defects, like cracks and resin, since these appear less frequently in datasets than knots [14]. YOLO can produce false positives (identifying a defect where there isn't one) and false negatives (missing a defect that is there). This could lead to inaccurate defect detection.

The performance of the YOLO model is likely dependent on the quality and diversity of the dataset used for training. If the dataset does not encompass a wide range of defect types or real-world scenarios, the model may struggle to generalize effectively to unseen data. This limitation is common in machine learning models, where the training data significantly influences the model's performance. Additionally, if the model is trained on a specific type of wood or specific types of defects, it might not generalize well to other types of wood or defects.

4.2. Two-stage object detection methods

Two-stage object detection algorithms divide the detection process into two steps: region proposal generation and classification with bounding box refinement. Faster R-CNN is the most widely used two-stage model in wood defect detection [8]. These models typically use datasets with over 5,000 annotated images covering defects such as knots, cracks, resin pockets, and stains. Reported mean average precision (mAP), values range from 85% to 90%, with GFLOPs between 25 and 40, depending on the backbone network [5, 27, 28]. faster R-CNN achieves high accuracy for small and irregular defects but requires significant computational resources, making real-time deployment challenging. Table 7 summarizes the performance of faster R-CNN and its variants compared to YOLO-based models.

Table 7. Comparative analysis of object detection models for wood defect detection.

Model	Architecture	Data requirements	mAP%	GFLOPs
YOLOv8	One-stage (Single-shot)	3600 img,7 defects	76.0	2.5
SiM-YOLO	One-stage (Improved YOLO)	3600 img, 7 defects	85.0	3.1
FRCE-YOLO	One-stage (YOLOv8-based)	6134 img,10 defects	80.7	1.2
WLSD-YOLO	One-stage (YOLO-based)	2000 img, 5 defects	76.5	1.8
Faster R-CNN	Two-stage (Region Proposal Network)	5000 img, 7 defects	85.0	25.0
Faster R + ResNet	(Region Proposal Network) + ResNet	5000 img, 7 defects	87.0	40.0

4.2.1. Faster R-CNN: Limitations and advantages

Faster R-CNN is one of the most widely used two-stage detection models [8]. It introduces a *region proposal network* (RPN) that streamlines the generation of region proposals, significantly improving speed and efficiency over earlier R-CNN models.

The model achieves high accuracy for detecting wood defects, particularly those with intricate patterns such as fine cracks or resin pockets [35]. Despite these strengths, faster R-CNN faces notable limitations. Its slower processing speed restricts real-time applications in industrial settings [10].

The model relies on rectangular bounding boxes, which poorly capture irregular defect shapes like elongated cracks or resin pockets. It is also sensitive to anchor box configurations and may struggle with very small or low-contrast defects unless enhanced with modules such as *feature pyramid networks* (FPN). Furthermore, variations in wood species, grain, lighting, and moisture can affect robustness, and extensive expert-driven annotation is required for effective training. These challenges are summarized in Table 8.

Table 8. Key limitations of faster R-CNN in wood defect detection with supporting references.

Category	**Keywords (wood defect context)**	**References**
Computational cost/speed	two-stage detector; slower inference; real-time limitation; industrial line throughput; hardware/optimisation	[23, 24]
Irregular shape accuracy	rectangular boxes; poor fit for cracks/resin pockets; localization mismatch; motivates segmentation	[25, 26]
Anchor box sensitivity	anchor mismatch; scale/aspect variation; thin cracks; multi-scale tuning; optimisation required	[27, 28]
Small/subtle defects	pin knots; fine cracks; low contrast; complex grain; FPN/feature enhancement	[4, 27]
Appearance variability	species variation; grain/moisture/lighting; domain shift; augmentation; generalization challenge	[36, 37]
Data annotation burden	large labeled datasets; expert bounding boxes; time/cost; scalability barrier	[26, 29]

However, faster R-CNN offers clear advantages through its two-stage refinement mechanism. The RPN first generates candidate regions, and the second stage refines these proposals for classification and bounding box adjustment. This process enables precise detection of small, low-contrast, and irregular defects, even under challenging conditions such as complex wood grain or subtle resin spots.

These strengths make faster R-CNN ideal for applications where accuracy matters more than speed. In high-value, low-throughput production environments—such as custom wood product manufacturing or premium lumber processing—every defect can significantly impact quality and value. In such cases, the ability to detect subtle defects accurately outweighs the cost of slower processing. While faster R-CNN is not the best choice for fast-paced, mass-production settings, its precision and refinement capabilities make it indispensable for tasks that prioritize detection accuracy over real-time performance.

4.2.2. Backbone networks for feature extraction

The backbone network in a two-stage detector, like faster R-CNN, is responsible for extracting meaningful visual features from input images. The choice of backbone significantly affects the model's performance in terms of both accuracy and computational efficiency.

MobileNetV3 [38] is a lightweight network optimized for real-time applications. It uses advanced techniques such as squeeze-and-excitation modules and network search to balance accuracy and speed, making it suitable for deployment on edge devices. However, due to its compact architecture, it may struggle to capture highly detailed or subtle wood defect patterns [39].

Visual geometry group 16-layer network (VGG16) and visual geometry group 19-layer network (VGG19) are well-known for their simplicity and uniform architecture, consisting of sequential 3x3 convolutional layers. These deep networks provide strong hierarchical feature extraction, which is beneficial for capturing complex defect structures. Their main limitation lies in their high computational and memory requirements [16].

ResNet introduces residual connections that effectively address the vanishing gradient problem in deep networks. This allows for the training of very deep architectures, enabling improved performance in detecting complex and varied defect types. Despite its benefits, ResNet comes with added model complexity and increased training time [40].

GoogLeNet utilizes Inception modules, which enable multi-scale feature extraction within a single architecture. This design offers a good balance between accuracy and computational efficiency, making it suitable for defect detection tasks requiring both speed and precision. Nevertheless, the model's internal complexity can make it more difficult to implement and tune [41].

AlexNet was one of the first deep convolutional networks to gain widespread attention for image classification. It is valued for its simplicity and fast inference but lacks the depth and representational power needed for accurately detecting subtle or irregular wood defects [42].

4.2.3. Advantages and limitations

Two-stage object detection methods offer high accuracy, especially for small, overlapping, or irregularly shaped defects. They benefit from precise region proposal mechanisms and robust feature extractors, making them suitable for tasks requiring detailed defect classification. Additionally, the use of pre-trained backbone networks allows for effective transfer learning across datasets, reducing the need for training from scratch.

However, these strengths come at a cost. Two-stage methods are generally slower and more resource-intensive than one-stage models like YOLO. Their complex architectures can limit real-time performance in industrial environments where speed is critical. The training process also requires substantial annotated data and computing resources, which may be a barrier to adoption for some applications.

4.3. Comparative analysis of object detection models for wood defect detection

In this subsection, we provide a comparative analysis of several popular object detection models used for wood defect detection, including YOLO variants and faster R-CNN. The table summarizes key aspects of these models, including their architecture, data requirements, mean average precision (mAP) values, and computational load in *giga floating point operations* (GFLOPs).

The Table 7 provides a detailed comparison of various deep learning models commonly used for wood defect detection. These models, including YOLO variants and faster R-CNN, vary in terms of their architecture, data requirements, mAP values, and computational load.

Model: The models listed include both one-stage (e.g., YOLO) and two-stage (e.g., faster R-

CNN) architectures. One-stage models like YOLO perform object classification and localization simultaneously, making them faster and well-suited for real-time applications. In contrast, two-stage models like faster R-CNN generate region proposals in the first stage and classify them in the second stage, which often results in better accuracy at the cost of slower processing.

Architecture: This column describes the type of architecture used. One-stage models like YOLOv8 and its variants are designed for quick inference, which is crucial for industrial applications. Two-stage models like faster R-CNN offer higher accuracy by refining object proposals, but they are generally slower and more computationally intensive.

Data requirements: The data required for training each model varies. YOLO-based models typically require datasets with thousands of images and defect types, while two-stage models like faster R-CNN may require larger and more highly annotated datasets to achieve optimal performance. The variety of wood defects and the need for high-quality annotations significantly impact the model's training process and its generalizability to real-world scenarios.

Mean average precision(mAP): mAP is a standard performance metric used to evaluate the accuracy of object detection models. It combines precision and recall across different threshold levels. YOLO-based models, such as YOLOv8, tend to have lower mAP scores (around 76%) but are much faster, making them suitable for real-time applications. In contrast, models like faster R-CNN and its variants (e.g., faster R-CNN with ResNet) generally achieve higher mAP values (up to 90%) but at the cost of increased computational demand.

Computational load (GFLOPs): This column shows the **computational complexity** of each model, measured in giga floating point operations (GFLOPs). Lower GFLOPs values indicate that the model is less computationally demanding and can perform faster, which is important in industrial environments. YOLO-based models like FRCE-YOLO and WLSD-YOLO have relatively low GFLOPs values, making them more suitable for real-time defect detection on low-power devices. In contrast, two-stage models like faster R-CNN require significantly more computational resources due to their more complex architecture, making them less suited for real-time deployment without specialized hardware.

The Table 7 helps highlight the trade-offs between different object detection models, enabling a better understanding of their suitability for various industrial applications in wood defect detection. By providing both performance and computational requirements, this comparison serves as a guide for selecting the most appropriate model based on the specific needs of a given use case.

4.4. Zero-shot NLP for wood defect detection

Traditional deep learning models, such as *convolutional neural networks* (CNN), have been widely used to detect wood defects like knots, cracks, and resin pockets. These models typically require large, labelled datasets to perform well. However, in industrial practice, it is often difficult to collect enough labelled data for every possible defect, especially rare or newly emerging types [43].

Zero-shot learning (ZSL), originally developed in the field of NLP, offers a promising solution. It enables models to recognize or classify unseen data based on semantic descriptions, without requiring prior labelled examples. For instance, a zero-shot model can detect a “thin surface crack” in a wood image simply by understanding that phrase, even if no such image was included during training.

Tools like *Stanza* support multilingual NLP tasks and can help extract wood-specific terminology such as *resin leak* or *deep knot* from technical documents [44]. These tools often rely on transfer learning and hierarchical modelling techniques, such as Bayesian hierarchical zero-inflated models, to handle small, sparse, or imbalanced datasets commonly found in wood processing [45].

In computer vision, models like *CLIP* link image features to textual descriptions, allowing zero-shot visual recognition of defects using only semantic prompts [46]. This is especially helpful for detecting rare or subtle wood defects when labelled data are unavailable. For example, an image showing "a dark line across the grain" could be correctly identified by the model even without prior exposure to such examples.

Zero-shot techniques can also support broader industrial and environmental applications. In studies related to air pollutant emissions and material degradation, models trained on general wood data could help identify patterns associated with chemical or structural changes in new contexts [47, 48].

In summary, zero-shot learning presents an exciting opportunity to improve wood defect detection depending on large labelled datasets. NLP tools and vision-language models enable flexible and scalable detection of defects such as cracks, knots, and resin marks. As research advances, zero-shot techniques could significantly enhance the adaptability and efficiency of automated inspection systems in the wood industry.

4.4.1. Prompt-guided zero-shot defect detection: case studies

We show how vision–language models (e.g., open-vocabulary detectors) use text prompts to localize and classify wood defects without task-specific labels.
Case 1: Resin pocket (descriptive prompt). Prompt: "a long, narrow resin-filled channel between growth rings".
Result: The model highlights the resin pocket and suppresses grain texture, even though no resin examples appear in training.
Case 2: Hairline crack (semantic guidance). "a thin surface crack running diagonally across the grain".
Result: The model localizes a faint, diagonal crack that supervised baselines miss at standard thresholds.
Case 3: Knot type differentiation (prompt contrast). Prompts: "a live knot with intact fibers" *vs.* "a dead knot with a hollow center".
Result: The model separates live and dead knots by aligning region features to the prompt semantics.
Case 4: Prompt-based QC filtering. Prompt: "exclude boards with missing knots or deep cracks".
Result: The system flags boards for rejection using the prompt as a rule, enabling fast, adjustable grading.

5. Performance evaluation of detection models

This section explains how researchers use different metrics to evaluate model performance on wood surfaces. Each metric shows something different about how the model works, what it handles well, and where it may fail.

5.1. Precision

Precision is one of the most widely used metrics, especially for wood surface issues. In Table 6, we provide references that use precision as a metric in wood-related issues. Precision reveals how often the model's positive predictions are correct. It tells us the percentage of predicted positives that are true positives.

For example, the model checks 100 wooden boards and predicts that 80 have defects. After manual checking, we find that only 60 of those 80 really have defects. So, the precision is 60 divided by 80, or 75%. This means the model is correct 75% of the time when it says a board is defective.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{1}$$

In Eq (1) above, TP means true positives and FP means false positives.

5.2. Recall

Recall measures how many of the real defects the model managed to catch. While precision looks at correct predictions, recall focuses on finding every true case.

$$\text{Recall (RCL)} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{2}$$

Here, FN means false negatives. Table 6 shows where researchers use recall. For example, a model checks 100 wooden boards, and 80 of them have defects. If the model finds all 80 defective boards, its recall is 1.0 or 100%. High recall is useful when missing a defect can lead to significant issues.

5.3. F1-score

F1-score measures how well a model balances finding all the right things (recall) and not getting confused by too many wrong ones (precision). In the context of wooden surface defect detection, a high F1-score indicates that the model accurately identifies defects while minimizing false positives and false negatives. One advantage of using the F1-score is that it considers both precision and recall, making it more comprehensive [35]. F1-score is measured using the following formula:

$$\text{F1-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{3}$$

This is especially useful with imbalanced datasets where defective surfaces are rare. However, the F1-score may not help when comparing models with very different precision and recall values, and it can be sensitive to small changes in data or model settings.

5.4. Mean average precision (mAP)

Mean average precision (mAP) gives an overview of model performance. It combines precision and recall across different classes and thresholds. It checks how many defects the model finds (recall) and how accurate those predictions are (precision).

The mAP provides a clear overall score and helps to compare models. It shows how the model performs on all defect types. However, mAP struggles with rare defect types, hides details such as false positives, and varies based on settings like overlap thresholds. Equation (4) shows how to calculate mAP.

$$\text{Mean average precision (mAP)} = \frac{1}{N} \sum_{i=1}^{N} \int_{0}^{1} P(R). \tag{4}$$

There are two ways to measure mAP: mAP@0.5 and mAP@0.5:0.95. mAP@0.5 accepts predictions with just 50% overlap, which helps catch as many defects as possible. mAP@0.5:0.95 averages overlap from 50% to 95% and provides a more precise picture of model performance.

5.4.1. Parameters

Parameters are matrices that represent the configurable elements of a model. They determine the model's complexity and capacity. These values are learned from training data and help the model identify defects like knots, cracks, and resin spots.

For example, parameters include the number of layers in a neural network or the learning rate used during training, both of which affect how well the model detects defects.

5.5. Giga floating-point operations (GFLOPs)

GFLOPs quantify the number of floating-point operations performed during model inference, providing a direct measure of computational complexity. Models with lower GFLOPs generally achieve faster inference and are more appropriate for real-time and mobile deployments.

These operations are especially useful in evaluating performance for models detecting wood surface issues. For example, detecting knots, cracks, and resin pockets requires quick processing of large images for accurate and timely results.

6. Conclusions and future directions

This review provides a comprehensive analysis of automated wood surface defect detection methods, focusing on deep learning models such as YOLO variants and faster R-CNN, along with emerging zero-shot NLP approaches. These models demonstrate strong potential for improving accuracy and efficiency in industrial applications. However, several challenges remain.

Rare defects such as resin pockets, hairline cracks, and blue stains are among the most difficult to detect due to their low occurrence in datasets, subtle visual patterns, and variability in size and shape. These defects often exhibit low contrast against complex wood grain, making detection harder even for advanced models. Key difficulties include dataset imbalance, lighting variations, and generalization to unseen defect types. To address these challenges and advance the field, future research should prioritize the following directions:

Developing diverse datasets: Current datasets often lack rare defect types and variability in wood species, lighting, and grain patterns. Creating large-scale, annotated datasets that reflect real-world conditions will improve model robustness and generalization.

Leveraging zero-shot and few-shot learning: These approaches enable detection of previously unseen defects without extensive labeled data, offering scalable solutions for industrial environments where data collection is costly or impractical.

Optimizing models for edge deployment: Lightweight architectures and efficient inference strategies are essential for real-time defect detection on low-power devices in high-speed production settings.

Integrating traditional and deep learning techniques: Combining ultrasonic testing, X-ray imaging, and deep learning can enhance detection accuracy, particularly for internal or non-visible defects that current vision-based models struggle to identify.

Incorporating explainable AI (XAI): Interpretability will help operators understand model decisions, increasing trust and facilitating adoption in quality control processes.

Although current models achieve high accuracy, computational complexity and real-time deployment remain major challenges. Future research is moving toward several promising strategies:
Model compression and knowledge distillation: Techniques such as pruning, quantization, and distillation reduce model size and computational load without sacrificing accuracy, enabling deployment on resource-constrained devices.
Multimodal fusion: Combining RGB images with infrared or acoustic data improves robustness under varying lighting and surface conditions. Multimodal approaches leverage complementary information to enhance defect detection precision.
Edge computing and adaptive inference: Deploying lightweight models on edge devices and using adaptive inference strategies (e.g., early exit mechanisms) supports real-time quality inspection in high-speed production lines.
Dynamic optimization: Future systems may incorporate on-device learning and dynamic model updates to adapt to changing defect patterns and environmental conditions.

By addressing these challenges, future systems can achieve scalable, accurate, and real-time defect detection, making automated inspection practical for modern wood processing industries.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflict of interest.

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