IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 3, June 2025, pp. 1696~1707
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i3.pp1696-1707

A review of recent deep learning applications in wood surface defect identification

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Article Info

Article history:

Received Mar 28, 2024
Revised Nov 19, 2024
Accepted Jan 27, 2025

Keywords:

Automated inspection
Deep learning
Defect identification
Transfer learning
Wood surface defects

ABSTRACT

Wood is widely used in construction, art, and home applications due to its aesthetic appeal and favorable mechanical properties. However, environmental factors significantly affect the growth and preservation of wood, often leading to defects that can reduce its performance and ornamental value. Researchers have introduced machine vision and deep learning methods to address the challenges of high labor costs and inefficiencies in identifying wood defects. Deep learning has shown great success in image recognition tasks, yielding impressive results. This paper reviews previous work on deep-learning strategies for identifying wood surface defects. It also discusses data augmentation techniques to address limited defect data and explores transfer learning to enhance classification accuracy on small datasets. Finally, the paper examines the potential limitations of deep learning for defect identification and suggests future research directions.

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1. INTRODUCTION

Since the Paris Agreement, endorsed by the United Nations in New York in 2016, countries worldwide have strived to preserve resources, use energy efficiently, and reduce carbon emissions. In this context, conserving forest resources and optimizing wood utilization have become increasingly important. Historically, wood has been one of the most abundant and valuable materials. In ancient times, it was essential for shelter, tools, fuel, and weaponry. As civilizations advanced, alternative materials began to replace wood for specific uses. However, there has been a resurgence in the production of new and diverse wood-based products. With rapid global economic growth, the demand for wood and wood products has surged as people seek an improved quality of life. Unfortunately, the current wood storage and processing capacity is insufficient to meet this demand. Limited wood supply and low utilization rates have hindered the development of the wood industry. Therefore, a comprehensive evaluation of log and board processing quality is necessary to improve utilization rates and enhance the quality of wood products.

Wood is widely used in manufacturing due to its strength, durability, and versatility, making it suitable for various applications. However, it is rare to find logs with flawless surfaces in wood manufacturing. As a natural biological material, wood is vulnerable to microorganisms that can damage its structure, leading to defects. These defects, such as irregular tissue formations and structural damage, can affect the quality and lifespan of wood products [1], [2]. Wood defects can be categorized into three types: growth defects (caused by physiological factors), pest damage defects (due to pathological factors), and processing defects (resulting from human error) [3]. Moreover, surface defects significantly impact the quality of wood finishes, influencing strength and aesthetic appeal [4]. Defects can be classified as permissible or non-permissible, depending on their severity. Permissible defects are minor and allowable, while non-permissible defects render wood unsuitable for products that require high structural integrity or visual perfection [5]. Wood or its components can be sorted based on the type, size, and number of defects, which helps determine whether it can be repaired, recycled, or discarded. Identifying defective wood surfaces was essential for maintaining high production quality and safety [6]–[9]. In wood manufacturing, defects reduced wood yield by an average of 10% [10]. Therefore, the early identification of defective items on the production line was critical to maintaining overall quality [11]. A thorough inspection was necessary to ensure that wood met the specifications for its intended use by implementing robust quality control processes [12], [13]. Quality control in wood manufacturing ensured that products met performance, safety, and aesthetic standards. Early identification of defects enabled manufacturers to take corrective action, helping to maintain product quality and consistency [8], [12].

Before the introduction of automated visual inspection (AVI), the wood industry relied on manual inspection methods, where human operators physically inspected wood surfaces to identify defects. This traditional approach was widely used in primary and secondary wood industries and did not require complex technical setups. However, it offered limited potential for future development due to frequent changes in standard operating procedures as new defects were identified. The manual inspection methods were often inaccurate, inefficient, and restricted production volumes, with accuracy rates of only about 70%, raising concerns about their reliability [14]–[16]. Additionally, manual inspections were costly, as training personnel required significant time and resources, and visual fatigue often led to misidentified defects [17]. Human error also varies depending on the workers' experience, skills, and alertness [18]. Furthermore, high production volumes and repetitive tasks over prolonged periods negatively impacted human operators, leading to exhaustion, stress, and reduced inspection quality [19]. As a result, manual inspections were not only slower but also less accurate compared to automated methods [20]–[22].

To overcome the limitations of manual inspection, the wood industry increasingly embraced technology integrated with intelligent algorithms [23]. These algorithms significantly enhanced defect identification processes, which became a primary focus within the industry [24], [25]. Researchers actively explored advanced techniques, such as deep learning to improve accuracy and efficiency. As a result, there was growing interest in machine vision systems, which offered faster and more precise approaches to defect identification [26]. AVI systems, equipped with artificial intelligence, gained traction as a solution to enhance quality control in the wood-based industry [5], [15], [27]. With advancements in artificial intelligence and computer vision technologies, deep learning emerged as a highly effective method for identifying wood defects [28]–[30]. Furthermore, due to their simplicity and affordability, AVI systems became popular for ensuring higher accuracy and production volumes by eliminating human limitations, improving reliability, and maintaining quality standards [14]. Despite advancements, the wood industry still requires solutions to improve processing efficiency and increase yield without compromising product quality. AVI has been highlighted for its role in ensuring consistent product reliability and addressing yield losses due to limitations in manual inspections. Research indicates that AVI offers 25% higher identification accuracy than traditional methods, leading to a 5.3% increase in yield and considerable cost savings for the average rough mill [31]. Furthermore, automated grading has shown greater precision and consistency than conventional inspections, which often struggle to optimize wood resources [32]. Studies also demonstrate that AVI outperforms human inspectors in identifying defects and plays a crucial role in maintaining quality control, ultimately benefiting the secondary wood industry by improving yields and production quality [26].

Moreover, one significant advancement in deep learning for wood defect identification is using data augmentation and transfer learning techniques [33]. Data augmentation addresses the challenge of limited datasets by enabling models to generalize better and improve classification accuracy. On the other hand, transfer learning leverages pre-trained models, such as residual network (ResNet) and Inception, fine-tuning them for specific tasks like wood defect classification, reducing the need for retraining from scratch. As deep learning techniques evolve, further exploration of sophisticated augmentation methods and advanced transfer learning frameworks will be crucial for enhancing defect identification systems. This combination of techniques overcomes the limitations of manual inspection and significantly improves wood production efficiency, quality assurance, and resource utilization.

2. WOOD DEFECT IDENTIFICATION APPROACHES USING DEEP LEARNING

Detecting and identifying defects are crucial in manufacturing to maintain controlled and efficient production processes [34]. Traditionally, these tasks relied on skilled human operators. However, the introduction of AVI has enhanced the autonomy of manufacturing operations. AVI-based quality control has gained popularity in the secondary wood industry due to its ability to improve inspection accuracy, boost production rates, and lower labor costs. An AVI system typically involves several stages: image acquisition, image enhancement, segmentation, feature extraction, and feature classification [35]. Efficient material handling ensures smooth logistics, maintaining steady material flow, reducing vibrations, and regulating speed during timber imaging. Critical subsystems like sensors and lighting are essential for capturing, digitizing, and storing image data. The inspection process begins with defect detection, pinpointing the location of flaws in the wood. This is followed by defect identification, where defects' type, size, and frequency are analyzed. These components also offer guidelines for optimized timber cutting based on the identified defects. Finally, the collected data is used in the grading phase, where the timber is classified according to specific production standards.

In the wood industry, one of the most effective methods for identifying defects involves processing and analyzing images of wood surfaces. Numerous studies have explored using AVI systems, employing traditional image processing, specialized techniques, and artificial intelligence methods [36]. Deep learning represents a significant advancement within machine learning, characterized by the construction of multi-layered neural networks that emulate the complex processes of the human brain. It enables the recognition of diverse inputs such as images, sounds, and texts [37]. Within these neural networks, algorithms in each layer continuously perform calculations and predictions, progressively enhancing accuracy over time. This methodology adheres to data-driven principles, representing observed images in various forms, whether as pixel density value vectors or abstract features like edge sequences [38]. While deep networks often include more hidden layers than traditional neural networks, the effectiveness of learning outcomes does not depend solely on layer depth. Successful deep learning design hinges on determining the optimal number of hidden layers tailored to specific tasks [3]. This evolution has propelled deep learning into a leading approach in academic research and industry applications. Deep learning algorithms automated the feature extraction process, eliminating the need for manual input from experts. Convolutional neural networks (CNNs) exemplified this approach, extracting features directly from images in a fully automated manner [29]. The goal of applying deep learning was to independently process new data, make accurate decisions, and provide reliable recommendations based on thousands of calculations while significantly reducing the potential for human error.

Various advanced deep learning frameworks have proven particularly effective for wood surface defect detection, simultaneously learning feature extraction and classification during training. This innovative approach highlights the adaptability and robustness of deep learning methodologies in addressing real-world challenges. Table 1 summarizes significant studies from 2019 to 2024, showcasing the evolution of deep learning architectures for wood defect identification. These studies demonstrate the growing application of deep learning techniques, which have significantly improved defect detection accuracy in the wood industry.

Table 1. Overview of deep learning models used in wood surface defect identification

Reference	Year	Approach	Defect type
[39]	2024	Inception-ResNet-V2 CNN model	Cracks, knots, and undamaged
[40]	2024	Improved ResNet-50 model	Brown stain, blue stain, knot, borer holes, rot, bark pocket, wane, and split
[41]	2023	Inception-V3 model	Cracks, knots, and undamaged
[42]	2023	Improved ResNet-50 model	Knots, cracks, and color-related defects
[43]	2023	Improved RegNet model	Wormhole, dead knot, and live knot
[33]	2022	ResNet50 model	Brown stain, blue stain, knot, borer holes, rot, bark pocket, wane, and split
[11]	2022	Faster R-CNN model	Knot, wane, edge, stain, and branch.
[44]	2022	Inception-ResNet-V2 CNN model	Edge-glued
[45]	2022	Derived ResNet-v2 model	Wormhole, live joint, and dead joint.
[46]	2021	TL-ResNet34 model	Decay knots, dry knots, edge knots, encased knots, horn knots, leaf knots, and sound knots.
[47]	2021	Based bilinear fine-grained (BLNN)	Knot
[48]	2021	CNN model	Defective wood
[49]	2021	Deep convolutional neural network (DCNN) model	Not specified
[29]	2020	Multi-channel mask R-CNN	Dead knots, live knots, and cracks.
[30]	2020	DCNN model	Crack, knot, and mildew
[50]	2020	Mask R-CNN model	Dead knots, live knots, and insect holes
[51]	2019	Mix-FCN model	Dead knot, live knot, blue stain, crack, brown stain, and pitch streak
[52]	2019	AlexNet model	External defects
[53]	2019	ResNet18 model	Not specified
[14]	2019	Faster R-CNN model	Split, core, branch, and stain
[22]	2019	Faster R-CNN model	Knots and holes
[54]	2019	CNN model	Knots
[55]	2019	VGG-16 model	Not specified

Recent studies on wood surface defect identification have led to the development of several CNN architectures. In 2024, Ehtisham *et al.* [39] developed an automated method for assessing defects in wooden structures using CNNs and image processing techniques to enhance inspection efficiency. Traditional manual inspections, though effective, are time-consuming and costly. The study employed the Inception-ResNet-V2 CNN model, trained with a dataset of 9000 images divided into cracks, knots, and undamaged sections. The model achieved 92% classification accuracy on new test images, with minimal errors in defect quantification. This automated approach provided significant practical benefits for industry professionals by reducing labor costs, speeding up inspections, and improving accuracy, making it a valuable tool for maintaining the safety and durability of wooden structures. Next, in the same year, Chun *et al.* [40] investigated ways to enhance the classification accuracy of timber defect identification using deep learning, particularly ResNets. The focus is refining these networks by increasing depth and incorporating multi-level features to build a more effective framework for identifying different defect types. A series of ablation experiments were performed, testing the performance of three new architectures (R1, R2, and R3) against the standard ResNet50 model. While the R1 architecture achieved slight improvements over ResNet50, particularly with adding an extra layer called "ConvG," ResNet50 still showed better overall performance. Similarly, the R2 framework provided some improvements but still fell behind R1. The most significant results were achieved with the R3 architecture, which integrated fully pre-activation functions, leading to a 14.18% increase in classification accuracy compared to ResNet50. The R3 architecture also performed well across various timber species, though it showed slightly reduced accuracy for rubberwood. Nonetheless, R3 outperformed both ResNet50 and the other proposed models, highlighting the effectiveness of deeper networks and pre-activation functions. Statistical analyses, including independent t-tests and one-way ANOVA, confirmed that the improvements were significant across multiple species, demonstrating the potential of the R3 architecture for timber defect classification.

Next, in 2023, Zou *et al.* [42] proposed an improved modeling method based on ResNet-50 to enhance the accuracy and efficiency of wood defect identification, which was crucial for ensuring furniture manufacturing quality. Recognizing the complexities involved in data and the need for high efficiency, the study introduced a new optimization scheme that combined a convolutional block attention module with a cross-stage partial network (CSPNet) tailored for the ResNet-50 architecture. The research explored how varying the cross-stage parameters in CSPNet affected classification performance, revealing that the default parameters were not always optimal. Additionally, the author proposed the ranger optimizer, which showed superior performance over the traditional Adam optimizer in terms of training efficiency and prediction accuracy. Experiments conducted using a dataset of real-world wood surface defects demonstrated that the proposed model achieved an impressive overall detection accuracy of 86.25% in identifying defects such as knots, cracks, and color-related issues. These results underlined the effectiveness and feasibility of the new modeling approach in improving wood defect identification compared to existing state-of-the-art methods.

Next, in 2022, Ling and Xie [45] developed a derived model based on ResNet-v2 to address the limitations of traditional manual detection methods for wood defects, which are often time-consuming, inefficient, and inaccurate. This new model aims to accurately identify defect types such as wormholes, live joints, and dead joints on wooden surfaces, significantly improving classification accuracy while reducing labor requirements. The study highlights that the ResNet-v2-derived model demonstrates better recognition capabilities and enhanced generalization abilities than traditional CNN. Experimental results indicate that the classification accuracy of the ResNet-v2-derived network exceeds 80% for various configurations, with a peak accuracy of 97.27% under certain conditions. These findings suggest that the proposed model offers a more efficient and reliable solution for wood defect identification, making it a valuable tool in the industry for improving quality control and operational efficiency. In the same year, Mohsin *et al.* [11] proposed a novel method for automatic real-time defect detection and classification on wood surfaces. This approach utilized a DCNN framework called Faster R-CNN for detection, combined with MobileNetV3 as the backbone network for feature extraction. The key innovation of this method lies in its ability to efficiently detect knots and other defects while performing classification in real-time from input video frames. The study focused on achieving speed and accuracy, which were crucial for industrial quality control and inspection tasks requiring defect detection in real-time, particularly on computationally limited processing units or commodity processors. The model was designed to be lightweight, making it suitable for deployment on mobile and edge devices. MobileNetV3 was pre-trained on a large image dataset to enhance feature extraction, while Faster R-CNN was employed for defect detection and classification. The system processed input video frames at an average speed of 37 per second using a low-cost, low-memory graphics processing unit (GPU). The method achieved an overall accuracy of 99% in detecting and classifying defects, demonstrating its effectiveness for practical applications in wood surface inspection.

In 2021, Gao *et al.* [46] developed the TL-ResNet-34 model, a transfer residual neural network, to enhance the identification of wood knot defects with speed and accuracy. This model improved accuracy by over 0.78% through careful extraction of structural defect features and optimization of training parameters and datasets. By incorporating transfer learning, the model benefited from a pre-training phase that allowed for more effective learning from the limited available data. Experimental results demonstrated that TL-ResNet-34 achieved an impressive recognition rate of 99.22% on the training dataset, with a low training loss of 2.83% on the validation dataset while identifying seven distinct wood knot defects. Overall accuracy reached 98.69%, with minimal fluctuations in the loss and accuracy curves during testing, indicating the model's stability and reliability. Significantly, this method minimized the need for extensive image preprocessing and feature extraction, making it efficient and accurate in both the training and testing phases. The findings suggested that TL-ResNet-34 held significant potential for applications in wood non-destructive testing and wood defect identification, allowing for quick and accurate assessments of collected wood knot defects. This innovation could significantly improve wood utilization and resource conservation in the industry.

3. DISCUSSION

Based on the findings from recent studies on wood defect identification, several critical discussions can be drawn. The research highlights the growing importance of utilizing deep learning techniques, particularly CNNs, to enhance the accuracy and efficiency of defect identification in wood. The evolution of CNN architectures, such as Inception-ResNet-V2 and various ResNet models, has shown promising results in improving classification accuracy. For instance, the automated method developed in 2024 achieved a classification accuracy of 92%, demonstrating how deep learning can significantly outperform traditional manual inspection methods, which are often time-consuming and costly [39], [42], [46]. Next, as seen in the Faster R-CNN and MobileNetV3 framework, the emphasis on real-time detection and classification capabilities addresses practical needs in industrial settings where quick decision-making is essential. The ability to process video frames at 37 frames per second with an accuracy of 99% illustrates the potential of these advanced models to enhance quality control in wood processing [11], [46]. Moreover, integrating optimization strategies, such as convolutional block attention modules and transfer learning techniques, has improved model performance, addressing challenges like limited labeled datasets. These advancements promise substantial benefits, including reduced labor costs and enhanced safety, and they also optimize resource utilization in timber manufacturing, demonstrating a significant shift toward automation in wood defect identification. Furthermore, introducing the ranger optimizer and adjusting the CSPNet parameters contributed to better accuracy, underscoring the necessity of continual improvement in the model training process [39], [42], [46]. The studies also highlighted challenges, particularly the limited availability of labeled datasets in wood defect detection. Models like TL-ResNet-34, which effectively leverage transfer learning, show that even with fewer training examples, it is possible to achieve high recognition rates, emphasizing the importance of innovative approaches to data scarcity [46]. In addition, implementing these advanced detection systems in real-world scenarios promises significant benefits, including reduced labor costs, improved safety, and enhanced durability of wooden structures. By automating defect detection, industries can optimize their processes, leading to better resource conservation and more efficient use of timber [39], [42], [46].

The analysis of wood defect identification methods from 2019 to 2024 reveals a predominant reliance on CNN-based models, highlighting their effectiveness in identifying surface defects in wood. CNNs enhance defect identification through hierarchical feature learning, significantly reducing the time and effort associated with manual inspections [39]. Various architectures, including ResNet, Faster R-CNN, and Inception-ResNet, showcase the versatility and dominance of CNNs in this field. Their popularity stems from two main factors: high performance and ease of training [56]. The modular design of CNNs, comprising convolutional bases and fully connected layers, allows for robust feature extraction and accurate defect classification. This capability improves the precision of defect identification by capturing intricate features within high-dimensional data [57]–[59]. However, challenges persist, notably the substantial computational power required for effective CNN operation, often necessitating expensive GPUs and large datasets [60]. To overcome these barriers, research is needed to develop compact, efficient CNN models that can function on low-power computing resources, such as CPUs or FPGAs, making them more accessible for industrial applications. Furthermore, creating and sharing large, high-quality datasets of surface defects is crucial for enhancing model training and performance. Addressing these gaps will facilitate the broader adoption of CNNs in automated surface inspection systems, balancing computational demands with cost-effectiveness and data availability. Overall, CNNs play a vital role in advancing wood defect identification, offering superior feature extraction and classification capabilities essential for improving automation in the industry.

Furthermore, the analysis of models presented in Table 1 indicates significant advancements in the sophistication of CNN architectures, with notable models like Inception-ResNet-V2 and ResNet-50 demonstrating enhanced performance across various defect categories. These advancements highlight the robustness and adaptability of CNNs in real-time defect detection, as seen with models such as Faster R-CNN, which effectively identify defects like knots, holes, and stains in industrial applications. In 2024, the focus has shifted towards refining advanced models, particularly Inception-ResNet-V2 and improved versions of ResNet-50, underscoring ongoing innovation in defect identification methodologies. The previous years, 2022 and 2023, also reflected significant improvements in ResNet-50, emphasizing efforts to optimize accuracy and efficiency. While the models in Table 1 effectively address a range of defects from common issues like cracks and knots to specific problems such as wormholes and insect damage they often concentrate on a limited number of defect types. Most studies focus on knots, significantly impacting structural strength and product quality. This trend underscores the necessity for more comprehensive deep learning models capable of multiclass identification, allowing for a broader scope of wood defect detection. Moreover, several studies labeled defect types as "not specified," indicating a general focus on wood surface defects without detailing specific types. This presents an opportunity for future research to explore and document various defects, enhancing quality control in the wood industry.

In addition, the quality of the training dataset is crucial for effectively training deep learning models. Deep neural networks typically contain many trainable parameters, making them highly prone to overfitting, especially when training data is limited. Various regularization techniques have been developed to address this issue to enhance the model's generalization capability. One effective method is data augmentation, which directly impacts the training dataset. Data augmentation involves applying various transformations to input images to expand the training dataset artificially. It is essential to carefully select transformations appropriate for a specific problem, as these transformations should maintain the semantic meaning of the labels. Data augmentation is considered a standard approach in deep learning, especially when fewer data samples are available. It is widely used to improve the adaptability of neural networks for classification tasks and to mitigate overfitting issues. Numerous studies have explored the effectiveness of data augmentation in wood defect identification, demonstrating its potential to enhance accuracy and efficiency. Table 2 summarizes various data augmentation techniques employed in past research, highlighting the specific methods used by different researchers to improve the diversity and effectiveness of their training datasets.

Table 2. Techniques for data augmentation in wood defect identification

Researchers	Data augmentation techniques
[33]	Morphological transformations: x-reflection and rotation
[14]	Geometric transformations: flip, rotation transformation, and resize transformation.
[61]	Brighten change and Gaussian noise.
[30]	Rotating the training images at 90°, 180°, and 270°, randomly cropping the training images, flipping the training images horizontally, vertically, and diagonally, adjusting the brightness, contrast, saturation, or hue of the training images, and adding Gaussian and salt-and-pepper noises to the images

Research by Chun *et al.* [33] highlighted the efficacy of data augmentation in enhancing the performance of CNNs for classifying timber defects in various species. They employed morphological transformations, such as x-reflection and rotation, to expand the training dataset, which addressed the challenges posed by limited data availability. The results demonstrated a significant improvement in classification performance, with the best model, ResNet50, achieving an accuracy of 94.59%. Statistical analyses, including T-tests, confirmed that the enhancements in classification accuracy due to data augmentation were significant for most CNN algorithms tested, except for AlexNet. Furthermore, the authors observed that simply increasing the number of training epochs and the learning rate did not necessarily yield better classification precision, underscoring the importance of carefully tuning hyperparameters for optimal results. Overall, the study concluded that data augmentation was a vital technique for overcoming the limitations of small datasets and improving the classification capabilities of CNNs in the context of timber defect identification.

Next, Urbonas *et al.* [14] discussed the importance of data augmentation in enhancing the performance of AVI systems for identifying defects on wood veneer surfaces. They highlighted that traditional visual quality inspections in the lumber and wood processing industry were often performed by human operators, leading to potential errors due to the tedious nature of the task. To improve accuracy and speed, the authors proposed using a Faster R-CNN alongside data augmentation and transfer learning techniques. The authors specifically mentioned employing a synthetically augmented dataset to train their models, which included pre-trained networks like AlexNet, VGG16, BNInception, and ResNet152. Their experiments showed that data augmentation significantly contributed to the overall classification accuracy of defect identification, achieving an average accuracy of 80.6% with ResNet152 and an impressive 96.1% when combining all defect classes. This indicated that data augmentation effectively enhanced the robustness of the models, making them suitable for real-time industrial applications. Moreover, the authors acknowledged that while data augmentation and transfer learning improved defect detection, the method's reliance on manually labeled images for training presented a limitation, as these labels might not always be accurate. They suggested that future work could explore more complex data augmentation techniques and apply these methods to analyze surface defects in other types of wood panels, thereby broadening the scope of their approach. Overall, the authors emphasized that data augmentation was crucial in developing effective automated inspection systems for wood processing, demonstrating its applicability to various industrial materials.

Then, Romanovskis *et al.* [61] discussed the importance of data augmentation in optimizing the use of oak wood during industrial processing. The author trained two different Mask R-CNN models using the instance segmentation method. The first model was trained solely on the original data obtained from the scanner. In contrast, the second model included the original images and additional artificially adjusted images to expand the dataset. The authors employed two data augmentation methods "brighten change" and "Gaussian noise" which were selected because they did not alter the physical location of objects within the images. All new images were generated based on labeled images, eliminating the need for relabeling, as the original image JSON file was attached to the artificially generated images. This approach saved significant time in the marking process. The results indicated that the original model achieved an average accuracy of 73%. However, the model that utilized data augmentation showed an improvement of approximately 16%, reaching an average accuracy of around 89%. The authors concluded that the augmented model successfully identified and localized defects specific to oak wood, demonstrating that data augmentation is a valuable technique for enhancing model performance in the context of wood processing.

Lastly, He *et al.* [30] discussed the role of data augmentation in their proposed method for detecting wood features and classifying defects from images collected using a laser scanner. In their approach, the authors implemented data augmentation as a strategy to avoid overfitting during the training of the DCNN model. They collected a dataset comprising images of 600 pieces of red and camphor pine wood, which included specific defect categories such as knots, cracks, and mildew stains. The dataset was divided into training, validation, and testing subsets, with data augmentation applied to enhance the size and diversity of the training data. The results demonstrated that the DCNN model achieved an overall accuracy of 99.13%, with only 1.12 seconds required for detection, including image preprocessing and identification. Data augmentation significantly contributed to the model's performance, allowing it to recognize wood defects more accurately and effectively than conventional methods.

By incorporating transfer learning, the model benefited from a pre-training phase that facilitated more effective learning from the limited available data. In the rapidly evolving field of deep learning, transfer learning has emerged as a pivotal technique, particularly for tasks involving limited labeled data. Numerous pre-trained CNN models are readily available in the literature, providing significant advantages in learning comprehensive visual feature representations. These models have been extensively trained on large datasets, allowing them to capture complex patterns and intricate features, which is especially beneficial when working with small, task-specific training datasets [62]. Leveraging transfer learning enables researchers to adapt pre-trained models to meet their specific needs, offering a pragmatic and efficient approach for training deep learning models in scenarios with limited labeled data. This methodology allows practitioners to modify and fine-tune pre-trained models using domain-specific information, significantly accelerating the learning process for image classification and identification tasks. Instead of starting the training process from scratch, transfer learning utilizes existing models trained on larger datasets and adjusts their weights to align with the intended task. This technique enhances both accuracy and effectiveness across various applications [33].

Training deep learning models from scratch can be computationally expensive; therefore, utilizing models already published in the literature can save time and resources while achieving comparable performance in computer vision tasks [63]. Several deep neural network models, such as Xception, Inception, AlexNet, VGGNet, GoogLeNet, and ResNet, have been proposed for object classification over the past few decades. Moreover, transfer learning strategies have been widely applied in wood surface defect classification. Additionally, transfer learning has proven effective across various domains, including manufacturing, medical diagnostics, and baggage screening [64]–[66]. This approach eliminates the need for extensive datasets and minimizes the prolonged training periods typically associated with developing deep learning algorithms from scratch [67], [68].

Several studies effectively utilized transfer learning to identify wood defects. Urbonas *et al.* [14] discussed transfer learning as a critical technique in developing an AVI system for detecting defects on wood veneer surfaces. By employing pre-trained neural network models such as AlexNet, VGG16, BNInception, and ResNet152, the researchers aimed to enhance the accuracy of the faster R-CNN model for this specific task. Transfer learning allowed them to leverage the learned features from large datasets, resulting in the best average accuracy of 80.6% using ResNet152 and a remarkable 96.1% accuracy when combining all defect classes. Additionally, data augmentation was used to increase the diversity of the training dataset, further improving model performance. The findings suggested that these methods could apply to other industrial materials, showcasing the versatility of transfer learning. However, the reliance on manually labeled images for training posed a limitation, as labeling errors could impact results. The authors planned to explore more complex transfer learning and data augmentation techniques in future research and extend their methods to analyze surface defects in other types of wood panels.

Next, Gao *et al.* [69] discussed transfer learning as an integral component of their proposed model, ResNet-18, for detecting wood knot defects. In this study, transfer learning was leveraged to enhance the performance of deep learning techniques in the context of wood defect detection, which had historically faced challenges such as long training times, low recognition accuracy, and the need for manual feature extraction. Integrating transfer learning with the "squeeze-and-excitation" (SE) module into the residual basic block structure, the ResNet-18 model improved feature extraction in the channel dimension and effectively fused features across multiple scales. The experimental results indicated that the model achieved an impressive accuracy of 99.02% in detecting wood knot defects, significantly higher than the classical ResNet-18 model's accuracy of 90.83%. Additionally, the proposed approach reduced training time and eliminated the need for extensive image preprocessing and manual feature extraction, thereby greatly enhancing recognition efficiency. Overall, the author concluded that the ResNet-18 model, through its transfer learning, provided a promising solution for wood nondestructive testing and defect identification, paving the way for more efficient wood knot defect detection in future applications.

In addition, Hu *et al.* [50] discussed transfer learning as a crucial component of their proposed method for identifying wood defects in poplar veneer using a combination of a progressive growing generative adversarial network (PGGAN) and the Mask R-CNN model. In this study, transfer learning was employed to enhance the performance of the Mask R-CNN model, specifically by integrating it with a classifier layer. This approach allowed the model to learn from a pre-trained network, improving its ability to identify and classify defects such as dead knots, live knots, and insect holes in the veneer. The experimental results indicated that the model achieved high accuracy rates of 99.05% for live knots, 97.05% for dead knots, and 99.10% for insect holes, demonstrating the effectiveness of the transfer learning strategy in achieving precise defect detection. The author highlights that the classification accuracy of the Mask R-CNN model, which was based on ResNet50 and further enhanced through transfer learning, reached 98.4% when tested on an expanded dataset. Additionally, the use of PGGAN for data augmentation helped to improve the diversity of defect images and balance sample distribution, contributing to the overall performance of the detection model. The findings suggest that transfer learning can significantly enhance detection accuracy, especially when working with smaller datasets. The author concludes that this technology has potential applications in wood processing equipment, particularly in wood classification systems, indicating a promising avenue for future implementation.

Also, Ding *et al.* [1] discussed transfer learning as a key strategy in their approach to detecting wood defects, specifically in solid wood boards. This study applied the transfer learning method to the single-shot multi-box detector (SSD), a target detection algorithm, using the DenseNet network to enhance performance. The results indicated a mean average precision of 96.1% for detecting the three types of defects, showcasing the effectiveness of transfer learning in improving detection accuracy. The authors emphasized the potential of transfer learning and advanced neural network architectures in enhancing wood defect detection methods. They also intended to extend their model to identify other wood surface defects, such as wormholes and discoloration, and to improve target location precision in future research.

Then, Ehtisham *et al.* [41] discussed transfer learning as a crucial element in their study of identifying and classifying defects in wooden structures. The research evaluated ten pre-trained CNN models ResNet18, ResNet50, ResNet101, ShuffleNet, GoogLeNet, Inception-V3, MobileNet-V2, Xception, Inception-ResNet-V2, and NASNet-Mobile and each model was further trained and validated, demonstrating the effectiveness of transfer learning in adapting these pre-trained models for specific tasks. The findings indicated that the Inception-V3 model performed the best, achieving an overall accuracy rate of 97.3% and a training time of 97 minutes. This model's architecture, featuring 48 deep layers, allowed it to classify defects in wooden structures effectively. The study highlighted the efficiency of using pre-trained CNNs, as they significantly improved classification accuracy and reduced the time required for defect identification compared to traditional manual inspection methods.

Furthermore, Chun *et al.* [33] discussed transfer learning as a significant component in their study of identifying timber defects across four Malaysian timber species. They highlighted using the ResNet50 algorithm, based on transfer learning, outperforming other CNN models, achieving a classification accuracy of 94.59% when combined with data augmentation techniques. The research indicated that data augmentation addressed issues related to limited datasets and improved the classification performance of CNNs by 5.78%. The study evaluated the effectiveness of transfer learning in conjunction with various hyperparameter settings, such as learning rates and epochs, demonstrating that while these adjustments were important, higher values did not always lead to better accuracy in CNN classification. Overall, the findings suggested that data augmentation and transfer learning were effective strategies for enhancing the identification of timber defects, and the authors noted potential for future research in exploring more complex augmentation techniques and applying deep learning to analyze different types of timber defects across various species.

4. CONCLUSION

The growing importance of deep learning methods is evident, as recent research highlights their effectiveness in enhancing the accuracy and efficiency of wood defect identification, significantly outperforming traditional inspection methods and leading to improved quality control in the timber industry.

Advancements in CNN architectures, such as Inception-ResNet-V2 and various ResNet models, have demonstrated remarkable improvements in classification accuracy, reflecting a shift towards more sophisticated and practical techniques for defect identification. Furthermore, implementing frameworks like Faster R-CNN and MobileNetV3 showcases the ability of these advanced models to provide real-time detection and classification, which is essential for industrial applications where quick decision-making is crucial. Despite these advancements, challenges remain, particularly regarding the limited availability of labeled datasets. However, innovative approaches like transfer learning and data augmentation have proven effective in enhancing model performance, even when working with smaller datasets. The economic and practical benefits of integrating these advanced detection systems are substantial, including reduced labor costs, improved safety, and more efficient resource utilization in timber manufacturing, ultimately leading to significant process optimizations in the wood industry. While current studies predominantly focus on specific defect types, such as knots, there is an urgent need for more comprehensive models capable of multiclass identification to improve the detection of a broader range of defects and enhance overall quality control in wood processing. Future research should prioritize the creation of larger, high-quality datasets and developing compact, efficient CNN models that can function on low-power computing resources. Exploring more complex data augmentation techniques and applying transfer learning across various wood types and defect categories could further propel advancements in this field. In summary, the research emphasizes that significant strides have been made in utilizing deep learning for wood defect identification; however, ongoing innovation and adaptation are crucial to overcoming existing challenges and maximizing the benefits of these technologies in real-world applications.

FUNDING INFORMATION

This research is supported by the Ministry of Higher Education (MOHE), Malaysia, through the Fundamental Research Grant Scheme (FRGS/1/2022/ICT02/UTEM/02/2) and Fakulti Teknologi Maklumat dan Komunikasi, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
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Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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