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TOPICAL REVIEW

The Prospect of Artificial Intelligence-Based Wood Surface Inspection: A Review

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ABSTRACT The demand for solid wood is high in the construction and manufacturing industries, and the quality of the wood is crucial. Defects in solid wood can result in hazardous accidents or financial loss. While manual visual inspection of defects is time consuming and labor intensive, Automated Optical Inspection (AOI) systems provide a solution that is hindered by defect variations and environmental factors such as moisture content and lighting conditions. AOI systems coupled with machine learning algorithms have emerged as a promising approach for inspecting wood defects. Despite their promising results compared to manual visual inspection and AOI systems, machine learning algorithms have shown several limitations in terms of complex image processing methods, feature engineering, and hyperparameter dependence. Deep learning algorithms have tremendous potential and have become trends in wood defect inspection in recent years, particularly Convolutional Neural Networks (CNNs), single-shot detectors (SSD), You Only Look Once (YOLO), and faster region-based neural networks (Faster R-CNN) algorithms. The coupling of machine vision technology with deep learning algorithms can enhance the efficiency and accuracy of wood defect inspection, and their impact has been proven in several studies. This study aims to provide a comprehensive overview of wood defect inspection approaches by analyzing related studies on machine learning-based and deep learning-based defect inspection methods. Their principles, procedures, performance, and limitations were compared and discussed. Subsequently, future trends and challenges in wood defect inspection are also discussed to provide a detailed understanding and direction for related fields.

INDEX TERMS Deep learning, defect inspection, machine learning, machine vision, wood.

I. INTRODUCTION

Wood has been integral to human society for millennia, offering strength, durability, and versatility [1], [2], [3], and it has been widely utilized for construction [4], [5], [6], addressing the need for sustainable alternatives amid environmental concerns [7], [8]. Recent advancements have expanded their applications to include transparent wood [9], [10], [11], supercapacitors [12], [13], wood-based-solar steam production [10], [14], [15], [16], and wood-based sensors [17], [18], [19], [20], [21]. These studies have promoted the use of wood as a renewable, biodegradable, and environmentally benign resource.

Therefore, it is crucial to ensure the quality of the wood-based materials used in various applications. However, defects in wood are inevitable and can manifest in various manners [22]. There are some common types of defects found in wood, including knots, checks, shakes, splits, and wood decay, which compromise the structural integrity and strength. These flaws can arise during tree growth or industrial processing [23], leading to stress concentrations, dimensional instability, and moisture ingress. Other defects,

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such as holes, wanes, and deformations, further impact the wood quality, making it unstable and unsuitable for industrial use.

Therefore, inspection of wood defects has gained significance for enhancing wood quality and minimizing resource wastage. Traditional visual examination by human operators, while once the norm, is now being phased out because of its inherent subjectivity and limitations such as fatigue and declining attention span. Manual inspection is slower and less accurate than automated technologies such as machine vision, which utilizes image processing for defect localization and detection [24]. Machine vision, particularly Automated Optical Inspection (AOI) systems equipped with components such as cameras, light sources, processors, and controllers [25], has revolutionized wood defect inspection by overcoming the constraints of human vision and offering enhanced accuracy and efficiency.

Although AOI systems have improved wood defect inspection, challenges persist owing to variations in defect size, shape, and wood surface texture. Environmental factors such as moisture content and lighting conditions further complicate defect detection using cameras. To enhance inspection accuracy, AOI systems are often coupled with artificial intelligence (AI) algorithms such as Support Vector Machines (SVM) [26], K-means clustering [27], Principal Component Analysis (PCA) [28], and AdaBoost. These algorithms require image pre-processing and feature extraction, which are time-consuming and labor-intensive. In addition, their classifier nature may overlook defect locations, focusing instead on the preset defect types.

In recent years, deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have gained prominence in wood defect inspection, surpassing traditional machine learning methods. CNN-based algorithms eliminate the need for human intervention in data collection and feature engineering, thereby achieving superior performance in tasks, such as image recognition and processing. They have been extensively applied to various tasks in the wood industry, including resource surveying, wood type classification, and moisture content prediction [29]. Moreover, object detection models such as the single-shot detector (SSD) [30], You Only Look Once (YOLO) [31], and Faster Region-based Neural Network (Faster R-CNN) [32] are preferred for wood defect inspection because of their exceptional defect classification and localization abilities, combined with high accuracy and satisfactory inference speed.

In this context, both machine learning and deep learning rely on data such as images for training and feature learning. However, deep learning models are typically more complex with multiple layers, and autonomously extracting features at various levels of abstraction, in contrast to the manual feature engineering often required in machine learning.

This review aims to comprehensively explore both machine learning and deep learning algorithms for accurate and efficient detection of wood defects across various industrial applications. The scope of this study encompasses a thorough examination of wood defect detection methods with a focus on surface defects, catering to readers and researchers with diverse levels of expertise in the field. The research methodology involves defining objectives, systematically searching academic databases, selecting relevant literature, and analyzing key findings from studies up to 2023. This study outlines the principles and implementation steps used, which result in improving or degrading the inspection performance, evaluating their performance metrics, and critically assessing the limitations of the methods. Ultimately, this review study is expected to offer valuable insights to readers in related fields, aiding the planning of future research. The contributions of this study are as follows:

- A detailed research methodology for collecting related articles was provided, including keyword selection, predefined criteria used for the evaluation of retrieved studies, and the analysis and synthesis of articles chosen to summarize the key findings from existing wood defect inspection works.
- A comprehensive review of wood defect inspection methods in the past 10 years, which covered machine learning-based and deep learning-based methods, was presented.
- An exploration, including the principles and implementation steps used, which result in improving or degrading the inspection performance, was conducted to determine the advantages and disadvantages of these studies.
- The performance of previous studies in terms of evaluation metrics such as accuracy, precision, recall, mean Average Precision (mAP), and inference time is focused on and discussed. The performance of each proposed method is compared and summarized in a table for a better understanding.
- The future trends and challenges of both machine learning and deep learning algorithms are discussed, providing a clearer direction for readers in the related field.

The following section presents the research methodology used to conduct a systematic search of relevant literature. Section three reviews the existing machine learning-based inspection methods. Section four reviews the existing deep learning-based inspection methods. Section five presents the future trends and challenges of these algorithms for wood defect inspections. Finally, section six concludes the study.

II. RESEARCH METHODOLOGY

In this study, a research methodology was used to review wood defect inspection methods, particularly for wood surface defects. The research methodology used in this study, can be divided into four steps: defining the research, searching for relevant literature, evaluating the retrieved literature, and analyzing and synthesizing the selected studies.

A. DEFINING THE RESEARCH

- Define the research area: The research areas of this study are wood defect inspection using machine learning and deep learning methods, which are illustrated in deep learning, defect inspection, machine learning, machine vision and wood.

- Define the research objective: The objective of this study was to provide a comprehensive review of machine learning and deep learning algorithms for wood defect inspection.
- Define the research scope: The scope of this paper covers a review of existing wood defect inspection methods, especially for wood surface defects. This paper describes the concepts and approaches used, from feature extraction to algorithm training, compares their inspection performance, and discusses the strengths and weaknesses of the proposed methods.

B. SEARCHING FOR RELEVANT LITERATURE

- Select keywords: Relevant papers that match the keywords chosen for the past ten years (from 2013 to 2023) will be selected for further consideration. Five keywords were selected to search for papers: deep learning, defect inspection, machine learning, machine vision and wood.
- Select academic databases: A few academic databases were selected for searching papers related to wood defect inspection, which are listed as follows:
  - IEEE Xplore
  - Scopus
  - ScienceDirect
  - Springer
  - Web of Science
- Select related papers: Papers related to the research area and written in English were selected for further consideration.

C. EVALUATING THE RETRIEVED LITERATURE

- Filter the papers: The selected papers were first filtered and removed according to the following predefined criteria:
  - The contribution of the paper is not relevant to the research areas defined.
  - The publication date is out of the range of years selected.
  - The proposed methods used have no significant contribution to the research areas defined.
- Verified the papers: The papers remaining after filtering were further verified to ensure that they matched the research areas of this paper. This review focuses on the approaches used during feature extraction, robustness of the algorithm used, and inference performance. Papers that matched the criteria were cited to promote the value of this study. Other papers related to the concept of the algorithms used will also be cited to support these articles.
- Categorize the papers: All papers selected were categorized and stored in a few folders, including machine learning-based inspection methods, deep learning-based inspection methods, and supporting references, to ensure that the paper writing was smooth and well organized.

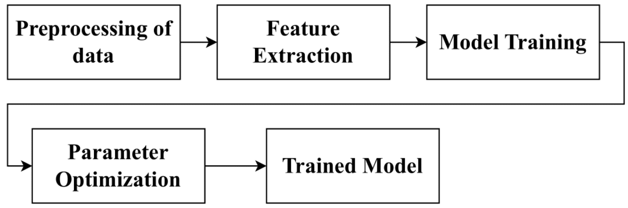

FIGURE 1. Process of training a machine learning model.

D. ANALYSING AND SYNTHESISING THE SELECTED STUDIES

- Analyze and synthesize the paper: The selected papers were analyzed and synthesized, and further analyzed by focusing on the proposed networks and approaches used from feature extraction to algorithm training. Specific image processing methods for feature extraction and modification of algorithms on the original structure will be focused on and synthesized.
- Summarize the paper: The papers were summarized using the performance metrics used in these studies to prove their contribution to the defined research area. Further discussion was conducted on the shortcomings of the methods proposed in these studies. A summary of the machine learning-based and deep learning-based algorithms is presented.
- Determining future trends and challenges: The future trends and challenges of wood defect inspection based on the reviewed existing research are discussed.

III. MACHINE LEARNING-BASED DEFECT INSPECTION

Machine learning is a computer algorithm that consists of the ability to learn, analyze, and make predictions based on the pattern of input data without the need for human instructions. Fig. 1 shows the general workflow of machine learning, starting with image preprocessing followed by network training to learn the key features and optimize the model parameters [33]. Machine learning algorithms have been applied across industries to tasks such as wood defect detection, surface inspection, and product assembly verification, leveraging their ability to make predictions from data patterns. Therefore, a few studies on machine learning-based defect inspections are reviewed in this section.

A. SUPPORT VECTOR MACHINE CLASSIFIER WITH BAG-OF-WORDS TECHNIQUE

In this context, [34] propose the use of an SVM classifier with a Gaussian radial basis kernel function to detect wood skin defects. The Bag of Words (BoW) approach is implemented, in which the features are extracted using the Speeded UP Robust Features (SURF) algorithm [35] and clustered by K-means clustering to create a visual dictionary as input data.

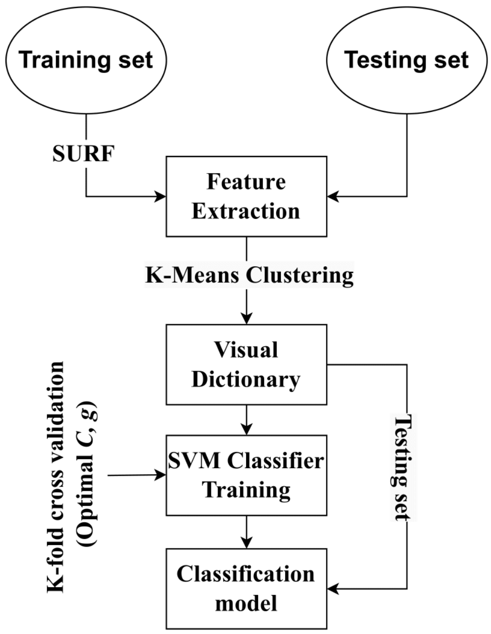

FIGURE 2. Flowchart of SVM classification with bag of words (BoW).

The kernel and loss functions are key aspects of the SVM because they affect the mapping function and maximization of the margin between different classes [36]. Fig. 2 shows a flowchart of the SVM classification with BoW, showing the stages of the main algorithms.

Despite the high recognition rate exceeding 94% across the three types of wood-skin defects, the proposed method has limitations. The selection of hyperparameter C of the kernel function and parameter K in K-means clustering does not account for the time required to determine the optimal value. In addition, the SVM simplifies the classification problem using quadratic programming, which is convex and requires complex matrix operations, leading to computational complexity [37].

B. FEATURE FUSION TECHNIQUE WITH COMPRESSED SENSING

In another study [38], the proposed wood defect detection system benefited from a combination of Principal Component Analysis (PCA) and compressed sensing [39]. Initially, the captured images were segmented using mathematical morphology to isolate the defect areas. PCA, as illustrated in Fig. 3(a), was then employed to fuse the features from segmented images, maximizing the variance across features with principal components [28]. Subsequently, compressed sensing was applied to reconstruct the original defect areas from the sparse feature set, including geometry features, regional features, texture features, and invariant moments, thereby enhancing defect representation. Subsequently, the discriminative power of the system was enhanced by incorporating Linear Discriminant Analysis (LDA) [40] to maximize inter-class separation and minimize intra-class variance, resulting in a 2% increase in the defect recognition rate [41], as depicted in Fig. 3(b).

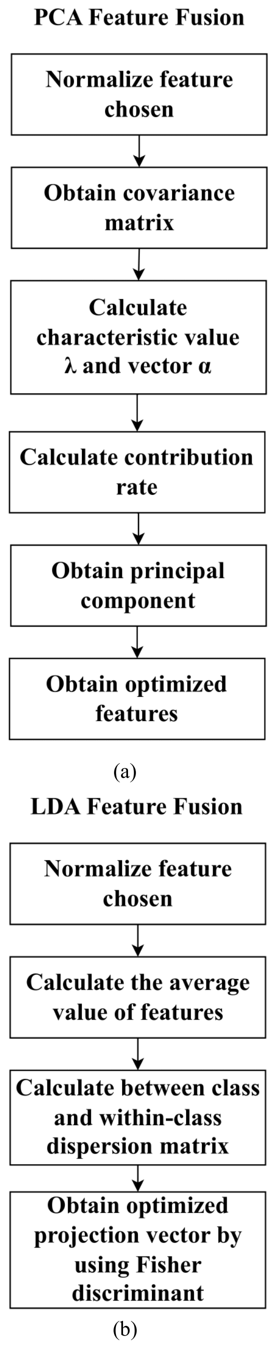

FIGURE 3. Feature fusion using (a) Principal component analysis (PCA) and (b) Linear discriminant analysis (LDA).

The proposed methods exhibit commendable performance, surpassing several neural networks by 7% in accuracy while reducing the classification time to 44.6ms with a classification rate of 94%. However, the features extracted in both studies were complex and required domain knowledge and increased computation. PCA and LDA use linear combinations that may be suboptimal for nonlinear relationships.

They cannot localize defects and are impractical for real-time applications owing to computational demands. In addition, the benefits of compressed sensing are limited without inherently sparse data, which making dictionary selection challenging.

C. WAVELET TRASNFORM AND K NEAREST NEIGHBORS

However, the outstanding success of the approach proposed in [42] for wood quality control, particularly knot detection, can be attributed to several crucial factors. Similarly [38], the image segmentation on the knot areas was performed using mathematical morphology. Subsequently, the utilization of the wavelet transform technique for feature extraction effectively decomposes defect images into approximation and detail components. This decomposition enabled the algorithm to capture both coarse- and fine-grained knot information, thereby enhancing the discriminatory power of the extracted features. Additionally, the K Nearest Neighbors (KNN) [43] algorithm classifies the test data by determining the class of neighboring data points with the shortest Euclidean distance, as shown in (1). The optimal number of neighbors (K) was determined through trial and error to ensure the algorithm tuning of the knot dataset.

$$D(C) = \sqrt{\sum_{j=1}^{N} (f_j(x) - f_j(C))^2} \tag{1}$$

where N is the feature vector, C indicates the class number, $f_j(x)$ indicates the test sample of the j^{th} feature, $f_j(C)$ indicates the j^{th} feature of the C^{th} class. The method proposed in [42] can detect knots with a success rate of 98%, which is better than that in [44]. However, certain limitations exist, such as the computational complexity arising from the multiscale wavelet analysis. Furthermore, the imbalanced data and K value selection impact prediction accuracy [45], whereas higher dimensions in datasets may degrade algorithm performance owing to sparse data points and the difficulty in finding meaningful nearest neighbors during the calculation of the Euclidean distance.

D. LAW TEXTURE ENERGY MEASURES AND FEED-FORWARD BACKPROPAGATION NETWORK

Using the same knot dataset as in [42], another study [44] achieved remarkable success by proposing a knot defect classifier using a feed-forward backpropagation (BP) neural network. First, the utilization of the optimal number of neurons in the BP algorithm, as shown in Fig. 4, enables effective classification of wood defects. By comparing the effectiveness of the gray-level co-occurrence matrix (GLCM) [46] and the laws of texture energy measures (LTEM) as feature extraction methods, this study explored different approaches for capturing spatial relationships and texture energy from wood defect images. GLCM and LTEM offer complementary insights, with GLCM focusing on the spatial relationships between pixel intensities and LTEM capturing the texture energy at different spatial scales.

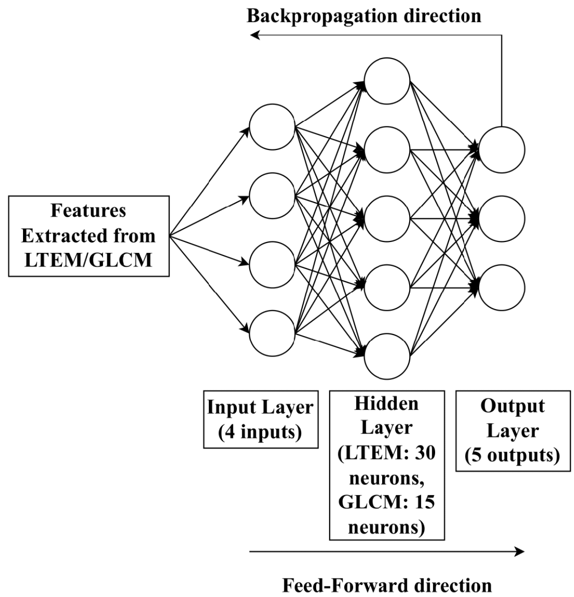

FIGURE 4. Feed-forward backpropagation (BP) Network with feature extracted from law texture energy measure (LTEM) or Gray-level co-occurrence matrix (GLCM) as input.

The proposed method demonstrated impressive results in defect classification, achieving 94.3% accuracy and an MSE of 0.10728 when utilizing features extracted from LTEM, outperforming GLCM with 94.3% accuracy and an MSE of 0.10728. However, both methods lack defect localization and require additional feature-extraction steps. The sensitivity of GLCM and LTEM can also lead to inconsistencies in feature extraction, impact co-occurrence statistics, and texture energy measures. Parameter adjustments in the feed-forward BP algorithm, such as neuron numbers, are time-consuming and may lead to suboptimal performance when applied to different defect types.

E. MODIFIED HU INVARIANT MOMENT AND BACKPROPAGATION NETWORK

In contrast to [42] and [44], the significant improvements achieved using the proposed method [47] for wood defect classification can be attributed to several factors. The segmentation process was performed by integrating modified Hu moments with wavelet moments in a BP neural network, addressing the limitations of each method individually. Although Hu moments offer computational efficiency, they lack translation, rotation, and scaling invariance, which is addressed by decomposition of the wavelet transform. Meanwhile, the normalization of features ensures consistency and comparability across different sub-images and wood defect samples. Fig. 5(a) and (b) illustrate the extraction methods and proposed BP algorithm, respectively.

The proposed method has great improvements in defect classification, achieving the highest accuracy of 97.33%

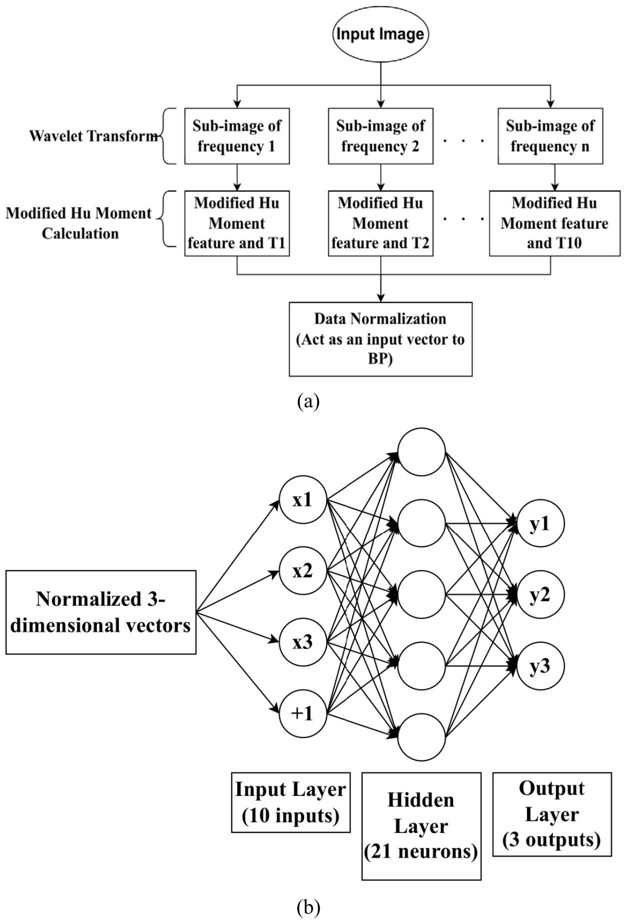

FIGURE 5. **(a) HU invariant moment feature extraction method and (b) Backpropagation (BP) Algorithm.**

among the defects and outperforming the original Hu moment. However, the proposed method introduces sensitivity to hyperparameter adjustment and increases the computational cost owing to double wavelet transform decomposition. Although it enhances feature sets by capturing shape and texture information, it is unsuitable for real-time application. Optimizing hyperparameters for both Hu and wavelet moments, such as decomposition levels and wavelet functions, is time consuming and affects the effectiveness of the method.

F. ARTIFICIAL NEURAL NETWORK CLASSIFIER WITH GRAY-LEVEL DEPENDENCE MATRIX

The proposed method [48] utilizes an Artificial Neural Network (ANN) [49], which offers the potential to outperform other standard classifiers, such as KNN, Naiyes Bayes [50] and Decision Tree (DT), by adjusting parameters to suit the timber defect detection system better. The diversity of the dataset, comprising nine types of wood defect images from four wood species, presents a challenging feature learning environment during the training process. By converting the dataset into grayscale images and extracting statistical features using a gray-level dependence matrix (GLDM), the algorithm effectively captured the characteristics of wood defects for classification. The focus on tuning parameters such as the number of nodes and epochs in the ANN algorithm ensures optimal model performance and adaptability to diverse defect patterns.

This study validates the proposed method with the highest F1-score of 84.01% among the four wood species and outperforms the other algorithms. However, this study has some limitations. Utilizing wildcard values for neuron numbers from the Waikato Environment for Knowledge Analysis (WEKA) may not yield optimal performance, and determining the epoch number range is time consuming. Further improvement is possible by adjusting parameters such as the hidden layer number and learning rate, which are essential for optimizing ANN performance.

G. CLASSIFICATION AND REGRESSION TREE WITH CONVEX OPTIMIZATION

In contrast, the method proposed in [51] employs a Classification and Regression Tree (CART) algorithm tailored for wood plate defect identification. The authors ensured that high-quality images were captured using an image capturing system under adequate lighting conditions. Convex optimization (CO) was then utilized to refine the images, followed by the OTSU technique for defect segmentation. Mean structural similarity (MSSIM) was calculated to measure the similarity between segmented and original images based on different weight values, and the optimal weight was chosen. Meanwhile, the manual extraction of geometric and intensity features through Commission on Illumination (CIE) lab transformation enhanced the feature richness of the CART algorithm input. The CART iteratively determines the best division points and builds decision trees, whereas the pruning technique removes less important attributes [52], as shown in Fig. 6.

The proposed method achieved satisfactory performance, with the highest accuracy of 96.3% among the defects. Despite its effectiveness, the OTSU technique is often sensitive to noise, requiring additional time-consuming post-processing steps, such as smoothing and denoising. Similarly, MSSIM's reliance on reference images and potential variability makes it less practical in certain scenarios, thereby increasing the computational workload. In addition, CART's use of two child nodes per node and a greedy approach to predictions may overlook intricate data relationships and result in suboptimal solutions.

H. K-MEANS CLUSTERING ALGORITHM

In addition, the proposed method [53] significantly enhanced wood defect classification by integrating an unsupervised algorithm and k-means clustering into the image segmentation process. Compared with previous studies, the proposed method does not require the use of a complicated illumination and image-capturing apparatus. In addition, the

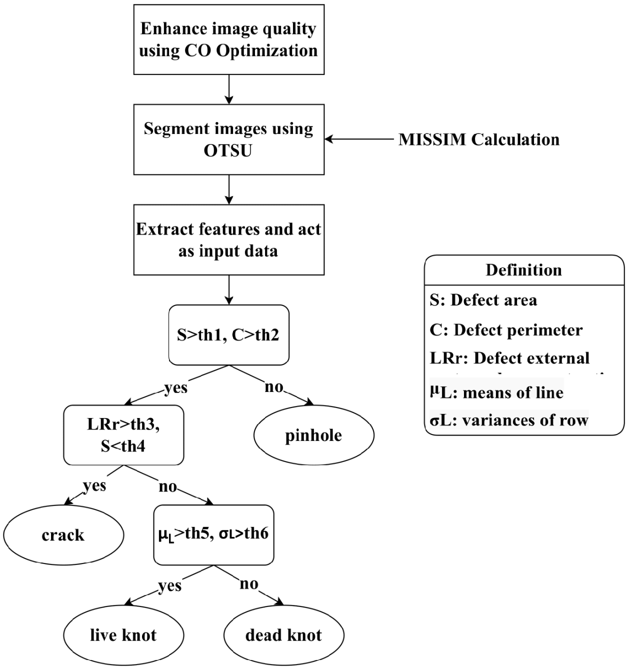

FIGURE 6. Modified classification and regression tree algorithm with convex optimization (CO).

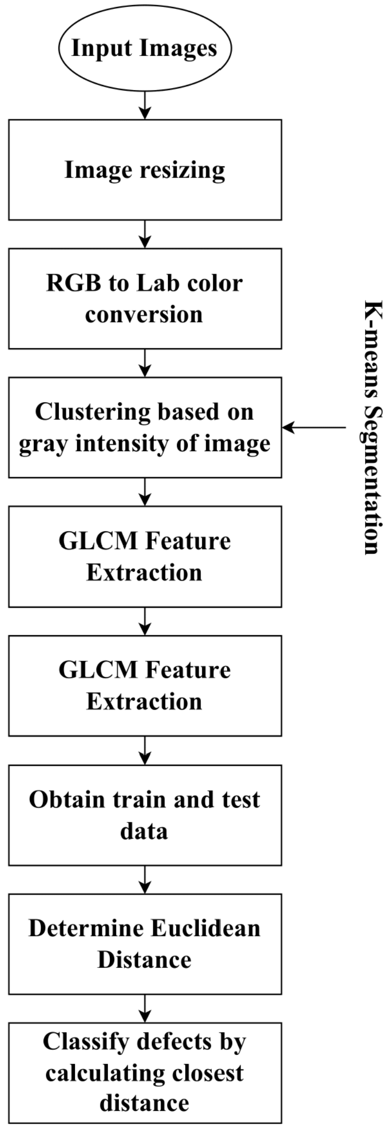

FIGURE 7. Flowchart of modified K-means clustering method.

implementation of *Lab* color space conversion enhances segmentation performance by making it easier to identify and isolate color information relevant to wood defects, surpassing the segmentation efficacy of alternative approaches, such as Luminance, In-phase, Quadrature (*YIQ*) color conversion with thresholding. In addition, iterative refinement and reassigning of data points in K-means clustering ensure convergence to optimal cluster classification [54], enabling the calculation of Euclidean distances to classify defects. Fig. 7 illustrates a flowchart of the proposed methods and shows the stages of the main algorithms.

The proposed method achieved an average accuracy of 95.33% with an F1-score of 95%, and an optimal average accuracy of 88.9% using a 3-fold cross-validation method. However, the dataset quality is limited by brightness variations and probable occlusions from camera instability. The proposed method struggles with larger augmented images, thereby indicating its limited applicability. Moreover, the K-means approach lacks clarity in selecting the number of clusters (K), introducing subjectivity and potentially improper assignments.

I. ADABOOST CLASSIFIER WITH DEEP LEARNING-BASED FEATURE EXTRACTION

Instead of relying solely on traditional image processing methods, [55] advocates for the integration of deep learning approaches, specifically leveraging deep convolutional generative adversarial networks (DCGANs) and Inception_v3 neural networks, coupled with the AdaBoost classifier for Pinus tree disease detection from unmanned aerial vehicle (UAV) images. By employing the concept of a generator and discriminator [56], along with Inception_v3 for background object elimination, AdaBoost effectively leveraged the extracted color and textural features of diseased and healthy trees for accurate disease recognition.

The proposed method outperformed the other machine learning and deep learning algorithms mentioned in this study, achieving a precision of 78.6%, recall of 95.7%, and F1-score of 86.3%. However, the proposed method relies on rigorous calibration of UAV cameras, making image acquisition complex and susceptible to noise. Additional denoising methods such as median filtering are required. Both the Inception_V3 and AdaBoost algorithms are computationally demanding and time-consuming owing to their ensemble nature, in addition to the overall processing time. Therefore, the proposed method offers an opportunity for further improvement.

J. EXTREME LEARNING MACHINE CLASSIFIER WITH DEEP LEARNING-BASED FEATURE EXTRACTION

Another study employed a CNN for feature extraction from wood images, serving as an input for an Extreme Learning Machine (ELM) for defect classification [57]. First, the utilization of the Non-subsampled Shearlet Transform (NSST) technique during image pre-processing effectively reduces redundancy and computational complexity, thereby improving feature extraction efficiency. In addition, the application of simple linear iterative clustering (SLIC) facilitates the creation of compact super-pixel image blocks, enhancing feature extraction by providing clearer contour edges for defects and backgrounds. This study utilized the advantage of CNN, which can extract low-level features, such as edges and textures of wood defects, as well as highly semantic features relevant to different types of defects. In addition, the implementation of a Genetic Algorithm (GA) in ELM as an optimization technique to search the solution space and iteratively evolve candidate solutions based on the performance of the ELM classifier leads to improved stability and performance. Fig. 8(a) and (b) show the proposed method, which utilizes a CNN and an ELM.

The proposed algorithm achieved an accuracy of 96.72% and a fastest detection time of 187ms. However, SLIC's reliance on user-defined parameters, such as the number of superpixels (K) and the compactness factor, poses limitations. Moreover, ELM's single-pass learning approach and the need to specify parameters such as the number of hidden neurons through GA increase time costs, making it impractical for real-world industrial applications.

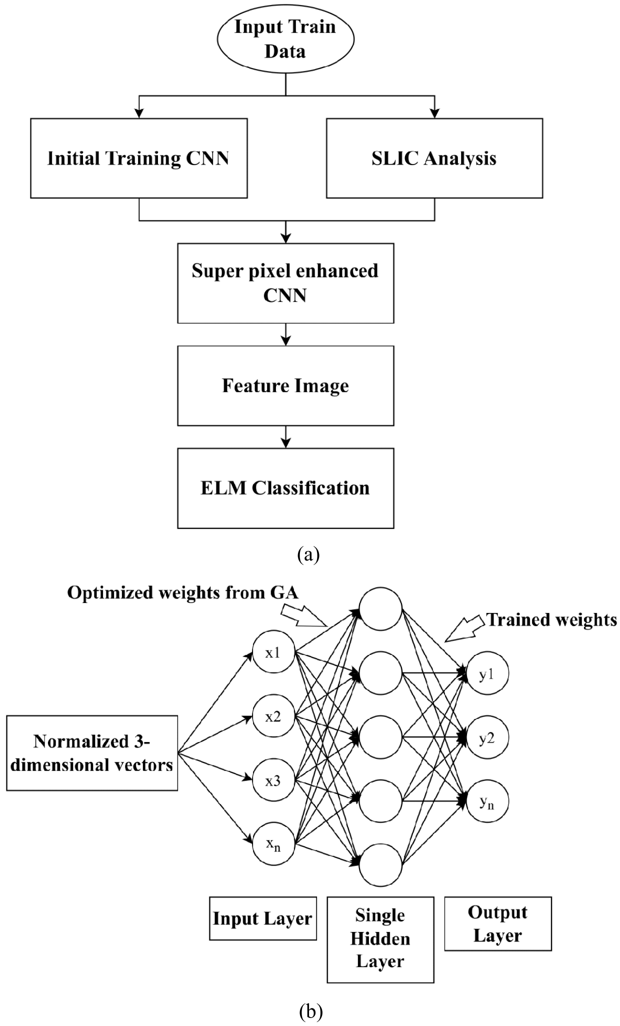

FIGURE 8. (a) Extreme learning machine (ELM) with CNN and (b) Algorithm with optimized weights from genetic algorithm (GA).

K. SUMMARIZATION OF MACHINE LEARNING-BASED INSPECTION

Table 1 summarizes the research on machine learning-based inspection methods. These studies were primarily concerned with the detection of surface defects in wood. However, there is a gap between them in real wood defect inspection applications in the industry. The input data of these algorithms must be preprocessed, and features must be extracted using traditional image processing and feature extraction methods, which are time-consuming and labor-intensive. Thus, the performance of the algorithms was heavily dependent on the extracted features. The following are some of the general limitations of machine learning-based inspections.

- Most of the reviewed studies had limitations in terms of data quality and dataset characteristics. Challenges include an imbalanced dataset, limitations in data quantity or quality, and difficulties in determining optimal parameters for model training and evaluation.
- Traditional image processing and feature extraction methods are required before defect classification. Owing to the nature of the chosen classifier, image processing and feature extraction methods are required to obtain the input data for the algorithm, which is typically difficult, poor, and time-consuming. Domain knowledge is typically necessary to interpret these features.
- The proposed algorithms are significantly dependent on the chosen hyperparameters. Hyperparameters, such as kernels, neuron numbers, and clusters, must be specified. Certain models may struggle with sensitivity to scale, rotation, and translation changes, and require adjustment for optimal performance.

Hence, the computational complexity of traditional image processing methods and machine learning algorithms poses challenges, particularly with large-scale datasets, leading researchers to turn to deep learning approaches, such as CNNs, for wood defect inspection. CNNs automatically extract features without manual engineering [58], offering superior performance in defect detection tasks and providing defect localization, making them well-suited for wood defect inspection applications, such as detecting concrete cracks [59] or even combining with other robust networks in defect detection, such as small surface defect detection [60]

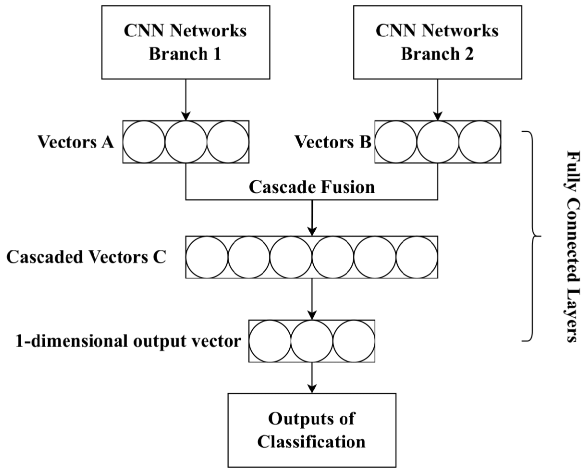

FIGURE 9. Modified bilinear fine-grained CNN.

and developing automated surface inspection (ASI) systems [61].

IV. DEEP LEARNING BASED-DEFECT INSPECTION

CNNs are used in computer vision tasks because of their ability to learn both low- and high-level image features, making them well suited for wood defect detection, where defects can appear at various locations in the image. Their weight-sharing network topology simplifies the model complexity and reduces the number of parameters [62], whereas deeper CNNs offer improved detection performance by capturing intricate patterns and hierarchical representations despite the increased computational cost during training.

A. BILINEAR FINE-GRAINED CONVOLUTIONAL NEURAL NETWORK CLASSIFIER

In the context of wood defect inspection, [63] proposed the use of a Bilinear Fine-Grained Convolutional Neural Network (BLNN) tailored specifically to distinguish closely related knot defect types. By leveraging data augmentation techniques, such as mirroring, rotation, Gaussian noise, hue value, and salt-and-pepper noise, to enhance the dataset size and prevent overfitting, the two BLNN subnetworks efficiently extract fine-grained features from different scales of the knots and combine them into a single output vector, as illustrated in Fig. 9. This enhances the model's ability to represent the complex patterns and structures of the knots. The proposed algorithm is then trained using optimized hyperparameters, including the epoch, batch size, and learning rate.

The proposed method achieves 99.02% accuracy and 79.5ms detection time by optimizing hyperparameters, surpassing other algorithms. Although it excels in wood knot detection, its applicability to other fine-grained recognition tasks may be limited owing to tailored features. Additionally, the use of only two subnetworks in the BLNN may restrict its ability to capture diverse features, potentially impacting its performance in new tasks.

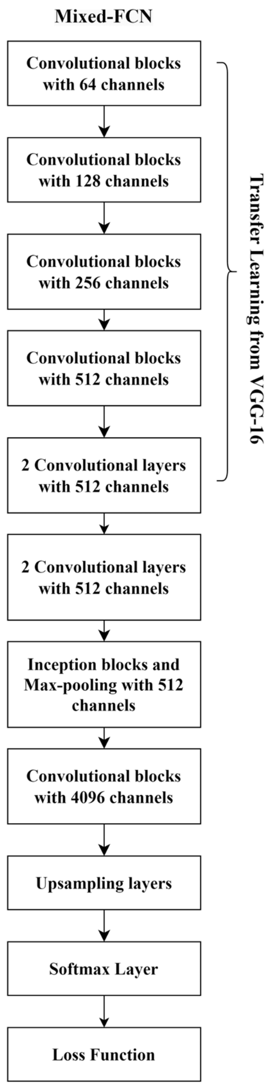

FIGURE 10. Replacement of visual geometry group (VGG) of 16 layers in mixed fully CNN.

B. MIXED-FULLY CONVOLUTIONAL NEURAL NETWORK WITH VISUAL GEOMETRY GROUP

On the other hand, [64] proposed a wood defect inspection model, a Fully Convolutional Neural Network (Mix-FCN), that integrates a Visual Geometry Group with 16 layers (VGG-16) network [65]. In this study, two wood defect datasets were augmented using rotation, diagonal flip, mirroring, hue value, Gaussian noise addition, and transformation with polar coordinates to ensure a better generalization performance on unseen data. For the proposed algorithm, Mix-FCN replaces the front half of the network with VGG-16, which employs max pooling for parameter reduction and upsampling layers to restore the images to their original sizes, as shown in Fig. 10. Techniques such as dropout regularization, L2 regularization, and transfer learning have been used to mitigate overfitting.

TABLE 1. Machine learning-based wood defect inspection methods.

Article	Method	Detection Criterion	Performance	Advantages	Disadvantages
[34]	SVM Classifier with BoW Technique	Recognition rate	94%	High classification rate	• Choices of hyperparameters and kernels • Using complex quadratic programming in SVM
[38]	PCA and LDA with Compressed Sensing	Recognition rate Detection time	94% 44.6ms	Fast classification time	• Required domain knowledge on feature extraction. • Challenges in choosing an appropriate representation dictionary
[42]	Wavelet transforms and KNN	Accuracy	98%	Outperform performance in [45]	• Computationally expensive • Imbalanced dataset • Determination of K value
[44]	LTEM and Feed forward BP network	Accuracy MSE	90.5% 0.0718	High accuracy and low misclassification	• Classification without defect localization • Sensitive to scale, rotation, and translation changes • Adjustment of neuron numbers
[47]	Modified HU invariant moment and BP network	Accuracy	97.33%	Improvement based on the original Hu moment	• Computationally expensive • Determination of optimal hyperparameter of moments
[48]	ANN Classifier with GLDM	F1-score	84.01%	Good performance on defect classification	• Limited choices of neuron number • Big range of epoch number • No hyperparameter adjustments
[51]	CART with CO	Accuracy	96.3%	High classification rate	• Time-consuming for image processing. • Required reference images. • Algorithm with a greedy approach
[53]	K-Means Clustering Algorithm	Accuracy F1-score Accuracy at 3-fold cross-validation	95.33% 85% 88.9%	High classification rate	• Data quality may constraint • Suitable for small sized dataset • Specifying cluster number
[55]	AdaBoost Classifier with DCGANs and DCNN	Precision Recall F1-score	78.6% 95.7% 86.3%	Good performance on disease classification	• Complex image acquisition method • Computationally expensive
[57]	ELM Classifier with CNN and GA	Accuracy Detection time	96.72% 187ms	High accuracy	• Sensitive to parameter defined in image processing method • Limited ability to adapt complex defects' patterns • Parameter selection of GA and neuron number

The modified Mix-FCN algorithm achieved an impressive overall classification accuracy of 99.14% and a pixel accuracy of 91.31%, surpassing other methods such as SegNet [66]. Although parameter reduction has been implemented, the detection time of 0.368s remains relatively long for real-world industrial applications. This is potentially due to the computational demands of the VGG-16 implementation. In addition, separate training of datasets on VGG-16 and Mix-FCN introduces overfitting risks and hyperparameter sensitivity and requires time-consuming optimization methods.

C. IMPROVED SINGLE SHOT DETECTOR WITH RESIDUAL NETWORK

Meanwhile, the proposed method [67] achieved performance improvements in classifying five types of wood defects, primarily because of the replacement of the VGG network with Residual Network of 101 layers (ResNet-101) [68] in

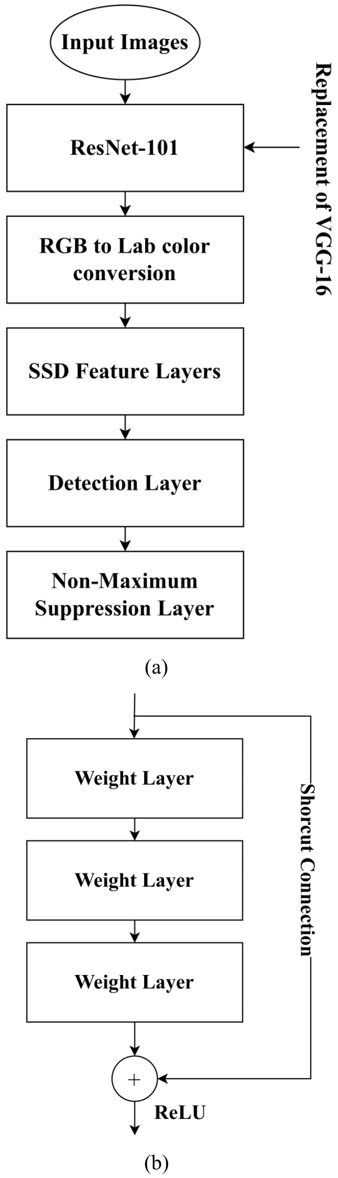

FIGURE 11. **(a) Modified SSD with residual network of 101 layers and (b) Shortcut connection.**

the single-shot detector (SSD) [30] architecture. Fig. 11(a) and (b) illustrate the SSD architecture enhanced with ResNet, showing the modifications made to incorporate ResNet for feature extraction. The shortcut connections of the ResNet model mitigate vanishing gradients and facilitate more effective feature optimization and learning with deeper layers, leading to an enhanced detection performance. Additionally, data augmentation techniques such as mirroring, rotation, contrast adjustment, and scaling contribute to improving the robustness of the model by increasing the dataset size and diversity.

The proposed method improved the accuracy to 89.7% and reduced the detection time to 90ms, surpassing the original SSD's 79.6% accuracy and 116ms detection time. However, ResNet's depth increases computational complexity and memory usage, limiting its applicability in resource-constrained environments. Furthermore, the proposed method experienced bounding deviations, which affected the defect localization accuracy and potentially caused significant losses in the industrial settings.

D. RESIDUAL NETWORK CLASSIFIER WITH TRANSFER LEARNING

The wood knot detection model proposed in [69] introduced the utilization of the ResNet-34 network with transfer learning, building on the success of their previous work [63]. Similar data augmentation techniques were employed to enhance the dataset size and diversity, along with the use of a deeper ResNet-34, which leveraged shortcut connections to address the gradient vanishing issue during training. The BLNN, the other hand, may not benefit from such shortcut connections, leading to a slower convergence. The algorithm utilizes the same loss function and optimizer as in previous work, with the addition of transfer learning by pre-training ResNet-34 on ImageNet [70], providing a valuable starting point for feature learning on the wood knot dataset and reducing the training time.

The proposed algorithm achieved superior performance compared to AlexNet, VGGNet-16, and GoogLeNet [71] with an accuracy of 98.69%, a recall of 98.66%, an F1-score of 98.46%, and a false acceptance rate (FAR) of 0.25% [63]. Despite the benefits of transfer learning, the use of a fully connected layer in the algorithm introduces computational constraints and potential overfitting, particularly when relying solely on identity mapping and residual learning provided by residual blocks. To address this, [72] we propose a study using a shallower ResNet-18 model with a global pooling layer (GAP) to reduce computational requirements.

E. AUTOMATED OPTICAL INSPECTION SYSTEM WITH INCEPTION RESIDUAL NETWORK V2

Furthermore, [73] advances have been made in edge-glued wood panel defect detection by evaluating CNN variations, including MobileNetV2 [74], ResNet-50 [68], InceptionResnetV2 [75], and DenseNet-201 [76]. In this study, raw and laser-aligned images of wood panels were captured using an industrial camera with structured light detection, and defect characteristics were extracted using k-means clustering with contours and morphological processing. In this context, the architecture of InceptionResnetV2 includes various modules, such as inception and ResNet modules, which are designed to extract features at different levels of abstraction. These models employ techniques such as multi-scale feature extraction, spatial aggregation, and residual connections, enabling them to capture both low- and high-level features in images.

They reported that InceptionResnetV2 achieved the best classification performance with real-time capabilities, with a precision of 97%, recall of 90%, and evaluation time of 80ms. However, the AOI-based image acquisition method faces

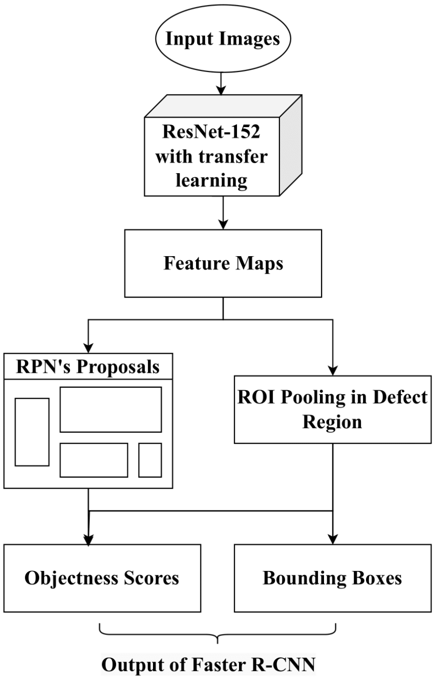

FIGURE 12. Faster R-CNN with pre-trained residual network with 152 Layers.

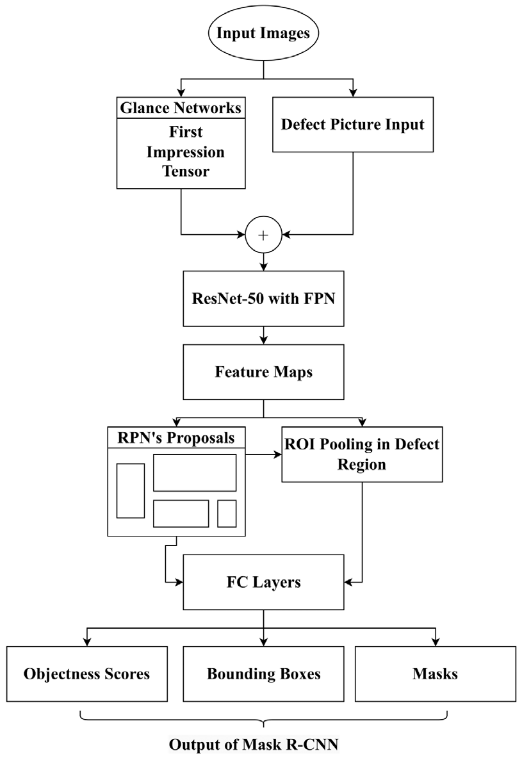

FIGURE 13. Mask R-CNN with glance network.

challenges, such as environmental sensitivity and the need for frequent recapturing, whereas the use of denoising and geometric filters adds complexity. In addition, the sensitivity of CNN algorithms to hyperparameters necessitates careful tuning to achieve an optimal performance.

F. FASTER REGION-BASED CONVOLUTIONAL NEURAL NETWORK WITH PRE-TRAINED RESIDUAL NETWORK-152

In this study [77], the adoption of more advanced object detection models, such as the Faster Region-based Convolutional Neural Network (Faster R-CNN) [32] with transfer learning, marked a significant advancement in wood defect detection instead of classification. In this study, the introduction of a Region Proposal Network (RPN) efficiently generated defect region proposals, enhancing accurate defect identification by handling variations in size and aspect ratio. Predefined anchor boxes aid precise defect localization. Meanwhile, Region of Interest (RoI) pooling coupled with max-pooling contributed to the efficiency of the algorithm by producing fixed-size outputs for the selected defect regions. Extensive training of pretrained models, such as AlexNet, VGG16, BNInception, and ResNet152, with various combinations of batch size and learning rate optimized the base networks for improved defect detection. Fig. 12 shows an illustration of the proposed Faster R-CNN and its defect detection operation.

The proposed method [77] achieved notable improvements in detection speed, but exhibited poorer accuracy compared to the other algorithms. Specifically, Faster R-CNN with ResNet-152 achieved an average accuracy of 80.6% with a detection time of 48.01ms. However, the algorithm still utilizes RoI pooling, which sacrifices spatial information and is invariant to object sizes. The use of fully connected layers introduces computational intensity and limits the receptive field owing to fixed-size windows.

G. MASK REGION-BASED CONVOLUTIONAL NEURAL NETWORK WITH GLANCE NETWORK

Instead of the Faster R-CNN, a study [78] adopted a Mask Region-based CNN (Mask R-CNN) [79] and achieved a significant advancement in wood defect detection by utilizing pixel-level segmentation. The incorporation of a glance network designed using neural architecture search (NAS) technology iteratively evaluates multiple architecture candidates and enhances the detection and classification of defects in wood veneers. By combining the intermediate features extracted from the NAS-designed glance network using genetic algorithms (GA), the proposed method combines relevant intermediate features. A multichannel mask R-CNN is then employed to detect defects by providing rectangular region proposals and predicting pixel-level masks for each defect, as shown in Fig. 13.

The proposed method achieved a high Overall Classification Accuracy (OCA) of 98.7% and mean Average Precision (mAP) of 95.31%, but with an inference time of 2.5s, making it unsuitable for real-time applications. However, the long inference time is attributed to the two-stage nature of Mask R-CNN and the separate feature extraction process for each

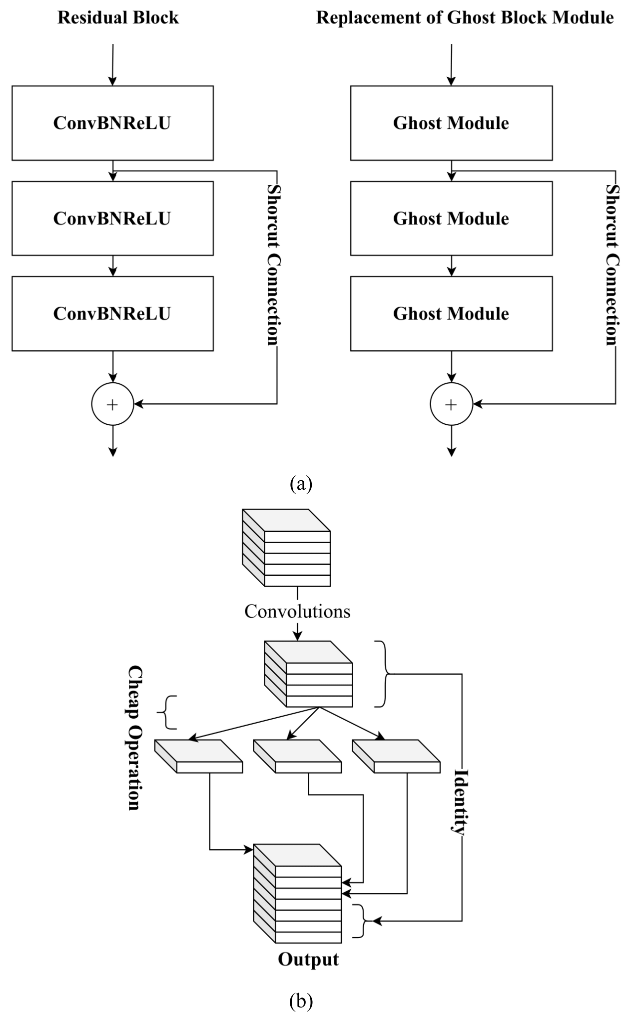

FIGURE 14. (a) Residual block and replacement of ghost block module, and (b) Ghost block basic operation.

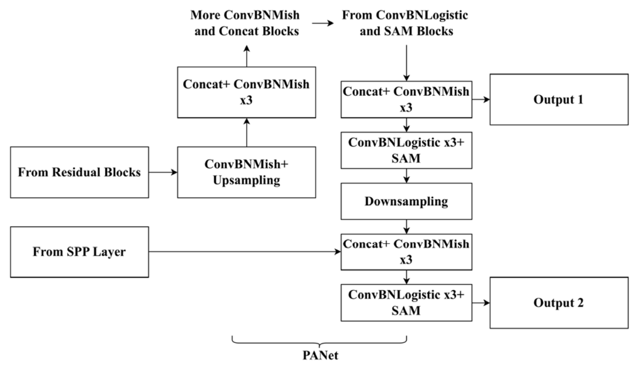

FIGURE 15. YOLOv4's path aggregation network (PANet) and output layer.

test image's region proposals. The implementation of GA can also lead to inconsistent results across different runs of the algorithm, making it less deterministic.

H. YOU ONLY LOOK ONCE V3 WITH GHOST BLOCK STRUCTURE

In another study [80], an enhanced version of You Only Look Once (YOLO), the YOLOv3 algorithm, was proposed for wood surface defect detection. By incorporating skip connections from ResNet in Darknet and replacing the residual blocks with a ghost block structure, the algorithm was simplified and optimized for limited computational resources, as shown in Fig. 14(a) and (b). In addition, GridMask [81] was introduced for data augmentation to aid the model in learning features that are invariant to various transformations and occlusions. The replacement of focal loss with confidence loss further improves the ability of the model to control false positives and negatives, ensuring more balanced scores and convergence.

The improved YOLOv3 algorithm achieved a notable improvement in wood defect detection with an mAP of 86.49% and 28FPS. However, compared to previous studies, the algorithm is slower and lacks robustness for real-time applications. This limitation may be attributed to the smaller input image size of 200×200 pixels, which was insufficient for YOLOv3's optimal size of 416×416 pixels. Furthermore, the algorithm struggles to accurately detect and localize larger objects, and the implementation of GridMask introduces sensitivity to the grid parameters. Despite efforts to reduce model weight, significant computational resources are required for inference.

I. IMPROVED YOU ONLY LOOK ONCE V4 WITH SPATIAL ATTENTION MODULE

A newer version of YOLOv4 was further enhanced and proposed for lumber surface defect detection, focusing on improving detection performance while maintaining efficiency [82]. The algorithm reduces the convolutional layers of CAP Darknet-53 and the path aggregation network (PAN) in the head part, along with reducing the channels of the backbone networks using a scaling coefficient α. The proposed algorithm also incorporates the Mish activation function to prevent exploding gradients and saturation, thereby enhancing gradient flow. To further enhance spatial information, a Spatial Attention Module (SAM) was implemented before the head part, as shown in Fig. 15, selectively attending to the relevant spatial locations for defect detection.

The proposed method outperforms previous versions in detecting wood defects across various input sizes, achieving mAPs of 91.5% with 77.1FPS, 93% with 54.4 FPS, and 92.8% with 40.9FPS at different resolutions. However, its inference speed remains low for real-time industrial applications, as the image size increases. Reductions in convolutional layers aim to alleviate computational demands, but may compromise pattern capture and feature representation. In addition, channel reduction results in less expressive feature representations, hindering the ability of the algorithm to learn relevant information effectively. Mish activation, while beneficial, requires careful parameter selection in addition to computational complexity.

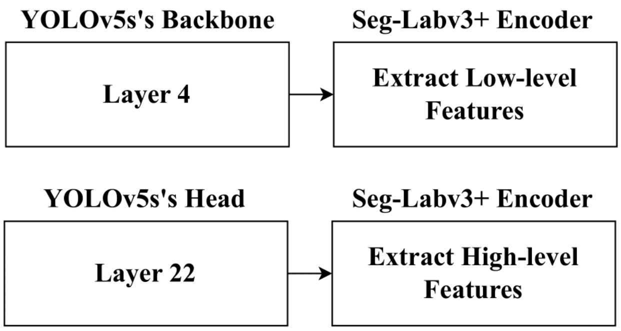

FIGURE 16. Seg-Labv3+ backbone with YOLOv5s.

J. DEEPLABV3+ WITH YOU ONLY LOOK ONCE V5 AND SQUEEZE AND EXCITATION

The YOLOv5 algorithm, known for its improved weight size and training speed, was utilized in [83] and leveraged as the backbone network in a DCNN architecture for defect detection on particleboard, as shown in Fig. 16, with the aim of improving the weight size while increasing training and detection speeds. In this study, the algorithm addresses the grid sensitivity of image edges, enhancing bounding box predictions for objects near image corners based on DeepLabv3+, [84] which introduces an encoder-decoder architecture with atrous convolutions and spatial pyramid pooling for semantic segmentation. Additionally, YOLOv5 incorporates attention mechanisms [82], specifically Squeeze and Excitation (SE) layers, in [85] which the squeeze operation reduces the spatial dimension of feature maps, whereas the excitation operations recalibrate the importance of different channels within each feature map by learning channel-wise weights, significantly improving feature representation and detection accuracy.

The combination of YOLOv5 and DeepLabv3+ achieved an mAP of 93.20%, a mean IoU of 76.63%, and an inference speed of 56.02FPS. Nevertheless, the inference speed of the algorithm requires improvement for real-time industrial applications, as observed in this study. DeepLabv3+'s use of dilated convolutions may struggle with fine detail capture, especially in small or occluded defects such as glue spots and sand leakage. In addition, the class imbalance in the dataset affects minority class learning, leading to higher error rates for specific defects. During real-world inferences in the wood industry, real-world inference times range from 183ms to 208ms, hindering practical real-time use in the wood industry.

K. STC-YOU ONLY LOOK ONCE V5

Another study [86] also used the concept of the attention mechanism in YOLOv5, combining a swin transformer to detect wood defects of various sizes. The implementation incorporates the Coordinate Attention (CA) mechanism [87] to capture spatial dependencies within feature maps and replaces the C3 layers in YOLOv5 with a transformer–encoder module for encoding both local and global contextual information. Meanwhile, weighted bi-directional feature pyramid network (BiFPN) in the network's neck enhances feature fusion efficiency, and the swine transformer in the detection layer captures global and contextual information with different head sizes to improve detection performance. Fig. 17 shows a section of the modifications in the proposed YOLOv5's backbone and neck network.

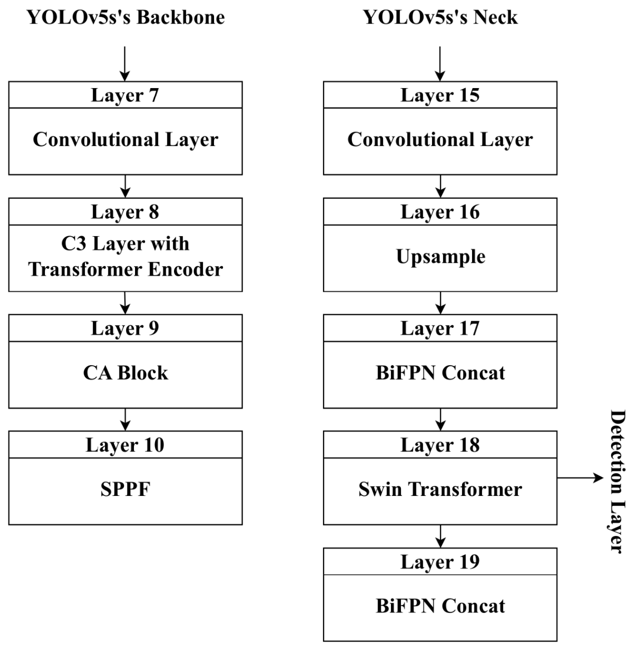

FIGURE 17. A section of YOLOv5 backbone with transformer encoder and coordinate attention (CA) and neck network with weighted bi-directional feature pyramid network (BiFPN) and swin transformer.

Finally, the improved YOLOv5 achieves an mAP of 84.2% and 74.6FPS with 6M parameters using a ghost network. However, the additional complexity introduced by the swine transformer in the detection part leads to a slower inference speed because it captures more diverse spatial relationships of the features. In addition, the implementation of the transformer encoder requires storing attention weights for the entire sequence of representations, resulting in significant processing time. These factors contribute to the slower inference speed of the proposed algorithm compared to that of the original YOLOv5.

L. YOU ONLY LOOK ONCE V5 WITH GHOST NETWORK AND SIMPLE, PARAMETER FREE ATTENTION

In this study [88], the concept of a ghost network and attention mechanism were integrated into the YOLOv5 backbone, resulting in a lightweight and efficient wood surface defect detection model. The ghost module, inspired by GhostNet [89], [90], replaces the C3 and SSPF layers in YOLOv5 and reduces the computational resources by downsizing feature maps and convolving and concatenating them to maintain the same channel number. Meanwhile, the simple, parameter free attention (SimAM) mechanism [90] allows the model to selectively focus on the relevant features within the input data and optimize the energy functions in each neuron without adding parameters, enabling the design of lightweight models suitable for real-time applications.

The proposed model outperforms the original YOLOv5 with a mAP@0.5:0.95 of 43.3% and an inference time of 1.4ms, and even surpasses YOLOv5m with a mAP@0.5:0.95 of 45.2% and an inference time of 4.8ms. Despite having only 0.82M and 7.46M parameters, suitable for real-time applications, its detection performance remains suboptimal for robust defect detection. Although efficient, the use of a cosine learning rate schedule may require manual adjustment for different datasets or architectures, and its sensitivity to hyperparameters can lead to suboptimal performance.

M. SUMMARIZATION OF DEEP LEARNING-BASED INSPECTION

Table 2 summarizes various deep learning-based inspection studies, predominantly employing CNN-based algorithms for automatic feature extraction and simplifying image processing. Object detection models, such as SSD, R-CNNs, and YOLOs, are utilized for defect localization and classification with variations in inference speeds. However, their performance can be influenced by factors such as the model architecture, training strategies, and optimization techniques. However, these deep-learning algorithms still need to be improved, and their general limitations can be summarized as follows:

- Most deep learning-based algorithms consist of deep layers to extract detailed features and improve detection performance. This contributes to the large number of parameters and high computational requirements, that are unsuitable for real-time applications and limited computational devices.
- Large and balanced datasets are required for algorithm training to achieve excellent inspection performance. Most deep learning algorithms exhibit poor performance with small datasets. However, high-resolution wood defect datasets are limited.
- Annotation of the dataset is required before training the algorithm. Object detection models require annotated datasets as the input data. Thus, careful annotation and labeling with correct classes is time consuming. Inaccurate bounding boxes result in a poor performance of the algorithms.
- Most deep learning-based algorithms are sensitive to the chosen hyperparameters. Different combinations of hyperparameters, such as epochs, batch size, learning rate, and neuron number, can cause differences in inspection performance. The selection of optimal values is time consuming.

V. FUTURE TRENDS AND CHALLENGES

A. FUTURE TRENDS IN WOOD DEFECT INSPECTION

Manual inspection, once relied upon for wood defect detection, has become impractical because of its subjective interpretation, high time cost, and low efficiency. The advent of AOI systems, integrating machine vision components such as cameras, light sources, processors, and controllers, has significantly enhanced inspection performance by offering more precise detection. Further enhancements have been achieved by incorporating machine learning algorithms into AOI systems. Since 2013, an increasing number of studies have focused on leveraging machine learning algorithms for automated defect inspection, resulting in higher efficiency and precision. Ongoing research continues to refine these algorithms to improve the wood inspection performance. In recent years, sophisticated algorithms, particularly deep learning algorithms such as CNNs, have significantly enhanced inspection performance by eliminating the need for humans.

B. CHALLENGES IN WOOD DEFECT INSPECTION

1) WOOD DEFECT DATASET

Designing a robust wood inspection system using both machine learning and deep learning algorithms requires a wood defect dataset that fulfils requirements such as high resolution, large dataset size, and a balanced class for each type of defect. From the reviews in sections three and four, most wood defect datasets are not available to the public but are obtained using self-developed AOI systems and image acquisition methods. Therefore, it is difficult to obtain high-quality wood datasets that satisfy researchers' demands. Although some open-source datasets are available, they have limited resolutions and defect types. To overcome these limitations, data augmentation techniques are required to increase the dataset size. However, over-augmentation can affect the representation of the dataset in real scenarios, which may cause suboptimal detection performance of the algorithm.

2) INSPECTION PERFORMANCE OF ALGORITHM

Most machine learning algorithms classify wood images as either defective or non-defective without obtaining the spatial information of defects, such as defect location. In addition, the additional image preprocessing methods required by machine-learning algorithms increase the inference time of the model. However, deep learning algorithms achieve high accuracy in defect inspection. However, the architecture of algorithms typically consists of deep layers and requires large computations, which are not suitable for limited resources. Object detection models are suitable for detecting defects with both classification and localization, but it is challenging to balance the accuracy, inference speed, computational resources, and mAP. In addition, most algorithms are specifically designed for detecting specific wood defects, and it is difficult to achieve high inspection performance by implementing a new dataset. Furthermore, most of the proposed algorithms are designed to classify only a few types of wood defects, which may be suboptimal in real-world scenarios because wood defects can be presented in various forms.

TABLE 2. DEEP learning-based wood defect inspection methods.

Article	Method	Detection Criterion	Performance	Advantages	Disadvantages
[63]	BLNN-based Classifier	Accuracy Detection time	99.02% 79.5ms	High accuracy	• The algorithm is less transferrable to a new task • Simple feature extraction
[64]	Mix-FCN Classifier with VGG-16	Classification accuracy Pixel accuracy Detection time	99.14% 91.31% 0.368s	High accuracy	• Long detection time • Complex and deep algorithm used • Time-consuming for training
[67]	Improved SSD with ResNet-101	Accuracy Detection time	89.7% 90ms	Improvement based on the original SSD	• Complex and deep algorithm used • Large computations required • Bounding box deviation
[69]	ResNet-34 Classifier with transfer learning	Accuracy Precision Recall F1-score FAR	98.69% 98.32% 98.66% 98.46% 0.25%	High accuracy and low error rate	• Fully connected layers introduced large parameters. • Heavily relying on identity mapping and residual learning
[73]	AOI System with Inception ResNetV2	Precision Recall Detection time	97% 90% 80ms	High accuracy	• Complex machine vision system. • Complex image processing method • Sensitive to hyperparameters
[77]	Faster R-CNN with Pre-trained ResNet-152	Averrage Accuracy Detection time	84.01% 48.01ms	Classification of nine types of wood defects	• Poorer accuracy • Invariant to object sizes • Fully connected layers introduced large parameters.
[78]	Mask R-CNN with Glance Network	OCA mAP Detection time	98.7% 95.31% 2.5s	High mAP	• Low detection speed • Time cost for finding the optimal glance network • Stochastic nature of GA
[80]	YOLOv3 with Ghost Block Structure	mAP Detection speed	86.49% 28FPS	High accuracy	• Low detection speed • Improper input size • Sensitivity of grid parameters chosen • Large model weight
[82]	Improved YOLOv4 with SAM	mAP Detection speed	91.5% and 77.1FPS (320x320 pixels) 93% and 54.4 FPS (512x512 pixels) 92.8% and 40.9FPS (608x608 pixels)	High mAP	• Low detection speed for larger images • Less expressive representation of features • Time cost for finding optimal hyperparameter of activation function
[83]	DeepLabv3+ with YOLOv5 and SE	mAP mean IoU Detection speed	93.20% 76.63% 56.02FPS	High mAP	• Sensitive to class imbalance dataset • Slow inference speed when applyied to real-world applications
[86]	STC-YOLOv5	mAP Detection speed	84.2% 74.6FPS	Fast detection speed	• Additional complexity on detection layer • Time-consuming • Require large computational resources
[88]	YOLOv5 with Ghost Network and SimAM	mAP@0.5:0.95 Detection time	43.3% with 1.4ms (YOLOv5n) 45.2% with 4.8ms (YOLOv5m)	Fast detection speed	• Low mAP • Sensitive and less transferrable learning rate decay strategy

3) DETECTION OF SMALL-SIZED WOOD DEFECTS

Previous studies on wood defect inspection have mostly focused on large- or medium-sized defects, which can easily be observed by the human eye. While the wood consists of complex wood grains and texture, some small-sized defects, such as pinholes and small knots, can be ignored by both the human eye and AOI system cameras. Object detection models such as SSD and YOLO pose challenges in detecting small-sized defects owing to their limited ability to capture the fine-grained details of these defects.

Therefore, setting appropriate confidence thresholds during post-processing is needed to find the correct balance to avoid false positives, whereas not missing true positives can be challenging. Modifications, such as the implementation of attention mechanisms in the algorithms, can potentially add to the complexity of the model and may inadvertently focus on irrelevant features.

VI. CONCLUSION

Wood defect inspection has undergone a remarkable evolution, transitioning from manual inspection methods to the adoption of automated optical inspection (AOI) systems. The integration of machine learning and deep learning algorithms into these systems has recolonized defect detection, offering unprecedented levels of precision and efficiency compared with traditional approaches.

Machine learning algorithms have played a pivotal role in enhancing the inspection performance by including extra feature extraction and learning from vast datasets. However, in recent years, there has been a notable shift towards deep learning techniques, particularly CNNs and even object detection models which have demonstrated superior accuracy and robustness by eliminating the need for manual feature engineering.

Anticipating continued advancements in deep learning methodologies, driven by improvements in model architectures, training algorithms, and computational resources. These advancements are expected to further enhance the capabilities of wood defect inspection systems, enabling them to achieve higher levels of accuracy and efficiency.

Object detection algorithms in reviewed studies such as YOLO have shown significant strides in addressing limitations such as computational expense and performance degradation. The integration of lightweight network architectures such as Ghost Network reduces the computational overhead while maintaining performance. In addition, attention mechanisms, such as self-attention or spatial attention, can enhance defect detection by allowing models to focus on relevant features and regions within images. Enhancement of inspection performance can be achieved by applying these modifications to YOLOv8 in the future.

Furthermore, the enhancement by the integration of advanced technologies such as reinforcement learning, generative adversarial networks (GANs), and attention mechanisms into defect inspection systems, opens up new avenues for enhancing performance and adaptability. In addition, emerging trends such as transfer learning, domain adaptation, and federated learning hold promise for improving model generation and deployment in real-world scenarios.

In conclusion, ongoing research and development in wood defect inspection, coupled with the adoption of cutting-edge machine learning and deep learning techniques, are poised to revolutionize the industry. By staying abreast of new trends and embracing emerging technologies, the efficiency, reliability and effectiveness of defect inspection systems can be improved, ultimately maximizing the utilization of wood products and driving sustainable advancements in the field.

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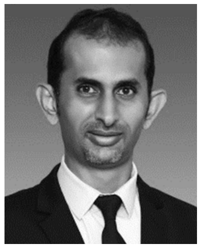

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