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CLASSIFICATION AND COMPUTING THE DEFECTED AREA OF KNOTS IN WOODEN STRUCTURES USING IMAGE PROCESSING AND CNN

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Abstract

Knots in wooden structures are common natural features in wood that result from where branches once joined the trunk of a tree. While they can add to the aesthetic appeal of wood, knots are often considered structural defects in construction because they can significantly affect the mechanical properties of wood. If knots are present in structural members, they cannot be ignored. Identifying the presence of knots and finding the corresponding defected area of a structural member is important to be able to reinforce the member, compensate for the reduced strength and ensure that it is safe and suitable for its intended use. In this study, the Inception-ResNet-V2 pre-trained Convolutional Neural Network (CNN) model is trained and validated with 2000 images for the classification of knots, and the defected area is calculated through Image Processing (IP) and other soft computing techniques. The images of knots are collected and equally classified into two categories: 1000 "Single knot" and 1000 "Multiple knots" images. 70% of the dataset is used for training, and 30% for model validation. Four statistical parameters, namely accuracy, precision, recall, and F1 score, are calculated to check the model performance for the classification task, as well as the corresponding confusion matrix. The model exhibited an overall accuracy of 84% in an independent evaluation with a new testing dataset of 200 images, while the defects could be properly quantified using IP techniques. The research work shows the potential of AI-based methodologies in structural health monitoring and damage identification. These methods can drastically improve our ability to assess the condition of structures and structural elements, offering enhanced precision and accuracy, real-time and cost-effective monitoring, predictive capabilities, and automation opportunities.

Keywords: Classification, Knots, Wood, Timber, Defected area, Image processing, CNN.

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1 INTRODUCTION

Wood has been an essential construction material throughout human history, with its use dating back to prehistoric times when early humans began creating tools and shelter. During the Neolithic period, timber framing became prevalent, a method still popular today. Ancient civilizations, like the Egyptians and Romans, also made extensive use of wood in construction. In more recent history, the industrial revolution saw the creation of new wood products like plywood and oriented strand board, expanding the versatility of wood in construction. Today, despite the emergence of alternative materials like steel and concrete, wood continues to be a fundamental material in construction due to its strength, flexibility, and sustainability.

Over time, wooden structures can face several issues due to various factors. One of the primary threats to wood is biological damage, which includes infestations from insects such as termites and beetles, as well as fungal growth that can cause wood rot. These biological agents can significantly weaken the structural integrity of the wood, leading to potential failure of the structure. Another issue with wood is that it is susceptible to environmental damage. Excessive moisture can lead to swelling and warping of the wood, and if not properly dried, it can also promote rot and mold growth. On the other hand, extremely dry conditions can cause the wood to crack and split. Other threats include fire damage, exposure to sunlight, chemical damage, and others. Therefore, while wood is a versatile and sustainable construction material, it requires regular maintenance and protective treatments to ensure its longevity.

Construction frequently uses wooden structures, especially for homes and small businesses. Wooden elements can serve a variety of functions, such as load-bearing walls, floor and ceiling framework, and support for cladding materials like masonry or siding [1]. Different factors, such as fluctuations in humidity and temperature, mechanical stress, and bug infestation, can result in cracks and knots in timber buildings. Depending on how old the timber is, it may develop cracks naturally or because of poor fitting or upkeep.

When a tree’s stem produces branches or limbs, those branches or limbs are eventually cut off, leaving a knot in the timber. Thus, knots are common natural features in wood that result from where branches once joined the trunk of a tree. While they can add to the aesthetic appeal of wood, particularly in decorative applications, knots are often considered structural defects in construction because they can significantly affect the mechanical properties of wood. They can lead to deviations in the woody tissue, cause trouble in processing, a decrease in the workpiece’s mechanical strength, and inferior wood quality [2].

Such knots may result in cracks forming and impair the wood’s structural stability as illustrated in Figure 1. It is critical to use wood that has been properly seasoned and treated to prevent fractures and knots from compromising the structural integrity. The structure should also be routinely maintained. Typically, structural components should be free of knots, whenever feasible. When designing the framework, it is crucial to take knots into account, as well as their type and location. For instance, since the internal forces on a beam are usually highest near the middle of the span, knots closer to the ends of a beam are typically less problematic than knots closer to the high-stress middle areas. It might be necessary to use a larger size of wood or to strengthen the member in some other way to make up for the knot’s decreased strength if it is in a crucial structural member and cannot be avoided. One should always seek the advice of a building engineer or other expert [3] in such cases.

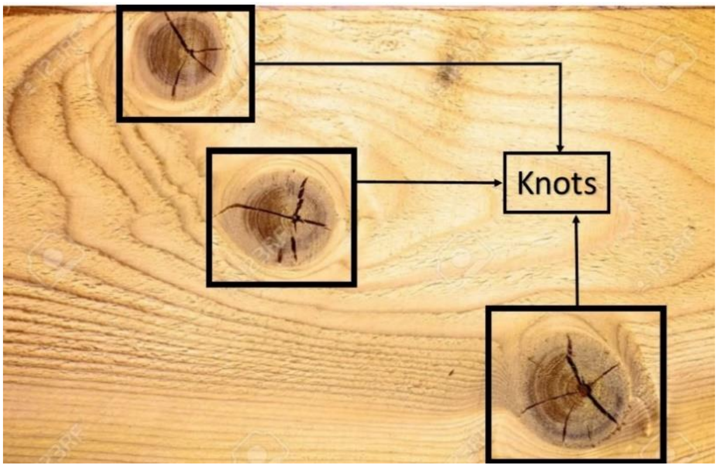


Figure 1: Knots in a wooden element.

The manual visual inspection of wooden structures can be challenging because many of the signs of decay or damage may not be immediately visible. For example, decay or damage may be hidden behind paint or other finishes, making it difficult to detect, while some parts of the structure may be difficult to access, such as locations under decks or porches, in crawl spaces or attics, or behind wall, and other unreachable areas. So, there is a need to automatically inspect the wooden structures to find defects like knots and their extent. In order to identify, pinpoint, and quantify harm or deterioration that might compromise the safety or functionality of the building, Structural Health Monitoring (SHM), is a procedure that involves tracking a structure's health and integrity over time [4], while similarly structural damage identification [5] involves assessing a building or other structure for signs of damage that may compromise its integrity. These processes are crucial in maintaining the safety and longevity of a structure.

Artificial intelligence (AI) methods have seen several applications in civil and structural engineering [6, 7], in many different areas such as: Structural modelling [8-10], structural design optimization [11], predictive maintenance [12, 13], SHM [14], risk assessment [15, 16], predicting strength [17, 18] and other structural characteristics [19], energy efficiency [20], construction planning and management [21], and others. AI methods have also been increasingly utilized in the field of structural engineering for damage detection, offering improved accuracy and efficiency compared to traditional methods [22, 23].

By utilizing Deep Learning (DL) and Convolutional Neural Networks (CNN), SHM can identify early degradation indicators like changes in rigidity, damping, or natural frequencies, enabling prompt action to stop additional damage. The evaluation of large-span wood structures has gained attention because they are frequently a component of buildings that are assigned to higher consequence classifications [24]. As a consequence of recent improvements in non-contact sensing devices, the SHM community has seen a considerable surge in DL-based structural system condition assessment approaches. CNNs are commonly employed for classification in these DL approaches. CNNs are trained using a large variety of datasets for different types of damage and anomaly assessment as well as post-disaster assessment [25]. The classification task can be done by CNN, while for computing the characteristics of defects, such as the defected area, other image processing (IP) and soft computing techniques can be employed. Information extraction from digital images is a multidisciplinary area that integrates approaches from computer science, mathematics, and engineering [26].

In the present research work, the pre-trained model InceptionResnet-V2 is employed for the classification of single and multiple knots and then IP techniques are for the estimation of the defected area. The pre-trained model is trained and validated on two classes of knots named (i) “single knot”, and (ii) “multiple knots”, with a dataset of 1000 images in each class. The remainder of the manuscript is organized as follows: The literature review is presented in section 2. Section 3 presents the research methodology, followed by the numerical results and the relevant discussion in section 4. Finally, the conclusions of the work, together with future research directions and opportunities are presented in section 5.

2 LITERATURE REVIEW

Ehtisham et al. [27] attempted predicting the defects in wooden structures by using pre-trained CNN models and IP techniques. They collected a dataset of 5000 images of wooden elements via site visits and internet sources. 80% of the images showed defects, while the remaining 20% represented no defects. Five different classifications were used for the defects, namely: (i) Vertical crack; (ii) Horizontal crack; (iii) Diagonal crack; (iv) Knots; and (v) Uncracked. The accuracy, precision, recall, and F1 Score of the predictions as well as the impact of deep layers on them were examined using the pretrained CNN models ResNet18, ResNet50 [28], and ResNet101 [29]. Longuetaud et al. [30] developed a method to automatically find and quantify knots in computerized tomography (CT) images of softwood beams. The technique, which represents a novel method for measuring the knot diameter, is based on the use of 3D connex components and a 3D distance transform. The findings are encouraging; depending on the beams, detection rates range from 71% to 100%, and no false alarms were detected.

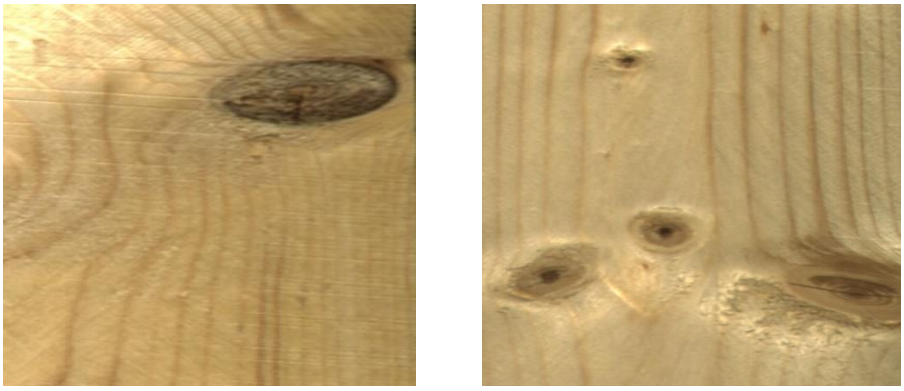
In [2], it was found that the modulus of elasticity (MOE) and compressive strength (Fc) of eucalyptus wood correlate with the size of wood knots. Small, medium, and large knots in 156 samples of Eucalyptus urophylla were classified into 3 groups, and samples from the same tree were chosen for the parallel fiber compression test to determine MOE and Fc. The MOE and Fc values of the smaller knot class (Class 1) were significantly different from those of the other classes with larger knots (Classes 2 and 3). In [31], a microwave technology is developed for producing and processing information on knots in wood prior to actually processing. The experimental setup consisted of a simple microwave emitter and receiver that was used to scan the wood samples for knots. After calibrating and boosting the signals, data storage and graphic display were carried out.

Qayyum et al. [32] attempted detecting cracks with CNN with variable image dataset, using the Inception-V3 CNN model, and dividing the dataset into four categories: Vertical crack, Horizontal crack, Diagonal crack, and Uncracked. To assess how the quantity of the dataset affects the models’ accuracy, the Inception-V3 model was trained on three train-test splits. The findings showed that classification accuracy is improved by training the models with larger datasets. Urbonas et al. [33] presented an automated visual inspection method for identifying and categorizing irregularities on the wood surface. For identifying flaws in wood veneer surfaces, they employed a faster region-based CNN (R-CNN). While faster R-CNN had been utilized effectively in object tracking and medical image processing in the past, it had not yet been employed to ensure the quality of wood panel surfaces. Pre-trained CNN models for transfer learning, such as AlexNet, VGG16, BNInception, and ResNet152 models were utilized. The results demonstrated the applicability of data augmentation and transfer learning techniques for the identification of four classes of wood veneer surface defects.

3 RESEARCH METHODOLOGY

3.1 Division of the dataset and methodology steps

A dataset of 2200 images is used in this study, which is acquired from the literature, in particular the work of Kodytek et al. [34]. Of these 2200 images, 2000 are equally categorized into the two classes: (i) “Single knot”, and (ii) “Multiple knots”, as illustrated in Figure 2, each set containing 1000 images. These images are utilized for training (70%) and validating (30%) the pre-trained CNN model. The remaining 200 images are also classified and used for testing the methodology, after the training has been completed. In the end, for illustration purposes, four images, two from each category, are used for testing the classification procedure and for estimating the defected area using image processing techniques. The steps of the methodology and are presented in Figure 3.



(a) (b)

Figure 2. The two classes of knots: (a) “Single knot”, (b) “Multiple knots”.

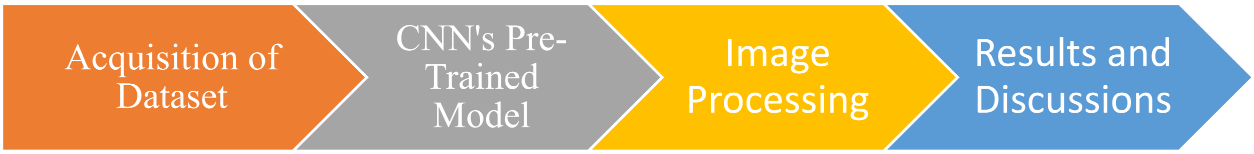


Figure 3. The steps of the research methodology.

3.2 CNN Model and image processing methodology

For the classification of the dataset, the InceptionResNet-V2 pre-trained CNN model is utilized [35]. InceptionResNet-V2 is a CNN architecture that is widely used for image classification tasks in the field of deep learning. The model combines ideas from two earlier CNN architectures, Inception and ResNet. Inception, also known as GoogLeNet, was known for its “network in network” design, which used modules of parallel convolutions with different kernel sizes to allow the model to learn different types of features from the input. However, as the Inception model became deeper, it became more difficult to train due to the problem of vanishing gradients. ResNet, or Residual Network, introduced a solution to this problem with the concept of “skip connections” or “shortcut connections”, which allow the gradient to be directly backpropagated to earlier layers. This innovation made it possible to train much deeper networks, with ResNet models commonly having hundreds of layers.

InceptionResNet-V2 combines these ideas into a single model, using Inception modules for effective feature extraction, and ResNet-style skip connections to improve the training of the deep network. The architecture is designed to provide high performance for image classification tasks, often achieving top-tier results on benchmarks like ImageNet. As with other DL models, InceptionResNet-V2 requires substantial computational resources to train, and its complexity means that it can be prone to overfitting, especially when training data is limited. However, pre-trained models are available that have been trained on large datasets like ImageNet, and these can be fine-tuned on a specific task with a smaller amount of data, like in the case of the present research work.

Several linked layers and convolutional blocks, such as convolutions, batch normalization, activation, ReLU, pooling, Max pooling, average pooling, completely connected, etc., make up the CNN architecture, as illustrated in Figure 4 [36]. InceptionResNet-V2 is a 164-deep layer network which has been trained with millions of images which span 1,000 different classes of objects, providing a broad and diverse range of data for the models to learn from. The network has an image input size of 299-by-299.

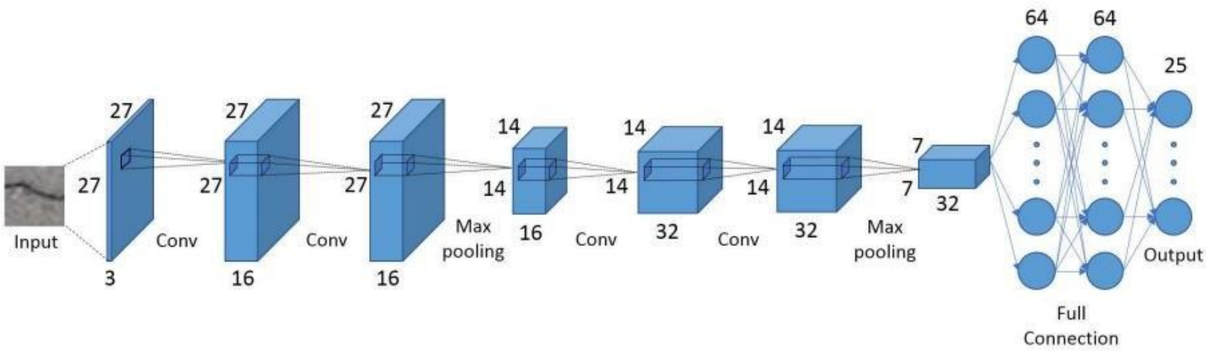


Figure 4. The CNN Architecture [37].

Digital image processing involves the use of computer algorithms to perform IP on digital images, with the aim to enhance their quality or extract valuable information from them. It is a subfield of digital signal processing and has a wide array of applications, ranging from computer vision to medical imaging and more. Image enhancing, picture restoration, image compression, image segmentation, and image recognition algorithms are used, among others, in this process [38]. In this study, we have used various digital image processing techniques in MATLAB for the estimation of the defected area of the knots present in an image, such as the commands *rgb2gray* (which converts RGB image or colormap to grayscale), *graythresh* (global image threshold using Otsu's method), *imbinarize* (binarize image by thresholding), *imfill* (fill image regions and holes), and others.

4 NUMERICAL RESULTS

4.1 Defects classification

The classification of the defects and the computation of the defected area of the knots are evaluated in this study. The knots are classified into two classes: (i) “Single knot”, and (ii) “Multiple knots”. The IncepResNet-V2 model is trained and validated on 2000 images and after training is completed it is independently tested on another 200 images. The accuracy is 84% for single and multiple knots, with a precision of 85% for multiple knots and 84% for single knots, recall values of 82% for multiple knots and 86% for single, and F1 score of 84% for both single and multiple knots [39]. The detailed results are shown in the confusion matrix of Figure 5. The accuracy of predicting multiple knots is slightly less than the accuracy of single knots by using this CNN model. The model took 1813 seconds to be trained on 2000 images with a per image resolution of 2800 × 1024 × 3 and image size of approximately 8 MB.

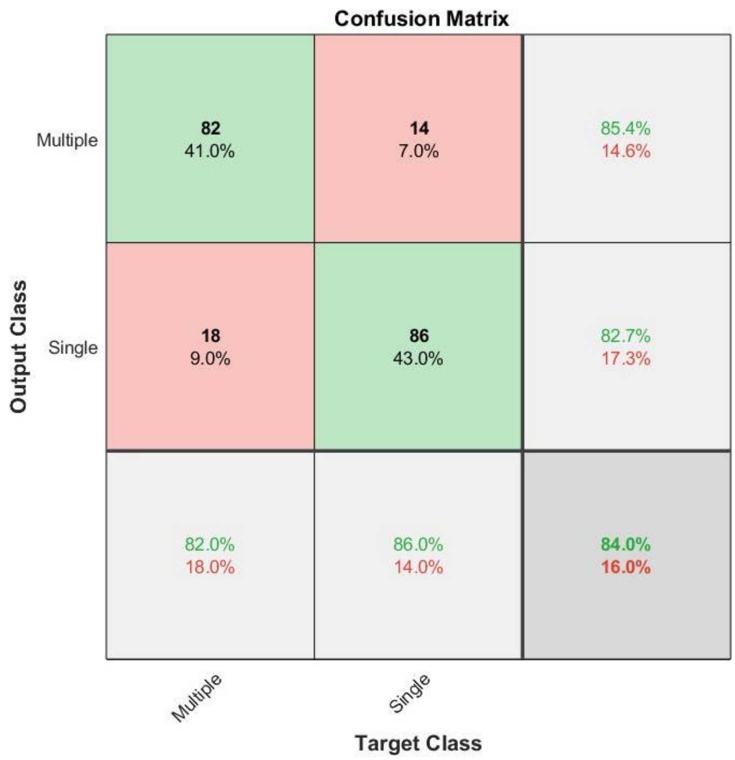


Figure 5. Confusion matrix for the 200 cases of the testing set images.

4.2 Defected area computation on selected images

Four images were randomly selected, two belonging to the single knot class and another two belonging to the multiple knots class, for testing the classification and also for calculating the defected areas using digital image processing techniques. First, the trained InceptionResNet-V2 CNN model truly classified all the images in their appropriate classes, i.e. two of them in the single knot class and the other two in the multiple knots class, as shown in Figure 6. Then the defected area was computed in terms of a percentage of the total image area. In Figure 6, the four original images are presented in the first column, on the left. The corresponding processed images are presented in the second (middle) column. In these images, the black pixels represent the intact (not defected) area, while the white pixels present the defected (knot) area. For illustration, the border between the two areas is highlighted with a red line. In the third column, on the right, the defected area is calculated as a percentage of the total image area and the results are presented for each individual case.

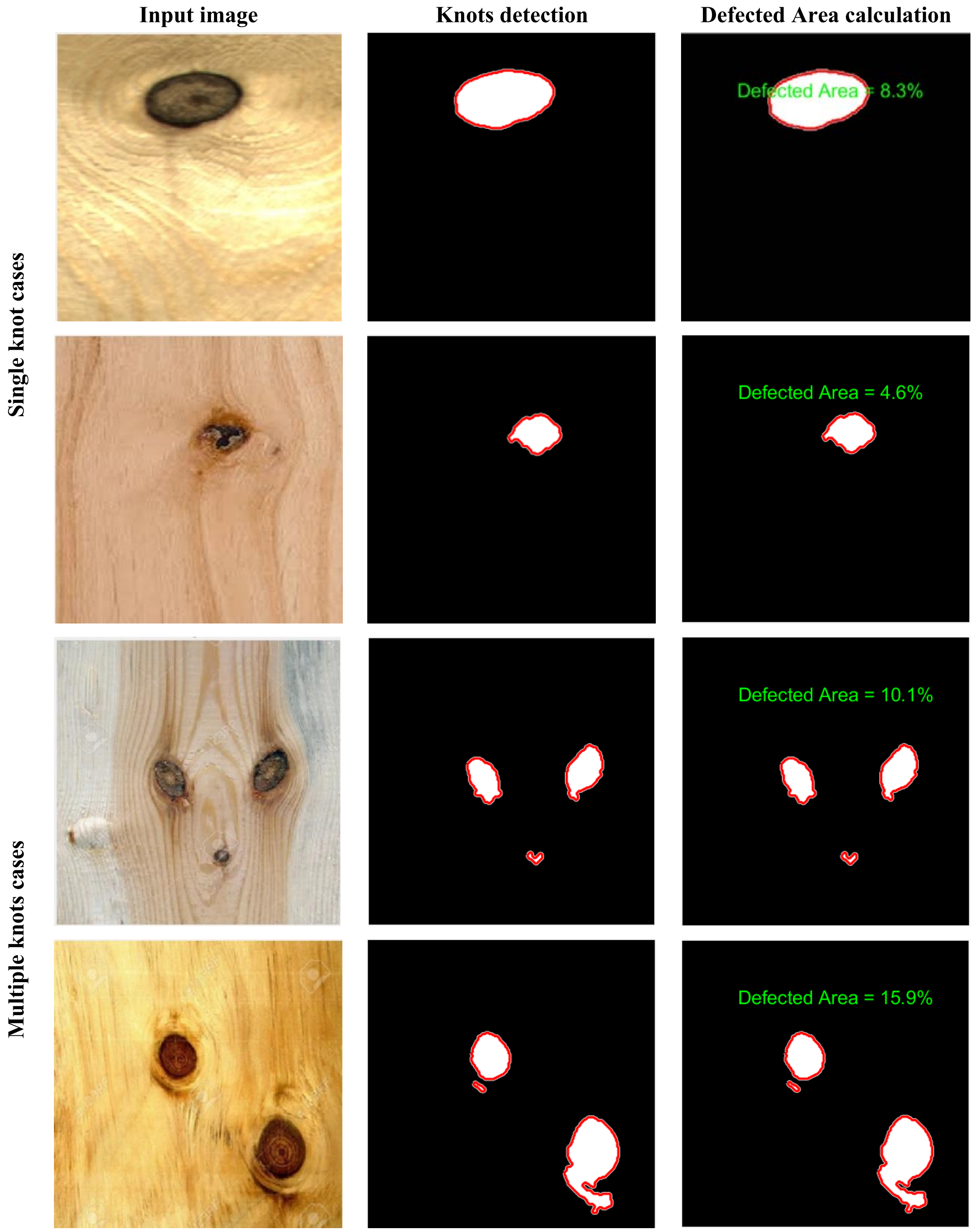


Figure 6. Knots classification and defected area computation.

5 CONCLUSIONS

Knots can add visual interest to wood structures and increase their aesthetic appeal. On the other hand, they can weaken the structural integrity if they are too large, too close together, or located in critical areas such as high-stress locations of load-bearing members. This is because knots can further create local stress concentrations that can lead to cracking, splitting, or even failure of the wood. In addition, knots can also reduce the quality and durability of wood by affecting its dimensional stability, moisture content, and decay resistance. Therefore, the effect of knots on wood structures depends on various factors, including the size, location, and type of knots, as well as the intended use and design of the structure. To ensure the optimal performance and longevity of wood structures, it is important to properly grade and select wood based on knot size and frequency, as well as to apply appropriate design and maintenance practices.

This research work is about the classification of knots in digital images and the estimation of the affected defective area. Single and multiple knots are the two categories into which the images of knots are divided. The IncepResNet-V2 model has been employed, exhibiting an overall accuracy of 84% in an evaluation with a dataset of 200 photos, after being trained and validated on a dataset of 2000 images. For further testing the methodology, four images have been selected, two from the “single knot” category and another two from the “multiple knots” one. First, the InceptionResNet-V2 model truly classified all images into their corresponding categories, then the defected area was estimated using digital image processing techniques.

The work shows the potential of AI-based methodologies in SHM and damage identification. Such methods can drastically improve our ability to assess the condition of structures and structural elements, offering enhanced precision and accuracy, real-time and cost-effective monitoring, predictive capabilities, automation opportunities and many more. Despite these benefits, there are also challenges to consider, such as ensuring the robustness and reliability of AI predictions, dealing with uncertainties in the data, and maintaining data privacy and security. However, with continued research and development, AI-based methodologies hold great promise for the future of SHM and structural damage identification.

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LIST OF ABBREVIATIONS

The following table describes the meaning of various abbreviations and acronyms used throughout the paper.

Abbreviation	Definition
AI	Artificial Intelligence
CNN	Convolutional Neural Network
CT	Computerized Tomography
Conv	Convolutional Layer
DL	Deep Learning
Fc	Compressive strength
IP	Image Processing
MOE	Modulus of Elasticity
R-CNN	Region-based CNN
ResNet	Residual Network
SHM	Structural Health Monitoring

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