

Computing the characteristics of defects in wooden structures using image processing and CNN

Rana Ehtisham^a, Waqas Qayyum^a, Charles V. Camp^b, Vagelis Plevris^{c,*}, Junaid Mir^d,
Qaiser-uz Zaman Khan^a, Afaq Ahmad^a

^a Department of Civil Engineering, University of Engineering and Technology Taxila, Pakistan

^b Civil Engineering Department, The University of Memphis, TN, United States of America

^c Department of Civil and Environmental Engineering, Qatar University, Doha, Qatar

^d Department of Electrical Engineering, University of Engineering and Technology Taxila, Pakistan

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ABSTRACT

Wood, a time-honored construction material prized for its exceptional properties, has been in use for millennia. Its enduring popularity is attributed to its remarkable strength, aesthetic appeal, and favorable environmental footprint. However, wooden structures are susceptible to various defects and imperfections that pose threats to their structural integrity, durability, and safety. These issues encompass knots, cracks, warping, twisting, decay, insect infestations, and more, all of which, if left unaddressed, can culminate in structural failures. Thus, a comprehensive strategy involving inspection, maintenance, and remediation is indispensable for safeguarding wooden structures. Traditional manual inspections, while effective, are characterized by their resource-intensive nature, entailing significant time and cost investments. This study presents a pioneering approach that leverages Convolutional Neural Networks (CNNs) and Image Processing techniques to revolutionize the assessment of damage in wooden structures using digital imagery. Initially, CNNs are employed to categorize images into three fundamental classes: cracks, knots, and undamaged sections. Subsequently, Image Processing techniques are harnessed to compute precise characteristics of these defects, including parameters such as crack length, width, angle, and the extent of the defective area within knots. The Inception-ResNet-V2 pre-trained model is utilized, fine-tuned and validated with a robust dataset comprising 9000 wooden defect images, evenly distributed across the three aforementioned categories. A prudent division allocates 70% of the dataset for model training, with the remaining 30% reserved for validation. Following successful training, the model demonstrates an impressive overall accuracy of 92% when classifying an independent test set comprising 100 new images. To illustrate the model's performance, two images from each damage category are selected and tested to compute the characteristics of the defects. The quantification error for crack angle is only 0.15%, while it is 0.99% for crack length, and 2% for crack width, demonstrating the high performance of the model. The practical implications of this work are profound. By automating defect assessment in wooden structures, our approach offers significant advantages to industry professionals. It expedites inspections, reduces labor costs, and enhances the accuracy of defect quantification.

Abbreviations: ANN, Artificial Neural Network; AOI, Automated Optical Inspection; CNN, Convolutional Neural Network; DL, Deep Learning; ELM, Extreme Learning Machine; FHT, Fast Haar Transform; GPS, Global Positioning System; GSV, Google Street View; IP, Image Processing; IPT, Image Processing Technique; PCA, Principal Component Analysis; R-CNN, Region-based Convolutional Neural Network; RGB, Red, green and blue; SHM, Structural Health Monitoring; SVM, Support Vector Machine; WDD-DL, Wooden panel Defect Detection using Deep Learning.

* Corresponding author.

E-mail addresses: Rana.Ehtisham@students.uettaxila.edu.pk (R. Ehtisham), Waqas.Qayyum@students.uettaxila.edu.pk (W. Qayyum), charles.camp@memphis.edu (C.V. Camp), vplevris@qu.edu.qa (V. Plevris), Junaid.Mir@uettaxila.edu.pk (J. Mir), dr.qaiser@uettaxila.edu.pk (Q.-u.Z. Khan), Afaq.Ahmad@uettaxila.edu.pk (A. Ahmad).

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1. Introduction

Wood has been utilized by humans for thousands of years, and its presence can be observed worldwide. It has served as a primary construction material in numerous cultures due to its widespread availability, affordability, and versatility. Particularly, it has been extensively employed in the construction of historically significant buildings due to its long-lasting nature and aesthetic appeal [1,2]. Recently, there has been a growing inclination towards employing wood as a building material for modern structures, serving various purposes such as residential and commercial buildings, bridges, and even sports stadiums. This emerging trend can be attributed to several factors, including its strength and durability, along with its status as a sustainable and renewable natural resource possessing significant aesthetic value.

The utilization of wood in contemporary structures brings forth notable sustainability advantages. Wood, being a renewable resource that can be sustainably harvested from managed forests, presents itself as an environmentally friendly alternative to materials such as steel or concrete, which possess a significantly larger carbon footprint. Another key benefit of wood is its strength and durability. Through advancements in technology and engineering, wood can now be employed in larger and taller buildings than ever before. In fact, wooden structures can exhibit comparable strength and durability to traditional steel and concrete counterparts. Furthermore, wooden buildings offer the advantage of being quicker and easier to construct compared to traditional steel and concrete structures. As a lightweight material, wood can be prefabricated offsite and swiftly assembled on location, resulting in reduced construction time and costs. Moreover, wood possesses an aesthetic appeal that resonates with many individuals. The natural grain and texture of wood introduce warmth and character to a building, while also allowing for the creation of unique and captivating shapes and patterns.

With advancements in technology and engineering, it is now possible to design and construct wooden structures that are more durable and resistant to fire and other hazards. However, it is important to note that wooden structures can still be prone to certain failures if not designed, constructed, and maintained properly. This is especially true for large timber structures, such as public buildings, which have become more prevalent in recent years.

The evaluation and monitoring of timber structures has become a critical issue in our society, particularly with the introduction of these enormous wooden buildings [3]. Over time, wooden structures are often exposed to unfavorable environmental conditions, including weathering

and mechanical effects. One of the earliest and most visible signs of damage in a timber building is the occurrence of cracks in the structural components, as shown in Fig. 1. These cracks are commonly found in wide-span wooden components, which are more vulnerable to changes in climate. Additionally, other defects such as live and dead knots, dry rots, and paint deterioration can also contribute to a loss of strength and stability in wooden structures [4].

In general, wooden structures that are well-constructed and properly maintained have the potential to last for several decades or even centuries. There are numerous examples of historic wooden structures worldwide that have stood for hundreds of years, such as traditional Japanese wooden temples or Scandinavian wooden houses. Wooden bridges, in particular, have shown remarkable longevity, remaining fully functional for periods ranging from 100 to 150 years, exceeding their original intended lifespan at the time of design [5]. Consequently, it remains crucial to thoroughly examine these structures, classify and identify any defects, and address any structural concerns in order to ensure public safety.

Structural Health Monitoring (SHM) [6] is the practice of continuously monitoring the condition and integrity of a structure throughout its lifespan to detect and assess any damage or deterioration that may pose a risk to its safety or functionality. This monitoring technique is commonly employed for critical structures like bridges, buildings, and dams, where failure could have significant economic and safety implications [7]. By monitoring the health of a structure over time, SHM can provide early warnings of potential issues, enabling timely maintenance and repairs to prevent failure and ensure safety and reliability. In the case of timber structures, SHM is particularly important due to the unique characteristics of wood as a building material. One of the key challenges with timber structures is their vulnerability to decay and infestation by insects. If left untreated, this can cause significant damage to the wood, compromising its structural integrity and leading to potential failure. SHM can detect early signs of deterioration, such as changes in stiffness, damping, or natural frequencies, allowing for prompt intervention to prevent further damage. Given that these structures are often part of buildings that fall under higher consequence classes, the evaluation of large-span timber structures has attracted attention [8,9]. In both research and practical applications, the SHM community has shown increased interest in employing computer vision technology for monitoring at both local and global levels. This technology typically involves using cameras or sensors to capture images or video of the structure, which are then processed using computer algorithms to identify potential issues. It can be seen as a complementary

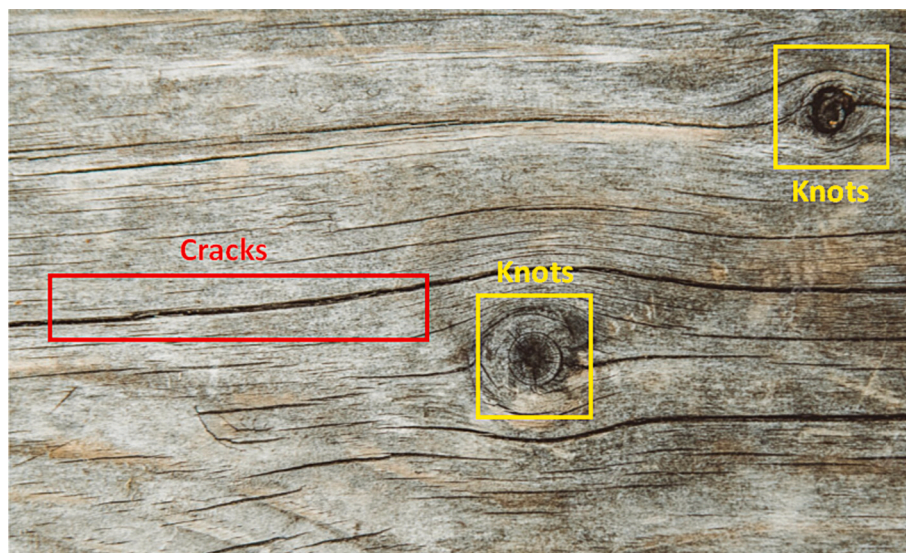


Fig. 1. Cracks and knots in wooden structures.

approach to traditional SHM techniques, offering unique advantages such as rapid detection, long-distance monitoring, low cost, non-contact measurement, and minimal interference with the structure's daily operations [10].

This research investigation delves into the classification and characterization of defects within wooden structures, specifically targeting anomalies such as knots and cracks. The predictive capabilities of Convolutional Neural Networks (CNNs) in conjunction with image processing techniques are harnessed for this purpose. It is noteworthy that prior research endeavors have explored defect classification and identification using CNNs and various segmentation methodologies. However, the current study introduces a novel dimension by extending the analysis to encompass additional defect characteristics. In addition to the conventional classification task, this research seeks to compute and quantify specific attributes of wooden structure defects. These attributes include but are not limited to the angle, length, width, and defective area associated with these anomalies. To facilitate the classification of defects, the Inception-ResNet-V2 pre-trained model is deployed and subsequently subjected to rigorous training and validation protocols. In parallel, the computation of these supplementary characteristics necessitates the utilization of image processing techniques. Stringent validation procedures are applied to ensure the robustness and reliability of the computed defect characteristics.

2. Background study

Every year, a substantial amount of money is allocated towards analyzing failures in critical infrastructure components such as buildings, bridges, and highways. The built environment, which includes these infrastructures, often suffers extensive damage due to natural disasters like floods and earthquakes. To ensure the structural and functional integrity of these infrastructures, regular visual examinations and evaluations are conducted, particularly after catastrophic events. Manual inspections are a time-consuming and labor-intensive process that also incur significant costs.

2.1. Image processing and CNN techniques for identifying defects

As an alternative to manual methods, image processing techniques (IPTs) and soft computing can be employed to examine collected photographs of the infrastructure components, identify any potential weaknesses, and detect defects in civil infrastructure, aiming to supplement, if not entirely replace, manual onsite examinations. Munawar et al. provided a comprehensive review of crack detection methodologies that utilize image processing and/or machine learning techniques [11]. For this, 30 scholarly articles, published over the past ten years, have been meticulously curated. An exhaustive analysis and juxtaposition of these methodologies have been undertaken to emphasize the most promising automated strategies for crack detection.

2.1.1. Applications in non-timber structures

In [12], the main objective of these IPTs is to thoroughly examine digital photographs and extract fault characteristics, such as cracks in concrete surfaces. However, the varying real-world conditions, including changes in lighting and shadows, can pose challenges for the widespread use of these techniques. To overcome these challenges, the article introduces a novel vision-based approach that leverages deep CNNs to detect concrete cracks without the need for explicit feature extraction via IPTs. An innovative approach to bridge inspection is presented in [13] by addressing the limitations of existing methods based on Structure from Motion (SfM) technology and digital image resolution. The research acknowledges the growing reliance on advanced equipment and algorithms, such as digital cameras and SfM, for bridge inspections. However, it highlights two critical challenges faced by conventional SfM-based methods: the computational inefficiency associated with lengthy 3D reconstruction processes and the

inability to accurately detect and measure fine cracks due to limitations in digital image resolution. To overcome these limitations, the study introduces a novel methodology that combines multi-sensor fusion SLAM (Simultaneous Localization and Mapping) and image super-resolution techniques.

Qayyum et al. [14] explored the issue of crack detection in engineering structures using seven pre-trained CNN architectures. The study aids in selecting the most suitable CNN architecture for automatic crack detection and orientation, based on accuracy and training time considerations. Park et al. efficiency [15] introduced a method for the automated visual inspection of surface parts to identify anomalies such as dirt, scratches, burrs, and wear. Employing imaging analysis with CNNs, training samples serve as the basis for confirming the presence of defects within specified regions of an image. The study encompasses the construction and evaluation of several deep network architectures, varying in terms of depth and layer nodes, to determine the most suitable configuration for surface defect inspection. The experimental results underscore the substantial advantages of the method in terms of time and cost savings when compared to traditional manual inspection systems. Cha et al. [16] proposed an autonomous structural visual inspection system capable of detecting multiple damage types in quasi real-time using region-based deep learning and in particular a Faster Region-based CNN (Faster R-CNN)-based structural visual inspection method. The robustness of the methodology is evaluated and demonstrated using 11 new 6000×4000 -pixel images taken from different structures.

Chaiyasarn et al. [17] examined an automated image-based system for detecting cracks in masonry structures. They propose a crack detection framework that amalgamates the strengths of deep CNNs and Support Vector Machines (SVMs). The CNN undertakes the task of feature extraction from RGB images, while the SVM serves as an auxiliary classifier, acting as a potent alternative to the conventional softmax layer, thereby augmenting classification prowess. The hybrid model exhibits superior performance compared to a CNN-only model, achieving an impressive detection accuracy of 86% on validation images [17]. In their research, Abdel-Qader et al. [18] conducted an investigation into edge-detection techniques employed for the purpose of crack identification in bridge structures. This study entailed a comprehensive comparative analysis of the efficacy of four distinct crack-detection methods, namely the fast Haar transform (FHT), fast Fourier transform, Sobel, and Canny algorithms, all of which were implemented within the MatLab programming environment and subjected to simulation utilizing a dataset comprising 50 concrete bridge images. The findings of this investigation revealed a notable and statistically significant superiority of the FHT technique over the other three edge-detection methods in the context of crack identification.

In [19], a deep architecture of CNNs is utilized and a method is presented for classifying pavement image degradation using CNN models. In this work, inexpensive, high-definition cameras are installed on a vehicle to capture the dataset. The images are tagged with GPS information and time stamps. By eliminating the need for an additional positioning system, the integrated system achieves overall cost reduction. The model's true positive rates for each category were found to be 75.7% for "pothole," 84.1% for "patch," 76.3% for "marking," 79.4% for "crack-linear," and 83.1% for "crack-network" [19]. Fan et al. [20] applied a methodology based on CNN for the automatic pavement crack detection, which has the capability of dealing with different pavement conditions. A CNN is used to learn the structure of the cracks from raw images, without any preprocessing. A strategy based on modifying the ratio of positive to negative samples is proposed. The method is tested on two public databases and compared with five existing methods with promising results.

The study by Zhang et al. [21] presents an innovative approach for reconstructing rock cracks from CT images. The authors address the limitations of previous studies by introducing a pixel-level labeled dataset consisting of 1000 CT images that encompass a wide range of

rock types. To enhance crack detection accuracy, they propose three novel modules: (i) an inverted residual block featuring three hierarchical residual-like mixed connected branches, (ii) an attention-based upsampling method that facilitates multi-layer feature fusion, and (iii) a multi-representative vector classifier. These components are incorporated into two attention-based networks which include skip connections for improved crack detection.

2.1.2. Applications in timber structures

Some limited applications of CNN can be also found for timber structures. In order to develop a model for identifying wood image defects with a high level of accuracy, Yang et al. [22] integrated the extreme learning machine (ELM) classification approach with the deep learning feature extraction method. With deep learning pre-training, the distributed input data features are inherently structured in a layered format. Remarkably, the accuracy of wood defect recognition using this method attains 96.72% [22].

He et al. [23] introduced a sophisticated learning technique designed to discern timber characteristics and autonomously categorize imperfections derived from timber images obtained via laser scanning. This method is executed through a deep convolutional neural network (DCNN) which is trained using TensorFlow. By leveraging the refined DCNN model, the authors attained a commendable accuracy rate of 99.13%, surpassing traditional techniques in accurately and efficiently identifying timber defects from images.

2.2. Use of pre-trained CNN models

Pre-trained CNNs refer to models that have been previously trained on a large benchmark dataset, typically on computer vision tasks, and can then be employed or fine-tuned for a different, potentially related, task without starting the training process from scratch. They are designed to perform various tasks, such as Image classification, Object detection, semantic segmentation, instance segmentation, and visual question answering. The functions of pre-trained CNN models depend on the specific architecture and the task they were trained for.

Four different pre-trained CNN models were employed in [24] to detect cracks in concrete structures and predict their orientation. A dataset of 32,000 images was collected from online sources, with 75% of the images showing cracks and 25% showing no cracks. The ResNet50 model achieved the maximum classification accuracy of 86.2% with an average training time of 8208 s. Qayyum et al. [25] employed the Inception-V3 [26] model for the detection of cracks in civil constructions using a variable image dataset to evaluate the impact of the number of images on the accuracy of model. The study confirmed that models trained with a larger dataset have better accuracy for classifying un-cracked, diagonal, horizontal, and vertical cracks. In [27], Bai et al., address the crucial task of assessing the safety of structures following events such as earthquakes. They employ deep learning techniques to enhance structural health monitoring and post-earthquake reconnaissance. The authors begin by creating an image dataset focused on mechanical damage to reinforced concrete components. They adopt EfficientNet-V2 as the baseline model for damage recognition tasks. The study introduces a discrete wavelet transform module that incorporates frequency information, thereby improving both the model's performance and its interpretability.

Zhang et al. [28] address the common problem of crack damage in concrete structures, which can significantly impact their durability and structural integrity. They highlight the extensive use of deep learning techniques in image-based crack detection but emphasize that existing approaches often lack the ability to assess the uncertainty associated with their diagnostic results. The paper introduces a novel hybrid probabilistic deep learning method for classifying concrete surface damage. This approach incorporates Bayesian inference into a deep CNN and modifies the parameters within probability layers to follow Gaussian distributions. This not only ensures accurate crack recognition

but also provides a valuable measure of uncertainty in the results.

Similarly, the application of pre-trained CNN models has found utility in various contexts within the realm of timber structures. Within the wood-based furniture manufacturing sector, a paramount emphasis is placed on ensuring the quality of production to effectively meet the ever-increasing demands of the market. The task of identifying diverse categories of defects within edge-glued wooden panels presents a formidable challenge. In this context, Chen et al. [29] endeavored to discriminate between defects classified as low, high, normal, overlong, or short through the employment of computer vision and deep learning methodologies. The proposed framework involved the acquisition of both raw and laser-aligned images from a camera, with the primary objective of enabling the detection of defects in edge-glued wooden panels. This research aimed to introduce an advanced defect detection solution that aligns with the specific requirements of the wood-based furniture manufacturing industry, thereby achieving automation of the detection process. To facilitate defect identification, the system leverages a comprehensive pre-processing approach, encompassing techniques such as Gabor filtering, Harris corner detection, morphology analysis, structured light detection, and curvature calculation. For the subsequent task of defect classification, the Inception-ResNet-V2 [30] is employed, ultimately yielding superior results.

Urbanas et al. [31] employed the Faster Region-Based CNN (Faster R-CNN) methodology for the purpose of defect identification on wood veneer surfaces. To enhance the quality of results, transfer learning was leveraged, utilizing pre-trained neural network models, namely AlexNet, VGG16, BNInception, and ResNet152. This approach was supplemented by the utilization of a synthetically augmented dataset. The highest average accuracy of 80.6% was achieved when employing the pre-trained ResNet152 model. Furthermore, the amalgamation of all defect classes culminated in a remarkable 96.1% accuracy in the detection of wood panel surface defects.

Ehtisham et al. [32] evaluated three pre-trained models of CNN, ResNet18, ResNet50, and ResNet101 [33] on five classifications for the detection of defects in wooden structures using a dataset of 5000 images. The same group of authors recently assessed ten pretrained CNN models: ResNet18, ResNet50, ResNet101 [33], ShuffleNet [34], GoogLeNet [35], Inception-V3 [26], MobileNet-V2 [36], Xception [37], Inception-ResNet-V2 [30], and NASNet-Mobile [33], for their efficacy in classifying and predicting several defects within wooden structures [38]. To measure the performance of each CNN model, statistical metrics, namely accuracy, precision, recall, and F1-score, were used. The Inception-ResNet-V2 and the Inception-V3 models emerged as the most adept CNN architectures for discerning defects in wooden structures. Based on these results, in the present study we employ the Inception-ResNet-V2 model for classification purposes.

3. Convolutional neural network (CNN)

Artificial neural networks (ANNs) are a machine learning algorithm inspired by the structure and function of the human brain [39]. They have been widely applied in various fields, including civil and structural engineering [40,41] due to their ability to model and analyze complex systems [42]. Applications include areas such as structural health monitoring [6], identification of structural damage [43,44], dynamic analysis of structures [45], structural modeling [46,47], risk assessment [48], planning and management of construction projects [49], prediction of strength and other structural attributes [50,51], enhancement of energy efficiency [52], among others. ANNs have gained popularity because they can effectively solve intricate problems that traditional analytical methods struggle with [53]. Convolutional Neural Networks (CNNs), a form of deep ANNs, are commonly used for tasks involving image and video recognition and classification. CNNs mimic the hierarchical processing of the human visual system, extracting basic features like edges and shapes and combining them to recognize more complex features like objects and scenes. The use of CNNs in structural systems

for the detection, classification, and measurement of elements of interest has numerous advantages, such as cost reduction, process acceleration, and safety enhancement [54]. Recent advancements in non-contact sensing devices have increased the adoption of deep learning-based condition assessment methodologies in the SHM community. CNNs are extensively trained using large datasets to identify various types of damage and anomalies, as well as for post-disaster reconnaissance [55]. A typical CNN architecture includes multiple layers of convolutional filters, which are small matrices of weights applied to patches of the input image, as illustrated in Fig. 2. The network learns features like edges, corners, and textures by convolving the filters across the entire image. The output of one convolutional layer is then fed into the next layer, allowing the network to learn more complex features at each stage. In classification problems, the final output of the network consists of probabilities for each possible class or category [56]. One significant advantage of CNNs is their ability to automatically learn relevant features from raw input data, eliminating the need for manual feature engineering. This makes CNNs highly effective for tasks like image classification, object detection, and segmentation. Additionally, CNNs can handle input data of varying sizes and shapes, thanks to the use of convolutional filters applied to small patches of the input. This adaptability allows CNNs to be used with different types of input data, including images, videos, and natural language text [57].

4. Research methodology

The proposed methodology of this study consists of two main steps: the classification of wooden defects and the computation of their characteristics. These steps are illustrated in Fig. 3. At a local level, the dataset is obtained and divided into three categories: cracks, knots, and undamaged. After the images are classified, a pre-trained CNN model is trained and validated using this dataset. If the CNN model classifies a tested image as “cracks,” image processing techniques will be used to compute the angle, length, and width of the crack. If the image is classified as “knots,” the area of the knot defect will be computed. For images classified as “undamaged,” no further action will be taken after the classification.

5. Dataset acquisition

This study categorizes two common defects found in wooden structures, specifically cracks and knots. It is important to emphasize the significance of obtaining a high-quality and comprehensive dataset for the successful application of CNNs. The dataset must meet the following criteria:

1. It should be large enough to accurately represent the target population.
2. It should cover a wide range of variations to ensure diversity.
3. The dataset should be labeled correctly to guarantee the model's prediction accuracy.

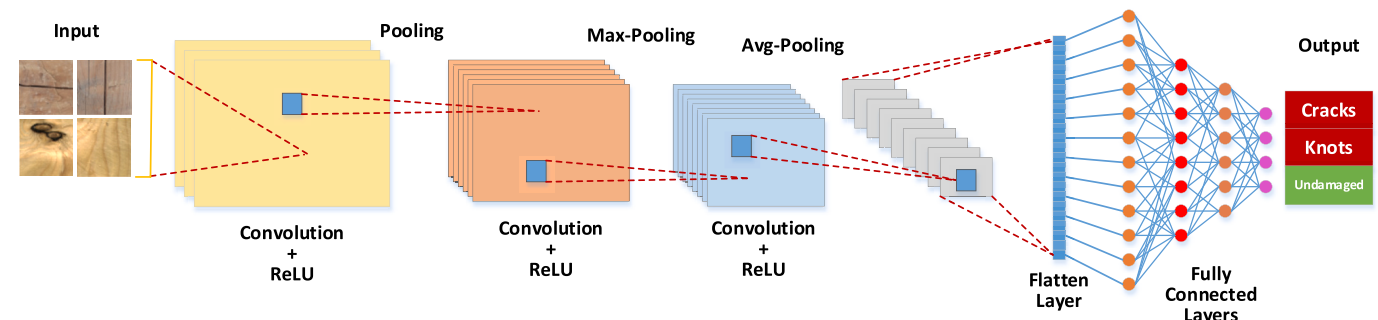


Fig. 2. Architecture of a typical Convolutional Neural Network (CNN).

In general, an image dataset consists of digital images that can be labeled or unlabeled and used for training, testing, or validating computer vision models like CNNs. These datasets can come in different forms and formats, including photographs, drawings, medical images, satellite images, or any other relevant digital images for the intended application.

In this particular study, a dataset of 9000 images was obtained and categorized into three classes: “cracks,” “knots,” and “undamaged,” as shown in Fig. 4. Each class contains an equal number of images, with 3000 images in each category. The dataset for knots was obtained from an available online source [58], while the images of cracks and undamaged structures were collected manually by visiting wooden structure sites.

To test the pre-trained model, a dataset of 100 images from each class was collected and used for classification. Two random images were selected to test the procedure by computing their characteristics with the assistance of image processing techniques.

6. Pre-trained CNN models

The Inception-ResNet-V2 pre-trained model is utilized for classifying predefined wooden defects in this study. The model was developed using a dataset of over one million photos from the ImageNet library. It consists of a network with 164 layers and has the ability to classify images into 1000 different object categories. For this study, 70% of the dataset is used for training the model, while the remaining 30% is used for validation. The model is designed to handle images with features of up to $299 \times 299 \times 3$ and has a file size of 213.41 MB. The architecture of the pre-trained model is shown in Fig. 5, with the entire Inception-ResNet-V2 network structure displayed on the left and the stem of the model illustrated on the right. Further details on the operation of the network, the different layers involved, and their functions can be found in the subsequent subsections 6.1–6.8.

6.1. Data processing

During the data processing phase, the images are loaded from files. Prior to reading them from the disk drive and inserting them into the appropriate encoder, the framework pre-processes the images. This procedure helps alleviate computational burden and enhances the overall applicability of the model [59].

6.2. Convolution layer

The convolution layer is a fundamental component of CNNs. In this study, the ReLU activation function was used in the 3×3 filter size [60]. The convolution layer applies a convolution operation to the input image using a set of filters that can be learned. Each filter is a small matrix of weights that is moved across the input image, calculating dot products at each location. The result of the convolution operation is a set of feature maps that emphasize various characteristics of the input

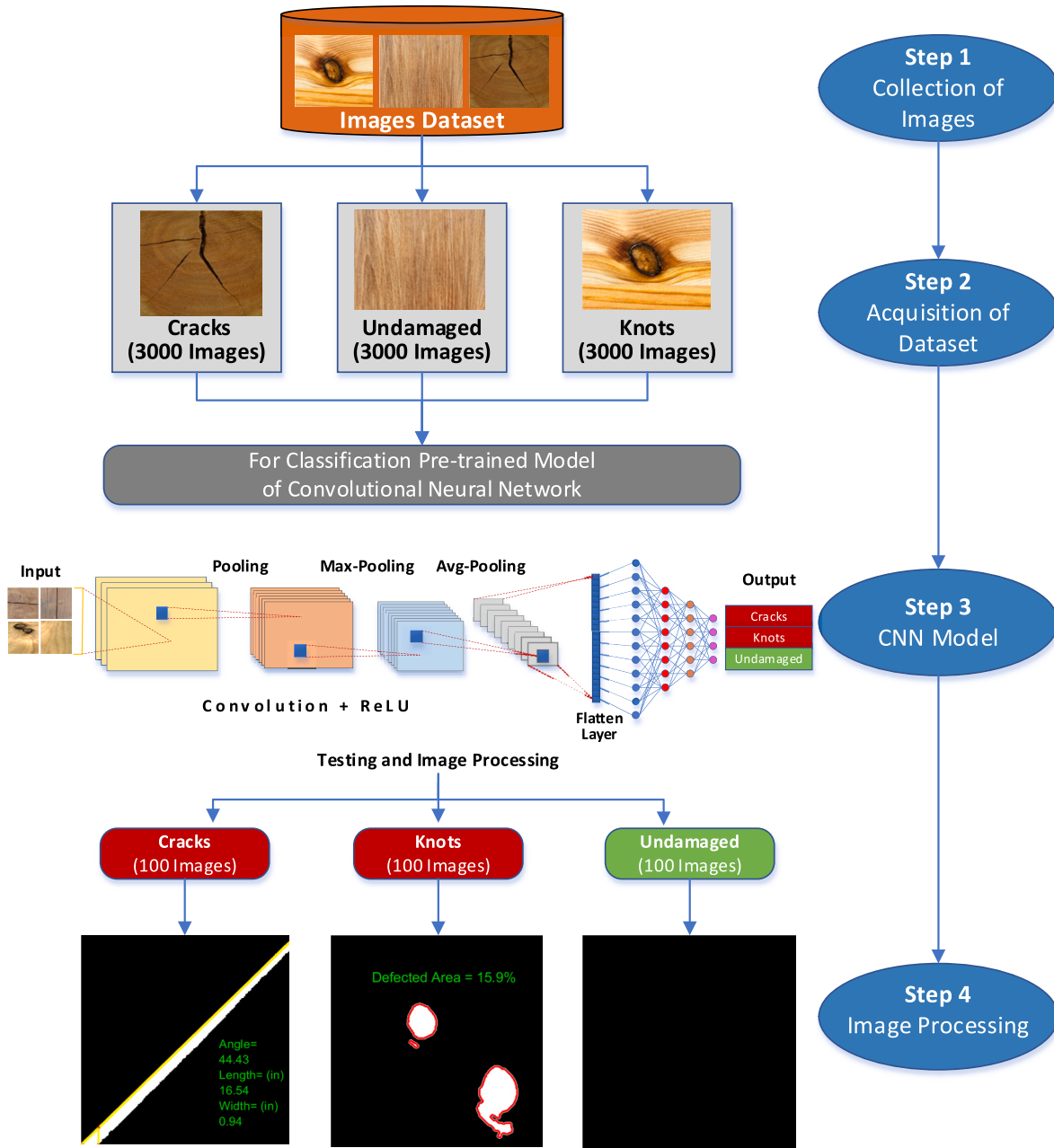


Fig. 3. Flowchart of the proposed methodology.

image.

6.3. Max pooling

The pooling layer's primary job is to execute downsampling, gradually lowering the size of the image, while maintaining the image's distinguishing characteristics, and serves as a beneficial tool for dimensionality reduction. In max pooling, a small window (typically 2×2 or 3×3) slides over the input feature map, and the maximum value of the pixels within the window is computed. The resulting output value is then placed in the corresponding location in the output feature map. This process is repeated for each non-overlapping window in the input feature map, resulting in a smaller output feature map with reduced spatial resolution. The max pooling operation is applied to each feature map independently. This reduces the spatial size of the feature map while preserving the most salient information.

6.4. Average pooling

Average pooling is a commonly used operation in CNNs that is similar to max pooling but uses the average value of each pooling window instead of the maximum. Its primary function is to downsample the feature maps and reduce the spatial dimensionality of the data, while retaining the most important information. The main advantage of average pooling is that it can help to reduce overfitting and improve the generalization of the model by reducing the sensitivity to small variations in the input. It can also help to improve computational efficiency by reducing the number of parameters in the model.

6.5. Stride

Stride is an essential hyperparameter utilized in CNNs to regulate the spatial downsampling of feature maps. Its purpose is to determine the step size of the sliding window employed in the convolution operation.



Fig. 4. Example images for each of the three subsets of the dataset: (i) Cracks; (ii) Knots; and (iii) Undamaged.

In a CNN, the input image undergoes convolution with a set of filters that can be learned, giving rise to a collection of feature maps. The dimensions of these feature maps are contingent on the filter size, padding, and stride. The stride value dictates the extent by which the filter shifts over the input image during each convolutional step. One notable advantage of employing a larger stride is its potential to decrease the spatial dimensionality of the feature maps, thereby enhancing computational efficiency and mitigating the risk of overfitting. Nevertheless, there is a drawback in that it may lead to some loss of information since larger strides can cause certain portions of the input image to be skipped during the convolution operation.

6.6. Dropout

The dropout technique is a widely employed regularization method in CNNs to mitigate overfitting. It entails randomly deactivating (i.e., setting to zero) a specific proportion of neurons within a layer during the training process. The dropout rate is a hyperparameter that determines the fraction of neurons to drop out during training. A typical value for dropout rate is 0.5, which means that each neuron has a 50% chance of dropping out during each training iteration. However, the optimal value for the dropout rate may vary depending on the specifics of the problem and is typically determined through experimentation and tuning. It is worth noting that dropout is only applied during training and is not used during testing or inference. During testing, the full network is used, but the outputs of the neurons are scaled by the dropout rate to account for the fact that some neurons were dropped out during training.

6.7. Reduction layer

A reduction layer is a type of layer commonly used in CNNs to reduce the spatial dimensionality of the feature maps while retaining the most important information. It is typically used after a set of convolutional layers to reduce the size of the feature maps before passing them on to

the next layer in the network. The most common types of reduction layers are max pooling and average pooling, which were already explained in the previous sections. In addition to these, there are other types of reduction layers such as strided convolutions and concatenation of feature maps. The choice of reduction layer type and parameters (e.g. pooling window size, stride size, etc.) is typically determined through experimentation and tuning, and depends on the specifics of the problem at hand.

6.8. Softmax layer

The Softmax layer is a type of layer commonly used in CNNs for classification tasks, such as image classification, where the goal is to assign an input image to one of a fixed set of categories. It is typically used as the final layer of the network, after a set of convolutional and fully connected layers. The Softmax layer takes as input a vector of real-valued scores, and outputs a probability distribution over a set of mutually exclusive classes. Each score in the input vector represents the strength of the evidence for the corresponding class, and the Softmax function maps these scores to a set of probabilities that sum to one. The output of the Softmax layer can be interpreted as the probability that the input belongs to each of the possible classes. The class with the highest probability is typically taken as the predicted class.

7. Image processing techniques

The classification of defects in timber structures can be achieved using CNNs, while the computation of defect characteristics such as angle, length, width of cracks, and percentage of defected area can be done using image processing and other soft computing techniques [61]. Image processing refers to the use of computer algorithms to analyze, manipulate, enhance, and transform digital images. It is a multidisciplinary field that combines techniques from computer science, mathematics, and engineering to extract valuable information from digital

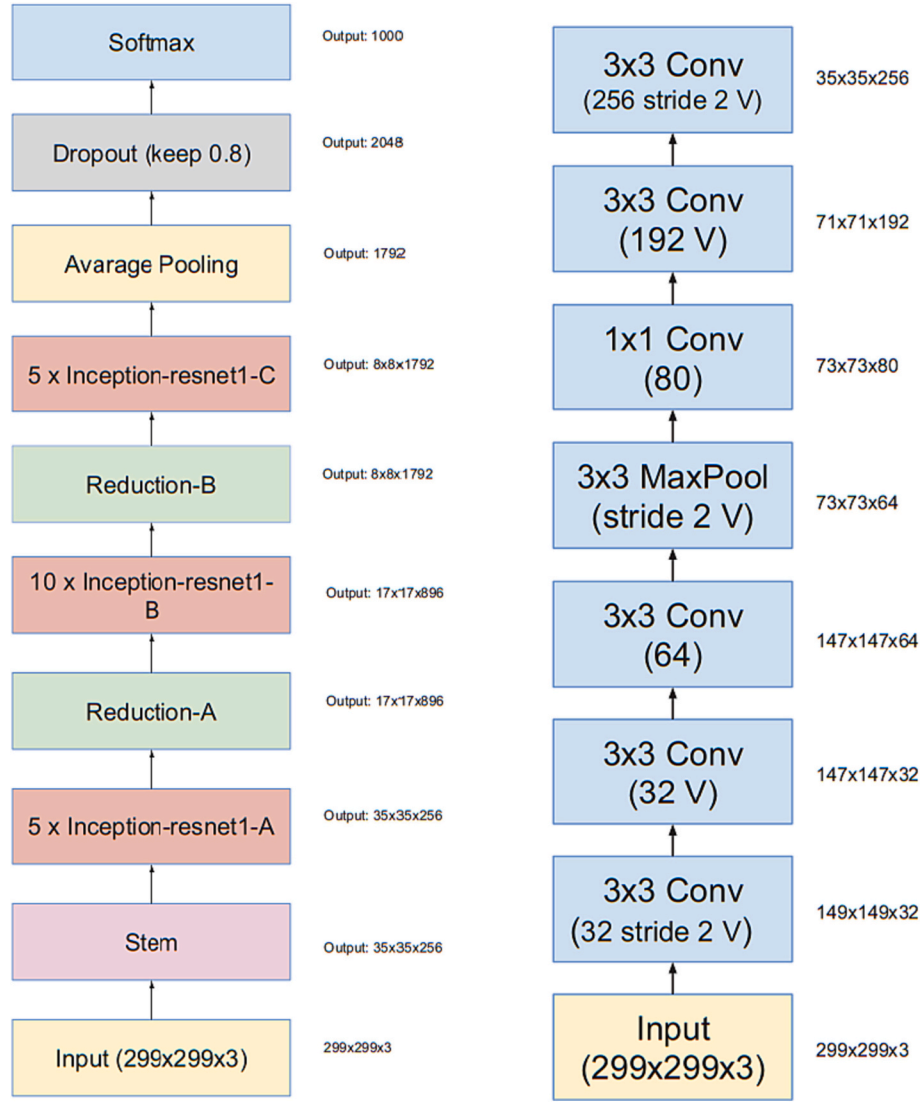


Fig. 5. Overall Schema (on the left) and Stem (on the right) of Inception-ResNet-V2 CNN Model [30].

images [62]. Image processing has a wide range of applications, including image enhancement, image restoration, image segmentation, object recognition, and pattern recognition, as shown in Fig. 6 for the case of timber structures. It is utilized in various fields such as medical imaging, remote sensing, robotics, and computer vision. Image processing algorithms typically involve several stages, including image acquisition, pre-processing, feature extraction, and classification. In the image acquisition stage, an image is captured using a digital camera or other imaging device. In the pre-processing stage, the image undergoes filtering, noise removal, and other techniques to improve its quality, clarity, and usefulness [63]. The feature extraction stage involves using algorithms to identify and extract key features from the image such as edges, corners, or texture patterns. These features are then used for image classification or other types of analyses like object detection or segmentation.

During the feature extraction phase, critical attributes like edges, texture patterns, and key elements are identified. In this research, after classifying the images, we leverage image processing techniques to determine defect characteristics, including angle, length, width, and affected area. The image processing functions were implemented in MATLAB taking advantage of the built-in commands *rgb2gray*, *graythresh*, *imbinarize*, *imfill*, *bwmorph*, *bwconncomp*, *bwareaopen*, and *sum*.

The process of quantifying a crack in an image consists of several

steps, including image segmentation, fracture identification, and measurement. To begin, the image is converted into a binary image using a core analysis approach. This is followed by noise removal and the merging of crack spaces. The next step involves obtaining the medial axis of the fracture network from the binary image, which allows for the identification of nodes and crack segments. Finally, various geometric properties of the crack network, such as the number of nodes and cracks, clod area, clod perimeter, crack area, breadth, length, and direction, can be automatically determined through computational methods [64].

In order to determine the characteristics of defects, all calculations are performed on binary images, which are digital images with black and white colors. To determine the length of a crack, two types of operations are utilized: horizontal moving operation and vertical moving operation. The horizontal moving operation scans horizontally from the top and bottom of the binarized image to locate the tip of the crack and measure its length. Simultaneously, the vertical moving operation scans from the left and right sides of the crack to locate the tip, specifically for horizontal cracks. For diagonal cracks, both operations are necessary to locate the tip. The width of the crack is determined by moving operations horizontally along each line to identify the maximum amount of white pixels for vertical cracks, and vertically along each line to identify the maximum amount of white pixels for horizontal cracks, as depicted in Fig. 7. For the width of diagonal cracks, both operations are employed

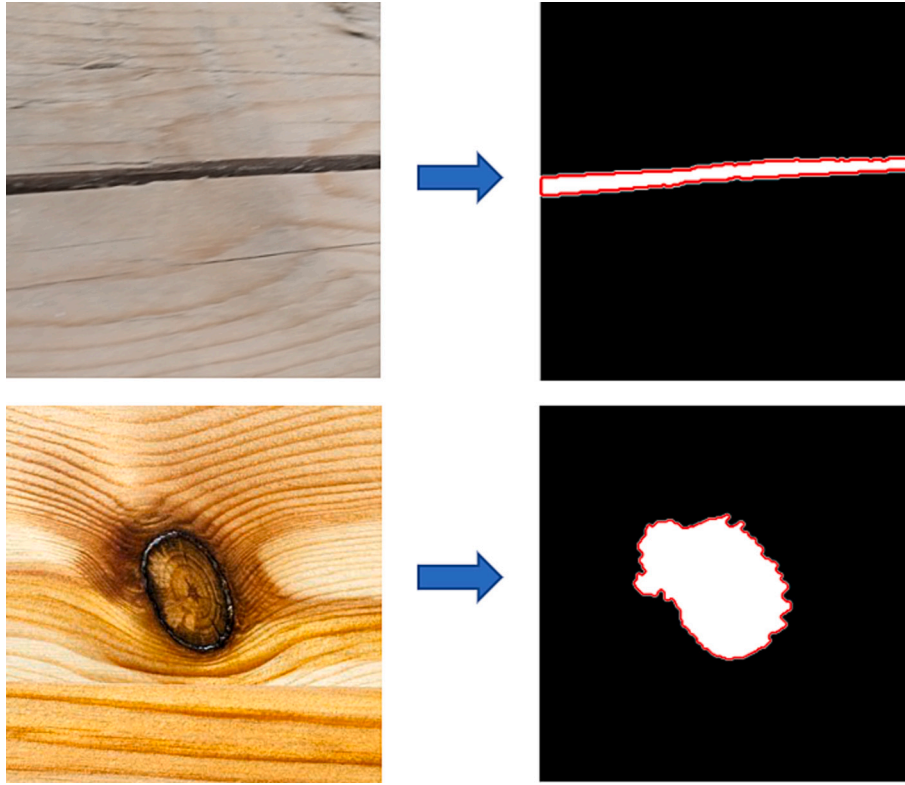


Fig. 6. Digital image processing in wood structures: Original Image and Processed Image.

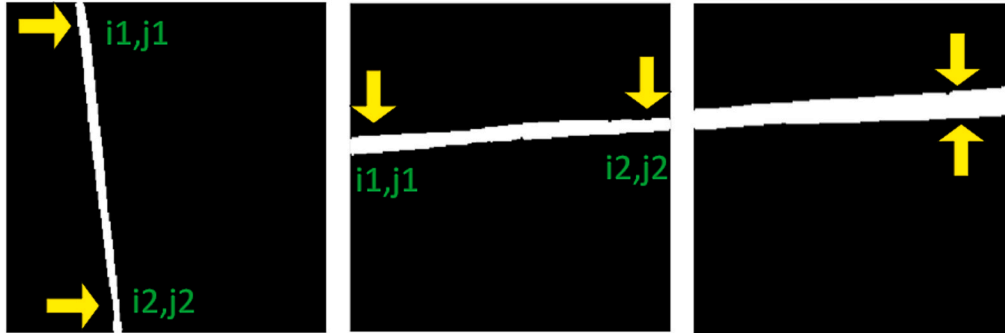


Fig. 7. Horizontal and Vertical movement of operations for Length, Width, and Angle.

to identify the maximum number of pixels in a single line. The crack angle is calculated from the slope of the crack length using the following simple equations.

$$Slope = \frac{j_2 - j_1}{i_2 - i_1} \quad (1)$$

$$Angle = \tan^{-1}(Slope) \quad (2)$$

8. Results and discussion

In this study, the Inception-ResNet-V2 CNN model is used to classify wooden structural defects and then image processing techniques are utilized for obtaining the characteristics of the defects. The CNN is trained and validated using a comprehensive dataset of wooden defects. The model's classification performance is then independently tested on 300 unseen images (100 from each class) that had not been previously used in the training process. The accuracy of the CNN model is determined by calculating the ratio of true positive and true negative

predictions to the total number of positive and negative predictions [65]. Of the 100 crack images, the CNN model correctly predicted 91 as cracks, 1 as a knot, and 8 as undamaged. From the tested knot images, the CNN model correctly identified 96 as knots, 1 as a crack, and 3 as undamaged. Lastly, from the undamaged class images, the model correctly identified 89 as undamaged, with 2 being identified as knots and 9 as cracks, as shown in Fig. 8. The accuracies for crack, knot, and undamaged classifications are $(91 + 190)/300 = 93.7\%$, $(96 + 197)/300 = 97.7\%$, and $(89 + 189)/300 = 92.7\%$, respectively. The precision of the CNN model quantifies the predictions of positive labels, with values of 90.1%, 96.9%, and 89.0% for cracks, knots, and undamaged, respectively. The overall precision performance of the model in classifying the three predefined categories of wooden defects is 92.0%.

8.1. Crack characteristics

After the defects have been classified, digital image processing is used to calculate the characteristics such as angle, length, width, and defected area. In order to test the accuracy of the CNN model, two

Confusion Matrix				
Output Class	Cracks	Knots	Undamaged	
Cracks	91 30.3%	1 0.3%	9 4.3%	90.1% 9.9%
Knots	1 0.3%	96 32.0%	2 0.6%	96.9% 3.1%
Undamaged	8 2.7%	3 1.0%	89 31.0%	89.0% 11.0%
	Cracks	Knots	Undamaged	
Target Class				
	91.0% 9.0%	96.0% 4.0%	89.0% 11.0%	92.0% 8.0%

Fig. 8. Inception-ResNet-V2 Confusion Matrix.

images from the cracks category were selected and their characteristics were computed. Firstly, the pre-trained model Inception-Resnet-V2 was used on these two images, correctly predicting that both of them belonged to the “Cracks” category. Subsequently, the angle, length, and width of the crack were calculated, as demonstrated in Fig. 9. The cracks are indicated in white color with a red boundary line in the “Crack” image (middle column). The angle for the first image in the first row was determined to be 44.4°, while the angle for the second image in the second row was calculated to be 3.8°. The crack length was measured as 16.54 in for the first image and 11.98 in for the second image, while the crack widths were determined to be 0.94 in and 0.98 in, respectively.

8.1.1. Validation of the results on cracks

The characterization of crack defects, such as angle, length, and width, is validated by manually marking a 1' × 1' patch around the crack image on-site. All the characteristics are measured and compared with the values predicted by the algorithm. This process has been performed for both of the images analyzed in the previous section. Additionally, the quantification error is calculated and the results are presented in Table 1. It can be observed that the quantification error is consistently small for all cases, ranging from 0.15% for the angle measurement of Image 1 to 2% for the width measurement of Image 2.

8.2. Knots characteristics

After analyzing the characteristics of the cracks, two additional randomly selected images from the “Knots” class were tested for both classification and characteristics tasks. Using the pre-trained model of CNN, the correct class prediction for both images was “Knots”. Subsequently, the framework was instructed to calculate the defected area of the knots, as depicted in Fig. 10. The defected area of the first image (top row) was calculated to be 15.9% of the total area of the image, while the defected area of the second image (bottom row) was found to be 10.1% of the total area. The knots are represented in white color and are enclosed by a red boundary line.

8.3. Undamaged cases

In addition to conducting tests on images depicting cracks and knots, two images without any damage were also tested for classification. In both cases, the CNN successfully classified them as “Undamaged,” indicating the absence of any defects. This outcome is visually represented in Fig. 11.

9. Discussion and conclusions

In this comprehensive study, we have embarked on a journey into the realm of automated inspection for wooden structures, aiming to achieve not only the precise identification of common wooden defects but also

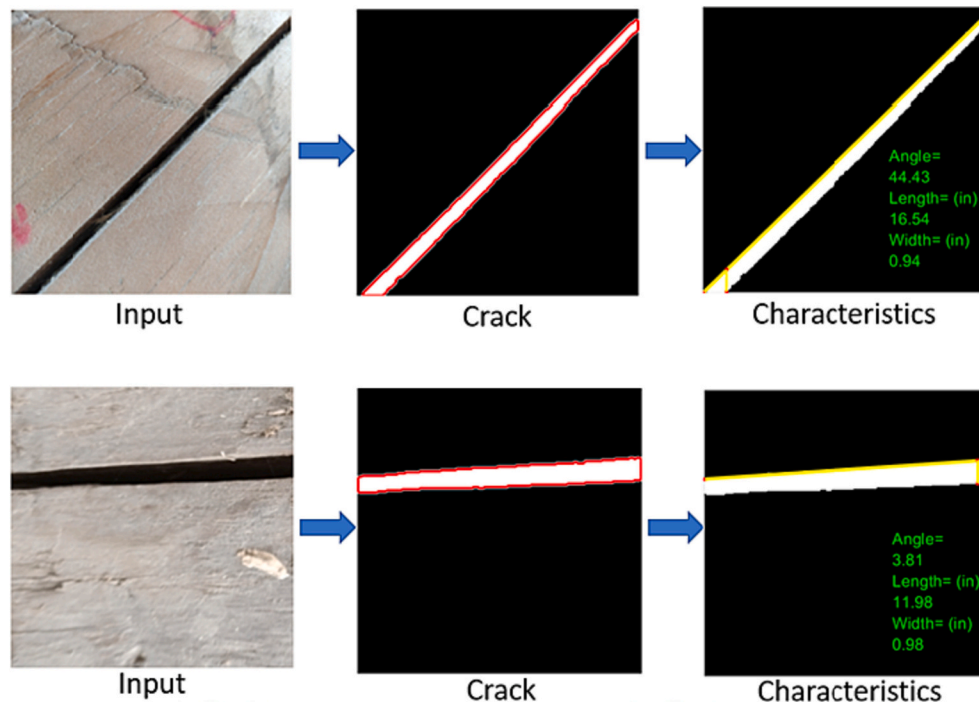


Fig. 9. Results of Cracks tested images.

Table 1

Crack characteristics: Results and quantification errors.

Tested image	Algorithm Predicted Values			Actual Site Values			Quantification Error		
	Angle (°)	Length (in)	Width (in)	Angle (°)	Length (in)	Width (in)	Angle	Length	Width
Image 1	44.43	16.54	0.94	44.5	16.80	0.90	0.15%	1.54%	4.2%
Image 2	3.81	11.98	0.98	3.90	12.10	1	2.3%	0.99%	2%

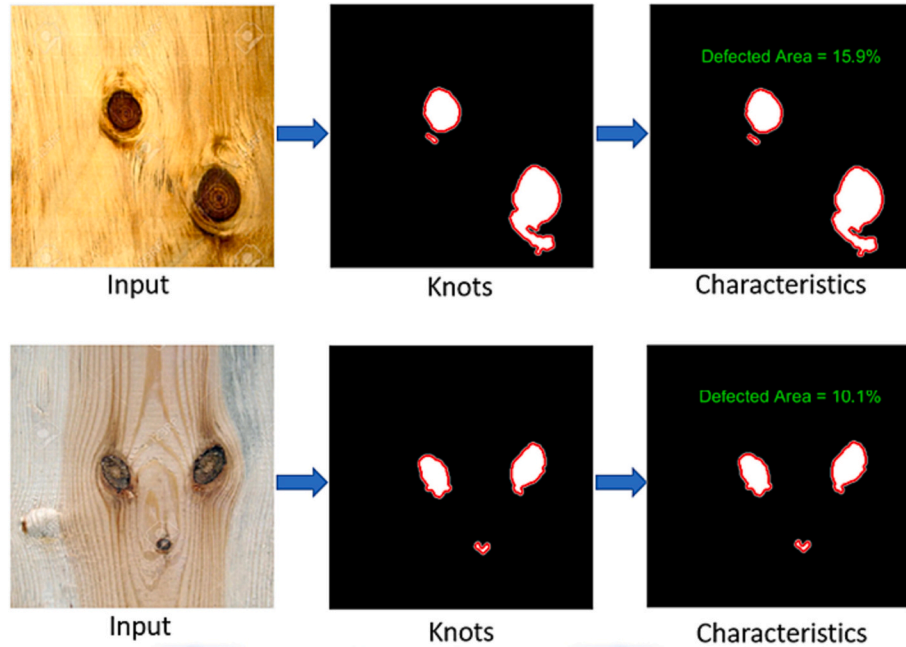


Fig. 10. Results of Knots tested images.

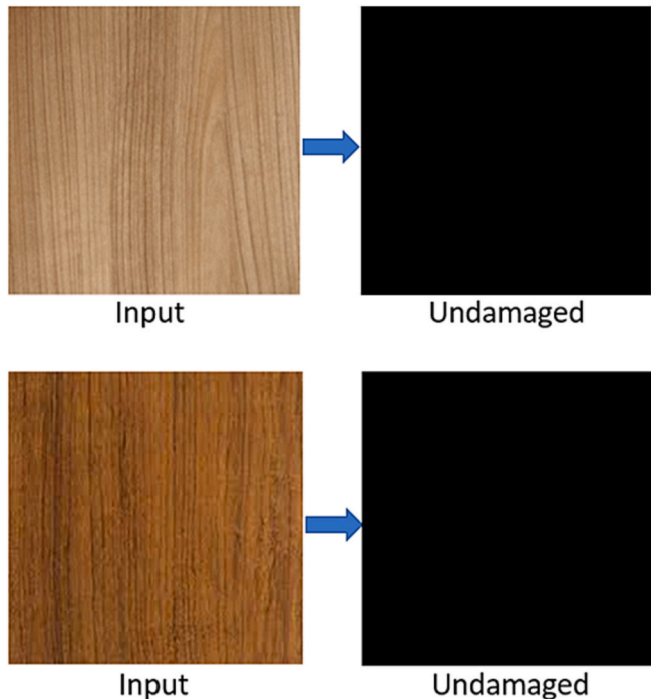


Fig. 11. Result of Undamaged class tested images.

the meticulous computation of their characteristics. Leveraging the formidable capabilities of the Inception-ResNet-V2 pre-trained CNN model, we have successfully categorized images into three pivotal classes: “cracks,” “knots,” and “undamaged” sections. The outcomes have proven highly promising: In our testing set for “crack” images, the CNN model accurately identified 91 out of 100 cases, showcasing its potential in defect classification. Furthermore, for the “knots” images testing set, the model achieved an impressive success rate of 96 out of 100 images, while for the “undamaged” testing set, it demonstrated a remarkable accuracy of 89 out of 100 images. Aggregating these results, the model yielded an impressive overall prediction accuracy of 92%.

Yet, beyond mere classification, we ventured deeper into the realm of defect characterization, employing image processing and soft computing methodologies to quantify specific defect attributes. These attributes encompassed the angle, length, and width of cracks, alongside the size of defective areas associated with knots. Our computations revealed maximum quantification errors of 2.3% for angles, 1.54% for lengths, and 4.2% for widths. These error rates, in the context of practical applications, are undeniably marginal, bolstering the efficacy of our methodology.

The significance of our research transcends mere innovation; it holds substantial promise for the wooden structures industry. Wooden structures, being a historically prevalent and ecologically sustainable construction choice, are undeniably prone to defects that can imperil their structural integrity and safety. Manual inspections, while indispensable, are laborious, time-consuming, and not always feasible, especially in hard-to-reach areas. Our method not only expedites the inspection process but also quantifies the extent of damage, offering critical data that can empower decision-makers to determine the most appropriate course of action. Furthermore, the ability to maintain comprehensive digital records enhances the long-term value of our approach, ensuring

continuous monitoring and easy referencing of structural health over time.

One of the notable innovations within our study is the seamless integration of advanced CNN models with image processing techniques. While each of these techniques has witnessed independent application in the past, our research framework has showcased their potential to synergize and elevate the precision of defect identification and quantification. This synergy paves the way for further refinements and optimizations, setting the stage for continued advancements in the field of automated wooden structure inspection.

In the immediate context, the advantages of the automated inspection methodology are evident, offering substantial time and cost savings for industry professionals. However, the long-term benefits are equally compelling. Our approach facilitates ongoing monitoring and data collection, contributing to an invaluable resource for informed decision-making, proactive maintenance, and the preservation of wooden structures' structural integrity and safety over their lifespan. Nonetheless, we acknowledge that our research is not without limitations. The integration of our model with real-time monitoring systems, as well as the implementation of our approach on a larger scale, stand as promising prospects for the wooden structures industry's continued advancement.

Looking ahead, there is ample room for future exploration in this domain. Subsequent research endeavors could consider the incorporation of additional defect categories to broaden the scope of our methodology. Additionally, refining algorithms to further decrease the quantification error rates could enhance the reliability of our approach. Expansion of the database to encompass diverse wood types and defects would bolster the versatility of our model. Furthermore, considering the integration of our model with real-time monitoring systems or drones could revolutionize how the wooden structures industry approaches safety and maintenance on a global scale.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Afaq Ahmad reports financial support was provided by Punjab Higher Education Commission.

Data availability

Data will be made available on request.

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