**Flexural behavior of wood in transverse direction investigated using novel computer vision and machine learning approach**

Shuoye Chen1\*, Tatsuya Awano1, Arata Yoshinaga1, & Junji Sugiyama1\*

1Laboratory of Tree Cell Biology, Division of Forest and Biomaterials Science, Graduate School of Agriculture, Kyoto University, Kyoto, 606-8502, Japan

**\*Corresponding Author**

Junji Sugiyama

Tel: +81 75 753 6238

Email: [sugiyama.junji.6m@kyoto-u.ac.jp](mailto:sugiyama.junji.6m@kyoto-u.ac.jp)

**Authors**

Shuoye Chen chenshuoye@gmail.com

Tesuya Awano: awano.tatsuya.7z@kyoto-u.ac.jp

Arata Yoshinaga: yoshinaga.arata.5a@kyoto-u.ac.jp

Junji Sugiyama: sugiyama.junji.6m@kyoto-u.ac.jp

**Highlights**

1. A semantic segmentation model with U-Net architecture was established to partition tracheid cells in cross-section of hinoki wood during micro three-point bending test.
2. The Crocker–Grier linking algorithm was applied to track the cell wall deformation
3. 2D mapping was constructed to evaluate the deformation intensity distribution at cellular level.
4. Rift-sawn specimens exhibited a unique shear deformation cell wall during the test.
5. The proposed approach can help in elucidating the relationship between the anatomical features and mechanical properties of wood.

**Abstract**

A deep-learning based semantic segmentation approach (U-Net) was used to partition the anatomical features in the cross-section of hinoki (*Chamaecyparis obtusa*) wood during a micro three-point bending test. Using the Crocker–Grier linking algorithm, thousands of cells were successfully extracted, and several parameters (area, eccentricity, fitted ellipse aspect ratio, bounding box aspect ratio) were used to evaluate the intensity of the cells’ deformation. Thus, the 2D map of the deformation intensity distribution was constructed. By analyzing flat-sawn, quarter-sawn, and rift-sawn specimens, it was confirmed that the annual ring orientation affects the flexural behavior of wood in the transverse direction. The quarter-sawn specimens exhibited the largest modulus of elasticity (MOE) and modulus of rupture (MOR). The ray tissue aligned against the load may have contributed to the restriction of cell wall deformation. The rift-sawn specimens exhibited the smallest MOE and MOR, possibly owing to the loading of the specimen in the in-plane off-axial direction, which induced the shear deformation of the cell wall. For all three specimen types, the fracture had high occurrence probability in the tension part of the specimen, which exhibited large cell deformation. Therefore, the proposed method can be adapted to the prediction of wood specimen fractures. With different test wood species, this approach can be of great help in elucidating the relationship between the anatomical features and the mechanical behavior of wood in the transverse direction to improve the effective utilization of wood resources.

**Keywords:**

Flexural behavior, Cell wall deformation, Semantic segmentation, Individual cell tracking, Computer vision, Deep learning

1. **Introduction**

Wood is a natural cellular material with complex structure and different cell types (anatomical features) acting together to serve the needs of the living tree [1]. As an anisotropic material, wood has excellent mechanical properties parallel to the grain (longitudinal direction), while its mechanical properties perpendicular to the grain (transverse direction) are relatively weak [2] and vary among different wood species in accordance with the species’ unique anatomical features [1].

Since ancient times, humans have used wood as a construction material and considered the microstructure of wood in the transverse direction. A relevant example is the traditional Japanese roofing method called kokerabuki [3]. In this method, quarter-sawn boards with a thickness of 2–3 mm, width of 90–150 mm, and length of 300 mm are stacked on the flat part of the roof, while rift-sawn boards are used for the curved surface of the roof, owing to their excellent flexibility in the transverse direction, of which Japanese artisans are aware through empirical knowledge. Understanding the relationship between the anatomical features and the mechanical behavior of wood is important for improving the effective utilization of wood resources. To clarify this relationship, wood scientists have developed several approaches from two main perspectives.

The first perspective is the top-down one, which refers to the direct microscopic observation of the deformation of anatomical features during or after a mechanical test. Ando and Onda [4] used a wet-type scanning electron microscope (SEM) to observe the compression of wood cell walls. Combined with image analysis, they found that the first fracture of the cell wall occurred in one tangential row of the earlywood tracheid just after the load–displacement curve exceeded the proportional limit. Müller et al. [5] observed the cell deformation of both softwood (spruce) and hardwood (oak and beech) at different yielding stages of the compression test using a SEM and a light microscope to obtain the different fracture patterns of the anatomical features of these species. Hwang et al. (2021) [6] used the replica method to intermittently analyze the cell wall deformation of flat-sawn, quarter-sawn, and rift-sawn specimens in the transverse direction of wood subjected to a three-point bending test. The rift-sawn softwood specimen exhibited a unique deformation pattern of the earlywood cell wall, which contributed to extremely large flexural deformation. These direct microscopic observation methods have provided important information that improve our understanding of the in-situ deformation of wood microstructures.

The second perspective is the bottom-up one, which refers to the mechanical simulation of wood properties with consideration to its hierarchical structure. Watanabe et al. [7, 8, 9] first used fast Fourier transform (FFT) to extract the axial length of the tangential and radial cell wall, cell wall thickness, and so on, of several conifer wood species to simulate the tangential Young’s modulus through cell wall modeling. Ando and Onda [10] used the generalized cell wall model to simulate the first buckling mechanism of the conifer wood cell wall under radial compression. Holmberg et al. [11] employed the finite element method (FEM) to simulate the nonlinear mechanical behavior with consideration to the irregular cell shape, anisotropic layer structure of the cell walls, and periodic variations of wood density. The simulated deformation and fracture of wood were similar to those observed in the process of wood refinement. De Magistris and Salmén [12] used FEM models to investigate the compression and combined shear and compression deformation of a cell wall with anisotropic one-layer cell walls and an orthotropic multi-layer cell wall. They found that cell structures are key factors influencing the deformation pattern. Recently, the multi-scale FEM was used to simulate the compression behavior of wood under both axis and transverse loading [13]. It was found that the transverse deformation of wood is gradual and uniform, while the loading velocity greatly affects the wood microstructure failure modes under loading in the axial direction. The above-mentioned approaches are useful in elucidating the mechanical behavior of wood.

In the field of computer vision, semantic segmentation has been proposed as an important approach for labeling each pixel of an image with a corresponding class of what is being represented. With the development of artificial intelligence, deep-learning-based semantic segmentation approaches, such as U-Net [14], LinkNet [15], Feature Pyramid Networks [16], and the Pyramid Scene Parsing Network [17], have been developed. These technologies have already been applied to autonomous vehicles [18] and the analysis of biomedical images for medical diagnosis [19]. If the approach of semantic segmentation can be adapted to the analysis of wood cell wall deformation, it will be easy to simultaneously analyze almost all local changes in the anatomical features and their interaction during a mechanical test. The obtained information can enable more accurate and quantitative image analysis. The collected cell wall geometry can also be used for more realistic mechanical simulation to optimize developed top-down and bottom-up approaches.

This study used an individual cell tracking algorithm to accurately analyze a semantic segmentation model that was built to partition the tracheids of hinoki wood and their local deformation during a micro three-point bending test.

1. **Materials and methods**
   1. **Specimen preparation**

This study investigated mature Hinoki (*Chamaecyparis obtusa*) wood. Three sample types (flat-sawn, rift-sawn, and quarter-sawn) were first prepared only from sapwood with consideration to the orientation of the annual ring, which was confirmed by visual observation. The angle of the annual ring aligned in the horizontal direction and vertical direction was 0° and 90°, respectively. The sample with an annual ring angle of 0° to 30° was defined as flat-sawn, that with a ring angle of 30° to 60° was defined as rift-sawn, and that with a ring angle of 60° to 90° was defined as quarter-sawn. Five flat-sawn, quarter-sawn, and rift-sawn, specimens were prepared with the dimensions of 10 mm (longitudinal) × 20 mm (width) × 1.5 mm (thickness), respectively. The cross-section of all specimens was smoothed by a sliding microtome (TU-213, Yamato kohki industrial Co., Ltd., Japan). Then, all specimens were conditioned in a plastic glove box at 60% relative humidity (RH) and 25 °C using sodium bromide solution for more than two weeks.

* 1. **Micro three-point bending test**

After the conditioning, all specimens were subjected to the micro three-point bending test. A customized metal jig (Fig.1(a)) was used for testing. A motor (BLM230P-GFV2, ORIENTAL MOTOR Co., Ltd., Japan) with a test speed of 1mm/min was used to horizontally bend the specimens. A 200-N load cell (LUR-A-200NSA1, Kyowa Electronic Instruments Co., Ltd., Japan) with a sensor interface (PCD-320A, Kyowa Electronic Instruments Co., Ltd., Japan) was used to record the force; the sampling speed was 1Hz. During the test, a stereo-microscope (Leica DMS300, Leica Camera AG, Germany) was set perpendicularly to the cross-section to record the deformation of the tracheid cells on video at 30 fps. The resolution was 1080p; the length of one pixel is equal to approximately 2.09 *µ*m. All experiments were conducted at 60% RH and 25 °C.

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**Fig. 1.** Illustration of micro three-point bending test: (a) illustration of mechanical test apparatus; (b) cross-section of wood specimen observed with stereo-microscope.

* 1. **Deep learning based semantic segmentation model**

To prepare the model training dataset, after capturing the video during the bending test, the first image at every second of the video was captured to compile an image sequence. Twelve original images with 256 × 256 pixels were cropped from the image sequence. The watershed segmentation implemented by Mahotas [20, 21] was first applied to label the boundary of the tracheid cells (Fig. 2(a)). The unlabeled part was manually modified to make the corresponding ground truth masks. The boundaries were labeled at the centerline of the adjacent cell walls. For a tracheid cell wall adjacent to the ray parenchyma cells, owing to the low contrast of the ray parenchyma cell lumen, the boundaries were always labeled at the center part of the ray parenchyma cell, which means that part of a ray parenchyma cell was recognized as a tracheid cell (Fig. 2(b)). In future work, the parenchyma cell walls should be labeled separately and the microscopic observation method should be improved.

Twelve sets of original images, and the corresponding ground truth masks with the cell boundaries labeled in white and the background labeled in black, were used to build the semantic segmentation model. For model training, the symmetric U-net architecture, which is achieved by using the “same” padding instead of “valid” in the original model [14], was used. The network was implemented using the Tensorflow framework (version 1.5.0) and Keras (version 2.2.4). The binary cross-entropy was used as the loss function, and Adam was used as the optimizer. The learning rate was 0.0001. During model training, the images were augmented by the image generator.

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**Fig. 2.** Preparation of dataset for semantic segmentation model training: (a) Cropped patch of wood cross section; (b) trachied cell boundary mask labeled by watershed segmentation algorithm; (c) manually corrected image mask. The scale bar indicates a length of 100 *μ*m.

* 1. **Model evaluation** **metrics**

Four metrics, namely, precision, recall, f1, and accuracy, were used to evaluate the trained model. These metrics were calculated from the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) obtained from the confusion matrix for the binary classification of the cell boundary and background. The following equations were used:

* 1. **Image prediction and individual cell tracking**

After model training, the trained model assisted by a patch blending algorithm [22] was used to partition all potential cells in the image sequence with 1920 pixels × 1080 pixels. After predicting all image sequences, watershed segmentation was used to achieve the instance segmentation of all cells. Finally, the coordinates of the centroid of the segmented cells were collected, and a tracking algorithm (Crocker–Grier linking algorithm) [23] implemented using Trackpy [24] was used to link the same cell walls in each image.

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**Fig. 3:** Tracking of cell deformation during mechanical test: (a) watershed segmentation of predicted image by trained U-net model to achieve instance segmentation; (b) centroid coordinates for each cell extracted as features for individual cell tracking; (c) centroid trajectories obtained by Crocker–Grier linking algorithm; the color of each trajectory was randomly generated.

* 1. **Parameter measurement for cell wall deformation analysis**

After tracking the individual cells that existed in every image sequence, the area, eccentricity, major and minor axis length of the fitted ellipse (Fig. 4 ① ②), and the vertical and horizontal length of the bounding box (Fig.4 ③ ④) for each cell wall were measured. The eccentricity was calculated from the fitted ellipse with the same second moments as the cell wall. The eccentricity of a circle is zero, while the eccentricity of an ellipse is greater than zero but less than one. These measurements were made using the Python scikit-image package [25]. The fitted ellipse aspect ratio and bounding box aspect ratio were calculated based on the following equations:

To evaluate the intensity of the cell wall deformation, the changes in the area, eccentricity, fitted ellipse aspect ratio, and bounding box aspect ratio were calculated based on the following equation:

where *n* indicates the order of the observed image sequence and *i* indicates the type of the measured parameters shown in Fig. 4.

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**Fig. 4.** Measurement parameters for evaluating intensity of cell wall deformation.

1. **Results and discussion**
   1. **Flexural behavior of flat-sawn, quarter-sawn, and rift-sawn specimens in transverse direction**

Figure 5 shows the difference in the mechanical properties of the flat-sawn, quarter-sawn, and rift-sawn specimens in the transverse direction. During the micro three-point bending test, the rift-sawn specimens exhibited the smallest load values with the largest displacement of approximately 3.3 mm, which resulted in the smallest modulus of elasticity (MOE) and modulus of rupture (MOR) (Fig. 5(a)). Assuming that the linear stage of load-displacement is the elastic region and the nonlinear stage is the plastic region, the rift-sawn specimens had the largest plastic region. In contrast, the quarter-sawn specimens exhibited the largest MOE and MOR (Fig. 5(b)) and had the smallest plastic region. These results are consistent with the results obtained by a previous study [6], which suggests that the orientation of the annual ring contributes significantly to the flexural behavior of wood in the transverse direction, and also demonstrates that the micro three-point bending test system is reliable for the investigation of the mechanical properties of wood in the transverse direction.

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**Fig. 5.** Mechanical properties of flat-sawn, quarter-sawn, and rift-sawn hinoki specimens in transverse direction: (a) load–displacement curve of three types of hinoki specimens during micro three-point test; (b) MOE and MOR of three specimen types. The error bars indicate the standard deviation.

* 1. **Validation of U-Net model and large image prediction**

With the development of artificial intelligence, fully convolutional network (FCN) models have been proposed for semantic segmentation [26]. The U-Net architecture was proposed by Ronneberger et al. [14] as an improvement of FCN, and is designed to use fewer training samples for model training. The U-Net architecture is a U-shaped architecture consisting of encoder blocks, decoder blocks, and skip connections, and has become a popular approach for semantic segmentation tasks. Recently, the U-net model was applied to the segmentation of plant tissues [27] and xylem vessels in stained cross-sections of wood [28], and achieved excellent accuracy. Therefore, this study selected U-Net to build the segmentation model.

Figure 6 shows the evolution of the binary cross-entropy loss during training for 100 epochs with the U-Net architecture. After training for approximately 40 epochs, the validation loss tended to become approximately constant and continued to decrease to approximately 0.1. The average values (standard deviation) of precision, recall, f1, and accuracy are 0.82 (0.017), 0.82 (0.019), 0.82 (0.017), and 0.92 (0.0006), respectively, which indicates that the constructed semantic segmentation model is accurate. Figure 6(b) shows an example of the original input image, and Figure 6(c) shows the image predicted by the trained model. The large image of the cross-section was satisfactorily predicted by combining the patch blending algorithm and the trained model. Most tracheid cells appeared to be satisfactorily segmented, whereas the partition of the latewood tracheid cells and some earlywood cell walls were not satisfactorily predicted, owing to the low contrast of the cell wall lumen. To overcome this problem, the microscopic observation method must be improved to increase the contrast of the cell wall lumen.

The geometrical parameters of a flat-sawn specimen were measured to further confirm the segmentation accuracy. The vertical bounding box and horizontal bounding box were considered as the cell radial diameter and cell tangential diameter. Figure 7 shows the distribution of the typical parameters measured from the segmented cells. The averaged values (standard deviation) of the area, cell eccentricity, cell radial diameter, and cell tangential diameter are 955 *μ*m (306), 0.596 (0.146), 37.5 *μ*m (7.63), and 34.8 *μ*m (6.62), respectively. These parameters are consistent with the geometrical parameters reported by a previous study [29].

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**Fig. 6.** Tracheid cell wall boundary prediction by trained U-net model: (a) binary cross-entropy loss plotted against training epochs; (b) original image input; (c) predicted image. The scale bar indicates the length of 400 *μ*m.

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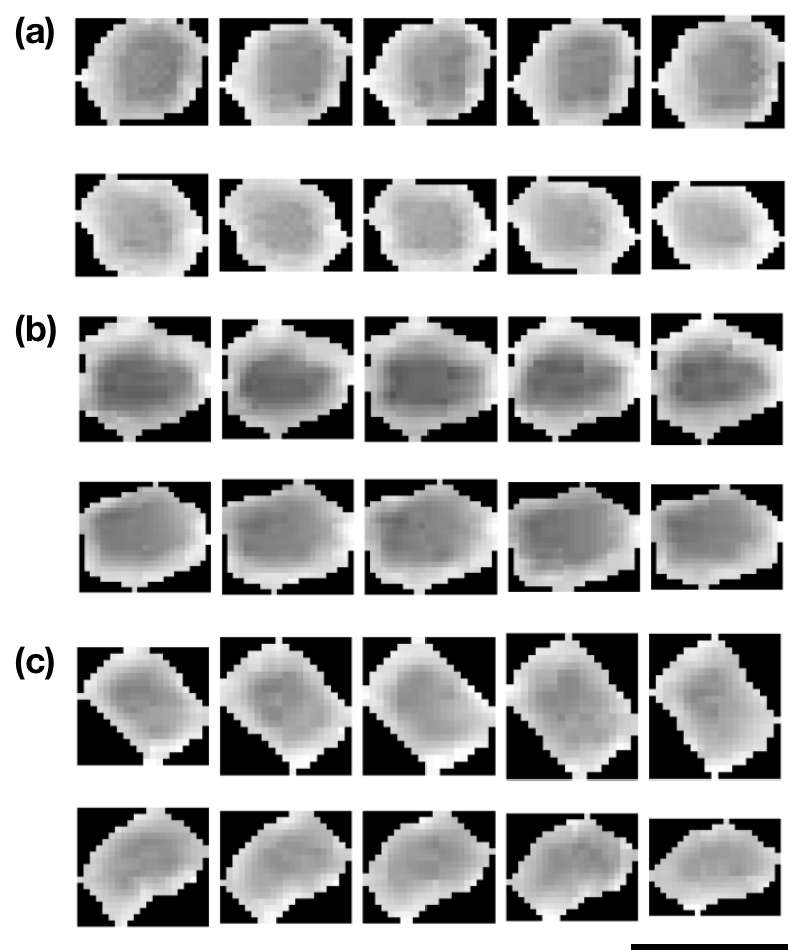
**Fig. 7.** Distribution of typical parameters measured from flat-sawn specimen before mechanical test: (a) cell area (*µ*m2); (b) cell eccentricity; (c) cell diameter (*µ*m) (yellow: cell radial diameter; gray: cell tangential diameter).

* 1. **Typical deformation patterns of tracheid cell wall in three specimen types**

Figure 8 shows the typical deformation patterns of a tracheid earlywood cell wall located in both the compression part and the tension part of the three specimen types. The changes in the shape of a single cell wall located in both the compression part and tension part of the three specimen types during the mechanical test were intermittently extracted and compared.

For the flat-sawn specimens, the uniaxial compression and tension of the tangential cell wall occurred under compressive and tensile stress during the bending test, respectively (Fig. 8(a)). Owing to the orthogonal orientation of the cell wall, similar deformation was observed at the radial cell wall in the quarter-sawn specimens. Because the quarter-sawn specimens fractured at the early stage of the bending test, when the displacement was only approximately 1 mm, the dimensional changes of the cell wall were relatively smaller than those of the flat-sawn specimens (Fig. 8(b)).

Unlike the flat-sawn and quarter-sawn specimens, the cell wall in the rift-sawn specimens exhibited different deformation pattern. The shear deformation of the cell wall along the vertical and horizontal direction was observed in the compression part and tension part, respectively. This orientation of the tracheid cells is somewhat similar to the uniaxial loading of honeycombs in the in-plane off-axial direction. Li et al. [30] simulated the in-plane yield strength of square honeycombs in different directions under compression using a theoretical approach and the FEM method. They concluded that square honeycombs exhibit strong anisotropy when loaded in different orientations. Their numerical simulation results revealed that the axial yield strength of the square honeycomb has minimum values at an angle of orientation of 37°–38°, which is in the range of the orientation of the annual ring of the rift-sawn specimens. Therefore, it is thought that the shear deformation induced by the off-axis loading of the tracheid cell is responsible for the large displacement and low MOE and MOR of rift-sawn specimens.



**Fig. 8.** Typical deformation pattern of tracheid cell wall for (a) flat-sawn, (b) quarter-sawn, and (c) rift-sawn specimens during micro three-point bending test. The upper row of each subfigure indicates the cell wall located in the compression part; the lower row of each subfigure indicates the cell wall located in the tension part. The scale bar indicates a length of 50 *μ*m.

* 1. **Visualization of distribution of tracheid cell wall deformation**

Using the Crocker–Grier linking algorithm, the coordinates of the centroids for each common tracheid cell that existed in each frame of the image sequence were linked, and thousands of common cells were extracted. These common cells were mainly the earlywood cells, which had sufficient cell wall lumen contrast. The latewood cells and earlywood cells, which had low cell wall lumen contrast along the radial direction, were not linked owing to their bad segmentation. After evaluating the intensity of the deformation by calculating the changes in the four parameters (area, eccentricity, fitted ellipse aspect ratio, and bounding box aspect ratio) described in Section 2, the 2D mapping of the cell deformation intensity for the three specimen types was constructed. The white color indicates that the measured parameters were unchanged; the darker red and darker blue color indicate larger increase and larger decrease in the measured parameters, respectively. The changes in the eccentricity and fitted ellipse aspect ratio of the cell wall are strongly depended on the original shape of the cell wall before the test to obtain both the increase and decrease of values under the same mechanical stress. The changes in the bounding box aspect ratio do not depend on the original shape. Therefore, the increase in the bounding box aspect ratio indicates the horizontal compression of the cell wall, while the decrease in the bounding box aspect ratio indicates the horizontal tension of the cell wall.

In the elastic region, all specimens exhibited relative slight and varied deformation for all parameters (Fig. 9(a, d, g, j); Fig. 10(a, d, g, j); Fig. 11(a, d, g, j). In the plastic region, the cell wall deformation distribution was different (Fig. 9(b, e, h, k), Fig. 10(b, e, h, k), Fig. 11(b, e, h, k). The intensity of the deformation reached the maximum before the fracture of the specimen (Fig. 9(c, f, I, l); Fig. 10(c, f, I, l); Fig. 11(c, f, I, l)).

For the flat-sawn specimens, the area appears to be the most appropriate parameter for deformation evaluation. As shown in Fig. 9(b, c), the cell area increased in the tension part and decreased in the compression part of the specimen. The intensity of the changes in the compression part is relatively smaller than that of the tension part, possibly owing to the existence of latewood at the compression part, which contributed to the restriction of cell deformation. The significant increases and decreases in eccentricity were concentrated in the tension part of specimen (Fig. 9(e, f)). Presumably, the horizontal tension of the wood cell wall induced both an increase in the eccentricity of circle-shaped cells and a decrease in the eccentricity of vertical ellipse-shaped cells, which resulted in a mixture of increase and decrease in eccentricity. For the same reason, a similar situation was observed in the case of changes in the fitted ellipse aspect ratio (Fig. 9(h, i)). For the bounding box aspect ratio (Fig. 9(k, l)), the results for the cells located in the central part of the specimen are reasonable. The increase and decrease in the bounding box aspect ratio were observed in the compression part and tension part, respectively. However, the bending test caused the curvature of the specimens, which changed the orientation of the cells located in the surrounding part of the specimens, and thus influenced the reliability of the specimens’ measured bounding box aspect ratio.

The quarter-sawn specimens exhibited the smallest plastic region among the three specimen types (Fig. 10), and the bounding box appears to be a promising parameter. The minor changes in the cell area varied even in the plastic region and before the fracture (Fig. 10(b, c). Similar to the flat-sawn specimens, the changes in the cell eccentricity and fitted ellipse aspect ratio are strongly depended on the original shape of the cells, and both an increase and decrease in the eccentricity and fitted ellipse aspect ratio were observed in the compression and tension part of the specimen, which indicates that these parameters may not be appropriate (Fig. 10(e, f, h, j). In the case of the bounding box aspect ratio, because the specimen exhibited minor curvature during the bending test, the compressive stress caused the ratio to increase, whereas the tensile stress caused the ratio to decrease. The neutral axis was observed approximately at the central part of the specimen with the smallest changes in the ratio (Fig. 10(k, l)).

For the rift-sawn specimen (Fig. 11), the area, eccentricity, and fitted ellipse aspect ratio appear to be appropriate parameters for the evaluation of deformation. Rather than in the flat-sawn and quarter-sawn specimens, the more concentrated and intensive deformation was observed at the innermost area of the compression part and outermost area of the tension part of the rift-sawn specimens. A decrease in the cell area was observed both in the compression part and tension part (Fig. 11(b, c)), and corresponds to the region exhibiting an increase in the cell eccentricity and fitted ellipse aspect ratio (Fig. 11(e, f, h, i). The reason for this is that the shear formation of the cell wall was the dominant deformation pattern and responsible for the increase in eccentricity and major axis length, and the decrease in the minor axis length. For the bounding box aspect ratio, the changes in the cell orientation led to unreliable cell deformation results (Fig. 11(k, l)), as in the case of the flat-sawn specimens.

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**Fig. 9**. Intensity of cell wall deformation of flat-sawn specimens during micro three-point bending test evaluated by four parameters: (a, b, c) changes in area (%); (d, e, f) changes in eccentricity (%); (g, h, i) changes in fitted ellipse aspect ratio (%); (j, k, l) changes in bounding box aspect ratio (%); (a, d, g, j) elastic region; (b, e, h, k) plastic region; (c, f, i, l) before fracture.

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**Fig. 10.** Intensity of cell wall deformation of quarter-sawn specimens during micro three-point bending test evaluated by four parameters: (a, b, c) changes in area (%); (d, e, f) changes in eccentricity (%); (g, h, i) changes in fitted ellipse aspect ratio (%); (j, k, l) changes in bounding box aspect ratio (%); (a, d, g, j) elastic region; (b, e, h, k) plastic region; (c, f, i, l) before fracture.

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**Fig. 11.** Intensity of cell wall deformation of rift-sawn specimens during micro three-point bending test evaluated by four parameters; (a, b, c) changes in area (%); (d, e, f) changes in eccentricity (%); (g, h, i) changes in fitted ellipse aspect ratio (%); (j, k, l) changes in bounding box aspect ratio (%); (a, d, g, j) elastic region; (b, e, h, k) plastic region; (c, f, i, l) before fracture.

* 1. **Clustering analysis of deformation pattern of individual cell and its relationship with stress–strain curve**

After selecting an appropriate parameter for the evaluation of deformation, the changes in the area, bounding box aspect ratio, and fitted ellipse aspect ratio were considered to investigate the cell deformation of the flat-sawn, quarter-sawn, and rift-sawn specimens, respectively. The k-means clustering algorithm, which was implemented through the Python scikit-learn package [31], was used to summarize the deformation patterns.

The clustering algorithm effectively summarized eight clusters corresponding to the intensity of cell deformation for the three specimen types (Fig. (12(a, b, c)). The cluster distribution for the three specimen types is shown in Fig. 12(d, e, f). Figure 12(g, h, I, j, k, l) shows the relationship between the eight summarized deformation patterns and the stress and strain for the three specimens types. In the elastic region, linear changes in the cell area, bounding box, and fitted ellipse aspect ratio for the flat-sawn, quarter-sawn, and rift-sawn specimens were observed as the stress and strain increased. However, the cell deformation pattern of those specimens was different in the plastic region.

For the flat-sawn specimens, in the middle stage of the plastic region, the clusters with the red and vermilion colors exhibited a slight monotonic increase in the cell area with the evolution of stress and strain (Fig. 12(g, j)). As shown in Fig. 13(a), the ray parenchyma cells appear to be a defect that facilitates fractures, and the detachment of the tangential cell wall between the cells was also observed. For the quarter-sawn specimens, a monotonic increase in the bounding box aspect ratio was observed in the late stage of the plastic region (Fig. 12(h, k)). The significant increase and decrease in the bounding box aspect ratio mainly occurred in the earlywood region near the previous latewood region (Fig. 12(b)). The earlywood cell wall located in that region exhibited a thinner cell wall with a large cell area, which resulted in weaker mechanical properties. This is assumed to be the reason for the initiation of the fracture of the specimen, which was induced by the detachment of the radial cell wall between the cells, in the earlywood region of the tension part (Fig. 13(b)). Because the ray parenchyma cells of the quarter-sawn specimens were aligned against the mechanical load, the ray parenchyma cells may have contributed significantly to the restriction of the cell wall deformation, which resulted in larger MOE and MOR compared with that of the flat-sawn specimens. For the rift-sawn specimens, two clusters with red and vermilion colors along the radial files exhibited exponential increase as the stress and strain increased (Fig. 12(i, l). This drastically large shear deformation contributed significantly to the flexibility of the rift-sawn specimens. Owing to the orientation of the annual ring at approximately 44.5°, the ray tissue appeared to impose a minor restriction on the cell walls. The detachment of the tangential cell walls between the cells along the radial direction dominated the fracture pattern of the specimens (Fig. 13(c)).

The fractures of the three specimen types had high occurrence probability in the corresponding tension part of their clustered image that exhibited large cell deformation. Therefore, the proposed method can be adapted to predict the fracture of wood specimens.

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**Fig. 12.** Results of k-means clustering for deformation patterns and their relationship with stress and strain of specimens: (a, b, c) clusterized images of flat-sawn, quarter-sawn, and rift-sawn specimens, respectively; (d, e, f) distribution of clusters of changes in area, bounding box aspect ratio, and fitted ellipse aspect ratio for flat-sawn, quarter-sawn, and rift-sawn specimens, respectively; (g, h, i) clusterized changes in area, bounding box aspect ratio, and fitted ellipse aspect ratio during mechanical test for flat-sawn, quarter-sawn, and rift-sawn specimens, respectively, and their relationship with strain. The light green and skyblue areas indicate the assumed elastic and plastic regions; (j, k, l) clusterized changes in area, bounding box aspect ratio, and fitted ellipse aspect ratio during mechanical test for flat-sawn, quarter-sawn, and rift-sawn specimens, respectively, and their relationship with stress. The light green and skyblue areas indicate the assumed elastic and plastic regions.

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**Fig. 13.** Typical fracture of (a) flat-sawn, (b) quarter-sawn, and (c) rift-sawn specimens after micro three-point bending test. The scale bar indicates a length of 400 *μ*m.

1. **Conclusion**

This study constructed a deep-learning-based semantic segmentation model with U-Net architecture to partition tracheid cells in the cross-section of hinoki wood during a micro three-point bending test. Using the Crocker–Grier linking algorithm, thousands of cells were extracted. Then, several parameters (area, eccentricity, major/minor axis length, vertical/horizontal bounding box length) were used to evaluate the intensity of the cells’ deformation, and the 2D mapping of the deformation intensity distribution at the cellular level was constructed. The following conclusions were drawn:

1. The area and bounding box aspect ratio parameters are appropriate for evaluating the cell wall deformation of flat-sawn and quarter-sawn specimens. Because the rift-sawn specimens exhibited the relatively large shear deformation of the cell wall, the area, eccentricity, and fitted ellipse aspect ratio are appropriate parameters for the evaluation of deformation.

2. The quarter-sawn specimens exhibited the largest MOE and MOR. The ray parenchyma cells aligned against the mechanical load may have contributed to the restriction of the cell wall deformation. The rift-sawn specimens exhibited the smallest MOE and MOR, possibly owing to the loading of the specimen in the in-plane off-axial direction, which induced the shear deformation of the cell wall.

3. For all three specimen types, according to the k-means clustering results for the cell wall deformation pattern, there was high probability of fracture occurrence in the tension part of the specimen, which exhibited large cell deformation. Therefore, the proposed method can be adapted to fracture prediction for wood specimens.

By considering wood species with different anatomical features, the proposed approach can achieve greater progress in clarifying the relationship between the anatomical features and the mechanical behavior of wood in the transverse direction.

1. **References**
2. Ross Robert J., Wood Handbook-Wood as an Engineering Material, WI : U.S. Dept. of Agriculture, Forest Service, Forest Products Laboratory, 2010. <https://doi.org/10.2737/FPL-GTR-190>
3. L.J. Gibson, M.F. Ashby, Cellular Solids: Structure and Properties, Pergamon Press, New York, 1998.
4. S. Yokoyama, Restoration discussion of Saitama prefecture specified tangible cultural property Yakyu Inari shrine (in Japanese). AIJ J. Technol. Des. 22 (2016) 1143-1148. <https://doi.org/10.3130/aijt.22.1143>
5. K. Ando and H. Onda, Mechanism for deformation of wood as a honeycomb structure I: effect of anatomy on the initial deformation process during radial compression, J. Wood Sci. 45 (1999) 120-125. <https://doi.org/10.1007/BF01192328>
6. U. Müller, W. Gindl, A. Teischinger, Effects of cell anatomy on the plastic and elastic behaviour of different wood species loaded perpendicular to grain. IAWA J. 24 (2003) 117–128. <https://doi.org/10.1163/22941932-90000325https://doi.org/10.1163/22941932-90000325>
7. S. Hwang, H. Isoda, T. Nakagawa, J. Sugiyama, Flexural anisotropy of rift-sawn softwood boards induced by the end-grain orientation. J. Wood Sci. 67 (2021) 14. <https://doi.org/10.1186/s10086-021-01946-y>
8. U. Watanabe, M. Norimoto, T. Ohgama, M. Fujita M, Tangential Young’s modulus of coniferous early wood investigated using cell models, Holzforschung 53 (1999) 209–214. <https://doi.org/10.1515/HF.1999.035>
9. U. Watanabe, M. Norimoto, T. Morooka, Cell wall thickness and tangential Young’s modulus in coniferous early wood. J. Wood Sci. 46 (2000) 109–114. <https://doi.org/10.1007/BF00777356>
10. U. Watanabe, M. Fujita, M. Norimoto (2002) Transverse Young’s moduli and cell shapes in coniferous early wood. Holzforschung 56 (2002) 1–6. <https://doi.org/10.1515/HF.2002.001>
11. K. Ando K and H. Onda, Mechanism for deformation of wood as a honeycomb structure II: First buckling mechanism of cell walls under radial compression using the generalized cell model, J. Wood Sci. 45 (1999) 250-253. <https://doi.org/10.1007/BF01177734>
12. S. Holmberg, K. Persson, H. Petersson, Nonlinear mechanical behaviour and analysis of wood and fibre materials. Comput. Struct. 72 (1999) 459-480. <https://doi.org/10.1016/S0045-7949(98)00331-9>
13. F. De Magistris, L. Salmén, Finite Element modelling of wood cell deformation transverse to the fibre axis. Nord Pulp Pap. Res. J. 23 (2008) 240–246. <https://doi.org/10.3183/npprj-2008-23-02-p240-246>
14. W. Zhong, Z. Zhang, X. Chen, Q. Wei, G. Chen, X. Huang, Multi-scale finite element simulation on large deformation behavior of wood under axial and transverse compression conditions. Acta Mech. Sin. 37 (2021) 1136-1151. <https://doi.org/10.1007/s10409-021-01112-z>
15. O. Ronneberger, P. Fischer, T. Brox, U-Net: convolutional networks for biomedical image segmentation, Lect. Notes Comput. Sci. (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 9351 (2015) 234–241. <https://doi.org/10.1007/978-3-319-24574-4_28>
16. A. Chaurasia, E. Culurciello, LinkNet: Exploiting encoder representations for efficient semantic segmentation, 2017 IEEE Visual Communications and Image Processing (VCIP) (2017) 1–4. <https://doi.org/10.1109/VCIP.2017.8305148>
17. T. -Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, S. Belongie, Feature pyramid networks for object detection, 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017) 936–944. <https://doi.org/10.1109/CVPR.2017.106>
18. H. Zhao, J. Shi, X. Qi, X. Wang, J. Jia, Pyramid scene parsing network, 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) （2017) 2881–2890. <https://doi.org/10.1109/CVPR.2017.660>
19. X. Liu, Y. Han, S. Bai, Y. Ge, T. Wang, X. Han, S. Li, J. You, J. Lu, Importance-aware semantic segmentation in self-driving with discrete Wassersetin training, Proceedings of the AAAI Conference on Artificial Intelligence 34 (2020) 11629-11636. <https://doi.org/10.1609/aaai.v34i07.6831>
20. D. Müller, F. Kramer, MIScnn: a framework for medical image segmentation with convolutional neural networks and deep learning, BMC Med. Imaging 21 (2021) 12. <https://doi.org/10.1186/s12880-020-00543-7>
21. L. Vincent and P. Soille, Watersheds in digital spaces: an efficient algorithm based on immersion simulations, IEEE Transactions on Pattern Analysis and Machine Intelligence 13 (1991) 583-598. <http://doi.org/10.1109/34.87344>
22. L. P. Coelho, Mahotas: open source software for scriptable computer vision, J. Open Res. Softw. 1 (2013). <http://doi.org/10.5334/jors.ac>
23. <https://github.com/Vooban/Smoothly-Blend-Image-Patches>
24. J.C. Crocker, D.G. Grier, Methods of digital video microscopy for colloidal studies, J. Colloid Interf. Sci. 179 (1996) 298–310. <https://doi.org/10.1006/jcis.1996.0217>
25. D. B. Allan, T. Caswell, N.C. Keim, C.M. van der Wel, Trackpy v0.5.0. (Version 0.5.0), Zenodo, April 13, 2021. <https://doi.org/10.5281/zenodo.4682814>
26. S. van der Walt, J.L. Schönberger, J. Nunez-Iglesias, F. Boulogne, J.D. Warner ,N. Yager, E. Gouillart, T. Yu, the scikit-image contributors, Scikit-image: image processing in Python. PeerJ 2 (2014) e453 <https://doi.org/10.7717/peerj.453>
27. J. Long, E. Shelhamer, T. Darrell, Fully convolutional networks for semantic segmentation, 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015) 3431-3440. <https://doi.org/10.1109/CVPR.2015.7298965>
28. A. Wolny, L. Cerrone, A. Vijayan, R. Tofanelli, A.V. Barro, M. Louveaux, C. Wenzl, S. Strauss, D. Wilson-Sánchez, R. Lymbouridou, S.S. Steigleder, C. Pape, A. Bailoni, S. Duran-Nebreda, G.W. Bassel, J.U. Lohman, M. Tsiantis, F.A. Hamprecht, K. Scheitz, A. Maizel, A. Kreshuk, Accurate and versatile 3D segmentation of plants tissues at cellular resolution, elife 9 (2020) e56713. <https://doi.org/10.7554/eLife.57613>
29. A. Garcia-Pedrero, I.A. García-Cervigón, J.M. Olano, M. García-Hidalgo, M. Lillo-Saavedra, C. Gonzalo-Martín, C. Caetano, S. Calderón-Ramírez, Convolutional neural networks for segmenting xylem vessels in stained cross-sectional images. Neural. Comput. Appl. 32 (2020) 17927-17939. <https://doi.org/10.1007/s00521-019-04546-6>
30. A. Wolny, L. Cerrone, A. Vijayan, R. Tofanelli, A.V. Barro, M. Louveaux, C. Wenzl, S. Strauss, D. Wilson-Sánchez, R. Lymbouridou, S.S. Steigleder, C. Pape, A. Bailoni, S. Duran-Nebreda, G.W. Bassel, J.U. Lohman, M. Tsiantis, F.A. Hamprecht, K. Scheitz, A. Maizel, A. Kreshuk, Accurate and versatile 3D segmentation of plants tissues at cellular resolution, elife 9 (2020) e56713. <https://doi.org/10.7554/eLife.57613>
31. Saiki H (1963) Studies on annual ring structure of coniferous wood II Demarcation between earlywood and latewood (in Japanese). Mokuzai Gakkaishi 9: 231-236.
32. X. Li, Z. Lu, Z. Yang, C. Yang, Anisotropic in-plane mechanical behavior of square honeycombs under off-axis loading. Mater. Des. 158 (2018) 88-97. <https://doi.org/10.1016/j.matdes.2018.08.007>
33. F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, E. Duchesnay, Scikit-learn: machine learning in python, J. Mach. Learn. Res. 12 (2011) 2825-2830. <https://dl.acm.org/doi/10.5555/1953048.2078195>

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**Author contributions**

SC and JS designed the experiments; SC mainly conducted experiments and wrote the manuscript; TA, AY, JS supervised the work. All authors approve the final version of the manuscript.

**Data Availability**

The datasets genereated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

All codes and the set of test images obtained by this study are available online at Github.com (https://github.com/pywood21/Tracking\_cell\_wall\_deformation).