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DATA NOTE

REVISED A large-scale image dataset of wood surface defects for automated vision-based quality control processes [version 2; peer review: 2 approved]

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Abstract
The wood industry is facing many challenges. The high variability of raw material and the complexity of manufacturing processes results in a wide range of visible structure defects, which have to be controlled by trained specialists. These manual processes are not only tedious and biased, but also less effective. To overcome the drawbacks of the manual quality control processes, several automated vision-based systems have been proposed. Even though some conducted studies achieved a higher recognition rate than trained experts, researchers have to deal with a lack of large-scale databases and authentic data in this field. To address this issue, we performed a data acquisition experiment set in the industrial environment, where we were able to acquire an extensive set of authentic data from a production line. For this purpose, we designed and implemented a complex technical solution suitable for high-speed acquisition during harsh manufacturing conditions. In this data note, we present a large-scale dataset of high-resolution sawn timber surface images containing more than 43 000 labelled surface defects and covering 10 types of the most common wood defects. Moreover, with each image record, we provide two types of labels allowing researchers to perform semantic segmentation, as well as defect classification, and localization.

Keywords
wood surface defects, high resolution dataset, wood industry, wood processing, wood quality control process, wood defects dataset

Open Peer Review

Approval Status ✔ ✔

	1	2
version 2 (revision) 27 Jun 2022	✔ view	✔ view
version 1 16 Jul 2021	? view	? view

1. **Mariusz Pelc** ⬤, Opole University of Technology, Opole, Poland University of Greenwich, London, UK

2. **Sri Rahayu** ⬤, Universitas Nusa Mandiri, East Jakarta, Indonesia

Any reports and responses or comments on the article can be found at the end of the article.

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Author roles: Kodytek P: Conceptualization, Investigation, Methodology, Software, Validation, Writing – Original Draft Preparation; **Bodzas A**: Software, Writing – Original Draft Preparation, Writing – Review & Editing; **Bilik P**: Funding Acquisition, Project Administration, Supervision

Competing interests: No competing interests were disclosed.

How to cite this article: Kodytek P, Bodzas A and Bilik P. **A large-scale image dataset of wood surface defects for automated vision-based quality control processes [version 2; peer review: 2 approved]** F1000Research 2022, **10**:581 https://doi.org/10.12688/f1000research.52903.2

First published: 16 Jul 2021, **10**:581 https://doi.org/10.12688/f1000research.52903.1

> **REVISED** **Amendments from Version 1**
>
> The introduction section in a new version is complemented by a brief description of wood defects acquisition techniques employed in other studies (Introduction, Paragraph 3). The revised version contains a diagram presenting the particular stages of our dataset acquisition experiment (Figure 1) and a figure demonstrating examples of all defects available within the dataset (Figure 4). The Software availability section is complemented by some descriptions of the software tools and their key features. The references in a reference list are unified according to a Harvard referencing style, and the paper was proofread and edited.
>
> **Any further responses from the reviewers can be found at the end of the article**

Introduction

In the wood industry, each step of the manufacturing process affects material utilization and cost efficiency.[1] The heterogeneity of wood material with the complexity of these manufacturing processes may result in various defects, which not only degrade the mechanical properties of the wood, such as the strength and the stiffness but also reduce its aesthetic value.[2] These mechanical and aesthetical defects have furthermore a large impact on the commercial value of the wood and can diminish the utilization of such materials for further processing. There are many various types of defects arising from many different causes. The major wood defects include knots, fungal damage, cracks, warping, slanting, wormholes, and pitch defects. The seriousness of a defect, and therefore the grade and the cost of the material, is primarily determined by four criteria, including the size, location, type of the defect, and the purpose for which the wooden product will be used.[3,4]

Even though the automation in this industrial sector is growing, many market leader companies still utilize trained domain experts to detect undesirable features and to perform quality grading.[5] Besides the fact that the manual examination is tedious and biased, it was found that domain experts are not able to check large production volumes. Moreover, the study conducted by Urbonas *et al.*[6] stated that due to factors such as eye fatigue or distraction, manual inspection rarely achieves 70% reliability. To overcome the drawbacks of the manual examination, researchers try to develop automated systems, which are accurate and won't slow down the manufacturing process. According to the repeatability and quality of the inspection, the study performed by Lycken[7] has already proven that automatic systems slightly outperform human graders. Most of these systems were based on conventional image processing techniques in combination with supervised learning algorithms, however, over the last decade, deep learning has achieved remarkable success in the forestry and wood products industry.[8]

Although researchers in this field were able to achieve satisfying results with an average recognition rate above 90%,[9] most of the authors worked with small-scale image datasets obtained in laboratory conditions by using self-developed vision system setups. For instance, Shi *et al.*[10] were able to collect 2 226 wood veneer images containing one or more defects by using data collection equipment developed in the laboratory. The acquisition equipment included two cameras recording images with 8-bit depth, a conveyor belt with a width of 0.6 m and a length of 4.5 m, a light source, and a photoelectric sensor, which was used as a camera trigger. To achieve the desired amount of data within this dataset, authors employed data augmentation and implemented rotation, magnification, and horizontal and vertical mirroring on all images. The information about the dataset size before the data augmentation is not provided. On the other hand, in a research performed by Fabijańska *et al.*,[11] authors present an acquisition technique for capturing wood core images. In the first phase of the acquisition process, the cores were collected from the trunks at a height of approximately 1.3 m. Afterward, the collected cores were dried and glued into wooden holders and cut with the preparation blades. Finally, the prepared cores were scanned with a resolution of 600 or 1 200 dpi, which resulted in a dataset containing overall 312 different wood core piece images from 14 European tree species. Another study performing acquisition in laboratory conditions was conducted by Urbonas *et al.*[6] Authors in this study utilized a laboratory setup constructed of a conveyor belt, a light source, and a line scan camera. The acquisition was synchronized with the moving conveyor belt, and the images were captured at a speed of 4 m/s. In this experiment, researchers used 250 wood veneers with a size of 1 525 × 1 525 mm, where each veneer was scanned at a resolution of 4 000 × 3 000 pixels. During this experiment, overall 4 729 usable images were captured, out of which only 353 veneer images had at least one wood defect. Several wood defects acquisition experiments have been conducted in the field of wood recognition and quality control, however, according to the research performed by Kryl *et al.*,[9] most of the studies worked with a dataset with a size in a range from 250 to 5 200 images.

Performing experiments in such conditions usually entails the disadvantage of a limited number of available products. In most of the studies,[2,6,12,13] researchers compensate for the lack of real products by using data augmentation techniques, which can expand the dataset up to 10 times its original size. From one point of view, data augmentation is considered to be an excellent tool to generalize the classification model and therefore prevent overfitting.[14] Nonetheless, it cannot

ensure that the variability of the observed phenomenon will be sufficiently captured, especially in cases where the variability might be limitless.

In order to address the lack of extensive databases in this field, we performed an experiment with the goal to acquire a large-scale dataset of timber surface defects. Unlike other conducted studies, our experiment was placed in an industrial environment during real production, which allowed us to acquire a large amount of authentic data from the production line. To face the challenges arising from the manufacturing process, such as the high speed of the conveyor belt and heavy vibrations, we designed a hardware as well as a software solution, which enabled the acquisition of high-resolution images at the acquisition rate of 66 kHz. In this experiment, we acquired 20 276 original data samples of sawn timber surface, from which 1992 images were without any surface defects, and 18 284 images captured one or more defects covering overall 10 types of common wood surface defects. The most frequent defects include live knots and dead knots, with an overall occurrence in the dataset of 58.8% and 41.2%, respectively. Furthermore, to provide a more valuable information in this data descriptor, all dataset samples were complemented with two types of labels: a semantic label map for the semantic segmentation and a bounding box label.

Methods

Due to the industrial environment where the experiment was set, the most challenging part of this work was the dataset acquisition. Performing data acquisition in such an environment entailed several negative factors. One of those factors was that the sawmill production line utilized for this experiment is used for more than 300 days per year, with minimal pauses, which allows to maximize the manufacturer's profits. Another problem we had to deal with was the high speed of the sawmill conveyor belt, which reached a value of 9.6 m s^{-1} at the place of the acquisition. This high speed of the conveyor causes constant heavy vibrations, which in some peaks may result in fluctuations that are even centimeters long. Therefore, the main goal was to create a robust and at the same time portable construction, which can be easily implemented in the sawmill environment. The entire process of acquisition, including the postprocessing steps, is depicted in Figure 1.

Acquisition equipment

To overcome the limitations of this environment, we developed a mechanical construction to carry the camera and the light source. The final construction assembled from ITEM aluminum profiles was at the place of the acquisition fixed to the construction of a production line and the floor that prevented images from being blurred. Although this solution didn't deal directly with heavy vibrations, it ensured the harmonization of the conveyor vibrations with the mounted camera. The final mechanical solution implemented in the sawmill environment is demonstrated in Figure 2.

In order to obtain high-quality images at a speed of 9.6 m s^{-1}, a trilinear line scan camera SW-4000TL-PMCL manufactured by JAI was chosen. This camera was able to acquire 3×4096 pixels per line at the speed of 66 kHz. The required speed of the acquisition was achieved by connecting the camera interface to a high-performance Camera Link frame grabber with the transfer speed parameter set to 10 tap mode. For this application, we selected the Silicon Software microEnable five marathon VCLx frame grabber with a PCIe interface that allows onboard high-speed data processing and high data throughput up to 1 800 MB s^{-1}. The required field of view, which obtains a part of the sawn timber piece, with a width of 15 cm and a full length of 500 cm was achieved by using the Kowa LM50LF line scan camera lens. The selected camera, together with a 50 mm focal length lens placed at a distance of 40 cm from the measured object, led to a horizontal resolution of 16.66 pixels per millimeter. The vertical resolution R_v of the image was computed before the experiment by the following formula.

$$R_v = \frac{1}{\frac{\frac{v_w}{60} * L}{v_c}} \tag{1}$$

where v_w is the velocity of the conveyor, L is the number of lines per image, and v_c is the line rate of the camera. The resulting vertical resolution of 6.67 pixels per millimeter was afterward experimentally verified during the acquisition process.
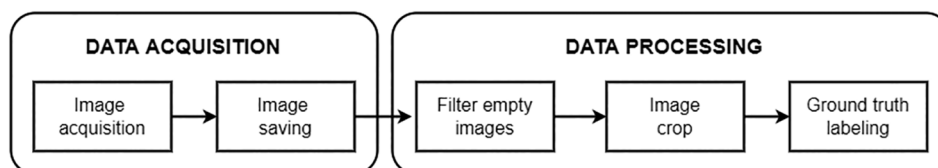

Figure 1. Research stages, including data acquisition and data processing steps.
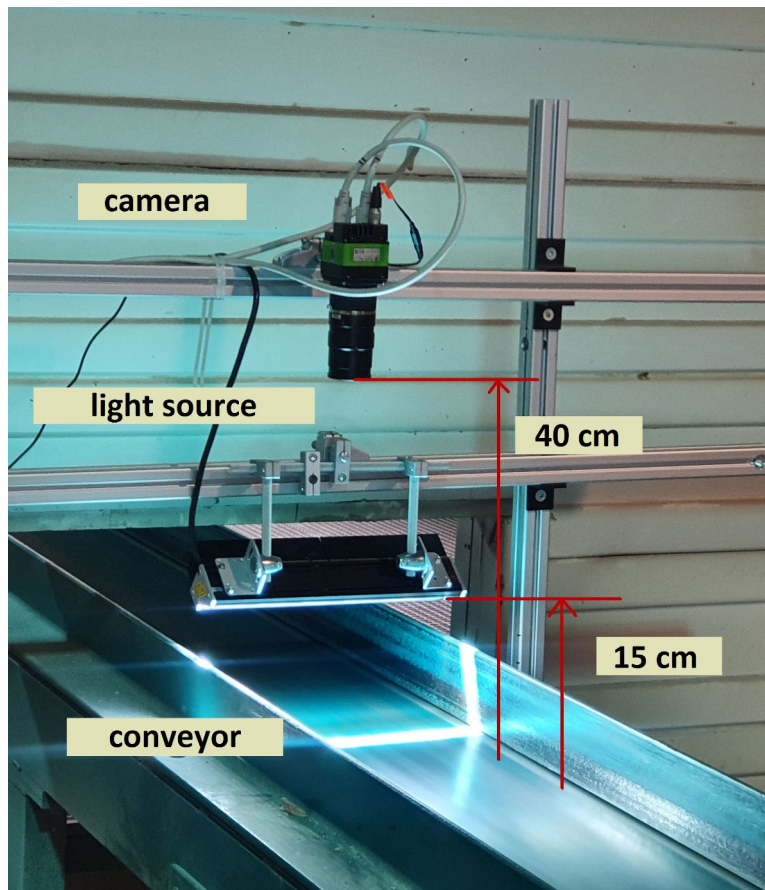
Figure 2. The mechanical construction, including the mounted camera and light source. The distance between the line scan camera and the light source from the conveyor belt is 40 and 15 centimeters, respectively.

Since the shutter of the camera was set to 3 μs, which ensured the high-speed image acquisition, we had to use a powerful light source, which would sufficiently illuminate the desired field of view. For this purpose, we selected one of the most powerful light sources on the market, a linear LED light Corona II by Chromasens with the ability to provide a light intensity of 3.5 million lux. To achieve the best possible images, a white spectrum of the light was utilized.

Data acquisition

Instead of saving every single line during the acquisition process, we captured a block of 1 024 lines, which resulted in an image resolution of 1 024×4 096. Such a high-resolution color image takes up approximately 12 MB of a disk space. The used sampling frequency of 66 kHz with the total number of captured pixels resulted in a data transfer speed of 773 MBs^{-1}, which means that we were able to capture 66.4 images per second. Even though we used a very powerful computer, we found the process of saving this amount of data at such a high speed quite challenging. To overcome this challenging task, we had to separate image acquisition and image saving into two different processes. While the acquisition process consisted of capturing a set of 84 images with a subsequent saving into the PC's RAM, the only task the saving process had was the transfer of the images from the computer RAM to the local hard disk drive. For this experiment, we employed two external 1 TB hard drives. To save CPU time during the acquisition and saving process, no online processing was performed.

Because transferring such a large amount of data between different software have a negative impact on CPU utilization and would decrease the frame rate, we used optimized frame grabber software, microDisplay X (runtime version 5.7) from Silicon Software.[15] To use this software in an automated way, we developed an automatic clicker with a feedback loop based on the captured computer screen. In simple terms, the software reads the desired information from the screen and based on the information decides whether the acquisition or saving process is already completed. Additionally, it automatically assigns an incrementing filename to each captured image. This was mainly realized by using Windows library user32.dll, which allows to control various aspects of mouse motion and button pressing. Since the saving process

(loop) was almost 10 times slower than the acquisition process, the acquisition loop had to be temporarily stopped in each cycle. Despite the fact that this caused a loss of data continuity, it does not affect the validity and the reliability of this study. We assumed that the acquisition process with the other support subroutines takes approximately 1.4 s while the saving process lasts 7.5 s. To maintain a predictable acquisition speed, including software delays, we introduced a synchronization, which started a new cycle every 9 s.

Data processing

During the four hours of acquisition, we acquired overall 60 480 images. Due to the limited third-party software functionality, the acquisition process had to be performed in a continuous mode, without any triggering option. This resulted in a large number of images of an empty conveyor or a partly captured wood surface. To filter these meaningless data from the dataset, an offline histogram-based algorithm was created. The basic idea behind this algorithm is the sum calculation of the image green color space histogram. The sum value of the histogram is in the next step divided by any number in the range from 5 to 10 (values in the range were deduced from the size of the images). The last step of the algorithm is based on a simple threshold, where all images with a resulting value of less than 10 were removed. Using this value of threshold ensured that only images that contained in the horizontal direction at least 40% of the wood surface were kept. Since this filtration approach proved 100% reliability in filtering images with no wooden surface on 1 500 randomly selected and manually sorted samples, we applied this filtering algorithm on the whole dataset. The filtering process reduced the dataset to a final number of 20 275 images.

Additionally, besides the filtration, we performed image cropping to remove the undesirable background from the images. This operation not only reduced the file size but also decreased the potential computation time for future use. To automatically crop each image in the dataset without any relevant data loss, we employed a simple straight-line edge detection technique in a vertical direction. Basically, the main principle of the algorithm is finding as many raising edge points in the desired direction as many points are needed to construct a line. The cropping operation was then performed on the image bounding box derived from the following formula.

$$BB(x_1, y_1, x_2, y_2) = \left(\frac{L_{x_1} + L_{x_2}}{2} - 150, L_{y_1}, \frac{L_{x_1} + L_{x_2}}{2} + 2650, L_{y_2} \right) \tag{2}$$

where $BB(x_1, y_1, x_2, y_2)$ is the cropped bounding box, and $L_{x_1 y_2 x_1 y_2}$ stands for the image coordinates of the detected straight edge. Cropping the image changed the image resolution to 2 800 × 1 024 and reduced the overall dataset size by almost 80 GB. An example of an image after the image crop operation is demonstrated in Figure 3.

Ground truth labeling

The dataset annotation in this study was performed manually by a trained person. To accelerate this time-consuming process, we developed a customizable annotation tool. In comparison with other annotation tools available on the market, which didn't fulfil our requirements, we created a universal application with the ability to manage bounding box labels, as well as labels for the semantic segmentation at the same time.[16]

For every single image, we created a BMP file representing a semantic map of the labeled defects. During the labeling process, the user manually painted zones in a displayed image, where each zone painted with a selected color represents a specific defect. Each drawn zone was then automatically bounded with a zone of the particular label and a bounding rectangle. From the created zones, the tool then automatically generated coordinates (left, top, right, bottom respectively) in the form of percent divided by 100, where a certain defect is located. For each processed image from the dataset, the annotation tool created a text file including labels and bounding box coordinates and a semantic segmentation map with the configured color labels.
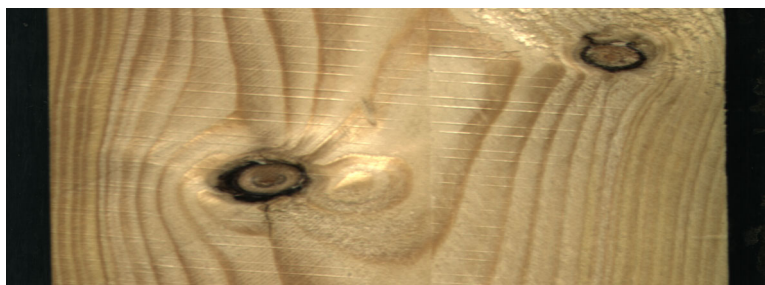

Figure 3. A dataset example of a sawn timber surface with dead knots.

Data records

The dataset containing the data acquired in this experiment is publicly available.[17] The dataset includes 1 992 images of sawn timbers without any defects and 18 283 timber images with one or more surface defects. On average, there are 2.2 defects per image, while only 6.7% of images contain more than three defects. The highest occurrence of defects, which was captured during the experiment, was 16 defects per image. In this dataset, we present altogether 10 types of wood surface defects, including several types of knots, cracks, blue stains, resins, or marrows. All types of defects within the dataset are demonstrated in Figure 4.

An overall overview of all available wood surface defects with a number of occurrences is summarized in Table 1.

Each color image with a resolution of 2 800×1 024 is provided in a BMP format in 10 separated zip folders labeled as *Images*.[17] Additionally, we provide two types of annotations, semantic label maps, and bounding box labels. Both labels are provided in separate zip folders. The bounding box labels are located in a folder *Bounding_Boxes* and named as *imagenumber_anno.txt*, where the *image number* corresponds to the name of the original image in the dataset. Each original image has therefore one assigned text file, which can have multiple label records for each defect in the image. All bounding box labels have the following structure, where the first record represents the object label, and the subsequent values correspond to the left, top, bottom, and right absolute positions of the defect in the image divided by 100.

<div align="center">

Knot_OK   0,421786   0,819336   0,571429   1,000000

</div>

Semantic label maps, used for semantic segmentation, are located in a folder, *Semantic Maps.* For each image in the dataset exists just one semantic map in a BMP format with the label name in the form of *imagenumber_segm.bmp*, where the image number represents the corresponding name of the original image. In comparison to bounding box labels, each pixel of the semantic map image has its label, which is determined by a specified color (see Figure 5).
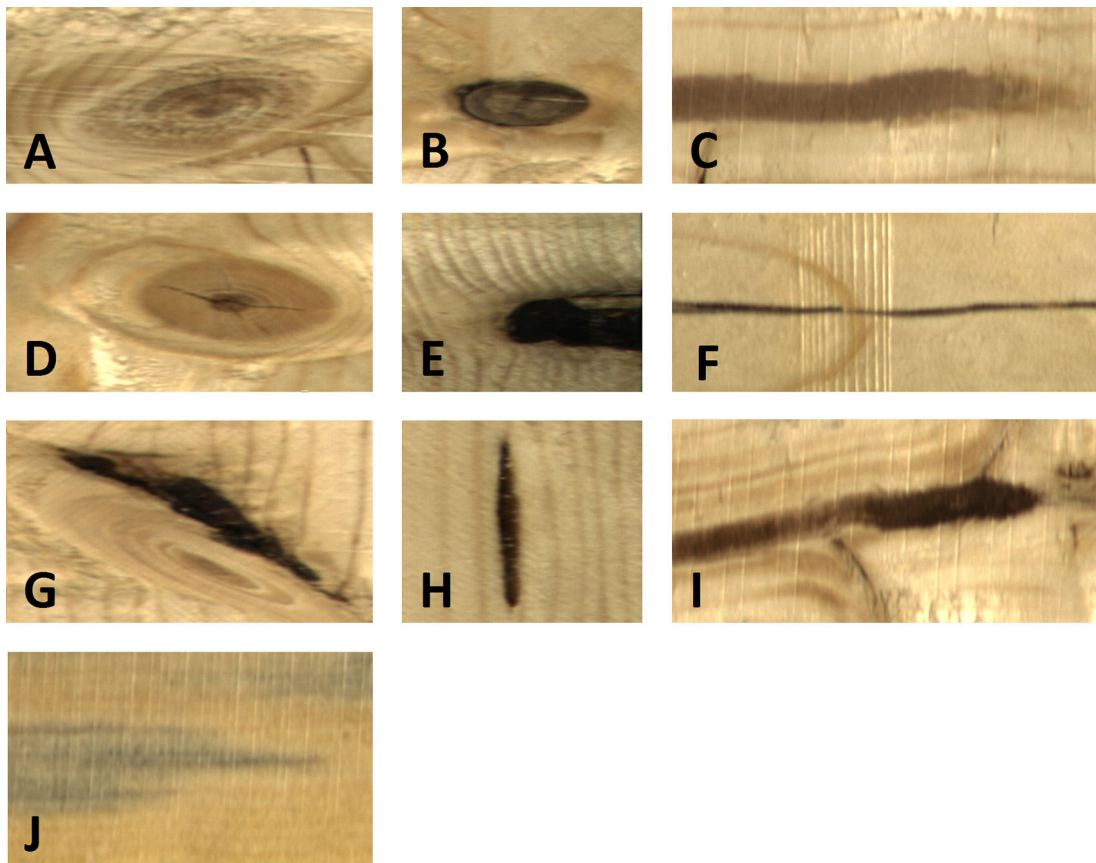

Figure 4. Typical samples of wood defects within the dataset: (A) Live Knot, (B) Dead Knot, (C) Quartzity, (D) Knot with crack, (E) Knot missing, (F) Crack, (G) Overgrown, (H) Resin, (I) Marrow (J) Blue stain.

Table 1. Wood surface defects included in the database with the number of particular occurrences and an overall occurrence within the dataset.

Defect type	Number of occurrences	Number of images with the defect	Overall occurrence in the dataset [%]
Live knot	21 224	11 912	58.8
Dead knot	11 985	8 350	41.2
Knot with crack	2 276	1 835	9.1
Crack	2 169	1 578	7.8
Resin	3 455	2 624	12.9
Marrow	1 181	1 060	5.2
Quartzity	1 075	847	4,2
Knot missing	503	478	2.4
Blue stain	96	77	0.4
Overgrown	10	6	0.03

Figure 5. Example of a semantic segmentation label. The red label represents dead knots, the green label stands for live knots, and the dark yellow represents knots with cracks.

Table 2. Annotation color specification for the provided dataset with hexadecimal color codes.

Defect type	Color	HEX color code
Live knot	Green	00FF00
Dead knot	Red	FF0000
Knot with crack	Dark Yellow	FFAF00
Crack	Pink	FF0064
Resin	Magenta	FF00FF
Marrow	Blue	0000FF
Quartzity	Purple	640064
Knot missing	Orange	FF6400
Blue stain	Cyan	10FFFF
Overgrown	Dark Green	004000

To see the exact label specification for the provided wood surface defect dataset, refer to *Semantic Map Specification* text file,[17] or Table 2.

Technical validation

The technical validation of the dataset was conducted by assessing the quality of the assigned labels by employing deep learning-based classification. For this purpose, we utilized a standard state-of-the-art convolution neural network detector based on the ResNet-50 model.[18] The selected neural network architecture was modified by adding Batch

Table 3. A detailed specification of the modified neural network parameters.

Parameter	Values
Sizes	[32, 64, 128, 256, 512]
Strides	[8, 16, 32, 64, 12]
Ratios	[0.3, 0.55, 1, 2, 3.5]
Scales	[0.6, 0.8, 1]

normalization and ReLu layers after each convolution layer. The input layer of the network, and therefore all dataset images were downsampled to 1 024 × 357. To train the neural network, we employed a transfer learning paradigm using pre-trained weights from the COCO dataset.[19] Moreover, we performed data augmentation, including horizontal, vertical flip, translation and scaling, and divided the dataset into a training and testing set in a conventional ratio of 40/60. To increase the detection of the labeled defects by the ResNet-50 model, several parameters were additionally modified on the basis of the trial-and-error process. These parameters included sizes, strides, ratios and scales (see Table 3).

At the beginning of the training, the first four layers of the network were frozen. After freezing the layers, the neural network was tuned by unfreezing the layers in reverse order except for the Batch normalization layer. The whole neural network was then finally fine-tuned at a low training speed. The overall number of epochs during the training was 30, while the training speed ranged between 10^{-4} at the beginning and 10^{-6} at the end of the training.

The trained ResNet-50 model resulted in an accuracy of 81%. Since the neural network outputted a large number of false positives, the dataset was re-evaluated by a trained person who didn't participate in the primary dataset labeling process.

Data availability
Underlying data
Zenodo: Underlying data for A large-scale image dataset of wood surface defects for automated vision-based quality control processes. 'Deep Learning and Machine Vision based approaches for automated wood defect detection and quality control'. http://doi.org/10.5281/zenodo.4694695.[17]

This project contains the following underlying data:

- Bounding boxes

- Images 1–10

- Semantic map specification

- Semantic maps

Data are available under the terms of the Creative Commons Attribution 4.0 International Public License (CC-BY 4.0).

Software availability
Zenodo: Software for labeling wood surface defects and managing images. 'Supporting tools for managing and labeling raw wood defect images'. http://doi.org/10.5281/zenodo.4904736.[16]

This project contains the following underlying data:

Labeler tool:

Custom-made labeling software that creates bounding boxes around the drawn area. After drawing the desired area, the software automatically creates a bounding box label, as well as a semantic label map. The software is fully customizable and allows full keyboard control together with a touch pen. A detailed description of the software can be found in the Ground truth labeling chapter.

Files

- Labeler_software.vi

- Readme.txt

- Labeler.ini

Support Utils:

Support tools that were used to crop and sort the images. The full description of the algorithm is mentioned in the Data processing chapter.

Files

- Cutter.vi

- Sorter.vi

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    Publisher Full Text

Open Peer Review

Current Peer Review Status: ✓ ✓

Version 2

Reviewer Report 12 July 2022

https://doi.org/10.5256/f1000research.135431.r142447

✓ **Sri Rahayu** (iD)

Universitas Nusa Mandiri, East Jakarta, Indonesia

The author has fulfilled the suggestions given.

A minor suggestion: provide some examples of currently available wood defect image datasets from previous researchers, as well as to make more references. Since the paper also produces a wood defect image dataset as well, I think it is better for the author to acknowledge other work to broaden the audience's view that other similar datasets are also available. If I had to mention examples of currently available wood defect image datasets from previous researchers, it is Riana *et al*., 2021[1].

References
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Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Single-cell technologies

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Reviewer Report 08 July 2022

https://doi.org/10.5256/f1000research.135431.r142448

Mariusz Pelc 🆔

[1] Faculty of Electrical Engineering, Automatic Control and Informatics, Opole University of Technology, Opole, Poland
[2] School of Mathematical and Computing Sciences, University of Greenwich, London, UK

I have read the revised version of the paper and I am happy to say that the paper has now reached the appropriate standard for indexing. Authors have made changes to the key elements (including use of English).

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Computer science, data / signal processing, automation and robotics, bio-medical engineering, expert sytsems.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

- -

Version 1

Reviewer Report 26 May 2022

? **Sri Rahayu** 🆔

Universitas Nusa Mandiri, East Jakarta, Indonesia

Wood defect datasets are still rare, so this research is very helpful for the wood industry and researchers interested in this field. The authors explain in detail the reasons for building this database with clear data acquisition and collection techniques.

Some of the methods used to construct semantic images and image testing may be replicated in others. The image acquisition technique used will be of great value if you mention the acquisition technique in other similar studies.

It would be even better if the authors provide examples of images for each image class and also presents the stages of the research in the form of a chart

Is the rationale for creating the dataset(s) clearly described?
Yes

Are the protocols appropriate and is the work technically sound?

Yes

Are sufficient details of methods and materials provided to allow replication by others?
Partly

Are the datasets clearly presented in a useable and accessible format?
Partly

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Single-cell technologies

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

> Author Response 22 Jun 2022
> **Alexandra Bodzas**, VSB-Technical University of Ostrava, Ostrava, Czech Republic
>
> The point-by-point responses to comments:
>
> 1. We complemented the Introduction section with a paragraph describing wood defects acquisition techniques used in other studies (Paragraph 3).
>
> 2. We complemented the paper with a diagram presenting the particular stages of the dataset acquisition (Figure 1) and a figure containing image examples for each class (Figure 4).
>
> *Competing Interests:* No competing interests were disclosed.

Reviewer Report 25 November 2021

https://doi.org/10.5256/f1000research.56234.r100946

? **Mariusz Pelc** [iD]
[1] Faculty of Electrical Engineering, Automatic Control and Informatics, Opole University of Technology, Opole, Poland
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This paper deals with a relevant problem which is detection of wood surface defects.

For the purpose of the research, the authors have come up with a coherent methodology allowing them to acquire all required data, then mapping and detecting defects. From an algorithmic viewpoint it all makes sense, besides, the whole methodology/algorithm validation has also been performed.

So, the paper ticks pretty much all the boxes (relevance, novelty, etc.) and as such it qualifies for publication.

However, the paper requires some substantial changes in the following areas:
1. There is no related work section which makes it really difficult to understand the authors' contribution to the field. I would recommend adding such a section (even if it is brief) where similar solutions would be discussed and confronted with what the authors are proposing in this paper.

2. Every single paper should include a conclusion section allowing all readers to understand key findings of the research. This paper is lacking a conclusion section which is quite an omission.

3. Some tables (e.g. Table 1) should be re-done as their versions included in the paper are hardly readable. Usually one look at a table provides a lot of information about the results whilst in this paper this is not the case. I would suggest the authors re-format all tables to make all the dates gathered in the table easy to see and understand.

4. The "Software availability" section should be rewritten. I would suggest the authors make this section easily comprehensible via adding some more description of the software tools used and maybe outline some key feature(s) of the software. Also, based on the section contents, the section title better reflecting this would be e.g. "Supporting software tools" where first paragraph should say that in this research the following software was used (then outline the software and how it was used).

5. Referencing - I only want to make sure that the authors have used the proper referencing style since the most frequently used are either Harvard or IEEE, whilst the authors have used a foot-note like referencing style.

6. The whole paper is written in maybe not error-free but still quite coherent and comprehensible English. But I would still recommend at least one more proof reading to make sure that there are no obvious mistakes left in the text.

Based on the above consideration I would recommend accepting the paper for indexing after revision.

Is the rationale for creating the dataset(s) clearly described?
Yes

Are the protocols appropriate and is the work technically sound?
Yes

Are sufficient details of methods and materials provided to allow replication by others?

Yes

Are the datasets clearly presented in a useable and accessible format?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Computer science, data / signal processing, automation and robotics, bio-medical engineering, expert sytsems.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 22 Jun 2022

Alexandra Bodzas, VSB-Technical University of Ostrava, Ostrava, Czech Republic

The point-by-point responses to comments:

1. Our paper was written in accordance with the journal guidelines for a Data Note article, which slightly differs from an original research article. Concerning the Data Note article, there is no related work section included in the article structure. However, to fulfill your requirements, we complemented the introduction section with a paragraph where we discussed similar solutions. The importance of this research is then explained in subsequent paragraphs.

2. The conclusion section is omitted intentionally again since we followed the data note article guidelines.

3. The tables in the article cannot be re-formatted since the article had been formatted by the editorial team before the publication. Table formatting is within the scope of an editorial team that formats the table according to the journal standards. Since the article is an online article, the tables are accessible and visible in full size after clicking on them.

4. The original Software availability section was rewritten before the publication to fulfill the editorial team's requirements. However, we complemented this section by adding some descriptions of the software. The title of this section cannot be changed since it follows the guidelines for a data note article and journal standards.

5. We unified the reference styles within the references. All references in a reference list are according to the Harvard referencing style. The in-text citation on the other hand are according to the journal standards, and the footnotes were added by the editorial team during the typesetting process

6. The paper was proofread and edited. The obvious mistakes were corrected.

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