



DATABASE

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A database of cross-sectional images for testing the biometric traceability of oak (*Quercus petraea* (Matt.) Liebl. and *Quercus robur* L.) logs under realistic acquisition conditions

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Key message

The *Biomtrace_extension* database contains 8341 RGB images of the butt end of 695 French oak logs. This database was created with the aim of developing biometric traceability methods based on realistic photo acquisitions in the field for tracking logs from the forest to primary processing. No such database was previously available. Photos of the same logs were taken on two dates several months apart, up to more than 100 days apart for some sites. Images were acquired in three specific cases in order to test the sensitivity and limitations of recognition algorithms under conditions that may occur in practice: (1) traceability based on photos taken before and after log extraction; (2) sensitivity of traceability to the quality of photos (angle of the shot and distance to the log); (3) robustness of traceability to partial or complete trimming of the log end. The database also includes manual reference measurements performed on the images, as well as outputs from image preprocessing algorithms. Tables containing site and image characteristics are also provided. The *Biomtrace_extension* database is available at <https://doi.org/10.57745/RKDTKY> and metadata are provided at: <https://metadata-afs.nancy.inra.fr/geonetwork/srv/fr/catalog.search#/metadata/5f2842a0-15ec-48be-8f1c-e44334654cc5>.

Keywords Image analysis, Segmentation, Log identification, Log recognition, Point matching

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1 Background

The *Biomtrace_extension* database was created with the aim of developing and testing biometric traceability algorithms under conditions that may be encountered in practice in the field between the forest (at the time of tree felling on the plot) and primary wood processing (after transport to the sawmill). One objective was to be able to test the limits of the algorithms in relatively extreme situations, which are detailed below.

The requirements for timber traceability are becoming increasingly stringent. This has resulted in a significant increase in research dedicated to this topic worldwide in recent years (Tonouéwa et al. 2024; Elias 2024; Pichler et al. 2026). In Europe, for wood products, the new EUDR



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regulation (<http://data.europa.eu/eli/reg/2025/2650/oj>) will require companies to prove that the timber is deforestation-free, legally harvested, and fully traceable through due diligence, including precise geolocation of the plots of origin. More specific issues related to different countries can also exist. In France, there is strong pressure on oak resources, which may be subject to illegal logging or exports. Indeed, oak is widely recognised as a high-quality, valuable wood species that is sold at high prices on the market. A specific label called “Transformation UE” has been created to encourage the local processing of oak resources with the aim of keeping as much as possible added value within the country. However, cases of fraud relating to this label have been observed. The plastic tags marking the logs are removed before loading into containers for illegal exports of labelled timber outside the EU (Abdelilah and Schmidt 2023a, b). More and more often, thefts of standing timber are also observed, particularly in private forests and for high-value species such as oak (Chermann 2025; Courageot 2025). Whether in the context of regulations or labels, it is necessary to strengthen traceability and associated controls. The idea behind biometric traceability for wood is to avoid relying solely on physical markers, which can be damaged or lost during transport and are easily falsified (Sun et al. 2021; Shirmohammadi 2022; Tonouéwa et al. 2024), by developing biometric traceability. According to Kaulen et al. (2023)’s literature review, biometric traceability is a very promising approach to develop. Very recent work has been devoted to developing algorithms for this purpose in several countries (Holmström et al. 2023; Wimmer et al. 2021, 2024; Martinetto et al. 2025b; Xie et al. 2025).

The *Biomtrace* project therefore aimed to develop biometric methods for the recognition and traceability of oak logs from photos of their cross-section (CS) taken on two dates several months apart. This study focuses on sessile oak (*Quercus petraea* (Matt.) Liebl.) and pedunculate oak (*Quercus robur* L.). These are the two most common species of oak in France, representing a cumulative total of nearly 700 million cubic metres of standing volume (IGN 2025). From a commercial perspective, these two species are not distinguished, and therefore they will also be considered without distinction in this study. The algorithms developed as part of this project have shown very high recognition rates: 100% in Martinetto et al. (2025b) and above 99.9% on an initial set of images (Longuetaud et al. 2024a, b, 2025a, b).

However, to build this initial database, the logs were not moved between photo shoots, which limited changes in the shape of the CSs. In particular, the side of the log embedded in the ground was the same for each shoot and changes in perspective were also limited. In addition, the time between two photo shoots was relatively short (25 to 63 days), although longer than in the few other databases available at the time.

This is why the *Biomtrace_extension* database was created in a second phase to assess the limitations of the algorithms previously developed in certain specific cases related to practices that may be encountered in the field. Such a database did not exist, and its creation was necessary in order to test log recognition algorithms under more realistic conditions. Three specific cases were studied as described below.

The first case (case study #1) concerns the traceability of logs based on photos taken before log extraction, immediately after felling the trees on the forest plot, and after log extraction, at the roadside storage area. In this new experiment, the logs were extracted from the forest plot, which led to rotations during transport and changes in perspective when taking photos. The side of the log CS embedded in the ground has changed, and the immediate environment of the log is different between the two photo sessions. In addition, dirt, particularly mud, could alter the appearance of the CSs between the two dates on which the photos were taken, thus complicating log recognition. When the photos for the second phase were taken in late spring, drying cracks may have appeared between the two dates, also making recognition more difficult.

The second case (case study #2) concerns the sensitivity of traceability algorithms to photo quality, particularly the angle of the shot in relation to the CS plane and the distance to the log. The purpose of these tests was to assess whether it was possible to take photos while standing, possibly stepping back a metre or two, rather than having to bend the knees to position oneself directly in front of the CS to be photographed. Indeed, if photos are to be taken routinely, the ergonomics of the task become an important aspect to study.

Finally, the last case studied (case study #3) aimed to test the sensitivity of traceability algorithms to partial (i.e. partial modification of the surface and contour of the CS) or total log end trimming (i.e. removal of a disc approximately 5 cm thick). Such changes in log CS could occur in cases of fraud. On the other hand, if all logs were recorded in a database, then the non-recognition of several of them due to the removal of their ends could prove suspicious and call for a thorough investigation of the situation.

This paper presents the detailed protocol for acquiring images under the various acquisition conditions studied, data on forest sites and images, manual reference measurements on images made available to the community, and outputs from image pre-processing algorithms that can be used as is or compared with outputs from other algorithms (when training was necessary, learning and test sets were also provided to enable the reproduction of the experiments).

2 Methods

The photo campaign, carried out between October 2024 and June 2025, enabled 8341 images to be collected representing 695 different oak logs. These are images of CSs of the butt end of oak logs. Since the database was designed for use in the development of biometric methods for log traceability, in most cases, photos of the same logs were taken on two dates (except for Case #3 below, which corresponds to the trimming of log ends; Sect. 2.3.3).

2.1 Image naming convention

Logging sites were generally identified by a “site identifier” provided by the National Forestry Office (ONF) and beginning with the letters FB (FB stands for “Fiche bois”, meaning timber data sheet; these sheets contain the timber volumes derived from one or more tree-marking sheets within the ONF timber supply chain and sales software called “ProductionBois”) followed by 9 digits (e.g. FB240036566). The image files were renamed using the “log number” prefixed by the “site identifier” and followed by the “photo sequence number” using an R script (R Core Team 2023) developed to automate the process. For instance, FB240043074_num_inrae_00151_R1 refers to the first image of the second photo session (the suffix R means Re-take of photos when there is a second date, and RR means second Re-take when there is a third date, for example) of log num_inrae_00151 taken at the logging site FB240043074. The way in which the different suffixes are coded differs depending on the on the different cases of image acquisition conditions in the field (see below). The file `Biomtrace_extension/tables/database_sites_extension.txt` (Longuetaud et al. 2025c) gives for each site the name of the forest in which it was located and its GPS coordinates, as well as information on the number of images and logs corresponding to the site.

2.2 General information about the photo-taking protocol

All photos were taken using standard smartphones: an Apple iPhone 8 and a Samsung SM-G981U1. All smartphones today have sufficient resolution. The operators were instructed to optimise image framing by positioning the device so that the CS of a log occupies as much of the image as possible without being cropped. Images were saved in JPG format. It should be noted that, depending on the camera, the saved image may include information about the rotation of an angle (90, 180 or 270 degrees) depending on the position of the camera when the photo was taken. This rotation information is recorded in the Exif metadata. Note that the dates of the photos in the Exif data of the images are incorrect for the Shot #4 directory of two sites: FB240035048 and FB240046857 (sites from

Case #2 below; Sect. 2.3.2). The correct dates for all sites and images are indicated in files `Biomtrace_extension/tables/database_sites_extension.txt` and `Biomtrace_extension/tables/database_images_extension`, respectively (Longuetaud et al. 2025c). The 8341 images are available on the data repository in `Biomtrace_extension/color_images` (Longuetaud et al. 2025c).

Additional information about the protocol is provided in Longuetaud et al. (2025b); for example, regarding the black and white checkerboard pattern placed on the log to retrieve pixel size information, or taking several photos per log on the same date by rotating the camera to increase the number of photos in the database.

2.3 Specific information about the photo-taking protocol for the three cases of acquisition conditions tested

2.3.1 Case #1: Traceability before/after log extraction

For this case study, the logs were photographed on two different dates. The first set of photos was taken on the plot at the base of the felled trees. The trees were not yet numbered, so four photos of each CS were taken by rotating the camera (Fig. 4 in Longuetaud et al. (2025b); image name suffixes _1 to _4), and a final photo was taken after affixing a label to the CS assigning a number to the tree (image name suffix _5). For some of the sites, four photos of each stump were also taken (image name suffixes _S1 to _S4). Photos were then taken at a later date (and for one site, on a third date as well) after log extraction and storage at the roadside on a storage area (image name suffixes _R1 to _R4, or _RR1 to _RR4 for a third date at the same place). The images collected for log FB240046691_num_inrae_00109 on two dates 146 days apart are shown in Fig. 1. For three of the sites, the time interval between photos taken in the stand after tree felling and those taken at the roadside after log extraction exceeded 100 days. During this period, relatively warm conditions may have occurred, leading to the development of drying cracks that were visible in the roadside photos (i.e. second acquisition) and that had not been observed to this extent during the previous campaign. This new data collection, much closer to real field conditions, enabled us to identify a major issue that will need to be addressed in order to ensure effective log traceability.

This experiment represents 4462 images from 422 logs (Table 1) sampled in six forests across seven sites.

In Table 1, column Shot #1 corresponds to the first date on which photos were taken (5 photos per log; 4 without labels and one with a label; image name suffixes _1 to _5); column Shot #2 corresponds to the second date on which photos were taken (4 photos per log; image name suffixes _R1 to _R4); 49 logs were photographed



Fig. 1 Example of images collected for one log from case study #1. On the first date, five photos were taken of the cross-section (including the last one with a label) (on the first row), as well as four photos of the stump (on the second row). On the second date, four photos of the cross-section were taken again (on the third row)

Table 1 Number of photos and logs for the Case #1 of traceability before and after log extraction

	Shot #1	Shot #2	Shot #3	Stump	Total
Number of photos	2110	1596	196	560	4462
Number of logs	422	399	49	140	422

on three dates, which corresponds to column Shot #3 (4 photos per log; image name suffixes `_RR1` to `_RR4`); and for 140 logs, photos of their stumps were also taken (4 photos per stump; image name suffixes `_S1` to `_S4`), which is given in column Stump.

The images are available in the file: `Biomtrace_extension/color_images/log_extraction_before_after.zip` (Longuetaud et al. 2025c).

2.3.2 Case #2: Traceability sensitivity to angle and distance

In this case study, the logs were photographed at different distances and angles, and also on two different dates. First, a photograph of the CS was taken from a distance of approximately 1 m, as far as possible in front of the section, i.e. by bending the knees (image name suffix `_1`). Then the operator stood up and, still at a distance of 1 m, took a photo at mid-height (i.e. camera at waist level; image name suffix `_R1`) and another at head height (image name suffix `_R2`), so as to obtain an increasingly strong perspective. The operator then took a step back (i.e. about 2 m away from the log). A photo was taken standing up, trying to limit the perspective (i.e. camera at waist level; image name suffix `_R3`), then

another after taking a step to the side (image name suffix `_R4`). Finally, the last photo in the series was taken after taking another step back (i.e. about 3 m from the log) in an attempt to limit the perspective (i.e. camera at waist level; image name suffix `_R5`). Then exactly the same sequence was performed at a later date, and the six corresponding images were marked with the suffixes `RR0` (distance approximately 1 m, by bending the knees, as far as possible in front of the section) to `RR5` (approximately 3 m from the CS, standing upright, limiting the perspective). For two sites, a third set of photographs was taken following exactly the same protocol (image name suffixes `RRR0` to `RRR5`). The images collected for log `FB240052963_01022` on two dates are shown in Fig. 2.

This experiment represents 3330 images from 222 logs (Table 2) sampled in four forests across four sites.

In Table 2, column Shot #1 corresponds to the first photograph in the series taken on the first date (image name suffix `_1`); column Shot #2 corresponds to all the other photos taken on the first date (image name suffixes `_R1` to `_R5`); column Shot #3 corresponds to all photos taken on the second date (image name suffixes `_RR0` to `_RR5`); 123 logs from two sites were photographed on three dates, which corresponds to column Shot #4 (image name suffixes `RRR0` to `RRR5`).

The images are available in the file: `Biomtrace_extension/color_images/shooting_angles_distances.zip` (Longuetaud et al. 2025c).

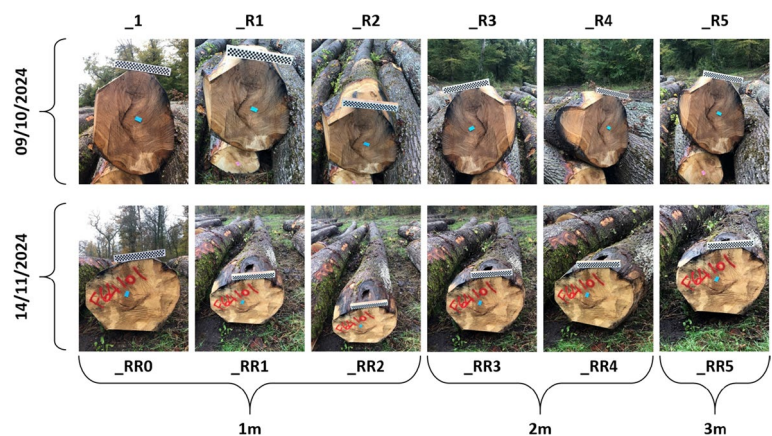


Fig. 2 Example of images collected for one log from case study #2. The photos taken on the first date are on the first row and those taken on the second date are on the second row. At the top left is the reference image taken straight on, bending the knees to limit the perspective

Table 2 Number of photos and logs for the Case #2 of traceability sensitivity to angle and distance

	Shot #1	Shot #2	Shot #3	Shot #4	Total
Number of photos	222	1110	1260	738	3330
Number of logs	222	222	210	123	222

performed (4 photos per log; image name suffixes `_R1` to `_R4`). Finally, a total log end trimming of a few centimetres was performed (4 photos per log; image name suffixes `_RR1` to `_RR4`). The images collected for log FB240036566_00018 are shown in Fig. 3.

This experiment represents 480 images from 40 logs (Table 3) sampled in two forests across two sites.

2.3.3 Case #3: Traceability robustness to log end trimming

The aim of this last case study was to test robustness in the event of partial or total trimming of a few centimetres at the log end. In this case, all photos were taken on the same date. First, the log end was taken as is (4 photos per log; image name suffixes `_1` to `_4`). Then, a modification of the contour or partial log end trimming was

Table 3 Number of photos and logs for the Case #3 of traceability robustness to log end trimming

	Shot #1	Shot #2	Shot #3	Total
Number of photos	160	160	160	480
Number of logs	40	40	40	40



Fig. 3 Example of images collected for one log from case study #3. The initial cross-section is on the first row; the cross-section whose outline has been slightly modified is on the second row; the cross-section after complete log end trimming is on the third row

Table 4 Number of photos and logs for the SIA 2025

	Shot #1	Shot #2	Shot #3	Total
Number of photos	15	7	7	29
Number of logs	3	3	1	3

Table 5 Number of photos and logs for the video shooting

	Shot #1	Shot #2	Total
Number of photos	32	8	40
Number of logs	8	2	8

In Table 3, column Shot #1 corresponds to the four photographs taken of the intact log end (image name suffixes _1 to _4); column Shot #2 corresponds to the four photographs taken after partial modification of the CS outline image name suffixes _R1 to _R4; and column Shot #3 corresponds to the four photographs taken after complete log end trimming (image name suffixes _RR1 to _RR4).

The images are available in the file: `Biomtrace_extension/color_images/trimming_before_after.zip` (Longuetaud et al. 2025c).

2.3.4 Additional images

Some additional images were collected for traceability demonstrations at special events such as the *Salon International de l'Agriculture 2025* (SIA 2025; Table 4) and a video shooting (Table 5). Photos were taken on several dates, as indicated by the columns Shot #1, Shot #2 and Shot #3 in Tables 4 and 5. These images can be found in the files: `Biomtrace_extension/color_images/logs_SIA_2025.zip` and `Biomtrace_extension/color_images/video_shooting_Barbonville.zip` (Longuetaud et al. 2025c).

2.4 Preliminary processing of images

In this section, we provide manual reference measurements and tools for pre-processing images. When algorithms have been tested, we provide the training, validation, and test sets so that the experiment can be reproduced and compared with other tools.

2.4.1 Image scale: Get the pixel size

The diameter of the logs is an important identification criterion. In order to retrieve pixel size information from the images, a black and white checkerboard pattern was positioned on the log to be photographed (except for 219 of the 8341 images collected; omission for a photo campaign of stumps or specific sites from Sect. 2.3.4).

Two algorithms for detecting and measuring the checkerboard pattern were applied: *detec_mire* and *pixel_grid*. The principle behind both algorithms is the same: detecting black squares in the image, identifying the checkerboard pattern, and numbering the rows and columns of the grid. They differ in this step of identifying rows and columns. The source codes are available on the following data repository: <https://doi.org/10.57745/9DBCL4>. Of the 8122 images containing checkerboards, 130 checkerboards were not detected by the algorithms. As the detection routine is common to both algorithms, they both failed for the same images, generally in cases of severe distortion (case study #2; Sect. 2.3.2) or because the checkerboard was too small in the image, which interferes with the detection of the checkerboard squares (shape or size). Figure 4 compares the pixel sizes obtained with these two algorithms on 7992 images. The 10 points with the greatest divergence between the two algorithms are highlighted in red.

For the 50 most divergent automatic measurements between the two algorithms on 7992 images, manual measurements were done (Fig. 5). The ImageJ software (Schneider et al. 2012) was used. The results are consistent with those presented in Longuetaud et al. (2025b): *pixel_grid* proves to be significantly more accurate than *detec_mire* even though it seems to slightly overestimate the size of the pixels. The RMSE and bias on the pixel size are, 0.0321 mm and -0.0245 mm, and 0.0508 mm and -0.0102 mm, for *pixel_grid* and *detec_mire*, respectively. The images from Case #2 (Sect. 2.3.2) are particularly difficult for algorithms to process due to the distortions caused by the significant variation in shooting angles.

All available measurements (automatic and manual) are provided in the `Biomtrace_extension/tables/database_images_extension.txt` table (variables *pixelSize_detecmire_mm*, *pixelSize_pixel_grid_mm* and *pixelSize_manual_mm*) (Longuetaud et al. 2025c).

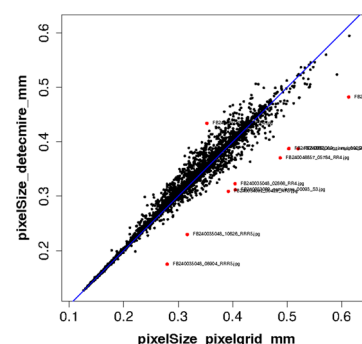


Fig. 4 Comparison of the two algorithms for automatic pixel size measurement, *detec_mire* and *pixel_grid*, on the 7992 images from the database on which the checkerboard pattern could be detected

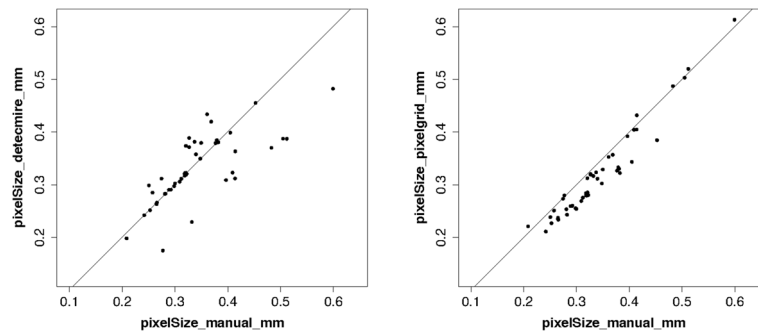


Fig. 5 Comparison of the outputs of the two algorithms for automatic pixel size measurement (*detec_mire*, on the left, and *pixel_grid*, on the right) with manual measurements for the 50 most divergent outputs between the two algorithms

In general, it is important to frame the photo correctly so that the CS occupies as much space as possible and to minimise perspective distortions when taking photos. In case study #2, we accentuated the distortions in order to test the robustness of different algorithms.

2.4.2 Segmentation of cross-sections

Segmentation consists of isolating the log CS from the background of the image. This is a necessary pre-processing step for applying log traceability algorithms. We needed a robust and accurate segmentation algorithm to segment all the images in the database.

To develop and validate the segmentation algorithms, we needed manual reference measurements. These manual measurements are very time-consuming, and the database contains a total of 1537 binary masks, distributed across the learning and three test sets described below, out of the 8341 images. The reference outlines were positioned underbark. Further details on the measurement method used are provided in Longuetaud et al. (2025b). The reference binary masks used to produce results in this section are available in the file `Biomtrace_extension/segmentation/cross_sections/segmentation_masks/manual.zip` (Longuetaud et al. 2025c).

AI methods are evolving very quickly. In this work, we have tested new segmentation algorithms including Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs). Very briefly, CNNs analyse images by looking at small local areas at a time, which makes them good at detecting simple visual patterns like edges or shapes. ViTs analyse the whole image at once by comparing different parts of the image to each other, which helps them understand more global structures but usually requires more data.

To evaluate each algorithm, the number of pixels in the CS correctly classified (true positives, *TP*) or incorrectly classified (false positives, *FP*) and the number of pixels in the background correctly classified (true negatives, *TN*) or incorrectly

classified (false negatives, *FN*) are calculated on the images in the test sets, and the following metrics are used:

$$Pre = \frac{TP}{TP + FP}$$

$$Rec = \frac{TP}{TP + FN}$$

$$Acc = \frac{TN + TP}{TN + TP + FP + FN}$$

$$Dice = \frac{2 \times TP}{2 \times TP + FP + FN}$$

$$IoU = \frac{TP}{TP + FP + FN}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

The datasets for which manual measurements are available are distributed as follow:

- **Learning set:**

This dataset contains 1195 images representing 1032 different logs. The list of images is provided in the file `Biomtrace_extension/tables/learning_set_article_benchmark_1195.txt` (Longuetaud et al. 2025c). This set has been divided into 5 subsets which will be used in turn for training and validation in a 5-fold cross-validation approach where each image is used only once in validation.

- **Test set #1:**

This dataset contains 150 images of 150 different logs. The list of images is provided in the file `Biomtrace_extension/tables/test_set_1_article_benchmark_150.txt` (Longuetaud et al. 2025c). The detailed results obtained for the different architectures tested (*U-Net*, *Mask R-CNN*, *PointRend*, *YOLOv11* and *OneFormer*) are given in Table 6 below. *OneFormer* uses

Swin, so it was not necessary to test *Swin* alone. *OneFormer* and *PointRend* gave excellent results, as did *YOLOv11* to a lesser extent. In the following, we have only retained the two architectures *OneFormer* and *PointRend*, which seemed the most promising.

- **Test set #2:**

This dataset of 52 images contains images that are not trivial at first sight, featuring elements such as cracks or shadows. The list of images is provided in the file `Biomtrace_extension/tables/test_set_2_benchmark_52.txt` (Longuetaud et al. 2025c) and the results are shown in Table 7.

- **Test set #3:**

This dataset contains 140 images of 140 different logs not already present in the learning set, chosen from among those that gave the most divergent results between *YOLOv11* and *PointRend*. The results are therefore logically not in favour of these two architectures, but we wanted to see how *OneFormer* performed on these images. The list of images is provided in the file `Biomtrace_extension/tables/test_set_3_benchmark_140.txt` (Longuetaud et al. 2025c) and the results are shown in Table 8.

The Learning set and Test set #1 image sets were used in a benchmark article (Martinetto et al. 2025a), but they

were mixed with images of softwoods (Douglas fir and spruce) to make the segmentation method more generic. Consequently, the data repository also contains the learning and test sets mixing softwood and oak images that were used for the benchmark article. This learning set contains 1195 images of oak and 755 images of softwood; the corresponding test set contains 150 images of oak and 100 images of softwood. The binary masks and original images from this experiment are in the file `Biomtrace_extension/segmentation/cross_sections/segmentation_experiment_data-sets.zip` (Longuetaud et al. 2025c).

The binary masks obtained for the entire database (i.e. 8341 oak images) using each of the two architectures, *PointRend* and *OneFormer*, are available in the file `Biomtrace_extension/segmentation/cross_sections/segmentation_masks/automatic.zip` (Longuetaud et al. 2025c) in PNG format. We do not guarantee that these outputs are all correct, but they are made available because they can be visually validated if necessary and can be used for comparisons with other potential methods. *PointRend* failed to segment 34 out of 8341 images. *OneFormer* failed to segment 15 images. Figure 6 compares the segmented surfaces for the two selected architectures. In the vast majority of cases, the two algorithms were consistent and segmentation

Table 6 Segmentation results obtained on the 150 images in *test set #1*

Method	Pre	Rec	Acc	Dice	IoU	MCC
U-Net	0.9059	0.9443	0.9528	0.9216	0.8597	0.8906
Mask R-CNN	0.9663	0.9831	0.9833	0.9733	0.9506	0.9623
PointRend	0.9767	0.9879	0.9889	0.9816	0.9655	0.9742
YOLOv11	0.9694	0.9926	0.9881	0.98	0.9624	0.9723
OneFormer	0.9803	0.983	0.989	0.9813	0.9639	0.9736

The best result for each metric is shown in bold

Table 7 Segmentation results obtained on the 52 images in *test set #2*

Method	Pre	Rec	Acc	Dice	IoU	MCC
PointRend	0.9619	0.9783	0.9815	0.9688	0.9419	0.9566
OneFormer	0.976	0.9622	0.9852	0.9601	0.9397	0.9531

The best result for each metric is shown in bold

Table 8 Segmentation results obtained on the 140 images in *test set #3*

Method	Pre	Rec	Acc	Dice	IoU	MCC
PointRend	0.9359	0.9496	0.9617	0.9371	0.8881	0.9149
OneFormer	0.9678	0.9636	0.9804	0.9641	0.9333	0.9515

The best result for each metric is shown in bold

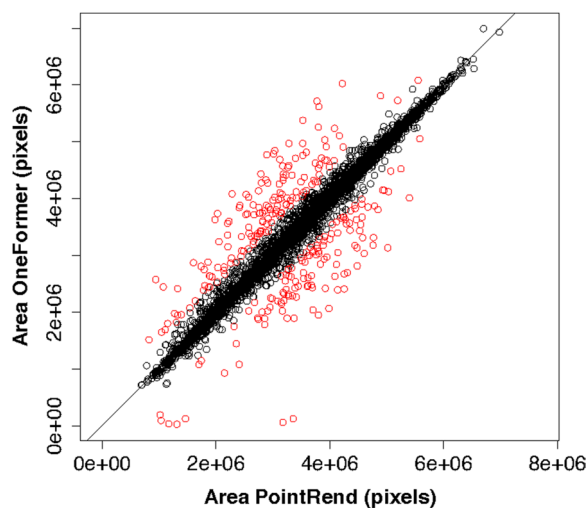


Fig. 6 Comparison of the segmented areas (in pixels) obtained with PointRend (on the x-axis) and with OneFormer (on the y-axis). Each point represents one of the 8301 images (out of 8341 available images) that were segmented by the two architectures. Differences greater than 500000 pixels between the two outputs are displayed in red

proceeded successfully. An R script allowed us to check the images for which the two algorithms diverged most strongly in terms of segmented areas and distance between centres of gravity. With regard to automatic image segmentation, the biggest problems encountered were with images of stumps (Sect. 2.3.1) or those from Case #2 (Sect. 2.3.2). This was because the outlines of stumps are extremely irregular compared to the more conventional CSs used to train the algorithms and, in Case #2, some shots had a very strong perspective and the CSs were highly distorted. The segmentation problems encountered were more frequent and more pronounced when the angles tested for taking photos were the strongest, i.e. in certain situations in case study #2 (i.e. suffixes R2, RR2, RRR2 and R4, RR4, RRR4). More than half of the strongest divergences between *PointRend* and *OneFormer* were obtained for images of stumps. For the images from Case #2, *PointRend* appeared to have more difficulty in processing these images than *OneFormer*. The 34 images not segmented by *PointRend* all came from Case #2. Furthermore, in Fig. 7, which illustrates cases of significant divergence between *PointRend* and *OneFormer*, we can see the difficulties *PointRend* had in processing these atypical images. There were no such images in the learning set (no stumps or significant distortion related to the photo capture). It is possible that adding images of this type to the learning set could resolve or at least reduce the problem. Furthermore, these segmentation problems are not necessarily problematic for traceability algorithms if the surface area

of the CS still represents a significant portion of the segmented area. We also point out that the purpose of this database was to test the limits of the algorithms in particularly extreme cases and that, in practice, there should not be as much perspective in the shots.

Measurements of the size and shape of these masks were obtained automatically by using the *Set Measurements* and *Analyze Particles* functions of the ImageJ software in batch mode. The surface area of the segmented CSs, the mean diameter and several shape descriptors are given in the `Biomtrace_extension/tables/database_images_extension.txt` table (`segm_area_pointrend_pixel` and following variables prefixed by `segm_`) (Longuetaud et al. 2025c). The definitions and units of the different variables are given in the `Biomtrace_extension/tables/database_images_extension_variables.txt` table (Longuetaud et al. 2025c).

2.4.3 Location of the pith

Manual markings of the pith (i.e. the point at the centre of the growth rings visible on a CS) were made on 2400 images by using ImageJ software. These images come from the “search database” of 5830 images described below (Sect. 2.5). Of the 2400 images, 2395 come from the initial *Biomtrace* database (<https://doi.org/10.57745/9DBCL4>) and five from the extension of the database described in the present data paper. The initial *Biomtrace* repository has thus been completed by adding a file containing the pith coordinates for the 2395 images concerned: `Biomtrace/tables/database_image_pith_measurements.txt` (Longuetaud et al. 2024b). While the coordinates of the pith of the five images from the extension of the database have been added to the `Biomtrace_extension/tables/database_images_extension.txt` file (Longuetaud et al. 2025c) as additional columns.

The pith is not always clearly visible on oak CSs. It is generally much more difficult to locate than on softwood CSs because the growth rings are sometimes very difficult to distinguish. In addition, there may be dirt or plastic tag present on the CS, which can make locating the pith very approximate. The position of the pith could be useful for correctly orienting the CS, for example in the pre-processing of traceability algorithms (Martinetto et al. 2025b). It could also help with the automatic detection of radial drying cracks.

2.4.4 Management of drying cracks

This new database, which includes longer intervals between photos (because the ground was waterlogged, delaying log extraction at some sites), made it possible to identify an unexpected problem that compromises



Fig. 7 Examples of the largest divergences obtained (in segmented surface area, for the first three rows, or in centre of gravity position, for the last three rows) for automatic segmentations performed using the *PointRend* (on the left) and *OneFormer* (on the right) architectures

log traceability: The presence of numerous drying cracks in some cases. Indeed, drying cracks can lead to traceability issues. This is because key-points (as described in Martinetto et al. (2025b)) tend to be positioned on the cracks by the algorithm, which prevents good matching between the two images taken on the two dates, as the points do not correspond before (image without cracks) and after log extraction (image with drying cracks). Faced with this new problem and with the aim of developing an algorithm capable of detecting drying cracks and filling them, we carried out manual measurements of the cracks on 22 identified images (as the corresponding logs failed to be recognised). The measurements are available in the file `Biomtrace_extension/segmentation/cracks/segmentation_masks/manual.zip` (Longuetaud et al. 2025c). These measures are very time-consuming to perform, which explains the low number of images processed manually. Figure 8 illustrates an example for the log `FB240033825_num_inrae_00255` and the corresponding manual measurement in the presence of drying cracks.

2.5 Traceability

We tested our traceability algorithm (Martinetto et al. 2025b) on this new database. While recognition rate was close to 100% on the initial *Biomtrace* database, the specific cases studied with this new database proved to be very useful. We effectively challenged the algorithms, and recognition rates were affected.

To evaluate the traceability algorithms, we created the “search database” which contains images taken on an initial date, and in which the algorithms will search for matches from images of logs taken at a later date. The “search database” was created from the two databases *Biomtrace* and *Biomtrace_extension*, and contains 5830 images, all with the suffix `_1`. In this database, there is only one image of CS for each log. The images included in the “search database” are listed in the file `Biomtrace_extension/tables/`

`image_search_database_5830.txt` (Longuetaud et al. 2025c).

Table 9 shows the final recognition rates for the images in Case #1. Of the 5830 images from Shot #1 in the “search database”, 422 belonged to Case #1. A total of 1792 images (including 4 images per log from Shot #2, i.e. 1596 images, and sometimes 4 images per log from Shot #3, i.e. 196 images) were tested for recognition in the “search database”. The log was correctly identified for only 1349 images out of 1792, representing an accuracy rate of 75.3% (the 443 cases of errors are presented in directory `Biomtrace_extension/error_cases_traceability/log_extraction_before_after` (Longuetaud et al. 2025c)). It is for this case study that we encountered the most significant difficulties. Indeed, the change in the appearance of the CSs due to the sometimes substantial time lapse between two photo shoots (including in some cases the appearance of drying cracks; Fig. 8) and the change in perspective related to the movement of the logs between the two photo shoots contributed to the failure of traceability algorithms in a number of cases. It is important to note that the cases of error occurred in the majority of cases for the later photo retakes (i.e. May and June), after episodes of spring heat (Longuetaud et al. 2025a).

Then, 222 images of the “search database” belonged to Case #2. Due to problems related to CS segmentation in the images (i.e. no segmentation output for these images), 3066 images from Case #2 were tested for recognition in the “search database” database, instead of

Table 9 Traceability results obtained for Case #1

Total number of images in the “search database”	Number of images to be found in the “search database”	Number of images tested for recognition	Accuracy (%)
5830	422	1792	75.3



Fig. 8 Image taken at a first date on 17 February 2025 (on the left); image taken at a later date on 30 June 2025 showing drying cracks (in the middle); binary reference mask for marking drying cracks (on the right)

the 3108 available in total in the Shot #1, Shot #2 and Shot #3 directories (in `Biomtrace_extension/color_images/shooting_angles_distances` (Longuetaud et al. 2025c)). Of these 3066 images tested, 14 failures were recorded, resulting in a recognition rate of 99.5% (Table 10). Given the extreme perspective changes tested in this case study, we can consider this a satisfactory recognition rate. In practice, the perspectives should not be so strong.

If the partial modification of the contour or section does not pose a major problem for the algorithms for log recognition (97.5 % in Table 11), a complete log end trimming causes them to fail completely, with a recognition rate of about 3%. This was expected because the key-points identified during the first photo capture were no longer physically present during the second photo session, and therefore matching was no longer possible.

Further details on the various traceability tests are provided in the final project report (Longuetaud et al. 2025a). Images illustrating all the errors obtained for the various cases studies are provided in the directory `Biomtrace_extension/error_cases_traceability` (Longuetaud et al. 2025c).

3 Access to the data and metadata description

The database (Longuetaud et al. 2025c) is available at the Recherche Data Gouv repository: <https://doi.org/10.57745/RKDTKY>. Associated metadata are accessible at: <https://metadata-afs.nancy.inra.fr/geonetwork/srv/fre/catalog.search#/metadata/5f2842a0-15ec-48be-8f1c-e44334654cc5>.

The arborescence of the `Biomtrace_extension` directory was detailed in the previous section and is summarised in Fig. 9.

Table 10 Traceability results obtained for Case #2

Total number of images in the "search database"	Number of images to be found in the "search database"	Number of images tested for recognition	Accuracy (%)
5830	222	3066	99.5

Table 11 Traceability results obtained for Case #3

Type of trimming	Total number of images in the "search database"	Number of images to be found in the "search database"	Number of images tested for recognition	Accuracy (%)
Partial	5830	40	160	97.5
Complete	5830	40	160	3.12

The `Biomtrace_extension/tables` directory (Longuetaud et al. 2025c) includes nine tables. The first two tables correspond to the description of the sites and images, and each is accompanied by a table describing the variables.

- The site table `database_sites_extension.txt` (15 rows $\times$ 29 variables) provides the name and location of each logging site. The dates of the photo sessions and the number of logs and images taken during each session are also recorded. This table is accompanied by a table describing its variables named: `database_sites_extension_variables.txt`.
- The image table `database_images_extension.txt` (8341 rows $\times$ 30 variables) provides the name of each image, the log name, the main data recorded in the Exif metadata (width and height in pixels, rotation, shooting date, camera model), the size of the pixels as calculated by two software programs or measured manually for some images (Sect. 2.4.1), and geometric measurements of the CSs (size and shape) obtained using ImageJ software on automatically generated segmentation masks (Sect. 2.4.2). This table is also accompanied by a table describing its variables: `database_images_extension_variables.txt`.

The other five tables are lists of images constituting different data sets described above.

- The file `image_search_database_5830.txt` provides the names of the 5830 images that constitute our final "search database" for traceability testing (Sect. 2.5). It consists of one image per log from the total database (i.e. the initial *Biomtrace* database and its present extension) taken in photo on an initial date. These are always images with the suffix `_1`.
- The file `learning_set_article_benchmark_1195.txt` provides the names of the 1195 images used for training the tested segmentation algorithms (Sect. 2.4.2). These images are part of the learning set used in the benchmark analysis of the different segmentation algorithms (Martinetto et al. 2025a).
- The file `test_set_1_article_benchmark_150.txt` provides the names of the 150 images from test set #1, one of the three test sets used to validate the segmentation algorithms (Sect. 2.4.2). These images are part of the test set used in the benchmark analysis of the different segmentation algorithms (Martinetto et al. 2025a).

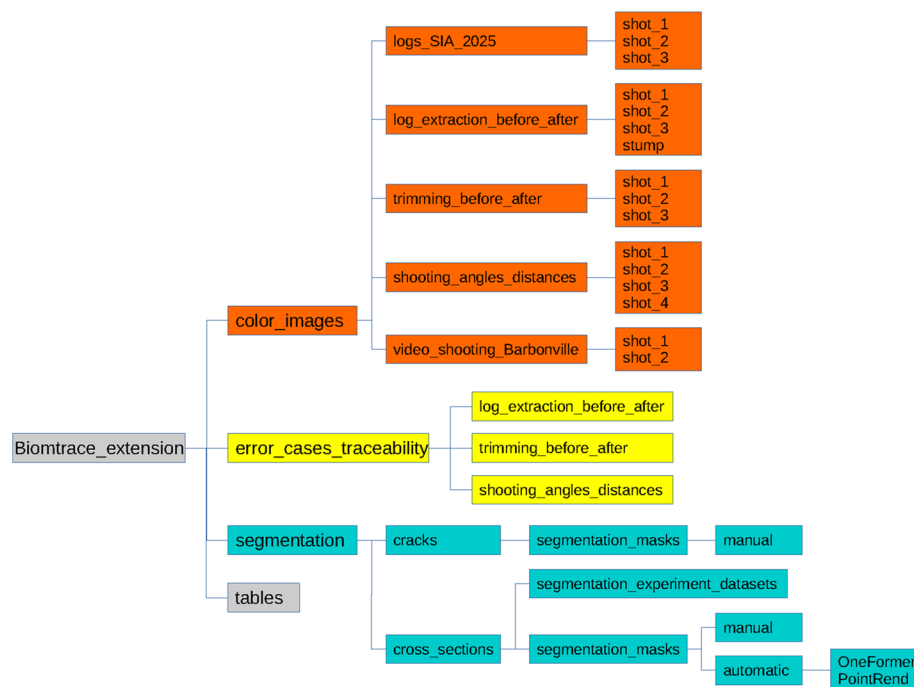


Fig. 9 Organisation of the data files

- The file `test_set_2_benchmark_52.txt` provides the names of the 52 images from test set #2, one of the three test sets used to validate the segmentation algorithms (Sect. 2.4.2). The images in this dataset were selected to present challenges such as logs split in two through the pith (e.g. first row in Fig. 7) or the presence of shadows.
- The file `test_set_3_benchmark_140.txt` provides the names of the 140 images from test set #3, one of the three test sets used to validate the segmentation algorithms (Sect. 2.4.2). These images were selected from among those leading to the most divergent results between *YOLOv11* and *PointRend*.

4 Technical validation

The log numbers were carefully read from the images by an operator in order to correctly rename the image files and ensure that each identifier (site number and log number) was assigned to all photos of the same log, and that each identifier corresponded to a single log. An R script (R Core Team 2023) was used to automate this renaming process.

Manual measurements (i.e. measurement of the black and white checkerboard, segmentation of the CS of interest in images, segmentation of drying cracks in CSs and marking of the pith) were carefully performed by experienced operators and verified.

Automatic measurements on the images (i.e. checkerboard measurement and CS segmentation in the images)

were obtained using software tools specially designed for this purpose and validated using manual measurements. For automatic checkerboard measurement, a comparison of the results of the two software tools developed was carried out (as had already been done in Longuetaud et al. (2025b)) in order to detect any measurement errors in either of them. Additional manual checkerboard measurements were carried out for the images for which the two algorithms diverged most from each other, in order to evaluate them. Similarly, the outputs of different segmentation algorithms were compared in order to identify images that could pose problems for some of them (i.e. comparison of segmented surfaces and centre of gravity positions). With regard to automatic measurements, errors or inaccuracies are always possible (e.g. Fig. 7), and these automatic outputs should be used with caution.

Finally, applying traceability algorithms to this dataset, which was the initial objective behind the creation of this new image database, also enabled data control, particularly the renaming of images.

5 Reuse potential and limits

All data tables are in plain text format with tabulations as separator. They can be imported easily with R (R Core Team 2023) or with any spreadsheet software. RGB images are in standard JPG format and binary segmentation masks are in PNG format.

The first database called *Biomtrace* contained 33390 images of 5135 different oak logs (Longuetaud et al. 2024b, 2025b). The database presented in this paper, called *Biomtrace_extension*, was specifically created to evaluate the robustness of various algorithms (pre-processing and biometric traceability) under more realistic image acquisition conditions, including cases considered relatively extreme, such as significant perspectives for photo shoots or complete trimming of log ends. This new database contains 8341 images of 695 different logs and a set of corresponding manual and automatic measurements. Combining the two databases, a total of 41731 images of 5830 oak logs were therefore collected as part of this project on biometric traceability.

The *Biomtrace_extension* database provides realistic examples of photos taken of log ends, particularly before and after log extraction. The logs were extracted from the forest between the first and second photo shoots, which may have led to significant changes in the appearance of the CSs in the photos: dirt, rotation of the logs, embedding into the ground, changes in the immediate environment of the log, and changes in perspective in the photos. Drying cracks may also have appeared due to the fact that more than 100 days may have elapsed between the two photo sessions at certain sites. This long period of time was due to heavy rainfall and waterlogged soil preventing the extraction of logs, and therefore contributes to reflecting realistic acquisition conditions. In this article, we have clearly demonstrated the importance of creating this new and more realistic image database for the development of reliable and robust algorithms that can be used in practice. Indeed, the traceability results obtained on the first database, which was already more realistic than the databases available in the literature, were excellent: 100% recognition in Martinetto et al. (2025b) or above 99.9% across the entire initial *Biomtrace* database (Sect. 5.2 in Longuetaud et al. 2025a). However, the results obtained on this new database with more complicated images (e.g. significant distortions due to the perspective from which the photos were taken, drying cracks) are less satisfactory and highlight the need for further research, particularly on biometric traceability methods. Approaches based on algorithms using “triplet loss” are not effective enough, and we have demonstrated the potential of approaches based on point matching (Martinetto et al. 2025b). This database is made available to the community to further develop high-performance traceability methods.

The database can also be used to develop or improve algorithms for image pre-processing or wood quality assessment, for example: automatic CS segmentation, CS outline and shape characterisation, CS orientation, pith

location and eccentricity measurement, and also detection of rot, holes and drying cracks. CS segmentation algorithms have been developed for softwoods (Decelle and Jalilian 2020) and oak (Martinetto et al. 2025a), but they could be improved, particularly in cases where CSs are severely distorted (e.g. case study #2; Longuetaud et al. (2025a)). Detecting drying cracks is also important in order to better guide the traceability algorithm so that it does not place its key-points for matching on the cracks once they have appeared, for example. The management of drying cracks and their impact on matching for log recognition is an issue that still needs to be addressed (Longuetaud et al. 2025a). The detection of pith is a subject that has already been addressed for softwoods (Decelle et al. 2022; Marichal et al. 2025) for example, where growth rings are generally clearly visible, for tropical wood (Kurdthongmee 2020), but not for raw oak CSs. However, detecting pith could be very useful for orienting CSs and could facilitate recognition, which is very sensitive to the orientation of logs (Schraml et al. 2016; Rajabli 2021; Martinetto et al. 2025b). To this end, we provide a set of reference measurements carried out by experienced operators for the segmentation of CSs in images and drying cracks in CSs, the location of the pith and the size of pixels. Researchers may also be interested in the degradation and changes in appearance of log CSs over time. These topics are recognised as being of interest by the wood science research community (Sandvik et al. 2024).

Authors' contributions

F.L. initiated and drafted funding applications, managed the project from a scientific perspective, participated in data collection and analysis, supervised students, and drafted the manuscript; F.M. participated in software development, data collection and analysis, and manuscript drafting; D.M. is carrying out his doctoral thesis based on this database and played a major role in the development of algorithms, data analysis, and manuscript writing; P.N. participated in writing funding applications, developing algorithms, analysing data, supervising students, monitoring the project, and writing the manuscript; D.R. participated in data collection; F.B. participated in data collection; P.J. participated in the development of algorithms; B.V. participated in data collection; A.P. participated in data collection and analysis, as well as student supervision and project monitoring; I.D. participated in student supervision and project monitoring; A.A. launched the *Biomtrace* project and the search for funding, and participated in data collection and analysis, as well as project monitoring; C.R. launched the *Biomtrace* project and the search for funding, and participated in data collection and analysis, as well as project monitoring.

Data availability

The *Biomtrace_extension* database is available at <https://doi.org/10.57745/RKDTKY> and associated metadata are available at: <https://metadata-afs.nancy.inra.fr/geonetwork/srv/fre/catalog.search#/metadata/5f2842a0-15ec-48be-8f1c-e44334654cc5>.

Declarations

Competing interests

The authors declare no competing interests.

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