X-ray imaging and supervised classification based on the oxygen transfer of punched natural cork stoppers

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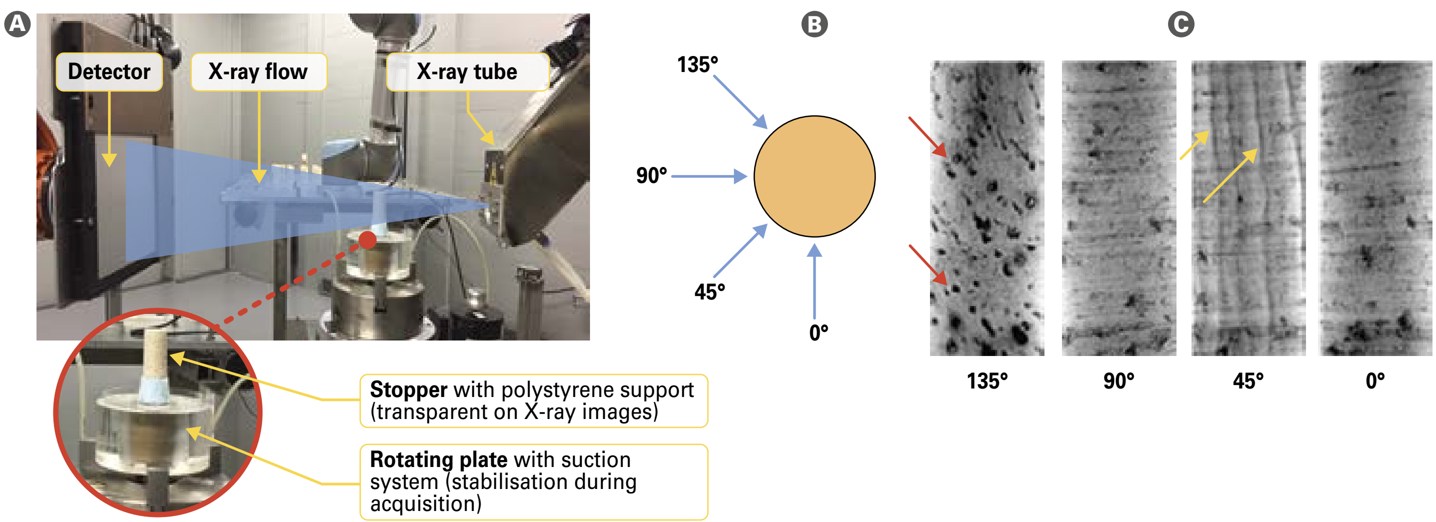
TECHNICAL

Introduction

Natural cork stoppers, produced by punching a plank of cork oak bark, are considered in the wine industry to be a high-quality solution for keeping wine in bottles. The increased demand for properly aged wines from both winemakers and consumers has pushed the industry to optimise the selection of natural cork stoppers. Quality control has long involved a visual sorting of stoppers, whether done manually or using machines equipped with increasingly sophisticated optical cameras. The literature includes studies on automatic sorting with cameras, based on classification algorithms ***[1-3]***. However, cork stopper classification is still done based on aesthetic surface criteria. The finest stoppers, classified as "Flor" grade, do not have any apparent defects (no holes, woody lenticels, colour defects, etc.). However, it remains difficult to correctly determine the overall quality of a stopper by extracting information only about its outer surface. The good quality of a natural cork stopper actually depends on its mechanical and elastic properties and on its structural ability to allow reasonable quantities of oxygen to pass from the outside to the inside of the bottle, and thus enter into contact with the wine. Wines have differing levels of oxygen-consuming tannins, and the stopper's physical sealing properties will affect the kinetics of oxygen ingress, thus directly influencing the wine's sensory profile after it has been conserved in bottles. Recently, Chevalier *et al.* ***[4]*** published measurements of OIR (Oxygen Initial Release: the quantity of oxygen released in a bottle during the first six months, expressed in mg) with natural cork stoppers classified visually as being premium, i.e. displaying few surface defects. These measurements demonstrate that the sorting performed by equipment currently used by cork producers does not help classify stoppers according to their oxygen ingress performance. In batches of stoppers visually classified as premium, it is common to find that wines undergo different sensory evolutions owing to these permeability variations. Some stoppers may be considered permeable to gas, which will lead to rapid oxidative evolution of the bottled wine. Some studies have used methods of analysis to probe the heart of the stopper ***[5, 6]***, such as Lagorce-Tachon *et al.* ***[7]***, showing that the number of surface defects on stoppers leads to an under-estimation of their internal porosity. To our knowledge, there is no industrial-scale, non-destructive analysis highlighting one or more criteria that can be used to determine whether the stopper structure will enable adequate oxygen ingress or not, in order to offer winemakers a range of natural cork stoppers whose OTR (Oxygen Transfer Rate) is well known, with an acceptable standard deviation, in terms of sensory impact. Unlike visual sorting, X-ray imaging takes into account the entire internal structure of stoppers and seems suitable for making inferences about their quality. Therefore, the present study proposes a supervised classification (i.e. a classification based on learning a classification rule from a training dataset, whose classification is already known) of

■ **Figure 1: Ⓐ Acquisition unit. Ⓑ Diagram of acquisition angles for the projections used and Ⓒ examples of the corresponding projections. The 0° angle is collinear with the lenticels** (two examples indicated by red arrows) **and the 90° angle is collinear with the cork growth rings** (yellow arrows).



"permeable/ impermeable" stoppers produced from SVM (Support Vector Machines) classification algorithm, taking as input the criteria extracted from X-ray images of punched cork stoppers. The supervision of this classification comes from the OIR measurement of the stoppers. A first batch (batch 1) of 142 punched natural cork stoppers was thus measured for OIR as well as acquired by tomography. The 2D and 3D X-ray images were pre-processed, and the sorting criteria were defined. These criteria constitute the input data provided to the SVM classification algorithm. Batch 1 classification results are presented for 3D and 2D data, as is the influence of experimental parameters on this classification. The purpose of the classification based on 3D images is to assess the quality of results that may be obtained by having more complete information for each stopper. The purpose of the classification based on 2D images is to assess the quality of results that may be obtained under conditions found in an industrial context. 2D images from batch 1 will then be used as a training dataset in order to directly assess batch 2, containing 436 stoppers from other production sources, without prior OIR measurement. Batch 2 classification results are presented and verified later on by a new OIR analysis. The results obtained by including batch 2 in the training dataset are also assessed.

OIR measurements and X-ray imaging

The OIR measurement was conducted on stoppers that had been visually sorted and classified as top grade by the industry (Superior, Extra and Flor batches). Oxygen transfer measurements were conducted by chemiluminescence over 60 days. The equipment used is a Fibox 3 LCD Trace V6 oxygen meter from PreSens Precision Sensing GmbH. The system is composed of a transceiver probe, which emits a blue light flow. This flow is directed towards a sensor (also called a dot) glued on the inside wall of a transparent bottle. These sensor dots contain fluorescent compounds, which absorb the light energy emitted by the probe and then return it as red light. The measurement is based on the fact that the intensity of the reflected signal is inversely proportional to the oxygen concentration in the bottle. This method is widely known in the industry ***[8, 9]***. From these measurements, stoppers are classified into two categories, "Permeable" and "Impermeable", based on OIR measurements ***[4]***. A stopper will be deemed permeable if its OIR is over 3 mg and not permeable if its OIR is under 3 mg. In batch 1, there are 40 permeable stoppers and 102 impermeable stoppers. Stoppers were analysed by X-ray tomography. This consists in acquiring a set of projections (or Radiography) at several viewing angles. This is illustrated for several angles in ***Figure 1***.

These 2D images are the projection of the stopper's volume. With these various angles, it is possible to obtain a 3D image of the stopper by using a reconstruction algorithm. An example of two axial cross-sections extracted from two reconstructed stopper volumes is presented in ***Figure 2***. For these acquisitions, the selected parameters provide a good compromise between contrast and spatial resolution, with the latter being estimated at 60 µm. For each tomographic acquisition, 720 projections per 0.5° angular increment were acquired in order to reconstruct a 3D image of the stopper. Images produced by radiography or tomography do not lead to immediate discrimination of a permeable or impermeable stopper.

The classifier takes the characteristics calculated from the images as input. However, the projections (2D images) and reconstructions (3D images) obtained cannot be used directly (presence of background on the images, stoppers differently oriented, required

Figure 2: Cross-section of a 3D reconstruction of a stopper. Cross-section Ⓐ : stopper with OTR of 0.004 cm³/day (impermeable). **Cross-section Ⓑ : stopper with OTR of 0.071 cm³/day** (permeable).

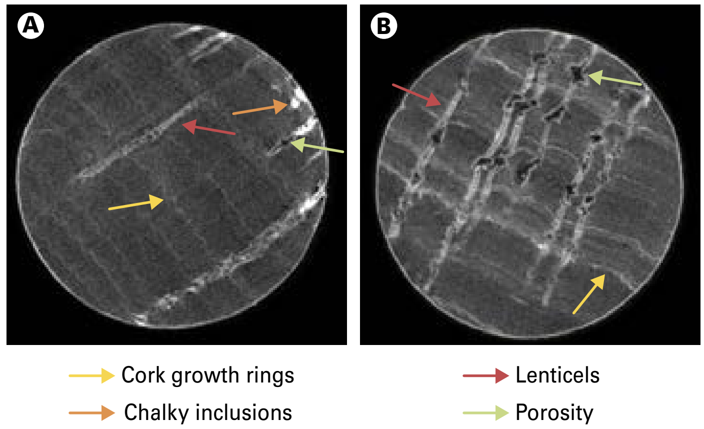
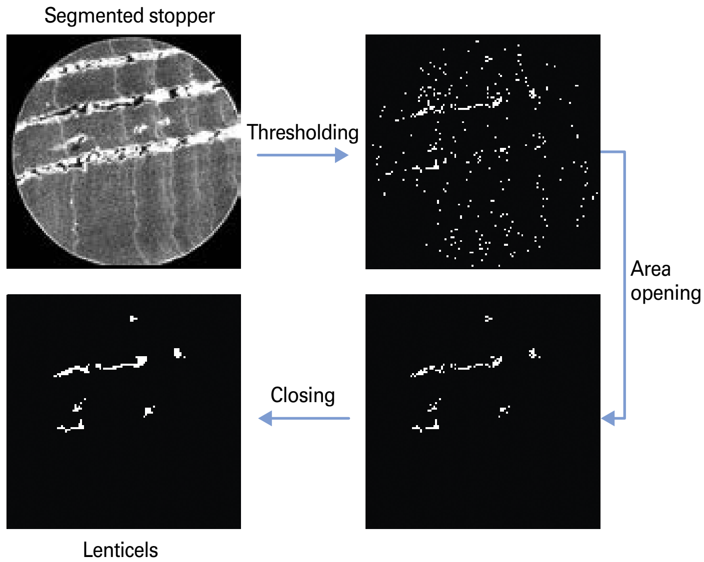


Figure 3: Segmentation diagram of lenticels on 3D tomographic images based on segmented stoppers.



areas of interest) and must be pre-processed. These pre-processings will not all be detailed here, but they consist in:

– detecting the image zone where the stopper is present, in 2D and 3D, *via* the segmentation method;

– readjusting the stopper orientations in order to conduct the analysis of growth rings;

– segmenting the lenticels and woody areas.

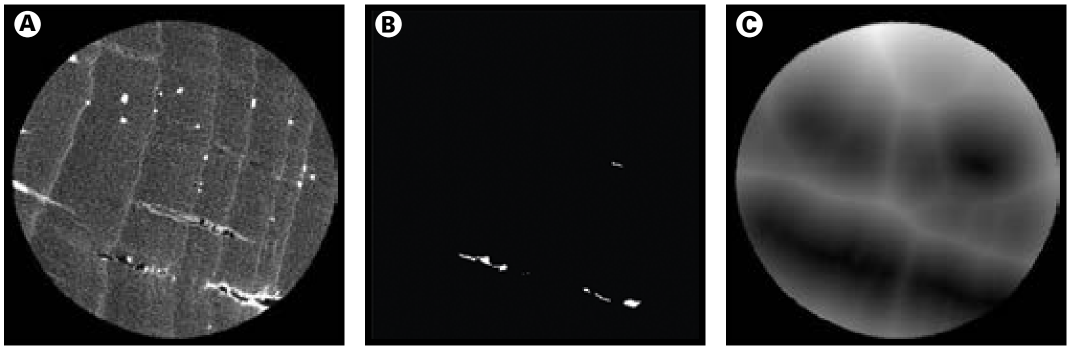
This last pre-processing is illustrated in ***Figure 3***. Lenticels are cut out from a segmented image of the stopper according to the following method: lenticels are extracted by means of thresholding as a first step. To refine this segmentation, an area opening (elimination of connected components with a volume below a given threshold) is applied. Finally, a morphological closing ***[10]*** is applied in order to reconnect the components of the lenticels. Each step is conducted in 3D, but only a cross-section is presented in ***Figure 3*** for the purposes of visualisation.

Criteria and classification method

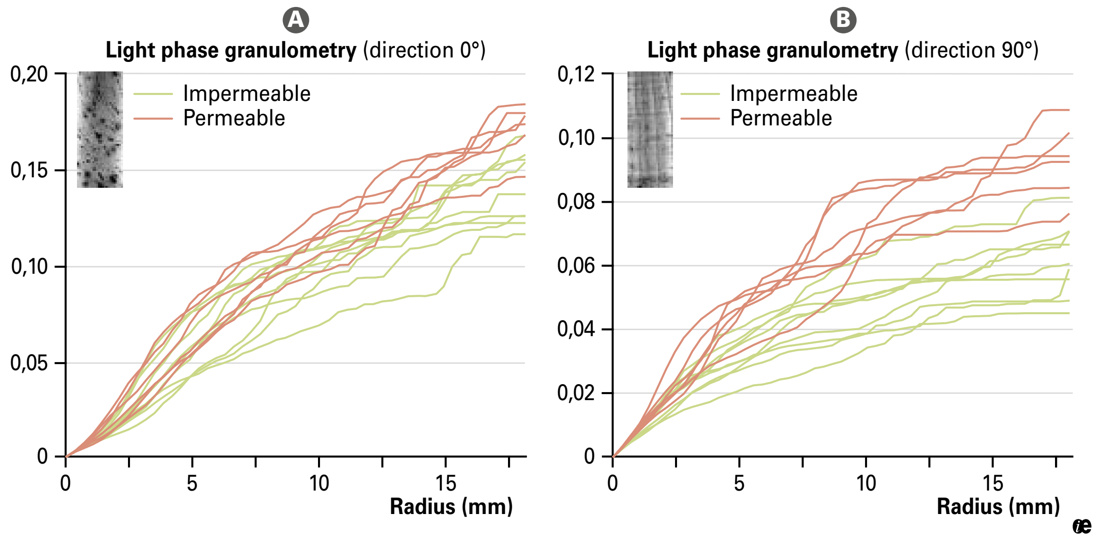
Criteria

Criteria were established from various hypotheses made during this study to explain how the stopper's microstructure may influence its OIR. The sorting criteria established may be specific to the type of images in question (2D or 3D). It is then a question of

■ **Figure 4: Example of distance map calculation, illustration by tomographic cross-section. Ⓐ the 3D image; Ⓑ the 3D image of lenticels is segmented; and Ⓒ the 3D distance map to the lenticels is calculated:** a high distance value is represented by a colour close to white (whereas a short one is black).



■ **Figure 5: Granulometry curves of the light phase of permeable and impermeable stoppers resulting from X-rays taken Ⓐ at a 0° angle, collinear with the lenticels, and Ⓑ at 90°, perpendicular to the lenticels.**



assessing the stopper's texture (in the sense of image processing), the spatial distribution of various stopper components, their volume, percolation between the top and bottom of the stopper, the effect of growth rings and, of course, grey levels on the images (their mean and Standard deviation). All these criteria cannot be detailed here, but two examples may be given for illustration. The first criterion is the distance map histogram: it is obtained from a segmented image, by taking each voxel (3D pixel) of a given phase and assigning to it the distance to the voxel of the closest complementary phase. For example, if we consider the segmented image of the lenticels, we obtain the distance to the closest lenticel for each voxel outside the lenticels ***(Figure 4)***. This calculation is done here in 3D.

The histogram of the resulting values is then used as a characteristic for classification. The purpose of this criterion is to assess whether the separation of the various areas in question (lenticels/woody areas/lenticels and woody areas) is characteristic of low oxygen ingress. Another criterion that can be used as an example is granulometry ***[10]***. This criterion represents the size distribution of objects in the image. We are interested here in dark objects (lenticels, local porosity) and light objects (mineral inclusions and growth rings) on the image. ***Figure 5*** presents granulometry curves for two X-rays Radiography (0° and 90°) ***(Figure 1)*** for the light phase. It seems that with this single criterion we cannot clearly distinguish permeable stoppers, represented by red curves, from impermeable ones, represented by green curves. To do so, a more advanced method needs to be used, as described below.

Classification method

A supervised classification method relying on a support vector machine (SVM) algorithm is used here to classify permeable and impermeable stoppers. The principle of supervised classification consists in learning a classification rule from a set of data (training dataset) whose classification is already known. Once the classification is learned, it can be applied to classify new data. SVMs, introduced by Cortes and Vapnik in 1995 ***[11]***, are a family of algorithms well known for their ability to generalise. They are often used for problems of small size (< 10^4 examples in the training set) and possess a large range of practical applications (optical character recognition, image classification, etc.). Additionnally, it is necessary to apply weighting that is inversely proportional to the corresponding class size during the training stage in order to take into account the unbalance in the number of stoppers between the two classes (102 impermeable stoppers, 40 permeable stoppers). Various classifiers are then considered, and in particular we must choose relevant characteristics calculated from 2D or 3D images. To do so, results from various classifiers are assessed using the Leave One Out (LOO) strategy. This strategy consists in successively removing each stopper from the training dataset in order to conduct the learning with this new base, and then to classify the stopper removed from the base. The results obtained are presented in the form of a confusion matrix containing:

– the number of impermeable stoppers classified as impermeable: true positives (TP);

– the number of permeable stoppers classified as permeable: true negatives (TN);

– the number of impermeable stoppers classified as permeable: false negatives (FN);

– the number of permeable stoppers classified as impermeable: false positives (FP).

Results are quantified in this study using *precision, recall* and *accuracy* measurements, defined as follows:

$$Precision = \frac{TP}{(TP+FP)}\ ;\quad Recall = \frac{TP}{(TP+FN)}\ ;\quad Accuracy = \frac{TP+TN}{Total\ population}$$

Accuracy represents the percentage of correctly classified stoppers. *Precision* represents the percentage of truly impermeable stoppers among all stoppers classified as impermeable. In a practical manner, the FP value corresponds to the number of permeable stoppers that have been certified as impermeable by the method. It is reflected in the *precision* value. The FN value corresponds to the number of stoppers we certify as permeable using this method when they actually are not. It is reflected in the *recall* value. These three criteria must be maximised. The complete classification method is summarised in ***Figure 6***.

Results and discussion

Batch 1 classification based on 3D images

Various combinations of criteria have been tested. The following combination gives the best classification results:
- volume fraction and mean volume of lenticels/woody areas/lenticels and woody areas taken together;
- thickness without lenticels/without woody areas/without lenticels and woody areas;
- percolation;
- number of growth rings and autocorrelation.

Stopper classification results are reported in the confusion matrix presented in ***Figure 7***. On this same figure, TN, TP, FN and FP distribution is presented according to five classes resulting from the OIR measurements. Based on the confusion matrix, *accuracy* is found to be 80%. It can be observed that for high-quality stoppers (< 0.55, < 1.1 and < 3.0 mg of oxygen released over 60 days), the classification limits impact the cost of production, with an 82% *recall* value. In other words, while 95 stoppers were classified as impermeable, 18 more could have been marketed as well. However, for permeable stoppers in the < 8.0 and > 8.0 mg classes, the classification limits imply the sale of stoppers certified as impermeable but which are actually permeable (11 out of 95 stoppers); this is quantified by the 88% *precision* value. A *precision* value close to 100% must be reached to certify sale of only impermeable stoppers. FP and FN stoppers are uniformly distributed over the five classes.

Batch 1 classification based on 2D images

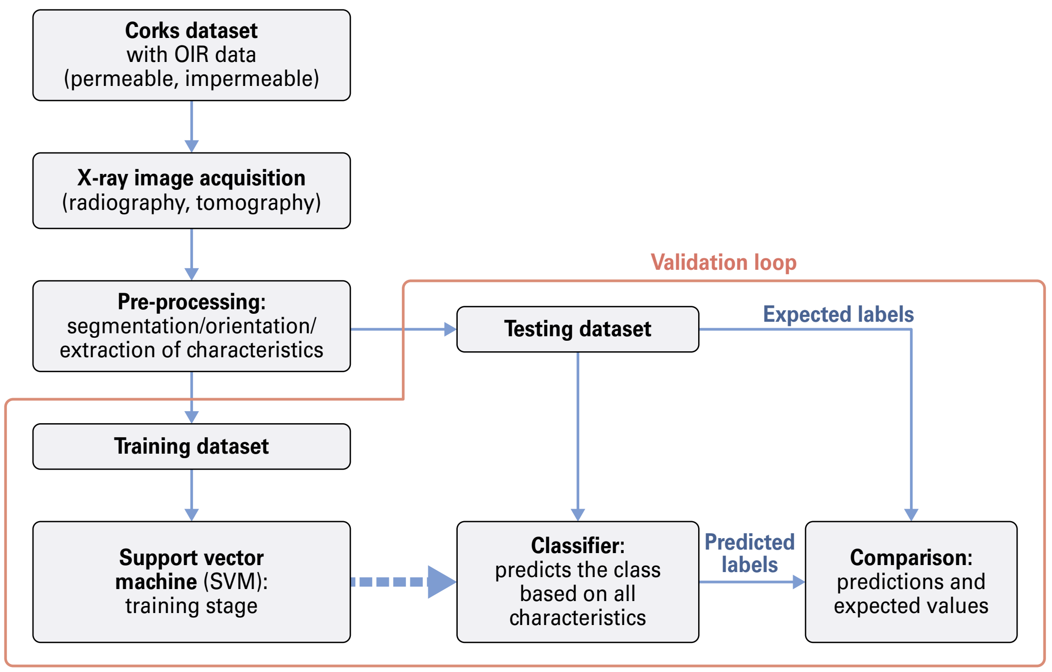
This involves implementing a classification algorithm not using the reconstructed 3D images, but rather the 2D projection images directly, in order to have a configuration that can be applied in an industrial context. Different combinations of the images presented in ***Figure 1*** are considered. Among the characteristic/projection combinations envisaged, the one giving the highest *accuracy* is the particle size distribution of light structures (statistical distribution of their size ***[10]***) calculated from the 0° and 90° images. The *accuracy* value is then 77% ***(Figure 8)***. The *precision* value is 83%. In other words, among the 105 stoppers classified as impermeable, 18 would be marketed even though they are actually permeable. The *recall* value is 85%, which corresponds to the fact that, in addition to the 105 stoppers certified as impermeable, 15 stoppers classified as permeable could have been marketed but were removed or re-qualified, even though they were actually impermeable. To use these stoppers, a *recall* value close to 100% would be needed. Note that with only two well-selected projections of the cork structure, i.e. collinear with the lenticels for one and collinear with cork growth rings for the other, we lose little in terms of *accuracy* and *precision*, and we even increase the *recall* value slightly, in comparison with the results obtained from 3D images. This is satisfactory with regards to the classification using 3D images, which is much longer and more difficult to implement, for both acquisition and classification.

Experimental parameters, such as X-ray source size, which causes blur on the image or even acquisition noise, can influence image quality and therefore classification quality. Without going into detail, our work has shown that, for 2D images, noise or blur has little influence on the supervised classification; it seems that the granulometry operator is especially robust.

Batch 2 classification based on 2D images

Following the results on batch 1, the classification of 436 stoppers from batch 2 was done with 2D images (0° and 90°) using granulometry operator. ***Figure 9*** presents the confusion matrix following classification, with the training dataset being composed of batch 1 images. Moreover, the classification can be reiterated by using batch 1 and batch 2 as the training dataset through a LOO strategy. The confusion matrix for this latter case is also shown in ***Figure 9***. As such, *accuracy* values are 57% and 69%, respectively; *precision* values are 58% and 66%, respectively; and *recall* values are 71% and 86%. We can see that with a training dataset of stoppers resulting from batch 1 alone, the classification of stoppers from other sources does not give satisfactory results. In fact, we can observe that batch 2 stopper images are sometimes very different from those of batch 1. This may be due to different cork origins or to stoppers of varying quality (batch 1 contains only Flor, Extra and Superior stoppers). When these batch 2 stoppers are put in the training dataset (LOO strategy), the classification is improved. Nonetheless, the *precision* and *recall* values remain significant. Out of 298 stoppers classified as impermeable, 101

■ **Figure 6: Diagram of the classification method used.**



are in fact permeable. Moreover, 33 are wrongly classified as permeable, even though they are impermeable.

Conclusions and outlook

This study presents a supervised classification method for punched natural cork stoppers using X-ray images. This method was used because it appears that the internal structure of punched cork stoppers may be very similar for a highly permeable or highly impermeable stopper. Thus, stoppers may be very airtight even though X-ray images show the presence of significant porosity, which may contain oxygen pockets. In contrast, stoppers whose X-ray images show the absence of significant defects may be quite permeable. It is thus difficult for even a skilled operator to discriminate accurately between stoppers based on raw images. A large number of criteria were thus tested and assessed on 2D and 3D images. For an industrial application, especially one with a high output rate requirement, we have found that the use of two 2D images following collinear and perpendicular angles with respect to the lenticels would be satisfactory. To anticipate problems related to industrialisation, we have also demonstrated the classifier's robustness in response to acquisition conditions, such as blur caused by the X-ray source or noise, which may be non-negligible on an industrial line in comparison with laboratory conditions. However, *precision* values are still too low to deploy the method at the industrial scale. In fact, in the case of 2D images from batch 1 (acquisition that can be industrialised), 17% of stoppers were in fact permeable (OIR > 3 mg over 60 days). The *recall* values may be acceptable in terms of a guarantee that a punched cork stopper is impermeable. In the case for 2D images from batch 1, this value corresponds to 14% of stoppers, which thus have to be removed or re-qualified. The non-destructive identification of traditional cork stoppers as either permeable or airtight still remains a challenge. However, areas for improvement are being studied, including of course, the expansion of the training dataset with new OIR measurements. Cork is indeed a material with great variability, which makes it essential to have a large training dataset to ensure its statistical representativeness. The difficulty lies in obtaining OIR data, which can be time-consuming. The first classification results presented here are encouraging, despite the small dataset size and provided that, under our experimental conditions, the structural analysis of the stopper by X-ray imaging actually reveals all parameters indicative of permeability. In addition, the method requires only a few views (2 X-rays Radiography), with acceptable robustness to acquisition noise, which may open up the possibility of adaptation to online control. ■

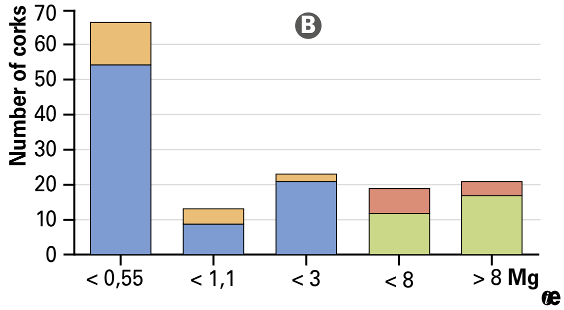
*Editor's note: The bibliographic references indicated in this article from **[1]** to **[11]** are available on the Revue des Œnologues website: **search.oeno.tm.fr***

■ **Figure 7: Ⓐ Confusion matrix resulting from 3D image classification. Ⓑ Distribution of TP and FN stoppers in classes < 0.55, < 1.1 and < 3.0 mg of oxygen released over 60 days and TN and FP stoppers in classes < 8.0 and > 8.0 mg.**

Ⓐ

Confusion		Estimated classes	
		Permeable	Impermeable
OIR classes	Permeable	29 (TN)	11 (FP)
	Impermeable	18 (FN)	84 (TP)

Ⓑ

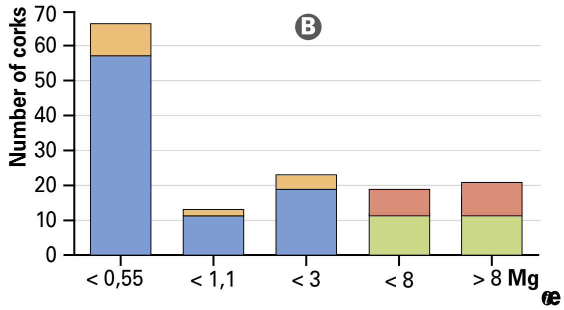


■ **Figure 8: Ⓐ Confusion matrix resulting from 2D image classification at 0° and 90°. Ⓑ Distribution of TP and FN stoppers in classes < 0.55, < 1.1 and < 3.0 mg of oxygen released over 60 days and TN and FP stoppers in classes < 8.0 and > 8.0 mg.**

Ⓐ

Confusion		Estimated classes	
		Permeable	Impermeable
OIR classes	Permeable	22 (TN)	18 (FP)
	Impermeable	15 (FN)	87 (TP)

Ⓑ



■ **Figure 9: Ⓐ Confusion matrix resulting from 2D image classification at 0° and 90° of batch 2 with batch 1 training dataset. Ⓑ Confusion matrix resulting from 2D image classification at 0° and 90° of batch 2 with batch 1 and 2 training dataset** (LOO strategy).

Ⓐ

Confusion		Estimated classes	
		Permeable	Impermeable
OIR classes	Permeable	87 (TN)	119 (FP)
	Impermeable	67 (FN)	163 (TP)

Ⓑ

Confusion		Estimated classes	
		Permeable	Impermeable
OIR classes	Permeable	105 (TN)	101 (FP)
	Impermeable	33 (FN)	197 (TP)

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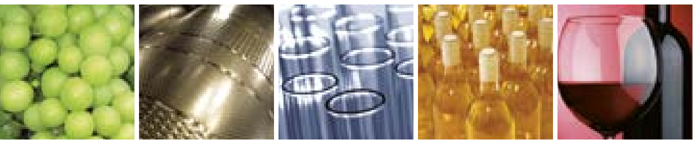

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