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Evaluation of the Effect of Postharvest Lacto-Fermentation on Radish Using Innovative Discriminative Models Based on Textures of Images †

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Abstract: The objective of this study was to evaluate the changes in the textures of slice images of radish subjected to lacto-fermentation. The models developed for individual color channels of images and color spaces RGB, Lab, YUV, XYZ were used to distinguish between fresh and lacto-fermented radishes. The discrimination accuracy reached 100% in the case of models built for each color space and color channels *B*, *b*, *Z* and *U*. In these cases, the values of TP Rate, Precision, F-Measure, ROC Area and PRC Area were equal to 1.000. The usefulness of image analysis for the evaluation of the postharvest processing of radish was proven.

Keywords: spontaneous fermentation; color images; radish slices; texture parameters; machine learning algorithms; discrimination performance

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1. Introduction

Radish (*Raphanus sativus* L.) is a vegetable with fleshy roots. It belongs to the Brassicaceae family. Radish is widely cultivated around the world. Roots are rich in carbohydrates, vitamin C, minerals, protein, crude fiber, polyphenols, folic acid, and glucosinolate [1,2]. The edible parts of radishes are roots as well as leaves and sprouts. The color of the radish root surface is mostly red, white, purple, green or black and flesh is white. The red color of the root depends on the content of anthocyanin pigments. The root can be consumed raw, e.g., in salads, or in processed and preserved forms. It can be cooked, salted, dried [3]. The root can also be pickled or fermented [3–6]. Fermentation is very beneficial for preserving and prolonging the shelf life of fresh vegetables and allows obtaining products with unique flavors, aromas, textures and chemical compositions [4]. There are many methods of identifying and classifying agricultural and horticultural products. Image-based methods, especially those that rely on image features, have been noted as effective methods [7–9]. Also, the results of previous studies performed by the author of this paper indicated that textures extracted from the images allow for an accurate, objective, fast and inexpensive quality evaluation of food products [10–12]. Machine learning (ML) can be useful for food quality evaluation based on empirical data. The information provided by intelligent systems can be also used to extend the shelf life of food products [13]. Nowadays, machine learning is often combined with image processing [14]. Such procedures are useful in practice for postharvest classification of horticultural products and can be more effective than a manual approach [15].

The objective of this study was to evaluate the changes in the textures of slice images of radish subjected to lacto-fermentation after harvesting. The models for distinguishing the lacto-fermented and fresh radishes were developed based on texture features of slice images.

2. Materials and Methods

2.1. Materials

The radishes were harvested from a garden located in northeastern Poland. One hundred and twenty radishes were collected. After harvesting, radish roots were washed using potable water and air-dried under room conditions. Sixty radish roots were subjected to the spontaneous lacto-fermentation and the other sixty were intended for immediate imaging after harvesting in fresh form. The lacto-fermentation was carried out in glass jars using the whole radish roots, potable water including sodium chloride (table salt) at the final concentration of 3% in brine, horseradish, garlic and dill. The samples were stored at room temperature of about 20 °C (3 days). Then, a lower temperature of 11 ± 1 °C was applied. These samples were stored for two months before imaging.

2.2. Image Processing

For both fresh and fermented samples, 50 representative undamaged radishes were selected. Each radish root was cut in half using a sharp knife and one slice for each half was obtained. For each root, two images of cross-sections were acquired with the use of a digital camera. Thus, 100 slice images of fresh radish and 100 slice images of lacto-fermented radish were obtained. The examples are shown in Figure 1. The images were converted to color channels *R*, *G*, *B*, *L*, *a*, *b*, *U*, *V*, *X*, *Y*, *Z* using the MaZda software (Łódź University of Technology, Institute of Electronics, Poland) [16]. Color channels *R* (red), *G* (green), and *B* (blue) create the RGB color space; color channels *L* (lightness component from black to white), *a* (green for negative values and red for positive values), and *b* (blue for negative values and yellow for positive values)—Lab color space; color channels *X* (represents the color information), *Y* (lightness), and *Z* (represents the color information)—XYZ color space; color channels *Y* (luminance of the color), *U* (determines the color itself—chromaticity), and *V* (determines the color itself—chromaticity)—YUV color space [17].

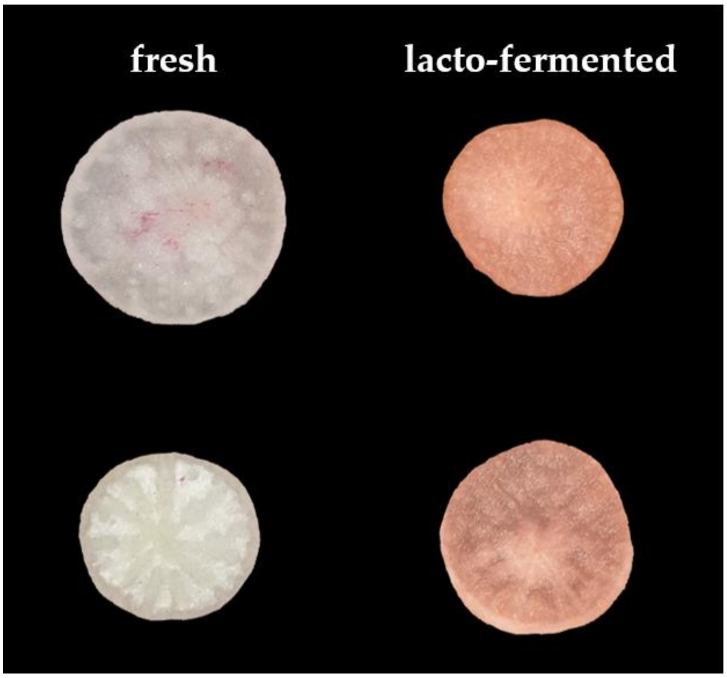

Figure 1. The slice images of lacto-fermented and fresh radish.

2.3. Discrimination of Lacto-fermented and Fresh Radish Samples

The effect of lacto-fermentation on the radish quality was evaluated using the innovative discriminative models built based on sets of selected textures of images. The texture selection and discrimination analysis were performed using the WEKA application (Machine Learning Group, University of Waikato) [18–20]. The models were developed for individual color channels *R*, *G*, *B*, *L*, *a*, *b*, *U*, *V*, *X*, *Y*, *Z* and color spaces RGB, Lab, YUV, XYZ using different machine learning algorithms from the groups of Trees, Bayes, Functions, Rules, Lazy. The classification was performed using the 10-fold cross-validation mode. The data set was randomly divided into 10 parts. Each part was considered as the test set and the remaining—as the training sets in turn. The results were presented as the averages of 10 estimates for learning carried out 10 times using different training sets [20]. The accuracies of discrimination for fresh and lacto-fermented radishes, average accuracies for both samples as well as True Positive Rate (TP Rate), Precision, F-Measure, Receiver Operating Characteristic Area (ROC Area) and Precision-Recall Area (PRC Area) were determined. The formulas for the computation of the above metrics are presented in Equations (1)–(8) [21,22]:

$$\text{Accuracy} = (TP + TN)/(TP + FP + TN + FN) \times 100 \tag{1}$$

$$\text{TP Rate (Recall)} = TP/(TP + FN) \tag{2}$$

$$\text{FP Rate} = FP/(FP + TN) \tag{3}$$

$$\text{Precision} = TP/(TP + FP) \tag{4}$$

$$\text{F1-Measure} = 2TP/(2TP + FP + FN) \tag{5}$$

$$\text{ROC Area} = \text{Area Under TP Rate vs. FP Rate Curve} \tag{6}$$

$$\text{Recall} = TP/(TP + FN) \tag{7}$$

$$\text{PRC Area} = \text{Area Under Precision vs. Recall Curve} \tag{8}$$

where TP—True Positive; TN—True Negative; FP—False Positive; FN—False Negative.

The evaluation of the effectiveness of discrimination models and the selection of algorithms were performed based on the most satisfactory values of the above performance metrics. Therefore, the results obtained using the Logistic and Multi Class Classifier were chosen to be presented in this paper. The parameters applied in the WEKA for the Logistic algorithm were: batchSize: 100; debug: False; doNotCheckCapabilities: False; useConjugateGradientDescent: False ridge: $1*10^{-8}$, and for the Multi Class Classifier: batchSize: 100; debug: False; doNotCheckCapabilities: False; randomWidthFactor: 2.0; seed: 1; classifier: Logistic -R $1*10^{-8}$ -M -1; logLossDecoging: False; usePairwiseCoupling: False; method: 1-against-all.

3. Results and Discussion

Among the tested machine learning algorithms, the Logistic and Multi Class Classifier turned out to be the most effective and produced high discrimination accuracies reaching 100% and the values of TP Rate, Precision, F-Measure, ROC Area and PRC Area equal to 1.000. The high values of these metrics indicated large changes in selected textures of lacto-fermented radishes compared to non-processed ones allowing for complete distinguishing these samples. In the case of models built for sets of textures selected for individual color channels of images, the best results were obtained for channels *B*, *b*, *Z* and *U*. The confusion matrices are presented in Figure 2 and the values of average accuracy and other metrics are shown in Table 1. Fresh and lacto-fermented radish slices were correctly discriminated in 100% and the other performance metrics were equal to 1.000 for both Logistic and Multi Class Classifier. In the case of color channel *R*, both Logistic and Multi Class Classifier algorithms provided 92.7% of discrimination of fresh and lacto-fermented samples. The fresh radishes were correctly discriminated in 92% and the lacto-fermented samples—in 93.3%. The models developed based on sets of textures selected from color channel *L* and color channel *Y* provided average accuracies of 98.7% for the Logistic and Multi Class Classifier algorithms. The models built for the textures selected from individual color spaces RGB, Lab, XYZ and YUV using the Logistic and Multi Class Classifier produced accuracies of 100% for both fresh and lacto-fermented radish samples (Figure 3) and the values of other metrics equal to 1.000 (Table 2).

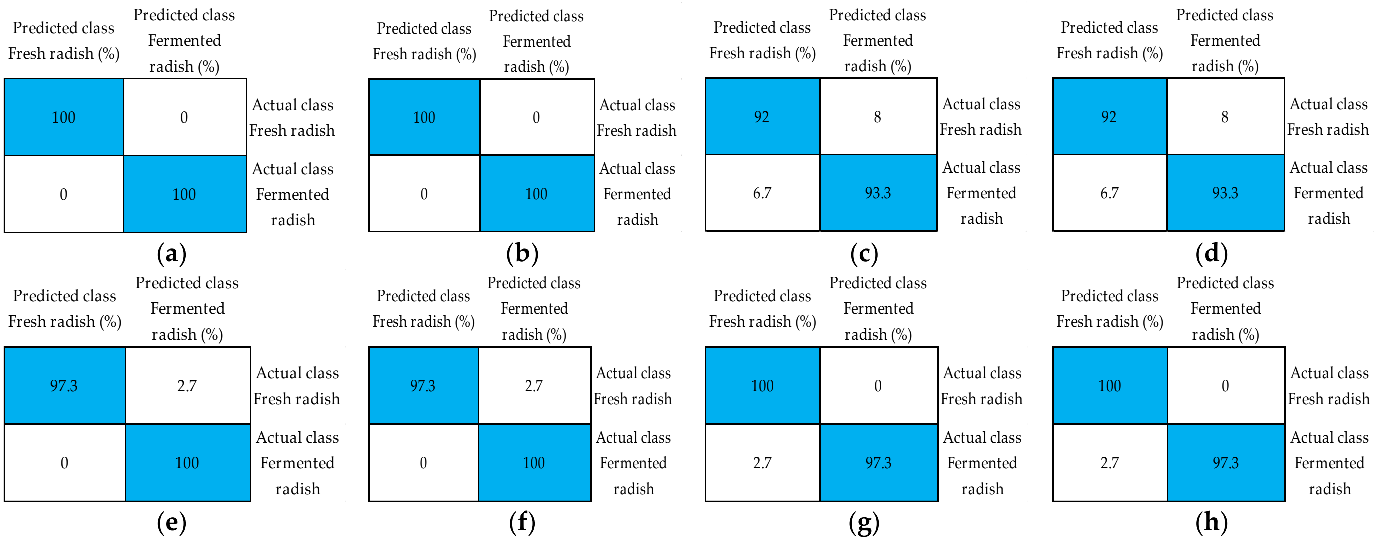

Figure 2. Confusion matrices for the discrimination of fresh and lacto-fermented radish roots using models built based on textures of slice images from each of the color channels: *B*, *b*, *Z* and *U* using the Logistic algorithm (**a**), each of the color channels: *B*, *b*, *Z* and *U* using the Multi Class Classifier algorithm (**b**), color channel *R* and Logistic (**c**), color channel *R* and Multi Class Classifier (**d**), color channel *L* and Logistic (**e**), color channel *L* and Multi Class Classifier (**f**), color channel *Y* and Logistic (**g**), color channel *Y* and Multi Class Classifier (**h**).

Table 1. The discrimination of fresh and lacto-fermented radish roots using models developed for selected individual color channels *B*, *b*, *Z*, *U*, *R*, *L*, *Y* of lice images.

Classifier	Class	Average accuracy (%)	TP Rate	Precision	F-Measure	ROC Area	PRC Area
		Each of the color channels: *B*, *b*, *Z* and *U*					
Logistic	Fresh radish	100	1.000	1.000	1.000	1.000	1.000
	Fermented radish		1.000	1.000	1.000	1.000	1.000
Multi Class Classifier	Fresh radish	100	1.000	1.000	1.000	1.000	1.000
	Fermented radish		1.000	1.000	1.000	1.000	1.000
		Color channel *R*					
Logistic	Fresh radish	92.7	0.920	0.932	0.926	0.938	0.877
	Fermented radish		0.933	0.921	0.927	0.942	0.946
Multi Class Classifier	Fresh radish	92.7	0.920	0.932	0.926	0.938	0.877
	Fermented radish		0.933	0.921	0.927	0.942	0.946
		Color channel *L*					
Logistic	Fresh radish	98.7	0.973	1.000	0.986	0.999	0.999
	Fermented radish		1.000	0.974	0.987	0.999	0.999
Multi Class Classifier	Fresh radish	98.7	0.973	1.000	0.986	0.999	0.999
	Fermented radish		1.000	0.974	0.987	0.999	0.999
		Color channel *Y*					
Logistic	Fresh radish	98.7	1.000	0.974	0.987	0.999	0.999
	Fermented radish		0.973	1.000	0.986	0.999	0.999
	Fresh radish	98.7	1.000	0.974	0.987	0.999	0.999

Multi Class Classifier	Fermented radish		0.973	1.000	0.986	0.999	0.999

TP Rate—True Positive Rate; ROC Area—Receiver Operating Characteristic Area, PRC Area—Precision-Recall Area.

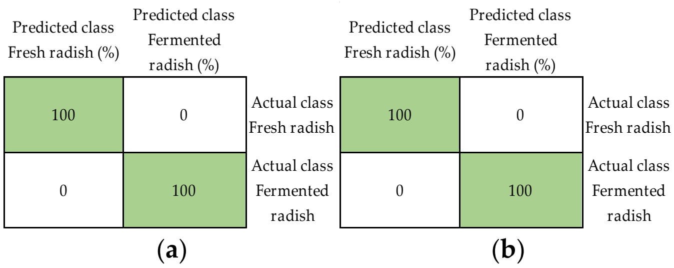

Figure 3. Confusion matrices for the discrimination of fresh and lacto-fermented radish roots using models built based on textures from color spaces RGB, Lab, XYZ and YUV of slice images using different algorithms: Logistic for each of the color spaces: RGB, Lab, XYZ and YUV (**a**), Multi Class Classifier for each of the color spaces: RGB, Lab, XYZ and YUV (**b**).

Table 2. The discrimination of fresh and lacto-fermented radish roots using models developed for color spaces RGB, Lab, XYZ and YUV of slice images.

Classifier	Class	Average Accuracy (%)	TP Rate	Precision	F-Measure	ROC Area	PRC Area
		Each of the color spaces: RGB, Lab, XYZ and YUV					
Logistic	Fresh radish	100	1.000	1.000	1.000	1.000	1.000
	Fermented radish		1.000	1.000	1.000	1.000	1.000
Multi Class Classifier	Fresh radish	100	1.000	1.000	1.000	1.000	1.000
	Fermented radish		1.000	1.000	1.000	1.000	1.000

TP Rate—True Positive Rate; ROC Area—Receiver Operating Characteristic Area, PRC Area—Precision-Recall Area.

The models built based on textures of slice images were useful for distinguishing fresh and lacto-fermented radishes. Future work can focus on the use of deep learning for the distinguishing of fresh and lacto-fermented radish. Traditional machine learning requires human-driven steps of the extraction and selection of features from the acquired images [23,24]. There are reports on the use of traditional machine learning for the quality evaluation of lacto-fermented beetroot [25,26] or pickles [27]. The application of deep learning enables performing feature extraction and classification based on raw images. Therefore, it is beneficial for discrimination purposes [28].

4. Conclusions

The results demonstrated the effect of lacto-fermentation on the radish root quality expressed in the changes in textures of cross-section images. The developed models allowed to distinguish between fresh and lacto-fermented radish slices with an accuracy of up to 100%. The most successful results were provided by the Logistic and Multi Class Classifier machine learning algorithms for the sets of image textures selected for individual color channels *B*, *b*, *Z*, *U* and individual color spaces RGB, Lab, XYZ and YUV. Due to demonstrating the usefulness of the combination of image processing and machine learning to evaluate the effect of lacto-fermentation on the changes in radish flesh, this approach can also be applied in practice for the quality evaluation of other fermented products as well as for other preservation techniques.

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