

COMPARATIVE ASSESSMENT OF RASPBERRY CULTIVARS FROM ORGANIC AND CONVENTIONAL CULTIVATION SYSTEMS USING IMAGE ANALYSIS AND TRADITIONAL MACHINE LEARNING ALGORITHMS

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ABSTRACT

The objective of this study was to evaluate the usefulness of image analysis and traditional machine learning algorithms for the discrimination of raspberry cultivars originating from organic and conventional cultivation systems. Images of the whole fruit of four raspberry cultivars: Polana, Polesie, Poemat, and Poranek, were acquired using a digital camera. Texture descriptors were extracted from images. The mean values of selected image features were compared, and the artificial intelligence models were developed. The mean comparison revealed significant differences in image texture descriptors among raspberry cultivars within both cultivation systems and between organic and conventional samples of the same cultivar. For cultivar discrimination of Polana, Polesie, Poemat, and Poranek in organically grown raspberries, the highest accuracy of 89.2% was achieved using the Subspace Discriminant classifier, followed by Quadratic Support Vector Machine (88.1%) and Wide Neural Network (86.0%). In conventionally cultivated raspberries, the highest accuracy of distinguishing cultivars reached 91.7% for the Linear Discriminant model, followed by Subspace Discriminant (91.3%) and Medium Neural Network (88.9%). All models were characterized by high area under the Receiver Operating Characteristic (ROC) curve (AUC) values, indicating excellent discrimination performance. Complete separation of organic and conventional raspberries for all analyzed cultivars with an accuracy of 100% was obtained. The results demonstrate that image texture analysis combined with traditional machine learning algorithms provides a rapid, objective, and non-destructive approach for raspberry cultivar identification and cultivation-system authentication. The proposed methodology shows considerable potential for applications in quality control, traceability, and verification of production practices in the raspberry industry.

Keywords: raspberries, production, image texture features, artificial intelligence algorithms, discrimination

INTRODUCTION

The common raspberry (*Rubus idaeus* L.) is one of the most economically important berry crops cultivated worldwide. Its fruit is highly valued by consumers due to its attractive appearance, distinctive flavor and aroma, as well as its high nutritional and health-promoting value. Raspberries are a rich source of bioactive compounds, including polyphenols, anthocyanins, vitamin C, and other antioxidants, which

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may play an important role in reducing oxidative stress and supporting the prevention of various chronic diseases [Lopez-Corona et al. 2022, Lo Piccolo et al. 2020]. Growing consumer awareness of the relationship between diet and health, together with increasing interest in high-quality foods and organically produced products, has contributed to greater interest in berry fruits, including raspberries [Sangiorgio et al. 2021, Dudziak and Kocira 2022, Kazimierczak et al. 2024]. Compared with conventional production, organic farming employs different fertilization, plant protection, and soil management strategies, which may affect plant growth and fruit quality [Sangiorgio et al. 2021, Kotuła et al. 2022].

Previous studies indicate that production systems may influence fruit chemical composition, bioactive compound content, and selected quality attributes important to consumers [Kotuła et al. 2022]. Therefore, the identification of traits associated with different production systems represents an important area of research from both scientific and practical perspectives. Fruit appearance is among the most important factors determining market attractiveness and consumer acceptance. Raspberry cultivars differ in morphological characteristics such as fruit size, shape, drupelet number, and other traits affecting market quality. These characteristics are determined by genetic factors, environmental conditions, and cultivation practices [Titirică et al. 2023]. Their objective evaluation is of considerable importance in breeding programs, quality control procedures, and studies of fruit marketability.

Traditional fruit quality assessment is based primarily on manual measurements and visual evaluation performed by specialists. Although widely used, these methods are time-consuming and may be affected by subjectivity. The rapid development of digital imaging technologies has created new opportunities for fast, objective, and non-destructive evaluation of fruit characteristics. Computer vision systems enable the acquisition and analysis of information related to color, texture, shape, and other visual features, providing valuable data for quality assessment and plant material classification [Bhargava et al. 2021].

Advances in artificial intelligence have further expanded the potential applications of image analysis in agriculture and horticulture. Algorithms such as support vector machines (SVM), decision trees, artificial neural networks, and deep learning models enable the automatic detection of patterns in image data and effective object classification [Kamilaris and Prenafeta-Boldú 2018, Liakos et al. 2018, Bird et al. 2022, Knott et al. 2023]. These methods have been applied to cultivar identification, ripeness assessment, damage detection, and fruit quality classification.

Numerous studies have demonstrated the usefulness of image-analysis-based approaches for assessing the quality of berry fruits. Ropelewska and Masny [2025] achieved high classification accuracy in the discrimination of strawberry cultivars and breeding materials using image analysis and machine learning techniques. Similar approaches have also been applied to raspberries. Rodríguez-Pulido et al. [2017] demonstrated the feasibility of assessing raspberry ripeness using colorimetric and near-infrared imaging techniques. Wang et al. [2022] demonstrated the effectiveness of combining hyperspectral imaging with chemometric methods for geographical origin identification and prediction of selected quality parameters of raspberry fruits. Quintero Rincón et al. [2022] developed a specialized RGB image database intended for the automatic quality assessment of raspberries using computer vision techniques.

Despite the growing number of studies on the application of image analysis and artificial intelligence in horticultural sciences, relatively little attention has been devoted to differentiating raspberry fruit originating from different production systems. In particular, studies investigating the possibility of distinguishing fruit of the same cultivars grown under organic and conventional production systems solely based on digital image features remain limited. A better understanding of these relationships may provide valuable insights into the effects of production technologies on fruit appearance and contribute to the development of tools supporting the identification of fruit origin.

The aim of this study was to evaluate the potential of image analysis and artificial intelligence methods for differentiating fruit of four raspberry cultivars grown under organic and conventional production systems.

MATERIALS AND METHODS

Raspberry samples

The study was conducted on fruit of four autumn cultivars of common raspberry (*Rubus idaeus* L.): Polana, Poemat, Polesie, and Poranek. The fruit samples were harvested at full harvest maturity from plants grown at two locations differing in production systems. Material from organic cultivation was obtained from the Organic Experimental Orchard in Nowy Dwór-Parcela, Polska while fruit samples from conventional cultivation were harvested at the Experimental Orchard in Brzezna, Polska. The Organic Experimental Orchard represented an established organic production system and contained all four cultivars included in the study. Therefore, when selecting the conventional orchard, particular attention was paid to obtaining fruit from the same four cultivars in order to minimize cultivar-related variation between the two production systems. An orchard located in the same or a geographically close region was also sought to reduce differences in climatic and atmospheric conditions between the two sites. The two experimental orchards are located within the same general climatic region, which was considered when selecting the study sites. The same four cultivars were therefore evaluated under both production systems, and fruits were collected at full harvest maturity. This approach was intended to minimize the potential influence of differences in cultivar composition and developmental stage and to facilitate comparison of the production systems across a common set of cultivars. Nevertheless, because the organic and conventional fruits were obtained from two different orchards, the effects of production system and orchard location cannot be completely separated in the present experimental design. Site-specific factors, including soil properties, microclimate, environmental conditions, and management history, may have contributed to the observed differences. Thus, the results should be interpreted as differences between fruit samples obtained under the two production systems at the respective experimental sites, rather than as definitive evidence that the cultivation system alone caused all observed differences.

Crop cultivation in both the organic and conventional systems was conducted in accordance with current agrotechnical recommendations for the respective production methods. Management practices included fertilization, weed control, irrigation, and plant protection in accordance with the principles applicable to the respective cultivation systems. For each cultivar and production system, 100 fruits were harvested. Subsequently, fruits were selected from the harvested material for image acquisition and further analysis. Only healthy fruits were selected for the study – those free from mechanical damage, disease symptoms, and pest feeding, uniform in size and shape, and at full harvest maturity. Overripe, deformed, or damaged fruits were excluded from further analysis. Immediately after harvesting, the fruit samples were transported to the laboratory, where it was cleaned and prepared for photography. The selected raspberries were characterized by uniform coloring typical of the cultivar.

Image acquisition

The whole raspberries representing belonging to four cultivars, Polana, Polesie, Poemat, and Poranek, from organic and conventional cultivation systems were imaged with 60 repetitions for each cultivar and cultivation system on a white background. Image acquisition was performed immediately after preparation of the selected fruit samples under laboratory conditions. The raspberry fruits were photographed using an Apple iPhone SE (2nd generation) (Apple Inc., Cupertino, CA, USA). The images were acquired at a resolution of 4032 × 3024 pixels, corresponding to a 4:3 aspect ratio, and stored in JPEG format. According to the EXIF metadata available in the original image files, the camera settings for the documented images included an aperture of f/1.8, an exposure time of 1/100 s, ISO 32, an exposure compensation of 0 EV, and a focal length of 4 mm.

The fruits were placed individually on a uniform, light-colored background and arranged without overlapping. The camera was mounted on a tripod at a height of 24 cm above the sample surface and positioned vertically above the fruit to obtain a consistent view of the fruit surface. The same camera position,

distance from the samples, sample arrangement, background, and imaging procedure were maintained throughout the image acquisition process in order to minimize variation unrelated to the external characteristics of the fruit. The photographs were acquired under laboratory conditions using a consistent imaging setup. However, detailed information concerning the exact illumination intensity and the white-balance setting was not available in the archived image metadata. Therefore, these parameters were not retrospectively specified.

The same image acquisition procedure was applied to the fruits from the different cultivars and production systems to ensure the comparability of the photographs used for subsequent image processing and classification.

Image processing

For mean comparison of image features and development of discriminative models using traditional machine learning algorithms, the obtained images were subjected to image processing using MaZda 4.7 software (Łódź University of Technology, Institute of Electronics, Łódź, Poland) [Szczypiński et al. 2007, Szczypiński et al. 2009, Strzelecki et al. 2013]. The procedure included conversion of images into individual color channels *R*, *G*, *B*, *L*, *a*, *b*, *X*, *Y*, *Z*, *U*, *V*, and *S*, segmentation, and determination of regions of interest (ROI), each corresponding to a whole raspberry fruit. For each ROI, 2172 texture parameters were computed.

Mean comparison

The statistical analysis of image texture features was performed to identify differences in fruit surface structure among the studied raspberry cultivars originating from an organically managed mother plantation or a conventional cultivation system, and to compare fruit samples from organic and conventional systems. For comparative analysis between samples, mean values of textures computed on the basis of the histogram (HMean) for individual color channels were selected, as RHMean, GHMean, BHMean, LHMean, aHMean, bHMean, XHMean, YHMean, ZHMean, UHMean, VHMean, SHMean. Mean comparison of image textures was performed using Statistica 13.3 (Tibco Software Inc., PaloAlto, CA, USA). Prior to the analysis, the normality of the data distribution was assessed using the Shapiro–Wilk test, and the homogeneity of variances was evaluated using Levene’s test. When the assumptions were satisfied, differences among means were assessed using Tukey’s honestly significant difference (HSD) test. The significance level was set at $p < 0.05$.

Discriminant analysis

The discriminant analysis was performed in the MATLAB environment (MathWorks, Inc., Natick, MA, USA). The initial image database contained 60 images of individual fruits for each cultivar in each cultivation system. The procedures were carried out in several steps to distinguish the following samples:

- 1) raspberry cultivars Polana, Polesie, Poemat, and Poranek from an organically managed mother plantation, with 60 images acquired for each cultivar, resulting in a total dataset of 240 images;
- 2) raspberry cultivars Polana, Polesie, Poemat, and Poranek from a conventional cultivation system, with 60 images acquired for each cultivar, resulting in a total dataset of 240 images;
- 3) Polana from an organically managed mother plantation vs. Polana from a conventional cultivation system, with 60 images acquired for each cultivation system, resulting in a total dataset of 120 images;
- 4) Polesie from an organically managed mother plantation vs. Polesie from a conventional cultivation system, with 60 images acquired for each cultivation system, resulting in a total dataset of 120 images;
- 5) Poemat from an organically managed mother plantation vs. Poemat from a conventional cultivation system, with 60 images acquired for each cultivation system, resulting in a total dataset of 120 images;
- 6) Poranek from an organically managed mother plantation vs. Poranek from a conventional cultivation system, with 60 images acquired for each cultivation system, resulting in a total dataset of 120 images.

Each image represented a separate fruit. Therefore, multiple images of the same fruit were not present in the datasets. Consequently, images of the same fruit could not be assigned to both the training and validation subsets. For each classification step, feature selection was performed using the MRMR

(Minimum Redundancy Maximum Relevance) feature-selection method. Image texture descriptors were selected from the complete set of 2172 extracted attributes and subsequently used to classify raspberry samples using traditional machine-learning methods. The MRMR procedure is a supervised feature-selection method that evaluates the relevance of each feature to the predefined class labels while simultaneously minimizing redundancy among the selected features. Features were ranked according to the MRMR criterion, which is based on the trade-off between maximum relevance to the target class and minimum redundancy with respect to the other selected features. The 30 highest-ranked texture attributes were selected for each classification task and used as input variables for the subsequent classification models. The feature-selection procedure was performed separately for each classification task, using the corresponding class labels (i.e., cultivar or cultivation system) as the target variable. The same MRMR procedure, parameter settings, and selection criterion were applied consistently across all classification tasks, with the number of selected attributes fixed at 30. This standardized procedure ensures reproducibility of the feature-selection process. Therefore, the models were developed using the selected features with the highest discriminatory power, which contributed to improved classification accuracy and reduced model development time. Subsequently, discrimination was performed using a 10-fold cross-validation procedure. In 10-fold cross-validation, each dataset was divided into 10 subsets (folds). In each iteration, 9 folds were used for model development, and the remaining fold was used for validation. This process was repeated 10 times so that each image was used once as part of the validation set. Model performance was assessed using accuracy and Receiver Operating Characteristic (ROC) curve (AUC) values.

In the case of the classification of raspberry cultivars derived from the organically managed mother plantation, three algorithms representing different machine learning approaches were selected, as providing the highest accuracies: Subspace Discriminant, Quadratic Support Vector Machine (SVM), and Wide Neural Network. The Subspace Discriminant model was trained using an ensemble of discriminant learners operating in randomly selected subspaces of the feature space. The model utilized 30 learners with a subspace dimension of 30. The prediction speed was approximately 290 observations/second, and the training time was 27.94 seconds. The Quadratic SVM classifier employed a quadratic kernel function and a one-versus-one multiclass strategy. The kernel scale was automatic. The box constraint level was set at 1. The standardize data option was used. The prediction speed was equal approximately 1200 observations/second, and the training time reached 10.77 seconds. The Wide Neural Network model consisted of a fully connected neural architecture with one hidden layer containing 100 neurons. The network was trained using the ReLU activation function, and the training process was performed with a validation-based optimization procedure. The iteration limit was 1000, and the regularization strength (Lambda) was 0. The model was characterized by the prediction speed of approximately 2200 observations/second and the training time of 55.48 seconds.

For the classification of raspberry cultivars sampled from the conventional system, Linear Discriminant, Subspace Discriminant, and Medium Neural Network algorithms were chosen. The Linear Discriminant classifier was constructed using a linear discriminant function for multiclass recognition. The covariance structure was full. The model was characterized by the prediction speed reaching approximately 1000 observations/second and the training time of 4.94 seconds. The Subspace Discriminant approach employed an ensemble learning strategy based on multiple discriminant learners operating on randomly generated feature subspaces. The ensemble consisted of 30 learners with a subspace dimension equal to 43. The prediction speed was approximately 240 observations/second, and the training time was 66.27 seconds. The Medium Neural Network model was characterized by a single fully connected hidden layer with 25 neurons, ReLU activation function, iteration limit of 1000, regularization strength (Lambda) of 0, prediction speed of approximately 760 observations/second, and the training time of 74.77 seconds.

For distinguishing raspberry samples of each cultivar from an organically managed mother plantation vs. a conventional cultivation system, Subspace Discriminant was selected. The classifier consisted of 30 learners, with the subspace dimension set to 14. The prediction speed and the training time were for Polana – approximately 98 observations/second and 59.31 seconds, Polesie – approximately 110 observations/second and 61.40 seconds, Poemat – approximately 100 observations/second and 54.95 seconds, and Poranek – approximately 100 observations/second and 53.00 seconds, respectively.

RESULTS

Distinguishing raspberry cultivars from the organically managed mother plantation

Mean comparison of selected image textures of raspberry cultivars from the organically managed mother plantation. Analysis of the mean values of selected texture parameters computed based on histogram (HMean) for images in color channels *R, G, B, L, a, b, X, Y, Z, U, V*, and *S* revealed significant differences among the selected investigated raspberry cultivars originating from organic cultivation (Table 1). The cultivar Poemat was characterized by a clearly statistically significantly higher RHMean value (79.83) than Polana (73.56). Whereas Polesie and Poranek showed intermediate values, not significantly different from the other cultivars. In the case of GHMean, significantly higher values were observed for Polesie and Poemat compared with Polana and Poranek. The BHMean parameter also differentiated the cultivars, with Poranek exhibiting the lowest value (27.49), whereas the remaining cultivars formed a statistically homogeneous group. Poemat was characterized by the highest LHMean value (76.27), significantly differing from Polana and Poranek. The aHMean parameter had the lowest value for Polesie, while the other cultivars showed significantly higher and not statistically significantly different values. For bHMean, three homogeneous groups were observed, with the highest value for Poranek. Clear differences in image textures were also observed for ZHmean, where Polesie and Poemat had the highest values, and Polana and Poranek had the lowest values. Distinct differences among cultivars were additionally observed for the parameter UHMean, with the lowest value for Poranek, the intermediate for Polesie and Poemat, and the highest for Polana. Conversely, in the case of VHMean and SHMean, the highest value was found for Poranek in one homogeneous group with Poemat, while Polesie exhibited the lowest values in one homogeneous group with Polana. This confirmed cultivar-dependent differences in fruit surface structure.

Table 1. Comparison of selected image textures among raspberry cultivars from an organically managed mother plantation

Image texture	Polana	Polesie	Poemat	Poranek
RHMean	73.56 a	75.06 ab	79.83 b	78.19 ab
GHMean	24.25 a	30.02 b	29.76 b	24.48 a
BHMean	32.60 b	34.40 b	34.37 b	27.49 a
LHMean	71.15 a	74.44 bc	76.27 c	72.91 ab
aHMean	144.99 b	143.26 a	144.80 b	145.91 b
bHMean	132.62 a	133.37 ab	134.39 b	136.66 c
XHMean	9.39 a	10.50 ab	11.51 b	10.36 ab
YHMean	6.23 a	7.48 bc	7.92 c	6.86 ab
ZHMean	4.31 a	5.08 b	4.99 b	3.75 a
UHMean	122.86 c	121.58 b	120.84 b	119.42 a
VHMean	151.00 ab	149.18 a	151.69 bc	153.64 c
SHMean	45.28 ab	42.47 a	47.44 bc	51.50 c

a, b, c – the same letters within rows indicate no statistically significant differences among cultivars

Cultivar discrimination of raspberries from the organically managed mother plantation using traditional machine learning algorithms. The models for distinguishing raspberry cultivars from the organically managed mother plantation based on image texture descriptors using traditional machine learning algorithms demonstrated high effectiveness. The applied algorithms achieved an accuracy of 89.2% in the case of Subspace Discriminant. The confusion matrix (Figure 1a) obtained for the model built using this algorithm indicated that the cultivar Polana was classified with the highest correctness of 96.9%. While Polesie was characterized by the lowest accuracy of 82.0%. Misclassifications were observed mainly between cultivars Polesie and Poemat. As many as 11.5% of cases belonging to the true class Polesie were misclassified as Poemat, and 6.2% of cases from the true class Poemat were incorrectly classified as Polesie.

Figure 1. Cultivar discrimination of raspberries from the organically managed mother plantation based on image textures by Subspace Discriminant using a confusion matrix (a), where shades of blue – correctly classified cases with higher percentages of correct classification represented by more intense blue color and other colors – misclassified cases; and Receiver Operating Characteristic (ROC) curves (b), where AUC – area under the curve and the diagonal dashed line represents random classification (AUC = 0.5)

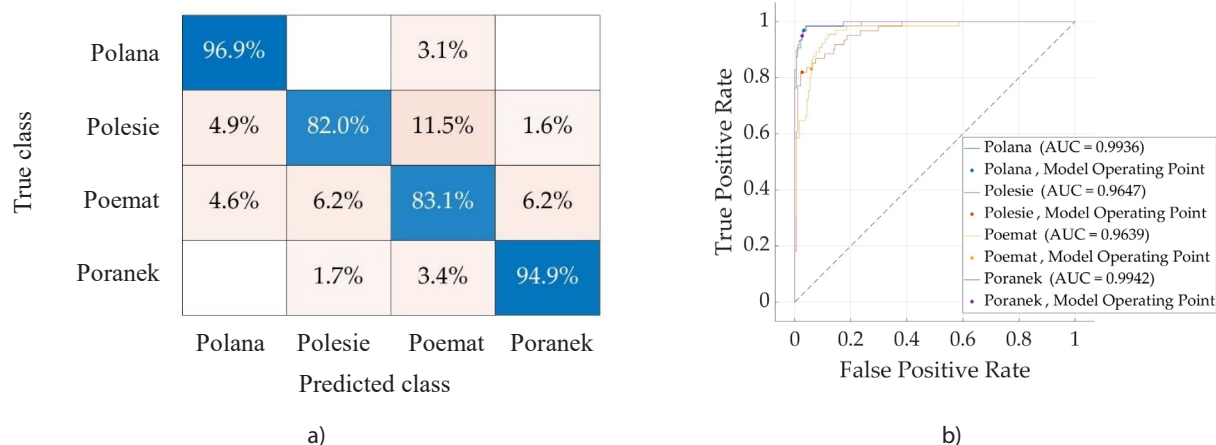
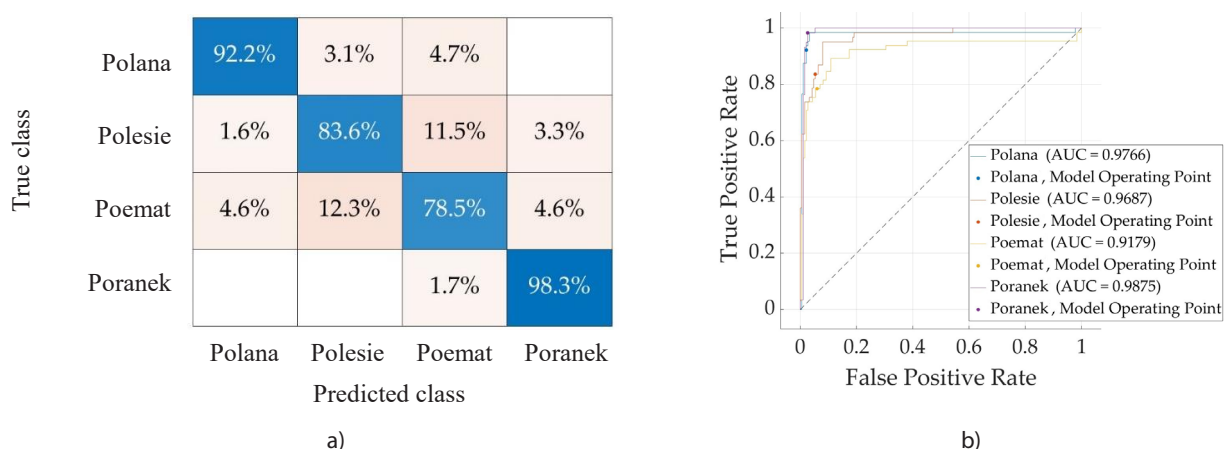


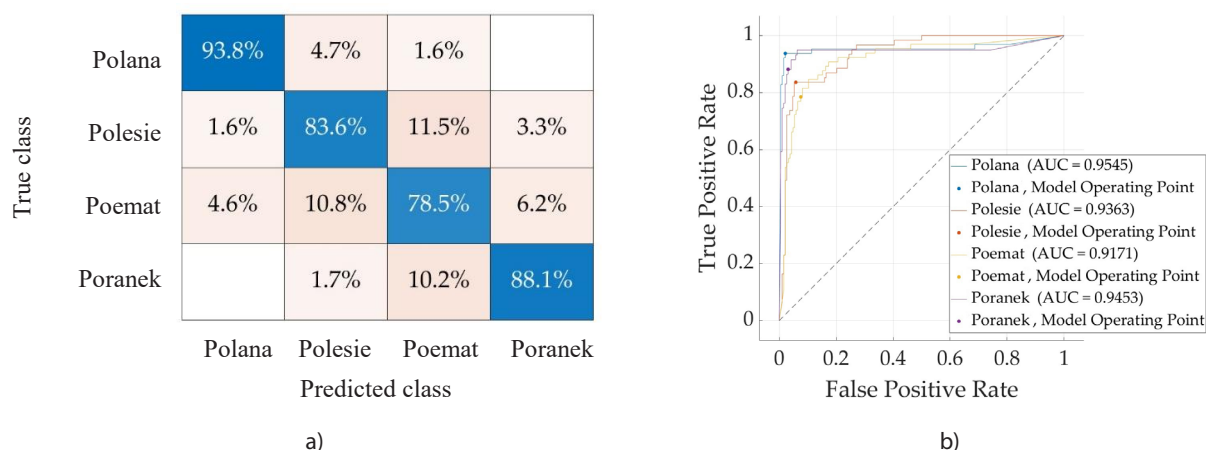
Figure 2. Discrimination of raspberry cultivars from the organically managed mother plantation by Quadratic SVM algorithm based on image texture features using a confusion matrix (a), where shades of blue – correctly classified cases with higher percentages of correct classification represented by more intense blue color and other colors – misclassified cases; and Receiver Operating Characteristic (ROC) curves (b), where AUC – area under the curve and the diagonal dashed line represents random classification (AUC = 0.5)



The Receiver Operating Characteristic (ROC) curves presented in Figure 1b demonstrated high discrimination performance of the Subspace Discriminant algorithm for cultivar identification of raspberries originating from the organically managed mother plantation based on image-derived features. All evaluated cultivars achieved very high area under the curve (AUC) values, confirming the strong predictive capability of the developed classification approach. Among the tested cultivars, Poranek and Polana achieved the highest classification performance with an AUC of 0.9942 and 0.9936, respectively. The slightly lower AUC values were observed for Polesie (0.9647) and Poemat (0.9639). The ROC curves located near the upper-left corner demonstrate the strong discriminatory power of the developed models. The operating points selected for the models further confirm balanced performance with low false positive rates and high true positive rates.

The Quadratic SVM classifier also provided satisfactory results, with an accuracy of 88.1%. The highest classification accuracy was achieved for the cultivar Poranek, with 98.3% of cases correctly classified (Figure 2a). The lowest classification performance was observed for Poemat (78.5%). Misclassifications

Figure 3. Classification performance for distinguishing raspberry cultivars originating from an organically managed mother plantation by the Wide Neural Network model using a confusion matrix (a), where shades of blue – correctly classified cases with higher percentages of correct classification represented by more intense blue color and other colors – misclassified cases; and Receiver Operating Characteristic (ROC) curves (b), where AUC – area under the curve and the diagonal dashed line represents random classification (AUC = 0.5)



occurred mainly between Polesie and Poemat, indicating the greatest similarity of their image-derived characteristics.

The ROC analysis demonstrated very good discrimination performance of the applied Quadratic SVM algorithm for raspberry cultivars originating from the organically managed plantation (Figure 2b). The highest predictive performance was obtained for Poranek (AUC = 0.9875).

The discriminant analysis performed using the Wide Neural Network model achieved an accuracy of 86.0%. The confusion matrix shown in Figure 3a revealed that the cultivars were generally well differentiated. Among the analyzed cultivars, Polana exhibited the highest classification accuracy (93.8%). Whereas Poemat and Polesie had the lowest accuracies of 78.5% and 83.6%, respectively, with the greatest misclassifications between these cultivars.

All raspberry cultivars achieved high areas under the ROC curve (AUC) exceeding 0.91 (Figure 3b). The cultivar Polana showed the highest AUC of 0.9545, while Poemat was characterized by the lowest AUC of 0.9171.

Distinguishing raspberry cultivars from the conventional cultivation system

Mean comparison of selected image textures of raspberry cultivars from the conventional cultivation system. It was observed that some analyzed raspberry cultivars originating from the conventional cultivation system differed significantly in image texture descriptors (Table 2). The cultivar Poranek had the statistically significantly highest values of RHMean (85.01), aHMean (146.71), XHMean (12.16), VHMean (154.65), and SHMean (52.88), as well as the lowest BHMean (34.39), whereas all the remaining cultivars were in one homogeneous group. For UHMean, raspberry Poranek was also distinguished by the lowest value of 120.26. However, the highest value of 124.28 was noted for Polana, and cultivars Polesie and Poemat were in one homogeneous group with intermediate values. This proves the greatest differentiation of the analyzed image texture features between Polana and Poranek.

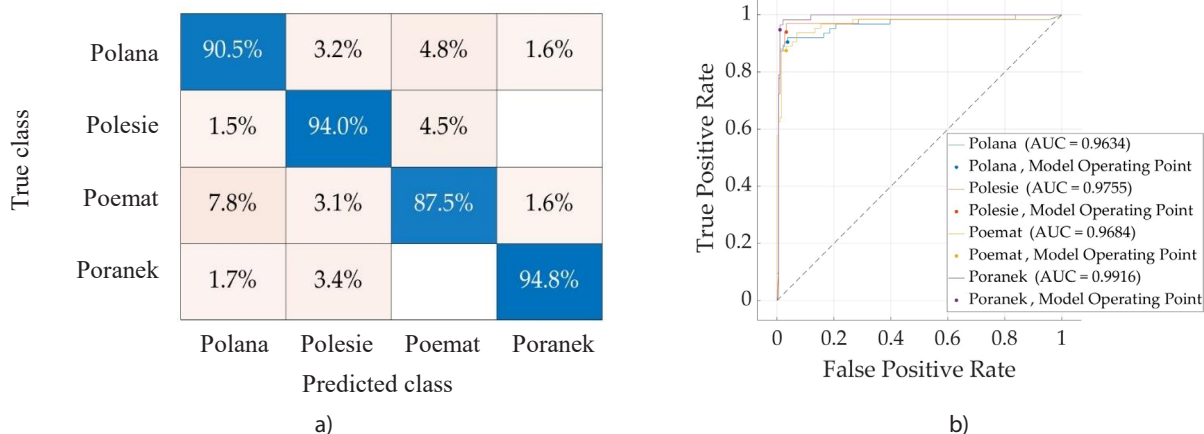
Cultivar discrimination of raspberries from the conventional cultivation system using traditional machine learning algorithms. The discrimination of raspberry cultivars originating from a conventional cultivation system performed using a traditional machine learning approach based on selected image texture parameters revealed very high accuracy of up to 91.7% for the Linear Discriminant model. The highest class-specific accuracy was observed for Poranek (94.8%) and the lowest for Poemat (87.5%). Misclassifications were relatively limited and mainly occurred between Poemat and Polana (Figure 4a).

Table 2. Comparison of selected image textures among raspberry cultivars originating from a conventional cultivation system

Image texture	Polana	Polesie	Poemat	Poranek
RHMean	71.18 a	74.58 a	74.91 a	85.01 b
GHMean	30.44 ab	32.50 b	31.93 b	28.86 a
BHMean	38.72 b	38.58 b	39.49 b	34.39 a
LHMean	73.54 a	75.63 ab	75.57 ab	78.05 b
aHMean	142.21 a	142.38 a	142.80 a	146.71 b
bHMean	130.17 a	131.47 b	130.92 ab	135.26 c
XHMean	9.21 a	10.33 a	10.27 a	12.16 b
YHMean	6.55 a	7.40 ab	7.30 ab	8.02 b
ZHMean	5.19 ab	5.42 b	5.52 b	4.65 a
UHMean	124.28 c	122.95 b	123.54 b	120.26 a
VHMean	146.71 a	147.55 a	147.89 a	154.65 b
SHMean	36.92 a	38.84 a	39.38 a	52.88 b

a, b, c – the same letters within rows indicate no statistically significant differences among cultivars

Figure 4. Classification performance for raspberry cultivar discrimination using Linear Discriminant algorithm based on selected image texture parameters using a confusion matrix (a), where shades of blue – correctly classified cases with higher percentages of correct classification represented by more intense blue color and other colors – misclassified cases; and Receiver Operating Characteristic (ROC) curves (b), where AUC – area under the curve and the diagonal dashed line represents random classification (AUC = 0.5)



The Receiver Operating Characteristic (ROC) curves (Figure 4b) further confirmed the robustness of the model, with area under the curve (AUC) values ranging from approximately 0.9634 (Polana) to 0.9916 (Poranek). This indicates excellent separability and strong discriminative power of the selected texture descriptors when combined with the Linear Discriminant classifier. The optimal operating points demonstrated high true positive rates with low false positive rates, supporting the reliability of the developed classification framework.

The Subspace Discriminant ensemble classifier provided a classification accuracy of 91.3%, confirming its high effectiveness in distinguishing between the analyzed cultivars. The highest classification accuracies were observed for Polesie (95.5%) and Poranek (93.1%), while the lowest performance was noted for

Poemat with an accuracy of 85.9%. The greatest misclassifications were observed between Poemat and Polana (Figure 5a).

The ROC analysis (Figure 5b) confirms the robustness of the Subspace Discriminant model, with AUC values reaching 0.9927 for Polesie and 0.9919 for Poranek. This indicates excellent discriminative ability and strong consistency in separating cultivar-specific texture patterns.

The classification of raspberry cultivars obtained from conventional cultivation conditions using a Medium Neural Network based on selected image texture descriptors reached an accuracy of 88.9%, indicating a strong, although slightly lower, discriminative capability compared to linear and ensemble-based approaches. The raspberry cultivar Poranek was distinguished with the highest accuracy of 96.6%, and Poemat had the lowest accuracy of 82.8%. The most incorrectly classified cases were between Poemat and Polesie, as well as between Poemat and Polana (Figure 6a).

Figure 5. Classification performance metrics for raspberry cultivar discrimination using Subspace Discriminant based on selected image texture parameters using a confusion matrix (a), where shades of blue – correctly classified cases with higher percentages of correct classification represented by more intense blue color and other colors – misclassified cases; and Receiver Operating Characteristic (ROC) curves (b), where AUC – area under the curve and the diagonal dashed line represents random classification (AUC = 0.5)

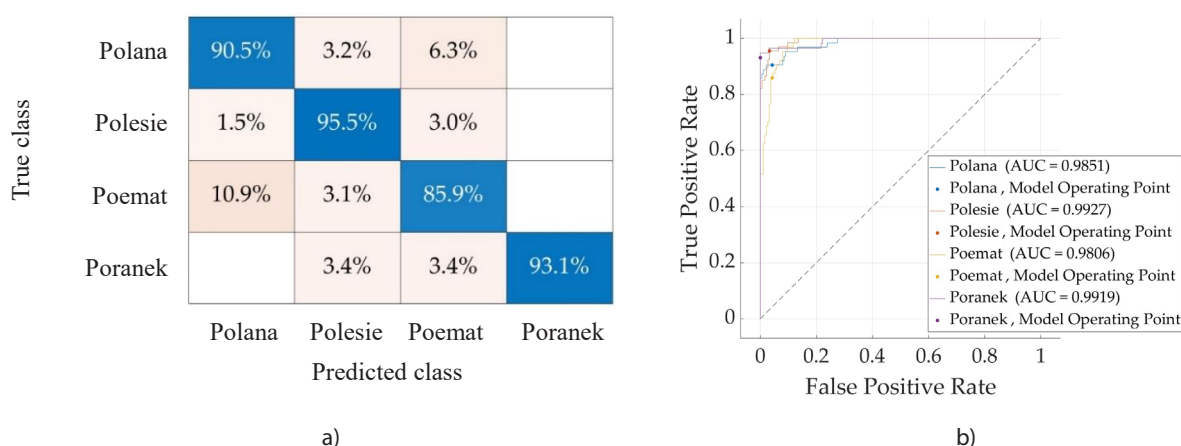
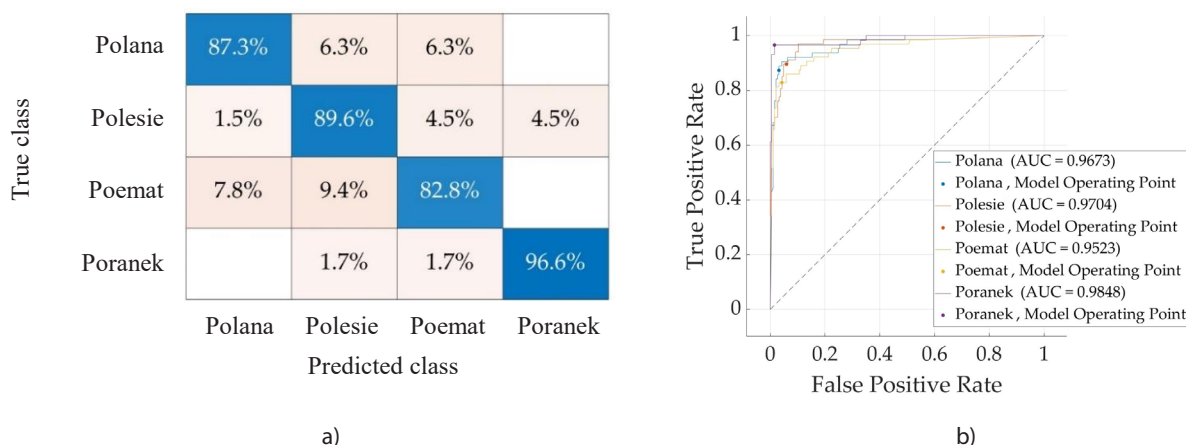


Figure 6. Classification results for raspberry cultivar recognition by a Medium Neural Network based on selected image texture features using a confusion matrix (a), where shades of blue – correctly classified cases with higher percentages of correct classification represented by more intense blue color and other colors – misclassified cases; and Receiver Operating Characteristic (ROC) curves (b), where AUC – area under the curve and the diagonal dashed line represents random classification (AUC = 0.5)



The ROC curves presented in Figure 6b confirm satisfactory classification performance of the neural network model. The AUC values remained high for all cultivars, reaching 0.9848 for Poranek (Figure 6b).

Comparison of raspberries from conventional and organic cultivation systems

Mean comparison of selected image textures between raspberries from conventional and organic cultivation systems. Raspberries of the Polana cultivar exhibited differences in selected image textures between samples from organic and conventional cultivation systems (Table 3). Raspberries from the conventional cultivation system were characterized by statistically significantly higher values of GHMean, BHMean, LHmean, ZHMean, and UHMean compared with fruit from the organic system. In contrast, organically cultivated raspberries showed significantly higher values of aHMean, bHMean, VHMean, and SHMean. No statistically significant differences were found for RHMean, XHMean, and YHMean. The results confirmed that the cultivation system significantly affected selected image texture parameters of Polana raspberries.

Table 3. Comparison of selected image textures between raspberries of the Polana cultivar from conventional and organic cultivation systems

Image texture	Cultivation system	
	organic	conventional
RHMean	73.56 a	71.18 a
GHMean	24.25 a	30.44 b
BHMean	32.60 a	38.72 b
LHMean	71.15 a	73.54 b
aHMean	144.99 a	142.21 b
bHMean	132.62 a	130.17 b
XHMean	9.39 a	9.21 a
YHMean	6.23 a	6.55 a
ZHMean	4.31 a	5.19 b
UHMean	122.86 a	124.28 b
VHMean	151.00 a	146.71 b
SHMean	45.28 a	36.92 b

a, b – the same letters within rows indicate no statistically significant differences between samples

According to the data presented in Table 4, conventionally cultivated raspberries Polesie had statistically significantly higher GHMean, BHMean, and UHMean values. In turn, organic samples were characterized by significantly higher bHMean, VHMean, and SHMean values. No statistically significant differences in terms of cultivation systems were observed for RHMean, LHMean, aHMean, XHMean, YHMean, and ZHMean.

The results shown in Table 5 revealed numerous statistically significant differences between cultivation systems for raspberries Poemat. Fruit from the organic system showed significantly higher RHMean, aHMean, bHMean, XHMean, VHMean, and SHMean values, whereas conventionally cultivated raspberries were characterized by significantly higher GHMean, BHMean, and UHMean values. No significant differences were observed for LHMean, YHMean, and ZHMean.

In the case of Poranek raspberry cultivar (Table 6), organically cultivated raspberries had statistically significantly higher bHMean. Whereas the conventionally cultivated samples were characterized by higher values of image texture parameters, such as RHMean, GHMean, BHMean, LHMean, aHMean, XHMean, YHMean, ZHMean and UHMean. No statistically significant differences were observed for VHMean and SHMean.

Table 4. Mean comparison of selected image textures between raspberries of the Polesie cultivar originating from conventional and organic cultivation systems

Image texture	Cultivation system	
	organic	conventional
RHMean	75.06 a	74.58 a
GHMean	30.02 a	32.50 b
BHMean	34.40 a	38.58 b
LHMean	74.44 a	75.63 a
aHMean	143.26 a	142.38 a
bHMean	133.37 a	131.47 b
XHMean	10.50 a	10.33 a
YHMean	7.48 a	7.40 a
ZHMean	5.08 a	5.42 a
UHMean	121.58 a	122.95 b
VHMean	149.18 a	147.55 b
SHMean	42.47 a	38.84 b

a, b – the same letters within rows indicate no statistically significant differences between samples

Table 5. Comparison of selected image texture features between raspberries of the Poemat cultivar from conventional and organic cultivation systems

Image texture	Cultivation system	
	organic	conventional
RHMean	79.83 a	74.91 b
GHMean	29.76 a	31.93 b
BHMean	34.37 a	39.49 b
LHMean	76.27 a	75.57 a
aHMean	144.80 a	142.80 b
bHMean	134.39 a	130.92 b
XHMean	11.51 a	10.27 b
YHMean	7.92 a	7.30 a
ZHMean	4.99 a	5.52 a
UHMean	120.84 a	123.54 b
VHMean	151.69 a	147.89 b
SHMean	47.44 a	39.38 b

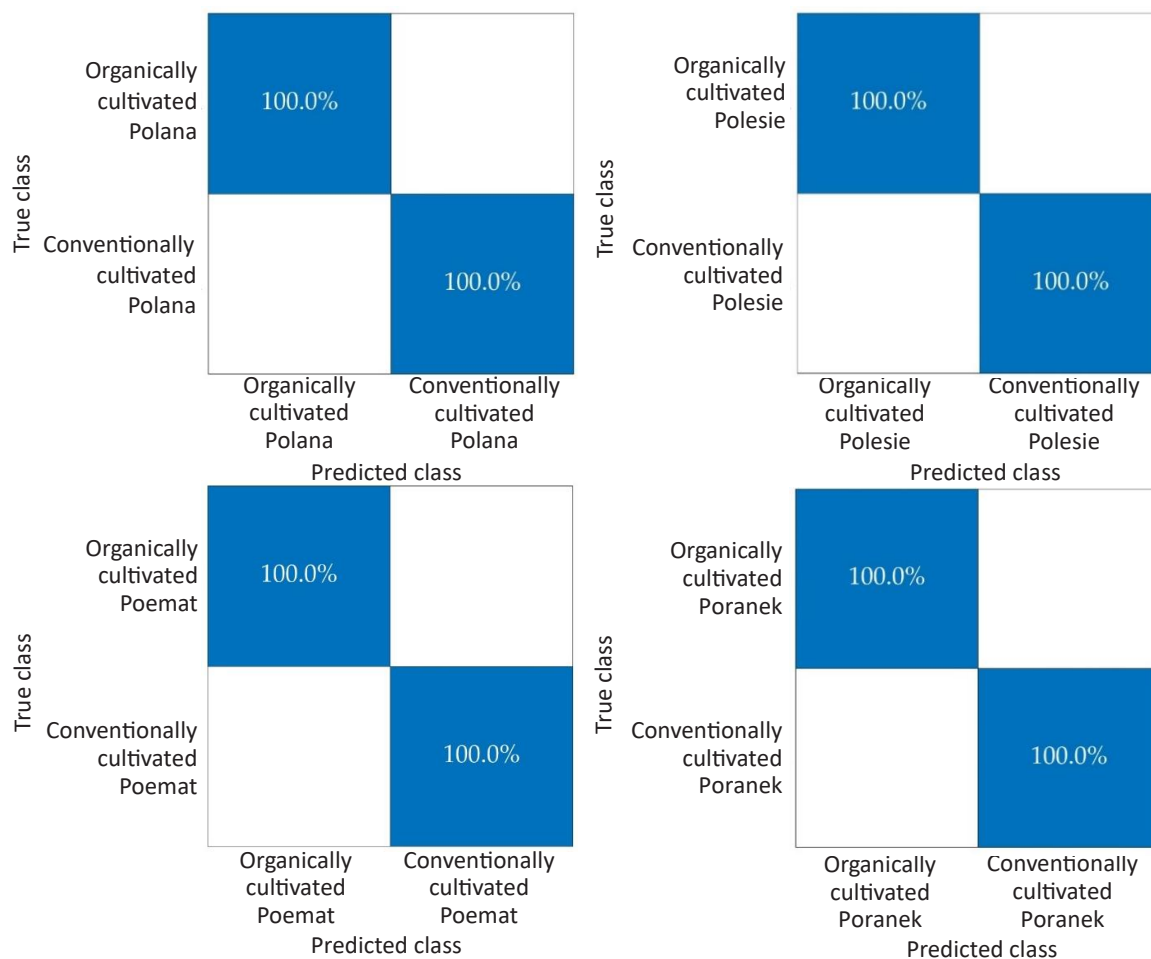
a, b – the same letters within rows indicate no statistically significant differences between samples

Table 6. Comparison of selected image textures between raspberries of the Poranek cultivar from conventional and organic cultivation systems

Image texture	Cultivation system	
	organic	conventional
RHMean	78.19 a	85.01 b
GHMean	24.48 a	28.86 b
BHMean	27.49 a	34.39 b
LHMean	72.91 a	78.05 b
aHMean	145.91 a	146.71 b
bHMean	136.66 a	135.26 b
XHMean	10.36 a	12.16 b
YHMean	6.86 a	8.02 b
ZHMean	3.75 a	4.65 b
UHMean	119.42 a	120.26 b
VHMean	153.64 a	154.65 a
SHMean	51.50 a	52.88 a

a, b – the same letters within rows indicate no statistically significant differences between samples

Figure 7. Distinguishing raspberries from conventional and organic cultivation systems using a model built by Subspace Discriminant based on selected image textures



Discrimination of raspberries from organic and conventional cultivation systems

Samples from organic and conventional cultivation systems were correctly distinguished in 100% based on image features selected from a whole set of 2172 attributes in the case of all analyzed raspberry cultivars (Figure 7). This indicates the existence of fruit image texture sets that allow for the complete differentiation of samples from organic cultivation from those from conventional cultivation.

DISCUSSION

The present study demonstrated that image analysis combined with traditional machine learning algorithms is an effective approach to discriminating raspberry cultivars originating from different cultivation systems. Both the statistical comparison of selected image texture descriptors and the classification results confirmed that raspberry fruit may have cultivar-specific and cultivation-system-dependent image characteristics that can be successfully extracted using computer vision techniques. Surface texture descriptors can reflect differences in the structural and physiological characteristics of fruit surfaces, including surface uniformity and spatial variation in colour and texture. These characteristics can be influenced by growing conditions, as fertilization and nutrient availability affect fruit ripening, phenolic metabolism, and the activity of enzymes involved in antioxidant responses [Frías-Moreno et al. 2021]. Frías-Moreno et al. [2021] demonstrated that organic and conventional fertilization regimes affected antioxidant enzyme activity as well as the content of anthocyanins and other bioactive compounds in raspberry fruit. At the same time, the effects of cultivation practices may depend on the cultivar, highlighting the importance of genotype × environment interactions [Anjos et al. 2020]. Therefore, differences in texture descriptors observed in images of fruit surfaces may be partly associated with changes in ripening-related metabolism, pigment accumulation, and plant responses to growing conditions.

The mean comparison of image texture parameters revealed significant differences among raspberry cultivars from organic and conventional cultivation systems. The observed variability indicates that each cultivar exhibits a unique combination of surface appearance attributes, reflecting genetic differences. The findings indicate that image texture analysis can capture subtle phenotypic differences in fruit. Similar observations have been reported in studies focused on cultivar identification across various fruit species, in which image-derived color, texture, and morphological features enabled successful discrimination of genotypes. For example, strawberry cultivars were effectively differentiated with an accuracy reaching 68% using multiple appearance attributes, such as color, shape, and size, extracted from fruit images, demonstrating the presence of cultivar-specific visual features [Yamamoto et al. 2015]. Ropelewska and Masny [2025] obtained an accuracy of up to approximately 96% of distinguishing cultivars and advanced clones of strawberry in the case of machine learning models developed based on image textures. Likewise, successful identification of plum cultivars based on endocarp size, color, shape, and texture features confirmed the usefulness of image-derived features for distinguishing closely related cultivars [Sarigu et al. 2017]. The effectiveness of stone texture descriptors in characterizing genetic variability of plum was also demonstrated by Ropelewska [2022], where machine learning models achieved high classification accuracy, reaching 96.67% based solely on image texture parameters. In blueberries, image texture parameters combined with both traditional machine learning and deep learning algorithms enabled highly accurate cultivar authentication with accuracy reaching above 91% for both approaches [Ropelewska and Koniarski 2025]. Whereas Ropelewska and Szymajda [2026] reported lower classification accuracies for distinguishing plum cultivars when using deep learning models compared to traditional machine learning. Deep learning also has limitations, such as the need for larger amounts of input data to build models, which can affect results [Ropelewska et al. 2022].

In our study, the cultivars Polesie and Poemat, particularly in the organic cultivation system, exhibited similar image texture characteristics. Nevertheless, despite this similarity, the developed models maintained high overall classification performance. This observation reflects one of the major challenges of visual recognition, namely the presence of small inter-class differences combined with considerable intra-class variability. Previous studies on plant recognition have highlighted that closely related cultivars often exhibit subtle visual differences that require advanced classification approaches for reliable iden-

tification [Šulc and Matas 2017]. The successful discrimination achieved in the present study suggests that the selected texture descriptors were sufficiently sensitive to capture these subtle differences among raspberry cultivars. In contrast, cultivars such as Polana and Poranek were generally recognized with the highest accuracy, suggesting the presence of more distinctive image attributes. Additionally, the comparison between organic and conventional cultivation systems revealed significant differences in image texture descriptors within each cultivar. Complete discrimination between organic and conventional raspberries was achieved for all analyzed cultivars. These findings suggest that cultivation practices influence fruit appearance to a degree that can be detected using computer vision techniques.

The effectiveness of the proposed methodology can be attributed to several factors. The analysis was based on a large set of image texture descriptors extracted from multiple color channels, allowing comprehensive characterization of fruit appearance. Furthermore, the feature selection procedure enabled identification of the most informative attributes while reducing data dimensionality. Moreover, the use of cross-validation ensured reliable model evaluation and reduced the risk of overfitting. Together, these elements contributed to the high predictive performance observed across all classification tasks. Similar strategies have proven to be effective in most recent research [e.g., Ropelewska and Szymajda 2026, Ropelewska et al. 2026a, 2026b] and as well as earlier ones [Ropelewska 2021, Ropelewska and Rutkowski 2023].

From a practical perspective, the obtained results demonstrate the potential of image analysis as a rapid, objective, and non-destructive tool for authentication and quality control of raspberry production systems. Visual assessment systems have the potential to reduce reliance on subjective evaluation, time consumption, the requirement for appropriate equipment, and highly experienced specialists. While increasing processing speed and consistency [De Nart et al. 2024]. Moreover, recent reviews emphasize that artificial intelligence-assisted non-destructive technologies are becoming increasingly important components of fruit quality monitoring, offering opportunities for real-time decision support throughout the production and supply chain [Fu and Sun 2026].

Nevertheless, several limitations of the approach applied in this study should be considered. The analyzed fruit originated from specific cultivation conditions and a limited number of cultivars. Therefore, further studies including additional cultivars, production locations, growing seasons, and environmental conditions would be beneficial to verify the generalizability of the developed models. The challenge of maintaining classification performance under variable environmental conditions has also been highlighted in other studies, where model robustness often decreases when evaluated on external datasets [De Nart et al. 2024]. Moreover, integrating image analysis with other non-destructive sensing techniques, such as hyperspectral imaging or fluorescence imaging, may further improve classification performance and provide deeper insight into the factors underlying the observed visual differences. Furthermore, in addition to traditional machine learning algorithms, deep learning models can also be applied. Therefore, multimodal approaches integrating various imaging systems with traditional machine learning and deep learning algorithms may represent a promising direction for future research on raspberry cultivar authentication and cultivation system verification.

CONCLUSIONS

Image analysis combined with traditional machine learning algorithms proved to be an effective approach for distinguishing raspberry cultivars and cultivation systems. Significant differences in selected image texture descriptors were observed among the analyzed cultivars within both organic and conventional production systems, confirming the existence of cultivar-specific visual characteristics. The developed machine learning models achieved high classification accuracies for cultivar discrimination. For raspberries originating from the organically managed mother plantation, the highest accuracy reached 89.2% using the Subspace Discriminant classifier, while for conventionally cultivated raspberries, the highest accuracy of 91.7% was obtained using the Linear Discriminant algorithm. The cultivation system significantly influenced raspberry image texture characteristics. Statistically significant differences between organic and conventional samples were identified within each cultivar, indicating that cultivation practices affect fruit

appearance and surface properties. The classification accuracy of organic and conventional raspberries reached 100% for all analyzed cultivars. This demonstrates the strong potential of image-derived texture features for the authentication of cultivation systems. Future studies could validate the developed approach using larger datasets, additional cultivars, and fruit originating from different growing regions and seasons.

CONFLICT OF INTEREST

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DECLARATION OF THE USE OF GENERATIVE AI IN THE PROCESS OF PREPARING THE PAPER

The authors declare that no generative AI tools were used in the preparation of this manuscript.

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