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A COMPARATIVE STUDY OF DISTINGUISHING APPLE CULTIVARS AND A CLONE BASED ON FEATURES OF SELECTED FRUIT PARTS AND LEAVES USING IMAGE PROCESSING AND ARTIFICIAL INTELLIGENCE

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ABSTRACT

This study aimed to identify the most useful white-fleshed apple samples to distinguish apple cultivars and a clone. Whole apples, apple slices, seeds, and leaves belonging to 'Free Redstar', clone 118, 'Ligolina', 'Pink Braeburn', and 'Pinokio' were imaged using a digital camera. The texture parameters were extracted from images in color channels *L, a, b, R, G, B, X, Y, Z, U, V*, and *S*. The classification models were built using traditional machine learning algorithms. Models developed using selected image seed textures allowed the classification of apple cultivars and a clone with the highest average accuracy of up to 97.4%. The apple seeds 'Free Redstar' were distinguished with the highest accuracy, equal to 100%. Machine learning models built based on the textures of apple skin allowed for the clone and cultivar classification with slightly lower correctness, reaching 94%. Meanwhile, the average accuracies for models involving selected flesh and leave textures reached 86.4% and 88.8%, respectively. All the most efficient models for classifying individual apple fruit parts and leaves were developed using Multilayer Perceptron. However, models combining selected image textures of apple skin, slices (flesh), seeds, and leaves produced the highest average accuracy of up to 99.6% in the case of Bayes Net. Thus, it was found that including features of different parts of apple fruit and apple leaves in one model can allow for the correct distinguishing of apples in terms of cultivar and clone.

Key words: apple skin, flesh, seeds, leaves, image processing, machine learning, classification

INTRODUCTION

Apple (*Malus* × *domestica* Borkh.) is widely cultivated and appreciated by consumers due to its distinctive flavor. Apples can be consumed as raw or processed products [Zhang et al. 2023]. They can be used to produce chips, purees, vinegar, jams, marmalades, juices, and teas [Taner et al. 2023]. Apple is an essential component of the human diet because of the presence of antioxidants, acids, sugars, and other compounds [Rasool et al. 2021]. Apple is characterized by an exceptionally high content of phenolic compounds, such as phenolic acids, flavonols, flavanols, and dihydrochalcones. The more significant part of phenolics is present in the cell vacuoles, and the concentration of phenolic compounds is higher in the fruit peel than in

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other tissues [da Silva et al. 2020]. Due to phytochemicals, apples have health benefits, including onco-preventive effects and lower incidence of other chronic conditions, e.g., asthma, cardiovascular disease, pulmonary disease, obesity, and diabetes [Nezbedova et al. 2021]. The chemical composition can vary significantly depending on apple cultivars/genotypes [Wu et al. 2007, Shafi et al. 2019].

Apples are characterized by high genetic variation. Furthermore, new individuals, which are produced from seeds, have different gene combinations. It leads to new cultivars. Therefore, thousands of cultivars have been developed by selecting promising variants [Krug and Hutschenreuther 2023]. The internal characteristics of apples, e.g., acidity, sweetness, firmness, tissue texture, polyphenolic compounds, or ascorbic acid, and external parameters, such as size, color, and surface texture, can be similar for different cultivars. However, each cultivar can be characterized by its flavor and unique characteristics that determine consumer preferences and prices [Ronald and Evans 2016]. Growing and postharvest handling of multiple apple cultivars next to each other may result in the risk of cultivar mixing during harvesting, storage, or marketing [Ronald and Evans 2016]. Therefore, the correct identification of apple cultivar and distinguishing it from others can have practical applications for the apple industry before apple consumption and processing.

The cultivar classification of apples can be challenging due to the high number of different cultivars, the similarities between different apples, the high variability of fruit belonging to one apple cultivar, and the few features distinguishing cultivars. The apple cultivar identification performed by experts can be subjective and depends on their experience [Krug and Hutschenreuther 2023]. The on-site observation can be based on the botanical characteristics of the apple tree, branch, fruit, or leaf in orchards. The other approach to apple cultivar identification can be related to testing the physiological indicators of fruit by experts in a laboratory using physical, chemical, biological, or molecular techniques. The procedures can be time-consuming, complicated, and expensive [Liu et al. 2020]. The apple cultivar recognition may also be performed using hyperspectral imaging or near-infrared spectroscopy. However, these techniques are unsuitable for widespread field application and may require expensive equipment and professional knowledge [Chen et al. 2022].

One of the aims of the apple breeding program conducted at the National Institute of Horticultural Research in Skierniewice, Poland, is to develop new genotypes either resistant or show low susceptibility to apple scab (*Venturia inaequalis*), apple powdery mildew (*Podosphaera leucotricha*) and fire blight (*Erwinia amylovora*). New cultivars should produce high yields of good fruit quality and be well adapted to the climatic conditions of Poland. Cultivating such cultivars enables the production of apples without or with deficient levels of chemical residues harmful to human health at markedly reduced production costs [Żurawicz and Zagaja 1999].

The state-of-the-art approach is distinguishing cultivars based on color images of apple fruit using machine learning. It is carried out for a more significant number of fruits. Applying a training set of features allows for objectively classifying cases belonging to a test set [Krug and Hutschenreuther 2023]. Apple fruit features obtained non-destructively can be helpful for processing, extraction, pattern recognition, development of classification models using machine learning, and decision-making [Fathizadeh et al. 2021]. Furthermore, in addition to apple fruit, leaf image analysis can help identify the apple cultivar [Liu et al. 2020, Chen et al. 2022]. Combining color image processing and machine vision can provide high correctness by detecting slight differences in a less time-consuming and more effortless manner than human vision. The machine learning models built based on image texture parameters for apple cultivar classification may be advantageous. Image textures define the function of spatial variation in image pixel values and provide numerical data of objects extracted from the images. Image texture parameters can help distinguish apple cultivars [Ropelewska 2021].

However, in the available literature, there is a lack of comprehensive research on the distinguishing apple clones and cultivars based on image texture parameters of images of whole apples, apple slices, seeds, and leaves analyzed separately and using a set combining selected features for all apple fruit parts and leaves. The objective of this study was to compare the correctness of the apple classification of samples belonging to ‘Free Redstar’, clone 118, ‘Ligolina’, ‘Pink Braeburn’, and 'Pinokio' using traditional machine learning models built separately for sets of selected image textures for apple skin, flesh, seeds, and leaves and a combined set for all parts. This study identified the apple samples (fruit parts or leaves) providing the most correct classification. The innovative aspect of the experiment included the development of machine learning models built using traditional machine learning algorithms from groups of Functions, Rules, Bayes, Trees, and Meta based on attributes selected from a set of 2172 textures from images in color channels *L*, *a*, *b*, *R*, *G*, *B*, X, *Y*, *Z*, *U*, *V*, and *S*. The novelty of the study was also related to distinguish an apple clone and cultivars using a set of combined image textures of apple fruit and leaves.

MATERIAL AND METHODS

Materials. Four white-fleshed apple cultivars ('Free Redstar', 'Ligolina', 'Pink Braeburn', 'Pinokio') and one clone 118 were evaluated at the National Institute of Horticultural Research, Skierniewice, central Poland. The experiment was established in the fall of 2012 on medium-quality soil in the Pomological Orchard. Clone 118 apples are characterized by green -yellow skin color, sometimes covered with some pink blush. The other tested cultivars produced apples with green or green-yellow skin color with various types of blush covering up to 100% of the skin. The randomized block design established the experiment in four replications with three trees per plot. The soil management and plant nutrition were applied as recommended for commercial apple orchards in Poland. In the growing season, plant protection sprays against pests were applied (in April against apple blossom weevil, in June and July against aphids and mites, and in July and August against codling moth). Trees were irrigated using the drip irrigation system, controlled automatically, and trained as a super spindle. Thinning of fruit sets was performed by hand when needed.

The "experiment performed in 2023" included different types of apple samples. Selected parts of the fruit, such as apple skin for whole apples, apple slices, and apple seeds, were tested. Additionally, apple leaves were examined. Apples were cut with a sharp stainless steel knife along the longitudinal axis to obtain slices. About four slices were sampled for individual apples. The seeds were manually extracted from apple chambers and cleaned.

Image analysis. The apple skin, slice, seed, and leaf images were acquired using a digital camera (Canon Inc., Tokyo, Japan) and LED (Light Emitting Diodes) illumination. Using a USB cable, the images were uploaded to the computer (HP Inc., Palo Alto, CA, USA). The digital camera included an optical image stabilizer to improve the stability of image acquisition, auto white balance with the imaging sensor, DIGIC 4+ processor, EF-S lens mount, 24.1 Mp APS-C CMOS sensor, 3fps continuous shooting, contrast detection AF9, AF points (f/5.6 cross-type at center) via the optical viewfinder, RGB primary color filter type, 3.0″ 920K-dot fixed LCD. The LED illumination had a light source of 24 LED, a related input current of 0.07 A, a related input voltage of AC110-240, V/50–60 Hz, and a related output power of 2.2 W. The images were obtained on a black background (sheet of paper with a width of 29 cm and a height of 21 cm). Whole apples were imaged from four sides of the lateral surface so that a total of 100 images for each apple cultivar and clone ('Free Redstar', clone 118, 'Ligolina', 'Pink Braeburn', and 'Pinokio') were obtained. Apple slices were drained of excess juice using a paper towel, and the whole areas of the slices were imaged. The images of 100 slices for each apple cultivar and clone were acquired. Also, the images of 100 seeds for each of 'Free Redstar', clone 118, 'Ligolina', 'Pink Braeburn', and 'Pinokio' were acquired. In the case of leaves, 100 images were also obtained for each apple cultivar and clone. The composition of the starting datasets of apple images has been clarified in Table 1. The collection of images was built separately for each part of apples (skin, flesh, seeds) and leaves. Each starting dataset for each apple part and leaves included 500 images, such as 100 images of 'Free Redstar', 100 images of clone 118, 100 images of 'Ligolina', 100 images of 'Pink Braeburn', and 100 images of 'Pinokio'. A combined set of all images of apple skin, slices (flesh), seeds, and leaves included all images obtained (2000). The sample images of whole apples (skin), apple slices (flesh), seeds, and leaves are presented in Figure 1. The image processing was carried out using Mazda software (Łódź University of Technology, Institute of Electronics, Łódź, Poland) [Szczypinski et al. 2007,

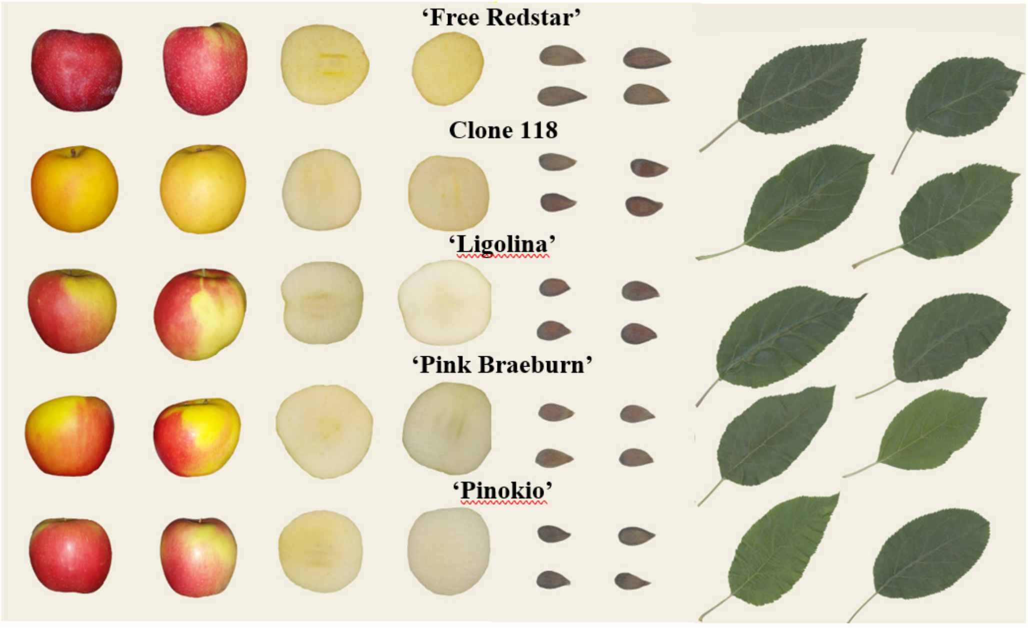

Fig. 1. The exemplary images of whole apples, apple slices, apple seeds, and apple leaves belonging to different cultivars and a clone

Table 1. The composition of the starting datasets of apple images

Whole apples (fruit skin)	Slices (flesh)	Seeds	Leaves
100 images of 'Free Redstar'	100 images of 'Free Redstar'	100 images of 'Free Redstar'	100 images of 'Free Redstar'
100 images of clone 118	100 images of clone 118	100 images of clone 118	100 images of clone 118
100 images of 'Ligolina'	100 images of 'Ligolina'	100 images of 'Ligolina'	100 images of 'Ligolina'
100 images of 'Pink Braeburn'	100 images of 'Pink Braeburn'	100 images of 'Pink Braeburn'	100 images of 'Pink Braeburn'
100 images of 'Pinokio'	100 images of 'Pinokio'	100 images of 'Pinokio'	100 images of 'Pinokio'

Szczypinski et al. 2009, Strzelecki et al. 2013]. The image conversion was performed to color channels *L, a, b, R, G, B, X, Y, Z, U, V*, and *S*. The images were segmented based on pixel brightness intensity, and apple samples were separated from the black background. The black background was characterized by a value of 0. The brightness threshold was determined manually as 1. The images of apple skin, flesh, seeds, or leaves were lighter than the background, with at least several or a dozen values. It facilitated the image segmentation. Each image was considered a region of interest (ROI). The 2172 texture parameters for each apple, slice, seed, and leaf image were extracted. This number (2172) consisted of 181 textures for each of the 12 color channels *L, a, b, R, G, B, X, Y, Z, U, V*, and *S* of images. The textures were computed based on the run-length matrix (20 texture parameters, including five features computed for four various directions), co-occurrence matrix (132 texture parameters, including 11 features computed for four various directions and three between-pixels distances), histogram (9 texture parameters), autoregressive model (5 texture parameters), Haar wavelet transform (10 texture parameters), and gradient map (5 texture parameters).

Image classification. The apple samples belonging to 'Free Redstar', clone 118, 'Ligolina', 'Pink Braeburn', and 'Pinokio' were classified with the use of WEKA 3.9 machine learning software (Machine Learning Group, University of Waikato) [Witten and Frank 2005, Bouckaert et al. 2016, Frank et al. 2016]. Whole apples, apple slices, seeds, and leaves of different cultivars and a clone were distinguished based on attributes selected from sets of textures extracted from images in color channels *L, a, b, R, G, B, X, Y, Z, U, V*, and *S*. A supervised attribute filter was used to select attributes. Best First performed the attribute selection as a search method and the Correlation-based Feature Selection algorithm as an evaluator. For each dataset, attributes with the highest discriminative power to distinguish analyzed classes were selected automatically and used for the classification model development. The twenty selected textures with the highest discriminative power were following: for whole apples (apple skin) dataset – aATeta2, YHPerc01, VATeta2, LHPerc01, SS5SH5Contrast, SS5SZ5Contrast, SATeta2, VATeta1, SHPerc10, XATeta2, SHPerc01, RS5SZ5Contrast, BHDomn10, SHPerc50, RS5SH5DifEntrp, BS5SZ5DifVarnc, UHPerc99, ZSGNonZeros, ZSGPerc01, ZSGPerc10, slices (flesh) – bHDomn10, UHMean, SHPerc10, bHPerc10, USGPerc01,SGNonZeros, USGPerc10, VHMean, VHPerc90, SSGNonZeros, US5SH5Entropy, aHPerc10, VHPerc99, VHDomn10, aS5SZ1DifEntrp, ZHPerc01, US5SZ5AngScMom, aHDomn01, aHPerc50, SS5SZ5Entropy, seeds – RAArea, aS4RHGLevNonU, RSGArea, BHDomn10, BHPerc01, GS4RHGLevNonU, RS4RZGLevNonU, aS4RZGLevNonU, aS4RVRLNonUni, YHDomn01, GHDomn10, LHPerc01, LS4RVGLevNonU, SHPerc10, aS5SH1Entropy, aHVariance, YS4RHGLevNonU, XS4RVGLevNonU, aS5SH5AngScMom, aHMaxm01, leaves – BHMean, BHPerc50, BS4RZLngREmph, BS5SH5InvDfMom, BHDomn10, LS5SN1InvDfMom, RS4RZShrtREmp, ZS4RHLngREmph, ZS5SN1Correlat, BHPerc01, ZS5SV3SumEntrp, BHDomn01, ZS5SZ5DifEntrp, US5SH5InvDfMom, ZHPerc50, US5SV5SumEntrp, BS4RHFraction, VS5SN5InvDfMomBS4RHLngREmph, LATeta1. In the case of a dataset including textures of apple skin, slices (flesh), seeds, and leaves, the twenty selected textures were SHPerc10, BHPerc01, SHMean, UHPerc99, BHPerc50, RSGArea, RAArea, BHMean, aS4RHGLevNonU, aS4RZGLevNonU, RS5SH3InvDfMom, aS4RVRLNonUni, BS5SV5Entropy, aATeta1, aATeta2, ZSGNonZeros, aS4RHRLNonUni, BHPerc99, BS5SV1SumEntrp, aS5SH1Entropy.

The classification was carried out using a test mode of the 10-fold cross-validation. Ten folds were appropriate to reach the best error estimate. The dataset was randomly divided into ten parts. Each part was considered the test set, and the remaining parts were treated as the training sets. The learning procedure was performed ten times, and the overall error estimate was the average of ten error estimates. The traditional machine learning algorithms from groups of Functions, Rules, Bayes, Trees, and Meta were applied. Two algorithms for each dataset of selected attributes were chosen, taking into account the highest average accuracies of the classification. In the case of chosen algorithms, the following classification performance metrics were determined: correctly and incorrectly classified cases, average accuracies [Eq. 1], the time taken to build a model, and the values of the Kappa statistic [Eq. 2], mean absolute error, root mean

$$\text{Accuracy} = \frac{(TP+TN)}{TP+TN+FN+FP} \quad (1)$$

$$\text{Kappa} = \frac{\frac{(TP+FP)(TP+FN)}{(TP+FP)(TP+FN)(TN+FP)(TN+FN)} + \frac{(TN+FP)(TN+FN)}{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}{(TP+FP)(TP+FN)(TN+FP)(TN+FN)} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4)$$

$$\text{F} - \text{measure} = \frac{2*\text{Precision}*\text{Recall}}{(\text{Precision}+\text{Recall})} \quad (5)$$

$$\text{MCC} = \frac{(TP*TN-FP*FN)}{\sqrt{((TP+FP)(TP+FN)(TN+FP)(TN+FN))}} \quad (6)$$

$$\text{TPR} = \frac{TP}{TP+FN} \quad (7)$$

$$\text{FPR} = \frac{FP}{FP+TN} \quad (8)$$

$$\text{ROC Area} = \text{area under TPR vs. FPR curve} \ (9)$$

$$\text{PRC Area} = \text{area under Precision vs. Recall curve} \ (10)$$

where TP is true positive; TN is true negative;
FP is false positive; FN is false negative;
TPR is True Positive Rate; FPR is False Positive Rate.

squared error. For the more detailed evaluation of the classification, the following performance metrics were determined for each class: TP (True Positive) Rate, FP (False Positive) Rate, Precision, Recall, F-Measure, MCC (Matthews Correlation Coefficient), ROC (Receiver Operating Characteristic) Area, and PRC (Precision-Recall) Area [Eqs 3-10] [Ropelewska and Szwejda-Grzybowska 2021, Matysiak et al. 2022, Ropelewska 2022, Ropelewska et al. 2023].

RESULTS AND DISCUSSION

Classification of whole apples based on selected skin image textures. The correctness of the classification of apples based on textures extracted from skin images was very high (Tab. 2). The model built using Multilayer Perceptron from the group of Functions revealed the highest average accuracy of 94%. 470 out of 500 cases were correctly classified. The time taken to build a model was 6.62 seconds. The Kappa statistic of 0.9250 was observed. The low mean absolute error of 0.0293 and root mean squared error of 0.1342 were computed. A high average accuracy of 93.4% was also obtained using a model built using LMT from the group of Trees. Four hundred sixty-seven cases were correctly classified. The model was developed in 1.07 seconds and was characterized by the Kappa statistic of 0.9175, mean absolute error of 0.0369, and root mean squared error of 0.1411. In the case of both models, apples belonging to Clone 118 were distinguished from the apple cultivars with the highest accuracy of 99%. It meant that the whole fruit of Clone 118 was the most different from other classes in terms of image texture parameters. Only 1% was incorrectly classified as 'Pink Braeburn'. Meanwhile, whole apples 'Pink Braeburn' were characterized by the lowest accuracy of 87%. As many as 9% of cases (for a model developed by Multilayer Perceptron) and 7% of cases (for a model built using LMT) belonging to the actual class of whole apples 'Pink Braeburn' were incorrectly classified as 'Ligolina' that meant that these apple cultivars were the most similar in appearance. Slightly less similarity was observed between the apple skin of 'Pink Braeburn' and 'Pinokio'.

Other performance metrics confirmed the highest classification correctness of whole apples belonging to Clone 118 (Tab. 3). In the case of both models built using Multilayer Perceptron and LMT, images of Clone 118 skin were distinguished from other classes with the highest Precision, ROC Area and PRC Area of 1.000, F-Measure of 0.995, MCC of 0.994, TP Rate and Recall of 0.990, and the lowest FP Rate of 0.000.

Classification of apples based on selected slice (flesh) image textures. The model developed using Multilayer Perceptron allowed for distinguishing apple slices based on image textures with an average accuracy of 86.4% (Tab. 4). It meant that 432 cases out of all 500 slices were correctly classified. The time taken to build a model was 7.84 seconds. Meanwhile, the values of the Kappa statistic of 0.8300, mean absolute error of 0.0628, and root mean squared error of 0.2075 were found. The images of apple slices (flesh) belonging to 'Free Redstar' were classified with the hi-

Table 2. The classification accuracies of whole apples based on skin image textures

Algorithm	Predicted class (%) 'Free Redstar' skin	Clone 118 skin	'Ligolina' skin	'Pink Braeburn' skin	'Pinokio' skin	Actual class	Average accuracy (%)
Multilayer Perceptron (Functions)	98	0	1	0	1	'Free Redstar' skin	94
	0	99	0	1	0	Clone 118 skin	
	0	0	92	7	1	'Ligolina' skin	
	0	0	9	87	4	'Pink Braeburn' skin	
	0	0	1	5	94	'Pinokio' skin	
LMT (Trees)	95	0	2	0	3	'Free Redstar' skin	93.4
	0	99	0	1	0	Clone 118 skin	
	0	0	93	5	2	'Ligolina' skin	
	0	0	7	87	6	'Pink Braeburn' skin	
	0	0	3	4	93	'Pinokio' skin	

Table 3. The classification performance metrics of whole apples based on skin image textures

Algorithm	Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Multilayer Perceptron (Functions)	‘Free Redstar’skin	0.980	0.000	1.000	0.980	0.990	0.987	0.999	0.998
	Clone 118 skin	0.990	0.000	1.000	0.990	0.995	0.994	1.000	1.000
	‘Ligolina’ skin	0.920	0.028	0.893	0.920	0.906	0.883	0.992	0.975
	‘Pink Braeburn’ skin	0.870	0.033	0.870	0.870	0.870	0.838	0.972	0.948
	‘Pinokio’ skin	0.940	0.015	0.940	0.940	0.940	0.925	0.994	0.978
LMT (Trees)	‘Free Redstar’ skin	0.950	0.000	1.000	0.950	0.974	0.969	0.991	0.990
	Clone 118 skin	0.990	0.000	1.000	0.990	0.995	0.994	1.000	1.000
	‘Ligolina’ skin	0.930	0.030	0.886	0.930	0.907	0.884	0.987	0.959
	‘Pink Braeburn’ skin	0.870	0.025	0.897	0.870	0.883	0.855	0.989	0.965
	‘Pinokio’ skin	0.930	0.028	0.894	0.930	0.912	0.889	0.991	0.924

TP Rate – True Positive Rate, FP Rate – False Positive Rate, MCC – Matthews Correlation Coefficient, ROC Area – Receiver Operating Characteristic Area, PRC Area – Precision-Recall Area

Table 4. The correctly and incorrectly classified cases and average accuracies of the classification of apples based on slice (flesh) image textures

Algorithm	Predicted class (%) ‘Free Redstar’ flesh	Clone 118 flesh	‘Ligolina’ flesh	‘Pink Braeburn’ flesh	‘Pinokio’ flesh	Actual class	Average accuracy (%)
Multilayer Perceptron (Functions)	99	0	0	0	1	‘Free Redstar’ flesh	86.4
	1	89	1	2	7	Clone 118 flesh	
	1	1	87	5	6	‘Ligolina’ flesh	
	0	3	15	77	5	‘Pink Braeburn’ flesh	
	0	6	6	8	80	‘Pinokio’ flesh	
Bayes Net (Bayes)	100	0	0	0	0	‘Free Redstar’ flesh	79.6
	2	85	4	6	3	Clone 118 flesh	
	1	1	82	12	4	‘Ligolina’ flesh	
	1	9	15	71	4	‘Pink Braeburn’ flesh	
	3	11	19	7	60	‘Pinokio’ flesh	

ghest accuracy of 99%, and only 1% was incorrectly classified as ‘Pinokio’. The lowest accuracies were observed for ‘Pink Braeburn’ (77%) and ‘Pinokio’ (80%).

A slightly lower average accuracy equal to 79.6% was observed for the model built using Bayes Net from the group of Bayes (Tab. 4). As many as 398 apple slices were correctly classified. The time taken to build a model was only 0.01 seconds. The Kappa statistic equal to 0.7450, mean absolute error of 0.0813, and root mean squared error of 0.2690 were determined. All cases of ‘Free Redstar’ flesh were correctly distinguished from other classes. The flesh images of ‘Pink Braeburn’ and ‘Pinokio’ were characterized by the lowest classification accuracies of 71% and 60%, respectively.

The most remarkable differences in selected flesh image textures between ‘Free Redstar’ and other samples were also confirmed by the highest values of TP Rate, Precision, Recall, MCC, ROC Area, and PRC Area, as well as the lowest FP Rate (Tab. 5).

Classification of apple seeds based on selected image textures. The model was built using the

Table 5. The performance metrics of the classification of apples based on slice (flesh) image textures

Algorithm	Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Multilayer Perceptron (Functions)	‘Free Redstar’ flesh	0.990	0.005	0.980	0.990	0.985	0.981	0.996	0.972
	Clone 118 flesh	0.890	0.025	0.899	0.890	0.894	0.868	0.977	0.955
	‘Ligolina’ flesh	0.870	0.055	0.798	0.870	0.833	0.790	0.959	0.849
	‘Pink Braeburn’ flesh	0.770	0.038	0.837	0.770	0.802	0.756	0.960	0.877
	‘Pinokio’ flesh	0.800	0.048	0.808	0.800	0.804	0.755	0.944	0.850
Bayes Net (Bayes)	‘Free Redstar’ flesh	1.000	0.018	0.935	1.000	0.966	0.958	0.997	0.976
	Clone 118 flesh	0.850	0.053	0.802	0.850	0.825	0.780	0.961	0.914
	‘Ligolina’ flesh	0.820	0.095	0.683	0.820	0.745	0.679	0.931	0.737
	‘Pink Braeburn’ flesh	0.710	0.063	0.740	0.710	0.724	0.658	0.941	0.823
	‘Pinokio’ flesh	0.600	0.028	0.845	0.600	0.702	0.656	0.920	0.819

TP Rate – True Positive Rate, FP Rate – False Positive Rate, MCC – Matthews Correlation Coefficient, ROC Area – Receiver Operating Characteristic Area, PRC Area – Precision-Recall Area

Table 6. The confusion matrices and average accuracies of the classification of apple seeds based on image textures

Algorithm	Predicted class (%)					Actual class	Average accuracy (%)
	‘Free Redstar’ seeds	Clone 118 seeds	‘Ligolina’ seeds	‘Pink Braeburn’ seeds	‘Pinokio’ seeds		
Multilayer Perceptron (Functions)	100	0	0	0	0	‘Free Redstar’ seeds	97.4
	1	96	0	2	1	Clone 118 seeds	
	0	1	97	1	1	‘Ligolina’ seeds	
	0	1	1	97	1	‘Pink Braeburn’ seeds	
	0	2	0	1	97	‘Pinokio’ seeds	
LMT (Trees)	99	0	0	1	0	‘Free Redstar’ seeds	96.6
	1	97	0	0	2	Clone 118 seeds	
	1	1	94	2	2	‘Ligolina’ seeds	
	0	0	3	96	1	‘Pink Braeburn’ seeds	
	0	3	0	0	97	‘Pinokio’ seeds	

Multilayer Perceptron based on seed image textures and correctly classified 487 cases (apple seeds) out of all 500 cases. Thus, the average accuracy was 97.4% (Tab. 5). The time taken to build a model was 15.7 seconds. The Kappa statistic was equal to 0.9675. The deficient mean absolute error of 0.0161 and root mean squared error of 0.0923 were determined. Only seeds belonging to the cultivar ‘Free Redstar’ were correctly distinguished from other classes in 100%. However, seeds of other cultivars, ‘Ligolina’, ‘Pink Braeburn’, and ‘Pinokio’, were classified with high accuracy equal to 97% and a Clone 118–96%.

Also, a model built using the LMT machine learning algorithm provided very satisfactory results (Tab. 6). The model allowed for the correct classification of 483 apple seeds (96.6%). The model was built in 0.78 seconds. The values of the Kappa statistic of 0.9575, mean absolute error of 0.0212, and root mean squared error of 0.1055 were observed. In the case of individual classes, the highest accuracy of 99% was obtained for ‘Free Redstar’, and the lowest accuracy of 94% was found for ‘Ligolina’.

Other performance metrics presented in Table 7 also indicated the highest correctness of classification of ‘Free Redstar’ seeds. It was proved by the highest values of TP Rate, Recall, and ROC Area of 1.000, PRC Area of 0.999, F-Measure of 0.995, MCC of 0.994, and Precision of 0.990 and low FP Rate of

Table 7. The classification performance metrics of apple seeds based on image textures

Algorithm	Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Multilayer Perceptron (Functions)	‘Free Redstar’ seeds	1.000	0.003	0.990	1.000	0.995	0.994	1.000	0.999
	Clone 118 seeds	0.960	0.010	0.960	0.960	0.960	0.950	0.997	0.992
	‘Ligolina’ seeds	0.970	0.003	0.990	0.970	0.980	0.975	1.000	0.998
	‘Pink Braeburn’ seeds	0.970	0.010	0.960	0.970	0.965	0.956	0.996	0.991
	‘Pinokio’ seeds	0.970	0.008	0.970	0.970	0.970	0.963	0.999	0.994
LMT (Trees)	‘Free Redstar’ seeds	0.990	0.005	0.980	0.990	0.985	0.981	1.000	0.999
	Clone 118 seeds	0.970	0.010	0.960	0.970	0.965	0.956	0.996	0.989
	‘Ligolina’ seeds	0.940	0.008	0.969	0.940	0.954	0.943	0.998	0.992
	‘Pink Braeburn’ seeds	0.960	0.008	0.970	0.960	0.965	0.956	0.996	0.989
	‘Pinokio’ seeds	0.970	0.013	0.951	0.970	0.960	0.950	0.998	0.991

TP Rate – True Positive Rate, FP Rate – False Positive Rate, MCC – Matthews Correlation Coefficient, ROC Area – Receiver Operating Characteristic Area, PRC Area – Precision-Recall Area

Table 8. The accuracies of the classification of apple leaves based on image textures

Algorithm	Predicted class (%)					Actual class	Average accuracy (%)
	‘Free Redstar’ leaves	Clone 118 leaves	‘Ligolina’ leaves	‘Pink Braeburn’ leaves	‘Pinokio’ leaves		
Multilayer Perceptron (Functions)	100	0	0	0	0	‘Free Redstar’ leaves	88.8
	0	94	2	2	2	Clone 118 leaves	
	2	8	80	4	6	‘Ligolina’ leaves	
	0	2	4	88	6	‘Pink Braeburn’ leaves	
	2	6	4	6	82	‘Pinokio’ leaves	
LMT (Trees)	96	2	0	2	0	‘Free Redstar’ leaves	84.8
	0	90	6	2	2	Clone 118 leaves	
	0	6	76	6	12	‘Ligolina’ leaves	
	0	2	8	82	8	‘Pink Braeburn’ leaves	
	2	6	8	4	80	‘Pinokio’ leaves	

0.003 for a model built using Multilayer Perceptron, and ROC Area of 1.000, PRC Area of 0.999, TP Rate and Recall of 0.990, F-Measure of 0.985, MCC of 0.981, and Precision of 0.980 and the lowest FP Rate of 0.008 for a model developed by LMT.

Classification of apple leaves based on selected image textures. In the case of the classification of apple leaves, the highest average accuracies of 88.8 and 84.8% were obtained for models built using Multilayer Perceptron and LMT, respectively (Tab. 8). For Multilayer Perceptron, a model was developed in 3.21 seconds. The Kappa statistic of 0.8600, mean absolute error of 0.0592, and root mean squared error of 0.1895 were computed. The images of ‘Free Redstar’ leaves were distinguished from other classes by 100%. The high classification accuracy was also obtained for Clone 118 leaves (94%). Whereas leaves belonging to ‘Ligolina’ were classified with the lowest accuracy of 80%. The model built using LMT was characterized by the Kappa statistic of 0.8100, mean absolute error of 0.0767 and root mean squared error of 0.2064, and it was built in 1.29 seconds. The images of leaves of ‘Free Redstar’ and Clone 118 were characterized by the highest classification accuracies of 96% and 90%, respectively. The lowest classification accuracy of leaves of apples, equal to 76%, was found for ‘Ligolina’.

The leaves of ‘Free Redstar’ were classified with the highest TP Rate, Recall, and ROC Area of 1.000,

Table 9. The classification performance metrics of apple leaves based on image textures

Algorithm	Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Multilayer Perceptron (Functions)	'Free Redstar' leaves	1.000	0.010	0.962	1.000	0.980	0.976	1.000	0.998
	Clone 118 leaves	0.940	0.040	0.855	0.940	0.895	0.869	0.991	0.967
	'Ligolina' leaves	0.800	0.025	0.889	0.800	0.842	0.807	0.960	0.894
	'Pink Braeburn' leaves	0.880	0.030	0.880	0.880	0.880	0.850	0.970	0.946
	'Pinokio' leaves	0.820	0.035	0.854	0.820	0.837	0.797	0.961	0.859
LMT (Trees)	'Free Redstar' leaves	0.960	0.005	0.980	0.960	0.970	0.962	0.999	0.996
	Clone 118 leaves	0.900	0.040	0.849	0.900	0.874	0.842	0.983	0.938
	'Ligolina' leaves	0.760	0.055	0.776	0.760	0.768	0.710	0.938	0.789
	'Pink Braeburn' leaves	0.820	0.035	0.854	0.820	0.837	0.797	0.978	0.943
	'Pinokio' leaves	0.800	0.055	0.784	0.800	0.792	0.740	0.943	0.825

TP Rate – True Positive Rate, FP Rate – False Positive Rate, MCC – Matthews Correlation Coefficient, ROC Area – Receiver Operating Characteristic Area, PRC Area – Precision-Recall Area

Table 10. The correctly and incorrectly classified cases and average accuracies of the classification of apples based on image textures of apple skin, slices (flesh), seeds, and leaves

Algorithm	Predicted class (%)					Actual class	Average accuracy (%)
	'Free Redstar'	Clone 118	'Ligolina'	'Pink Braeburn'	'Pinokio'		
Multilayer Perceptron (Functions)	100	0	0	0	0	'Free Redstar'	99.2
	0	100	0	0	0	Clone 118	
	0	0	99	0	1	'Ligolina'	
	0	0	2	98	0	'Pink Braeburn'	
	0	0	0	1	99	'Pinokio'	
Bayes Net (Bayes)	100	0	0	0	0	'Free Redstar'	99.6
	0	100	0	0	0	Clone 118	
	0	0	100	0	0	'Ligolina'	
	0	0	1	98	1	'Pink Braeburn'	
	0	0	0	0	100	'Pinokio'	

PRC Area of 0.998, F-Measure of 0.980, and MCC reaching 0.976 for a model developed Multilayer Perceptron, and Precision reaching 0.980 for a model built by LMT. The lowest FP Rate of 0.005 was observed for 'Free Redstar' leaves in the case of a model built using LMT (Tab. 9).

Classification of apple samples based on the combined set of selected image textures of apple skin, slices (flesh), seeds, and leaves. In the final stage of the analysis, classification models were built based on a dataset combining the selected image texture parameters of whole apples (apple skin), apple slices (flesh), seeds, and leaves. Including the selected image textures of all considered parts in one set increased the classification accuracy up to 99.6% in the case of a model developed using Bayes Net (Tab. 9). This model was built in 0.33 seconds and was characterized by the Kappa statistic of 0.995, mean absolute error of 0.0016, and root mean squared error of 0.0398. As many as four classes, such as 'Free Redstar', Clone 118, 'Ligolina', and 'Pinokio', were classified with an accuracy of 100%. Also, a high classification accuracy of 98% was determined for 'Pink Braeburn', and only 1% was incorrectly classified as 'Ligolina', and 1% – as 'Pinokio'.

A slightly lower average accuracy of 99.2% was observed for a Multilayer Perceptron model (Tab. 10). The time taken to build the model was 128.86 seconds.

Table 11. The performance metrics of the classification of apples based on a combined set of selected image textures of apple skin, slices (flesh), seeds, and leaves

Algorithm	Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Multilayer Perceptron (Functions)	'Free Redstar'	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
	Clone 118	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
	'Ligolina'	0.990	0.005	0.980	0.990	0.985	0.981	0.999	0.998
	'Pink Braeburn'	0.980	0.003	0.990	0.980	0.985	0.981	0.996	0.993
	'Pinokio'	0.990	0.003	0.990	0.990	0.990	0.988	1.000	1.000
Bayes Net (Bayes)	'Free Redstar'	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
	Clone 118	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
	'Ligolina'	1.000	0.003	0.990	1.000	0.995	0.994	0.999	0.990
	'Pink Braeburn'	0.980	0.000	1.000	0.980	0.990	0.987	1.000	1.000
	'Pinokio'	1.000	0.003	0.990	1.000	0.995	0.994	1.000	1.000

TP Rate – True Positive Rate, FP Rate – False Positive Rate, MCC – Matthews Correlation Coefficient, ROC Area – Receiver Operating Characteristic Area, PRC Area – Precision-Recall Area

A very high Kappa statistic of 0.9900 and low values of mean absolute error (0.0087) and root mean squared error (0.0601) were found. The Free Redstar and Clone 118 classes were correctly distinguished from other cultivars in 100%. On the other hand, an accuracy of 99% was found for 'Ligolina' and 'Pinokio', and 98% for 'Pink Braeburn'.

In the case of other performance metrics of the classification of apples based on image textures of apple skin, slices (flesh), seeds, and leaves, 'Free Redstar' and Clone 118 samples were distinguished with TP Rate, Precision, Recall, F-Measure, MCC, ROC Area, PRC Area of 1.000 and FP Rate of 0.000 for both models built using Multilayer Perceptron and Bayes Net (Tab. 11).

Previous literature reports have been published on classifying apple cultivars based on fruit image features. Ronald and Evans [2016] classified apples Golden Delicious, Honey Crisp, and Pink Lady based on fruit image characteristics using Naive Bayes with an average accuracy of 91%. Sabanci and Ünlerşen [2016] classified three apple cultivars based on fruit image features, obtaining an accuracy of 98.89% for a model built using Multilayer Perceptron. Multiple apple cultivars were discriminated by Bhargava and Bansal [2021], reaching an accuracy of 98.42% using the support vector machine (SVM) classifier. Taner et al. [2023] distinguished apples 'Red Braeburn', 'Red Chief', 'Golden Reinders', 'Fuji', 'Granny Smith', 'Kasel 37', 'Scarlet Spur', 'Mondial Gala', 'Starkspur Golden Delicious', and 'Starkrimson' based on image texture and color features and determined average accuracies of 98.17%, 96.67%, 98.62%, and 91.28%, for models built using Support Vector Machine (SVM), Random Forest Classifier (RFC), Multilayer Perceptron (MLP), and K-nearest Neighbor (KNN), respectively. In the previous studies performed by Ropelewska [2021], three apple cultivars were discriminated the total accuracy of reaching 93% for the model built based on selected apple skin textures, 100% for selected textures of flesh images of a longitudinal section, and 97 % for selected textures of flesh images of a cross-section.

Furthermore, Ropelewska [2020] obtained 100% accuracy in classifying two apple cultivars using a model developed based on selected seed image textures. Ropelewska and Rutkowski [2021] reported high classification accuracies of up to 93% of two cultivars of apple seeds using selected geometric features calculated from images. The apple cultivar can also be identified based on leaf image features. For example, Liu et al. [2020] developed a deep convolutional neural network (DCNN)-based model identifying leaf images of 14 apple cultivars with an overall accuracy of 0.9711. Chen et al. [2022] applied the Multi-Attention Fusion Convolutional Neural Network (MAFNet) to classify 30 apple leaf cultivars using image features, and the obtained classification accuracy was equal to 98.14%.

Imaging and artificial intelligence have broad applications in apple studies. In addition to cultivar classification, they were used, among others, for the identification of diseases of apples based on fruit images [Dubey and Jalal 2016, Buyukarikan and Ulker 2022, Azgomi et al. 2023] and apple tree leaves based on leaf images [Park et al. 2018, Chao et al. 2020, Ding et al. 2022, Zhang et al. 2023]. The procedure used in the present study successfully distinguished white-fleshed apple cultivars and a clone based on image texture parameters of skin, flesh, seeds, and leaves. In future studies, the developed approach can also be used to classify clones and cultivars of red-fleshed apples. Additionally, further research can involve deep learning and traditional machine learning algorithms for the quality assessment of apple fruit parts and leaves.

CONCLUSIONS

The results confirmed the usefulness of image texture parameters of skin, flesh, seeds, and leaves for the correct distinguishing white-fleshed apple cultivars and a clone. The developed procedures involving image textures and machine learning algorithms can be applied to identify apple cultivars and clones correctly. It can be used in the apple industry to distinguish and select desired apples before consumption and processing. The highest classification accuracy of 99.6% was revealed for a model based on a combined set of selected image textures of all apple fruit parts and leaves. The most successful model was built using Bayes Net from the group of Bayes. Among the apple fruit parts, seeds were characterized by the highest discriminative power, and models built using selected image seed textures classified apple cultivars and a clone with an average accuracy reaching 97.4% (Multilayer Perceptron). The features of the apple skin images were also beneficial for the classification (94%, Multilayer Perceptron). Meanwhile, models developed based on image textures of apple leaves and flesh were the least effective in the classification of apple cultivars and a clone, resulting in average accuracies of up to 88.8% and 86.4%, respectively. The research can be continued by involving more clones, cultivars, and other parts of apple trees, such as flowers. Image analysis and artificial intelligence can also be applied in further studies to distinguish red-fleshed apple cultivars and clones from white-fleshed apples. Furthermore, classification models can be built using deep learning.

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