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Combining algorithm techniques with mechanical and acoustic profiles for the prediction of apples sensory attributes

Riccardo Ricci [a], Annachiara Berardinelli [b,c], Flavia Gasperi [b], Isabella Endrizzi [d], Farid Melgani [a], Eugenio Aprea [b,*]

[a] Department of Information Engineering and Computer Science, University of Trento, Via Sommarive 9, 38123, Povo, Trento, Italy
[b] Center of Agriculture Food Environment C3A, University of Trento, Via Edmund Mach 1, 38098, San Michele all'Adige, Trento, Italy
[c] Department of Industrial Engineering, University of Trento, Via Sommarive, 9, 38123, Povo, Italy
[d] Sensory Quality Unit, Research and Innovation Centre, Fondazione Edmund Mach, Via E. Mach 1, San Michele all'Adige, Trento, Italy

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ABSTRACT

The research work shows the potentiality of advanced linear and nonlinear learning algorithm techniques in the prediction of apples texture sensory attributes as “hardness”, “crunchiness”, “flouriness”, “fibrousness”, and “graininess”. Starting from the information contained in the entire mechanical and acoustic curves acquired during samples compression test, the prediction performances of five different statistical tools as Partial Least Squares regression (PLS), Multilayer Perceptron (MLP), Support Vector Regression (SVR) and Gaussian Process Regression (GPR) are shown and discussed.

All Predictive models validations evidence best accuracies for texture sensory attributes “hardness” and “crunchiness” and in general for GPR learning algorithm. By combining mechanical and acoustic profiles, 5-fold cross validations produce values of coefficient of determination R^2 up to 0.885 (GPR) and 0.840 (GPR), respectively for “hardness” and “crunchiness”. These results, comparable to those obtained by considering a large number of mechanical and acoustic parameters extracted from acquired profiles as predictive factors, evidence a new and reliable way for the prediction of texture sensory attributes of apples. The proposed approach can overcome the necessity to define, in advance, number and type of features to be calculated from instrumental texture profiles and can be easily implemented in an automatic process.

1. Introduction

According to Szczesniak [1], texture can be defined as “sensory and functional manifestation of the structural, mechanical and surface properties of foods detected through the senses of vision, hearing, touch and kinesthetics”. In the fruit and vegetable sector, textural attributes can play a big role in consumer preferences as testified by literature [2,3] and are strongly correlated with product freshness as defined by ISO 7563:1998 in the list of general terms used in this context. Mechanical and textural properties are important parameters to determine quality and storability of apples. Such properties also influence consumers' choice for this fruit, in fact firmness and sweetness resulted to be the primary attributes driving fresh apple preferences by European consumers [4,5].

It is recognized that the macroscopic texture perception is mainly related to plant cell micro and nanostructure and, particularly, to cell walls polysaccharides architecture and to cell turgor pressure [6,7]. Fruit and vegetables mechanical properties have been described by using a poroviscoelastic model focusing on the role of the pectins in the load bearing properties. In detail, the model involves the combination of the structural deformation of the polysaccharide networks of plant cell walls with the hydraulic properties of the continuous water phase, behavior that changes according to cultivars and to biochemical changes occurring during growth at stage of maturity at harvest, also influenced by orchard altitude, and during postharvest processes [8–10],. Concerning apples, this multi-parameter attribute is composed by mechanical components as firmness, hardness, stiffness, and elasticity, and by acoustic components as crispness and crunchiness [1].

Descriptive sensory analysis conducted by using panels of judges is a recognized and comprehensive approach for the quantification of the texture attribute and employs a language reflecting the consumer's experience. These evaluations have been taken into consideration by

* Corresponding author.
E-mail address: eugenio.aprea@unitn.it (E. Aprea).

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scientists for fruit and vegetable cultivar selection and for harvest and post-harvest best practices [11,12]. However, it is also known that this tool is limited to small samples assessments, is expensive and not suitable for real time procedures and different sensory panels produce results difficult to compare [13]. For these reasons, different instrumental techniques have been developed and sensory analysis is nowadays considered the main reference for instrumental methods setting up [14].

Among instrumental tools, in general, a strong correlation between sensory attributes and mechanical parameters obtained through fruit uniaxial compression test with a cylindrical probe have been documented in literature [14–16]. The standardized mathematical processing leading to mechanical parameters extraction from the force-deformation curves is recommended by the Standards S368 from ASABE on the "Compression Test of Food Materials of Convex Shape" (ASAE, 2008). Concerning acoustic components, a great effort was dedicated to the setting up of instrumental tools able to assess them in a reliable way. Acoustic instrumental methods are mainly based on recording acoustic signals during uniaxial compression test by means of a microphone placed close to the tested sample [17] or through a contact acoustic detector characterized by a puncture probe equipped with accelerometer for vibrations assessment [18].

Research works evidenced that, for an exhaustive instrumental texture characterization of apples, it is recommended to consider both mechanical and acoustic components simultaneously [17,19]. According to the state of the art, this characterization is mainly based on the analysis of a considerable amount of mechanical and acoustic parameters extracted from the force displacement and acoustic time response profiles during the compression phase. These parameters appeared necessary to describe complex apple textural properties and the variability due to cultivars and postharvest handling and storage [20]. To give an example, apples have been clustered according to their crispness attributes using principal component analysis (PCA) by combining nine mechanical and acoustic parameters [21]. In another experiment, the sensory evaluation of apple firmness and crispness were predicted using partial least squares regression (PLS) by considering 16 instrumental parameters as independent variables with a root mean square error of cross validation (RMSECV) lower than 0.5 (on a 1–9 scale) [19]. To overcome the necessity of choosing the best number and combination of the extracted instrumental attributes, apple texture could be predicted starting from the entire information (all points) that characterizes the acquired mechanical and acoustic signals. This approach can be referred to as "texture fingerprinting". The proposed solution could simplify and, at the same time, improve the accuracy of predictive models of apple sensory attributes. Multivariate prediction tools such as PLS or artificial neural network (ANN) regressions, able to relate a matrix of independent variables (X) to an array of dependent ones (Y), are now considered standard procedures in food quality assessment for extracting useful information starting from high dimension independent variables. These statistical approaches can also integrate non-linear machine learning tools for significant improvements in the prediction of physical, chemical, and sensory properties of complex agri-food matrices [22,23]. The potentiality of these tools has been explored with particular effort on bi-dimensional matrices coming from indirect measurements such as the frequency-domain and time-domain analyses. These datasets have been mainly obtained by using techniques characterized by the interaction between the electromagnetic waves and the product [24,25]. In the research work conducted by exploring the potentiality of the Time Domain Reflectometry (TDR) in the assessment of water content in EVO oils, limits of the classical approach based on the TDR electromagnetic theory based on the extrapolation of the reflection coefficient, have been successfully overcame by PLS analysis of the entire time domain electric signal [26]. In the research work conducted in the field of fruit texture, kiwifruit flesh firmness was predicted through multi-layer perceptron (MLP) models starting from each point of the force time history obtained by using a non-destructive impact device characterized by a conveyer belt that throws the fruit onto a flat horizontal plate connected to a load cell [27].

The present work aims at pioneeringly exploring the potentiality of using the entire information contained in the mechanical and acoustic curves acquired during a compression test for the prediction of different main sensory attributes of apple texture To this end, a set characterized by a huge number of commercial and not commercial apple cultivars harvested over nine years will be considered in addition to the prediction performances of different statistical tools such as PLS, Multilayer Perceptron (MLP), Support Vector Regression (SVR) and Gaussian Process Regression (GPR). As for MLP, SVR and GPR machine learning techniques are extensively explored and compared to the traditional PLS tool in the spectroscopic food assessments for their ability in handling complex regression problems [28,29].

The performances in the prediction accuracy of the proposed approaches is compared to those of traditional procedures based on the extraction of mechanical and acoustic features from the curves, by avoiding problems related to the definition of the type and number of features able to characterize tested samples.

2. Materials and methods

2.1. Apple samples

The characterization based on sensory and instrumental analysis was conducted on a set of 323 apple batches coming from more than 80 commercial and not commercial apple cultivars (*Malus* × *domestica* Borkh.) harvested over a period of nine years (2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018). The research study includes the most common commercial cultivars as "Cripps Pink", "Gala", "Golden Delicious", "Granny Smith", "Fuji", "Red Delicious" and "Renetta".

Fruit were harvested at the commercial maturity stage (from the middle of July to the end of October) defined by exploring standard descriptors involving apple skin colour, flesh penetrometric firmness and starch degradation index [30].

For each batch, a minimum of 20 apples of homogeneous size characterized by the absence of any visible external damage was selected. Fruits were stored for two months (normal atmosphere at 2 °C and 95 % of RH) and then kept at room temperature for 24 h prior to sensory and instrumental assessments and weighed.

2.2. Experimental plan

The experimental plan describing samples preparation, sensory analysis, mechanical and acoustic assessments, elaboration, and validation of predictive models is shown in Fig. 1.

2.2.1. Sample preparation

Sensory and instrumental assessments were performed on flesh cylinders (diameter: 180 mm; height: 120 mm, ±2.5 g). For each apple cultivar under evaluation flesh cylinders were cut from 15 to 20 fruit, starting from three apple slices cut around the equatorial plane perpendicular to the core of the same fruit. The cylinders were treated with a solution of 0.2 % citric acid, 0.2 % ascorbic acid, and 0.5 % calcium chloride characterized by antioxidant properties as described in [31]. Sensory evaluations were performed within 1 h of sample preparation and texture analyses within 3 h. The absence of possible effects of the antioxidant solution on the sensory profile was tested in a previous work by Refs. [13] based on a discriminant analysis conducted by a trained panel (standard triangle test procedure) and confirmed by chemical analysis of titratable acidity and soluble solid concentration.

2.2.2. Sensory analysis

Five textural attributes were taken into consideration: hardness (resistance of the sample at the first chew with molars), crunchiness (sound, pitch/intensity, produced by the sample during 5 M chews), flouriness (degree of flesh breaking in small and dry fragments/granules

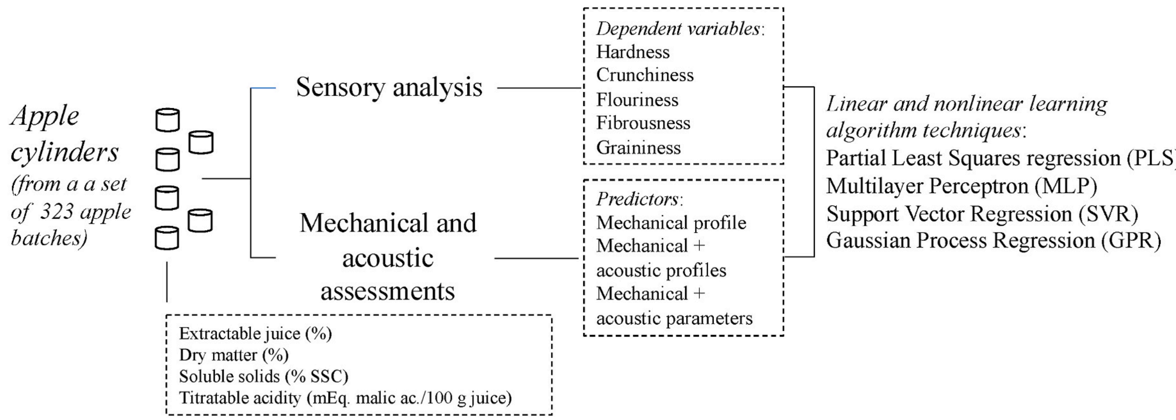

Fig. 1. The experimental plan.

during chewing), fibrousness (degree of flesh breaking during chewing in thick and fibrous fragments/granules), and graininess (numbers/size of fragments/granules produced during chewing). The intensity of each attribute was scored by the panel on a 100 mm linear scale, anchored at 0 (absence), 100 (extremely intense), and with 50 as the middle point.

Sensory evaluations were performed by a trained panel characterized by a minimum of 12 to a maximum of 23 judges, in individual computerised booths equipped with FIZZ software (2.46A, Biosystemes, Couternon, France).

In each session six apple samples (three batches replicated twice) were analysed: the samples were presented according to a balanced order over the panel in sealed containers (each container with eight cylinders put into a clear plastic cup encoded with a three-digit code randomly generated).

All details concerning the performed sensory profiling, the developed lexicon, panel training, definition, evaluation procedure, and reference standards for each attribute were previously described in Refs. [13].

2.2.3. Textural and acoustic assessments

A TA-XT*plus* Texture Analyzer equipped with a 30 N loading cell and a 4 mm cylindrical flat head probe, and an Acoustic Envelop Detector (AED) device (Stable MicroSystem Ltd., Godalming, UK) was used to perform uniaxial compression test on the apple cylinders (samples) described in the previous section.

Force/displacement curves were acquired by considering a test speed of 300 mm/min and a maximum sample deformation of 90 % [19]. Twelve mechanical parameters and four acoustic parameters were extracted from the acquired profiles as listed and described in Table 1. More details about the parameter description and extraction procedure were given by Ref. [19].

2.2.4. Juice extraction, dry matter and chemical measurement

Extractable juice (%) and dry matter (%) were expressed as percentages of fresh mass. The first parameter was obtained in duplicate, by weighing, for each cultivar, the liquid expressed from mechanical compression of eight flesh cylinders corresponding to eight different fruits. For the second parameter, a sample of eight flesh cylinders per cultivar was dried at 105 °C until they reached a stable weight.

The juice expressed from mechanical compression of 12 cylinders, corresponding to twelve different fruits, was used to measure, in duplicate, the concentration of soluble solids (% SSC) and titratable acidity (mEq. malic ac./100 g juice) by means of a DBR35 refractometer (XS Instruments, Poncarale, Brescia, Italy) and a Compact Titrator (Crison Instruments S.A., Alella, Barcelona, Spain), respectively (NaOH 0.1 N was used to titrate 5 g of juice to pH 8.16).

Table 1
Description of the mechanical and acoustic parameters extracted from the acquired profiles.

Parameter abbreviation	Description
Mechanical	
F yield (N)	Force measured at the yield point
F max (N)	Maximum force
F final (N)	Force measured the end
F peaks	Number of force peaks
W (N mm)	Mechanical work estimated by the area under the curve
F ld	Force linear distance
Y mod (N%)	Young's module
F mean (N)	Mean force
Delta F (N)	Difference between F yield and F final
F ratio	Ratio between F yield and F final
Peaks dist	Ratio between F peaks and distance
ld dist	Ratio between F ld and distance
Acoustic	
A Peaks	Number of acoustic peaks
A P max (dB)	Max acoustic preassure
A P mean (dB)	Mean acoustic pressure
A ld	Acoustic linear distance

2.2.5. Prediction models of the sensory attributes

Predictive models of the considered five sensory attributes were set up in Phyton programming language (Sckit-learn, 1.3.0). For both mechanical and acoustic curves, each measurement can be characterised by a different number of acquisition points since the acquisition stop when a sample deformation of 90 % is reached. In order to have all instrumental (mechanical and acoustic) curves characterized by the same number of predictors (independent input variables, X), useful for the prediction model setting up, the Cubic Spline Interpolation was taken into consideration for a resampling at 100 evenly spaced positions between 0 % and 90 % of sample "strain". In detail, the interpolation function is characterized by a set of piecewise cubic functions [32]:

$$S_i(x) = a_i x^3 + b_i x^2 + c_i x + d_i$$

valid for $x_i \leq x \leq x_{i+1}$, $i = 1, \ldots, n\text{-}1$.

At the end of the Cubic Spline Interpolation process, each instrumental curve (mechanical and acoustic) was characterized by 200 independent variables.

Sensory attributes as dependent variables (hardness, crunchiness, flouriness, fibrousness and graininess) were predicted by setting up models starting from three combinations of independent variables: from the entire mechanical profile, from the entire mechanical profile added to the entire acoustic profile, and from the mechanical and acoustic parameters extracted from the acquired curves. For models built starting from the entire mechanical profile, variables were arranged in a 323 (apple samples) × 200 (X variables, mechanical profile) matrix while for those set up by considering the combination between the two profiles, an X matrix characterized by 323 (apple samples) × 400 (X variables, mechanical profile = variables from 1 to 200 + acoustic profile = variables form 201 to 400) was considered. Finally, extracted parameters were then arranged in a 323 (apple samples) × 16 (X variables, combination of mechanical and acoustic parameters) matrix. For all defined models, five 323 (apple samples) × 1 (Y variable) vector columns were created, for dependent variables hardness, crunchiness, flouriness, fibrousness and graininess (sensory attributes), respectively.

Four different statistical tools coming from multivariate data analysis and machine learning techniques were tested: Partial Least Squares regression (PLS), Multilayer Perceptron (MLP), Support Vector Regression (SVR) and Gaussian Process Regression (GPR). Coefficient of determination (R^2) and Root Mean Square Error (RMSE) values were obtained and discussed by using a k-fold cross validation procedure (k = 5) in addition to an external validation test conducted by randomly dividing the data set into calibration set (80 % of the samples and k-fold cross validation for parameters optimization, k = 5) and test set (20 % of the samples).

For PLS, a well explored bilinear approach for data compression where new variables are built from the original reflecting the underlying or latent structure, the optimal number of PLS latent variables (LVs) was selected by analysing the validation residual variance plot and calculated where the prediction error is minimised [33].

The back-propagation neural modelling system was used to train multi-layer perceptron MLP models developed by means of the Mish activation function [34]:

$$f(x) = x \bullet \tanh(softplus(x))$$

where $softplus(x) = ln(1 + e^x)$ and x is the input variable.

The network design, the number of hidden layers (n = 2), and the number of processing elements in the hidden layers (16 and 4, respectively) were empirically obtained by monitoring and analysing the network error progress.

Concerning Support Vector Regression (SVR), aiming at finding a hyperplane in a high-dimensional space that maximizes the margin between the hyperplane and the training data, the grid search method was considered to optimize the estimation of epsilon (0, 0.01, 0.02, 0.03, …, 1) and C (range = 0.1, 0.5, 1, 5, 10, 100) hyperparameters. As defined, epsilon parameter is involved in the definition of the width of the margin while C in the control of the trade-off between maximizing the margin and minimizing the error [35].

Finally, Gaussian Process Regression is a Bayesan nonparametric method producing a posterior of the unknown regression function f, given the training data set, a prior distribution defined as a Gaussian process and a likelihood function characterized by a probabilistic model [36]. For the Gaussian process $GP(m, k)$, the mean function m and the kernel k (RationalQuadratic + White Kernel) were considered.

3. Results and discussion

3.1. Samples characteristics and sensory attributes

Table 2 shows a descriptive summary of samples characteristics in terms of fruit mass (g), extractable juice (%), dry matter (%), concentration of soluble solids (% SSC) and titratable acidity (mEq. malic ac./100 g juice), in addition to sensory attributes hardness, crunchiness, flouriness, fibrousness and graininess.

As can be observed, the research work was conducted by exploring samples characterized by a valuable range of variability in terms of mass and analysed parameters juice (%), SSC (%) and titratable acidity (mEq. malic ac./100 g juice). Concerning the five sensory attributes, the data set, based on a 100 mm linear scale, generally covers an important range of the scale characterised by minimum values from 1 (flouriness and fibrousness) to 6 (graininess) and by maximum values from 79 (graininess) to 89 (fibrousness). Confirming results reported by [13], hardness resulted positively correlated with crunchiness (r = 0.947) and fibrousness (r = 0.925) and negatively correlated with flouriness (r = -0.875) and graininess (r = - 0.871).

The main source of variability of compositional parameters and sensory attributes, in our samples, can be attributed to the cultivars since all the apples were harvested at commercial maturity stage selecting 20 fruit homogeneous in size.

Table 2
Apple characteristics: compositional parameters and sensory attributes (descriptive statistics of 323 apple samples).

	Mean	SD	Min	Max
Parameter				
Fruit mass (g)	219	39	97	321
Juice (%)	37.1	12.2	5.8	65.0
Dry matter (%)	9.5	3.6	3.2	19.4
SSC (%)	13.0	1.8	7.0	20.1
Titratable acidity[a]	6.8	3.1	0.2	16.9
Sensory attribute				
Hardness	44.2	19.9	4.0	86.0
Crunchiness	45.3	19.4	4.0	79.0
Flouriness	24.4	21.2	1.0	88.0
Fibrousness	35.3	20.2	1.0	89.0
Graininess	30.8	17.2	6.0	78.9

[a] mEq. malic ac./100 g juice. SD = Standard deviation.

3.2. Extracted mechanical and acoustic parameters

Mean values and relative standard deviations of the main mechanical and acoustic attributes extracted from the acquired curves are summarized in Table 3.

As observed for apples compositional properties and sensory attributes, the samples were characterized by an important range of mechanical and acoustic variabilities as testified by literature [20,37]. Examples of mechanical and acoustic curves obtained during compression of two cylinders from "Golden delicious" and "Renetta Bianca" cultivar samples are evidenced in Figs. 2 and 3. As known, according to flesh micro and nanostructures, each cultivar shows distinct mechanical and acoustic profiles due to distinct dynamics following the structural polysaccharide remodelling process occurring from fruit development until postharvest storage. In addition, the Pearson correlation matrix for mechanical and acoustic parameters extracted from the acquired profiles shown in Table 4, confirmed published results outlining the importance of a detailed dissection and comprehensive analysis of the two texture components [17].

Table 3
Means and standard deviations of the main mechanical and acoustic parameters extracted from the acquired profiles.

Parameter abbreviation[a]	Mean	SD	Min	Max
Mechanical				
F max (N)	10.7	2.9	4.2	21.2
Y mod (N%)	2.1	0.6	0.9	3.9
W (N mm)	12.1	2.3	6.0	19.0
Acoustic				
A P max (dB)	50.3	3.0	40.4	57.8
A P mean (dB)	46.8	2.8	38.0	54.0
A ld	266	39	204	389

[a] See Table 1. SD = Standard deviation.

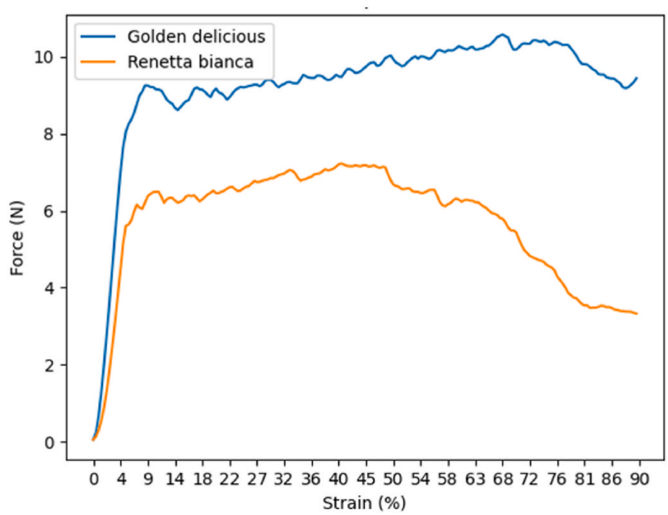

Fig. 2. Force (N) Strain (%) profiled during the compression of two different apple cylinders.

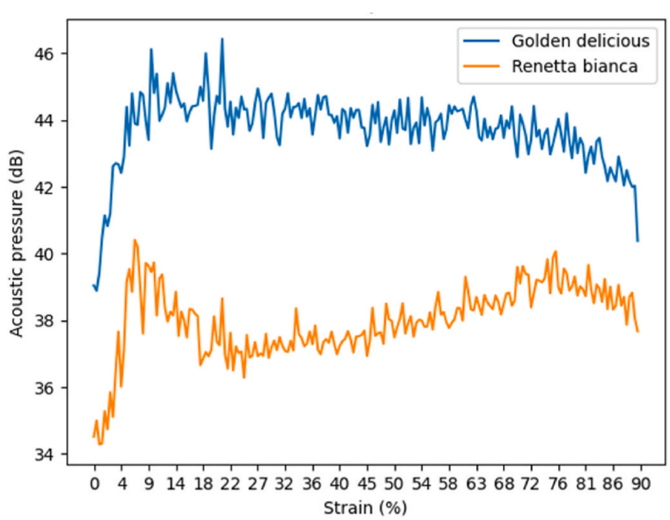

Fig. 3. Acoustic pressure (dB) deformation (%) profiled during the compression of two different apple cylinders.

3.3. Predictive models

The main results of the models set up to predict the sensory attributes hardness, crunchiness, flouriness, fibrousness and graininess, are summarized in Table 5 according to the three combinations of independent variables: the entire mechanical profile, the entire mechanical profile added to the entire acoustic profile, and the mechanical and acoustic parameters extracted from the acquired curves. The PLS, MLP, SVR and GPR model accuracies were described in terms of R^2 and RMSE obtained by 5-fold cross validation. Optimization parameters for PLS (number of latent variables, LVs), and SVR (epsilon and C) algorithms are also given in the table (see Table 6).

As can be observed, the best validation accuracies were obtained for sensory attributes hardness and crunchiness for all PLS, MLP, SVR and GPR models and X-variables combinations with R^2 values up to 0.885 (RMSE = 6.7) and 0.849 (RMSE = 7.4), respectively. These results appeared to confirm those obtained by Corollaro et al. [13] revealing higher predictive accuracies for hardness ($R^2 = 0.88$) and crunchiness ($R^2 = 0.85$) compared to flouriness ($R^2 = 0.79$), fibrousness ($R^2 = 0.80$) and graininess ($R^2 = 0.77$) PLS models, based on a selection of extracted mechanical and acoustic parameters.

Table 4
Pearson correlation matrix for mechanical and acoustic parameters extracted from the acquired profiles.

	F yield	F max	F final	F peaks	W	F ld	Y mod	F mean	Delta F	F ratio	Peaks dist	ld dist	A Peaks	A P max	A P mean	A ld
F yield	–	0.210	0.218	0.209	−0.252	0.210	0.077	−0.415	−0.087	0.203	−0.040	−0.071	−0.296	0.127	0.125	0.041
F max	0.210	–	**0.960**	**0.992**	0.088	**0.992**	**0.843**	**0.753**	−0.002	**0.818**	−0.356	−0.414	0.104	0.493	0.454	0.339
F final	0.218	**0.960**	–	**0.955**	0.085	**0.955**	**0.739**	**0.697**	0.041	**0.742**	−0.549	−0.584	0.084	0.487	0.438	0.293
F peaks	0.209	**0.992**	**0.955**	–	0.128	**1.000**	**0.849**	**0.763**	0.049	**0.834**	−0.315	−0.422	0.100	0.511	0.473	0.350
W	−0.252	0.088	0.085	0.128	–	0.128	0.329	0.231	**0.809**	0.219	−0.042	−0.254	0.164	0.303	0.335	0.310
F ld	0.210	**0.992**	**0.955**	**1.000**	0.128	–	**0.849**	**0.763**	0.050	**0.834**	−0.316	−0.423	0.100	0.512	0.473	0.351
Y mod	0.077	**0.843**	**0.739**	**0.849**	0.329	**0.849**	–	**0.726**	0.146	**0.911**	−0.088	−0.252	0.190	**0.619**	0.575	**0.612**
F mean	−0.415	**0.753**	**0.697**	**0.763**	0.231	**0.763**	**0.726**	–	0.060	**0.632**	−0.131	−0.234	0.280	0.354	0.315	0.283
Delta F	−0.087	−0.002	0.041	0.049	**0.809**	0.050	0.146	0.060	–	0.286	−0.013	−0.217	0.054	0.278	0.204	0.301
F ratio	0.203	**0.818**	**0.742**	**0.834**	0.219	**0.834**	**0.911**	**0.632**	0.286	–	−0.068	−0.242	0.124	**0.629**	0.520	**0.619**
Peaks dist	−0.040	−0.356	−0.549	−0.315	−0.042	−0.316	−0.088	−0.131	−0.013	−0.068	–	**0.798**	−0.037	−0.183	−0.167	−0.024
ld dist	−0.071	−0.414	−0.584	−0.422	−0.254	−0.423	−0.252	−0.234	−0.217	−0.242	**0.798**	–	−0.063	−0.331	−0.344	−0.131
A Peaks	−0.296	0.104	0.084	0.100	0.164	0.100	0.190	0.280	0.054	0.124	−0.037	−0.063	–	−0.024	0.014	0.044
A P max	0.127	0.493	0.487	0.511	0.303	0.512	**0.619**	0.354	0.278	**0.629**	−0.183	−0.331	−0.024	–	**0.906**	**0.677**
A P mean	0.125	0.454	0.438	0.473	0.335	0.473	0.575	0.315	0.204	0.520	−0.167	−0.344	0.014	**0.906**	–	0.457
A ld	0.041	0.339	0.293	0.350	0.310	0.351	**0.612**	0.283	0.301	**0.619**	−0.024	−0.131	0.044	**0.677**	0.457	–

Bivariate correlations in bold: $r > 0.6$; P-value ≤ 0.05.

Table 5
R^2 and RMSE values for the predictive models of sensory attributes.

X-variables	Tool	Hardness			Chrunchiness			Flouriness			Fibrousness			Graininess		
		Opt.	R^2	RMSE	Opt.	R^2	RMSE	Opt.	R^2	RMSE	Opt.	R^2	RMSE	Opt.	R^2	RMSE
Mechanical profile	PLS	LVs5	0.833	8.1	LVs3	0.707	10.3	LVs6	0.707	11.3	LVs6	0.759	9.8	LVs4	0.679	9.6
	MLP		0.826	7.5		0.723	9.1		0.764	9.5		0.735	9.5		0.695	8.5
	SVR	0.5; 0.05*	0.834	8.0	1; 0.1*	0.747	9.6	5; 0.05*	0.800	11.3	0.5; 0.01*	0.751	9.9	0.5; 0.01*	0.734	8.7
	GPR		0.853	7.5		0.789	8.8		0.768	11.3		0.763	9.7		0.761	8.3
Mechanical + acoustic profiles	PLS	LVs5	0.864	7.3	LVs4	0.818	8.1	LVs6	0.786	9.7	LVs3	0.789	9.2	LVs6	0.764	8.3
	MLP		0.744	6.7		0.727	7.5		0.794	9.4		0.786	8.5		0.751	7.8
	SVR	0.1; 0.01*	0.873	7.0	1; 0.05*	0.830	7.9	1; 0.05*	0.820	8.9	0.5; 0.1*	0.820	9.2	0.5; 0.05*	0.799	7.6
	GPR		0.885	6.7		0.840	7.6		0.824	8.8		0.719	8.5		0.806	7.5
Mechanical + acoustic parameters	PLS	LVs7	0.863	7.3	LVs7	0.834	7.8	LVs10	0.786	9.7	LVs2	0.755	9.9	LVs10	0.762	8.3
	MLP		0.860	6.9		0.828	7.3		0.809	8.9		0.765	9.8		0.767	7.8
	SVR	0.5; 0.05*	0.839	7.9	0.5; 0.05*	0.811	8.3	0.5; 0.01*	0.800	9.4	0.1; 0.01*	0.734	10.3	0.5; 0.01*	0.789	7.9
	GPR		0.874	7.0		0.849	7.4		0.828	8.7		0.761	9.8		0.797	7.7

LVs = number of latent variables; *values for C and epsilon hyperparameters, respectively.

Table 6
R^2 and RMSE values for the predictive models of sensory attributes (5-fold cross validation).

X-variables	Tool	Hardness			Chrunchiness			Flouriness			Fibrousness			Graininess		
		Opt.	R^2	RMSE	Opt.	R^2	RMSE	Opt.	R^2	RMSE	Opt.	R^2	RMSE	Opt.	R^2	RMSE
Mechanical profile	PLS	LVs5	0.911	6.4	LVs5	0.722	11.3	LVs7	0.675	13.0	LVs6	0.788	9.7	LVs6	0.622	9.6
	MLP		0.898	6.8		0.771	10.2		0.658	13.3		0.807	9.2		0.663	9.1
	SVR	1; 0.01*	0.911	6.4	1; 0.01*	0.814	9.2	5; 0.01*	0.775	10.8	1; 0.05*	0.817	9.0	5; 0.05*	0.772	7.5
	GPR		0.921	6.0		0.803	9.5		0.795	10.3		0.824	8.8		0.760	7.7
Mechanical + acoustic profiles	PLS	LVs4	0.913	6.3	LVs4	0.852	8.2	LVs5	0.824	9.6	LVs4	0.845	8.3	LVs4	0.762	7.6
	MLP		0.922	6.0		0.726	11.2		0.782	10.6		0.772	10.0		0.764	7.6
	SVR	0.5; 0.01*	0.900	6.8	0.5; 0.05*	0.881	7.4	10; 0.01*	0.831	9.4	1; 0.05*	0.866	7.7	0.5; 0.05*	0.795	7.1
	GPR		0.924	5.9		0.806	9.4		0.817	9.7		0.828	8.7		0.776	7.4
Mechanical + acoustic parameters	PLS	LVs7	0.906	6.6	LVs6	0.870	7.7	LVs6	0.803	10.1	LVs7	0.783	9.8	LVs10	0.712	8.4
	MLP		0.916	6.2		0.900	6.8		0.788	10.5		0.803	9.3		0.683	8.8
	SVR	0.5; 0.05*	0.890	7.1	0.5; 0.01*	0.850	8.3	0.5; 0.05*	0.809	10.0	0.1; 0.01*	0.750	10.5	0.5; 0.01*	0.734	8.1
	GPR		0.916	6.2		0.844	8.4		0.670	13.1		0.753	10.4		0.642	9.4

LVs = number of latent variables; *values for C and epsilon hyperparameters, respectively.

In general, the predictive models for all sensory attributes present improvements in the accuracy passing from the "mechanical profile" to the "mechanical + acoustic profiles" combination of independent variables. The reported results are in line with literature showing the importance of both textural components in the definition of apple sensory attributes [21]. The addition of the acoustic profile to the mechanical ones appeared to particularly affect the "crunchiness" attribute. This behavior is not surprising thinking to the role of the sound to the sensation of crispness and crunchiness [38,39]. In terms of R^2 values, the highest improvement can be observed for PLS validated models showing values from 0.707 (RMSE = 10.3) (mechanical profile only) to 0.818 (RMSE = 8.1) (mechanical + acoustic profiles).

Globally, the predictive performances observed for the algorithm techniques modelling the combination of mechanical and acoustic profiles can be comparable to those obtained by using the selected set of mechanical and acoustic parameters extracted from the profiles. To give an example, R^2 values for hardness GPR models were 0.885 (RMSE = 6.7) and, 0.874 (RMSE = 7.0) respectively for the two predictors combinations. The reported results significantly evidence how the use of the entire information contained in the mechanical and acoustic curves can accurately and reliablly describe the considered apple sensory attributes, simplifying the consolidated and critical definition of the extracted features.

For the sensory attributes of hardness and crunchiness, GPR models exhibited the best performance across all combinations of predictors. Fig. 4 presents the predicted versus observed values of the sensory attribute hardness obtained from 5-fold cross validations of GPR models showcasing results for the entire mechanical profile (a), the entire mechanical profile added to the entire acoustic profile (b) and for the mechanical and acoustic parameters extracted from the acquired curves (c). Similarly, for the sensory attribute crunchiness, Fig. 5 displays predicted versus observed values obtained from 5-fold cross validations of GPR models, illustrating outcomes for the entire mechanical profile (a), entire mechanical profile added to the entire acoustic profile (b) and for the mechanical and acoustic parameters extracted from the acquired curves (c).

The PLS, MLP, SVR and GPR model accuracies were also described in terms of R^2 and RMSE obtained by external validation. Optimization parameters for PLS (number of latent variables, LVs), and SVR (epsilon and C) algorithms are also given in the table.

External validation confirm best validation accuracies for sensory attributes hardness and crunchiness for all PLS, MLP, SVR and GPR models and X-variables combinations in addition to improvements in the accuracy passing from the "mechanical profile" to the "mechanical + acoustic profiles". Similalrly to 5-fold cross validation, for the sensory attributes of hardness, GPR models exhibited the best performance across all combinations of predictors.

~~Overall, for the attributes of flouriness, fibrousness and graininess,~~

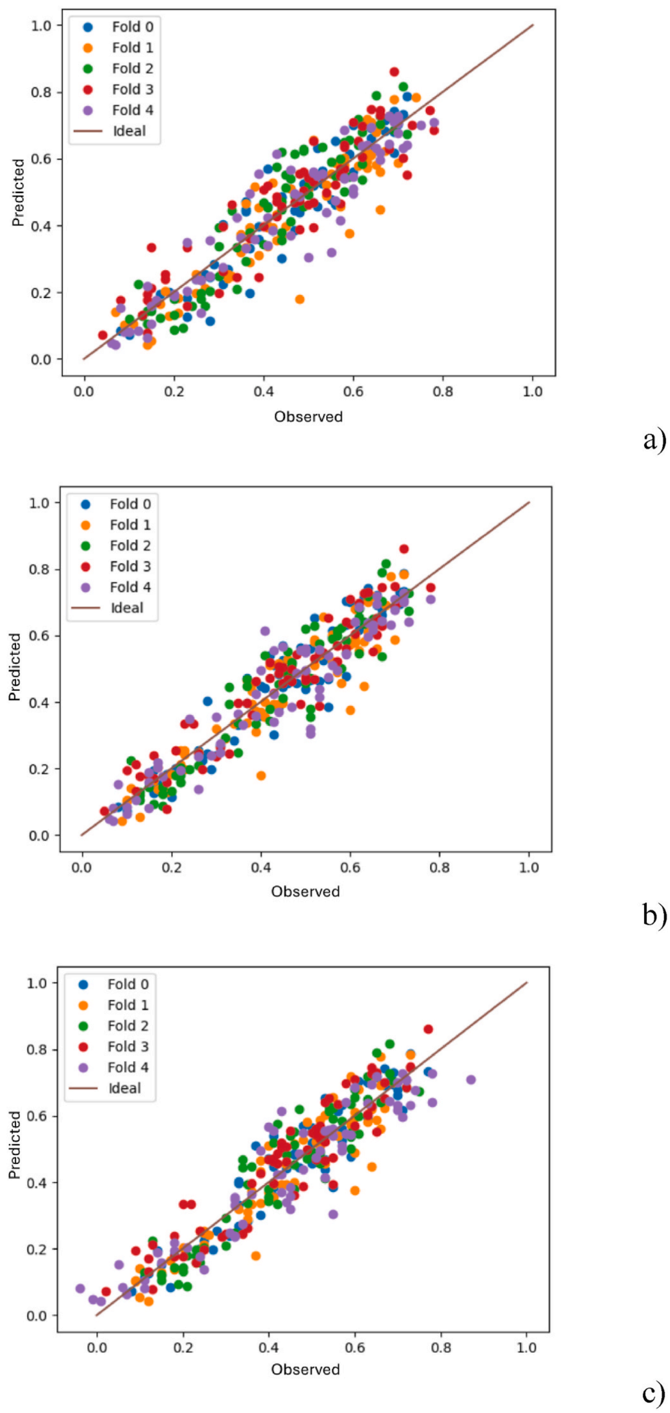

Fig. 4. Predicted versus observed values of the sensory attribute hardness (5-fold cross validations, GPR) for the entire mechanical profile (a), entire mechanical profile added to the entire acoustic profile (b) and for the mechanical and acoustic parameters extracted from the acquired curves (c).

~~GPR techniques seemed to produce the highest R^2 values.~~

~~In particular,~~ The nonparametric probabilistic regression GPR, appeared to outperform other explored techniques in effectively modelling the huge variability present in the samples in terms of mechanical and acoustic properties. As widely recognized, GPR is a machine learning technique that can solve complex input and output relationships, by combining linear and non-linear terms in the covariance function, demonstrating proficiency in addressing high-dimension multivariate linear and nonlinear problems [40,41].

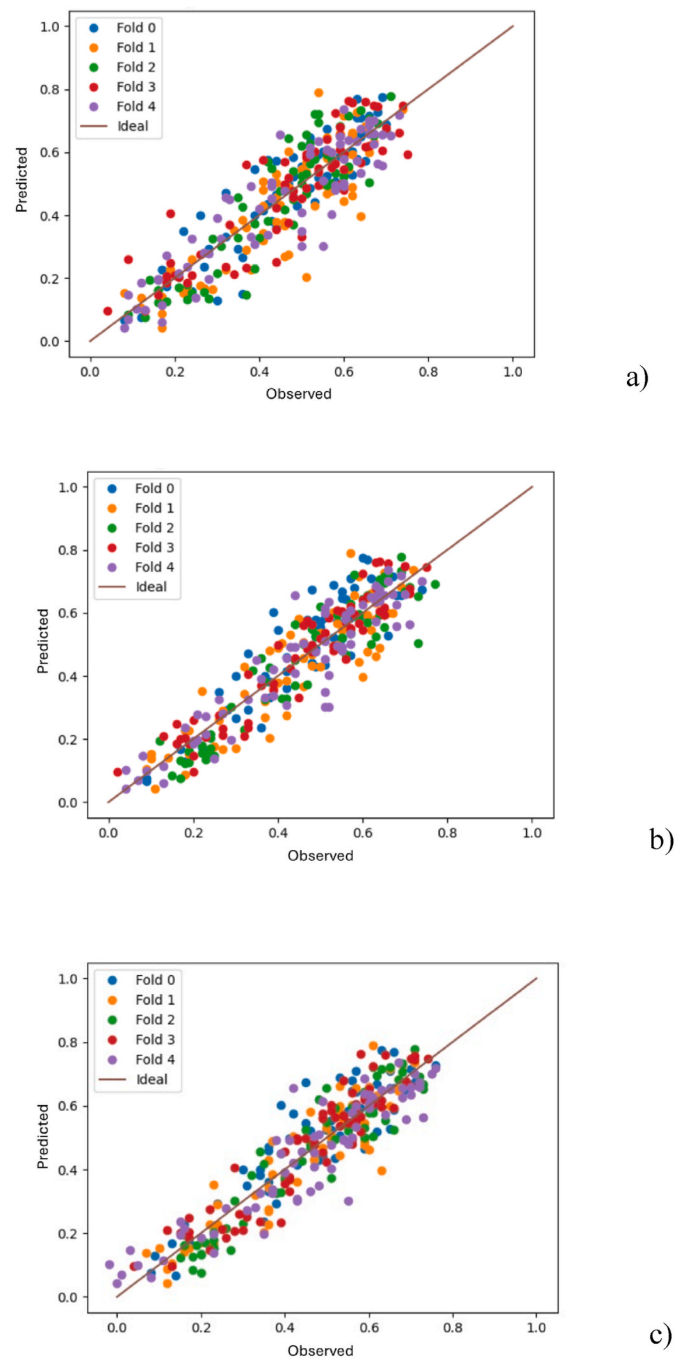

Fig. 5. Predicted versus observed values of the sensory attribute crunchiness (5-fold cross validations, GPR) for the entire mechanical profile (a), entire mechanical profile added to the entire acoustic profile (b) and for the mechanical and acoustic parameters extracted from the acquired curves (c).

Currently, GPR models are considered a robust alternative to traditional chemometric modelling tools, especially in the field of qualitative and quantitative spectroscopy assessments. Interesting examples refers to Near-Infrared spectroscopy [29,42,43], Infrared spectroscopy [44], Raman spectroscopy [45]and Terahertz time-domain spectroscopy [46] to name a few.

4. Conclusions

The information contained in the mechanical and acoustic profiles acquired during compression tests of high variables apple samples was modelled to predict hardness, crunchiness, flouriness, fibrousness, and graininess sensory attributes.

By taken into consideration PLS, MLP, SVR and GPR statistical techniques and different combinations of predictors, main results confirmed the role of both mechanical and acoustic components in the definition of apples sensory perception. Respect to models built by using only mechanical curves, those characterised by the combination of mechanical and acoustic profiles showed the best accuracies in terms of R^2 values.

The possibility to use the entire acquired profiles instead of a specific list of relative extracted features was also proven by the results of the present work, which focused on a huge number of commercial cultivars harvested over a period of nine years. As known from the literature, the definition of the type and number of features able to characterize the tested samples can be considered the main critical point. In addition, the results evidenced once again that the information contained in the mechanical and acoustic curves can replace, in a cheaper way (people are not always available and cannot evaluate more than 20–30 samples per day), the sensory panels assessments in the evaluation of the explored apple attributes, especially in real time procedures.

In terms of predicted sensory attributes, our investigation also confirmed higher accuracies for hardness and crunchiness respect to flouriness, fibrousness, and graininess.

Next steps could be dedicated to the improvements of the predictive power of the statistical tools by extending the techniques to other types of fruit.

CRediT authorship contribution statement

Riccardo Ricci: Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Annachiara Berardinelli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis. **Flavia Gasperi:** Writing – review & editing, Funding acquisition, Conceptualization. **Isabella Endrizzi:** Writing – review & editing, Conceptualization. **Farid Melgani:** Writing – review & editing, Supervision. **Eugenio Aprea:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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