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Prediction of textural characteristics in low-fat mozzarella cheese by Hyperspectral imaging using machine learning methods

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ABSTRACT

Changing the thermo-mechanical properties, variety of formulation and storage conditions, 36 samples of low-fat mozzarella cheese were produced and their hardness, adhesiveness, cohesiveness, springiness, cohesiveness, gumminess and chewiness were evaluated by TPA followed by analyzing data using completely randomized factorial design with univariate analysis through IBM SPSS Statistics. 26. Then, Imaging of the same samples with a Hyperspectral camera in the range of 400-1000 nm as well as pre-processing the spectra and preferring the important wavelengths by feature selection algorithms to developed the calibration models including multiple linear regression algorithms, partial least squares regression, support vector machine with a linear kernel, multilayer perceptron neural network, random forests and majority voting algorithm was performed in Python software followed by the performance of models were evaluated. Results showed that the more increased the stretching time in hot water from 2 to 8 minutes, the more the hardness, springiness, gumminess and chewiness and cohesiveness increased, but adhesiveness was decreased. The majority vote algorithm (VOTING) revealed the highest performance in hardness prediction (R^2p=0.878, RMSEp=2606.52 and RPD=2.12) and was able to predict the cohesiveness of mozzarella with higher accuracy more than other algorithms. Multiple linear regression couldn't predict the adhesiveness properly, but random forest method with high performance predicted this feature (R^2p=0.808, RMSE=56.49, RPD=1.90). The multi-layer perceptron neural network with the least error, predicted springiness (R^2p = 0.848, RMSEp = 0.094, RPD = 2.12) and chewiness (R^2p = 0.84, RMSEp = 1117.21, RPD = 1.96) with high accuracy. All methods except random forest were able to predict the gumminess of mozzarella with high efficiency. In this study, it was cleared that the process conditions had significant effects on the textural characteristics and the Hyperspectral imaging was found to be a suitable alternative method for estimating the textural characteristics of mozzarella cheese.

1- Introduction

Mozzarella belongs to the Pasta-Filata family, which literally means “spun paste” or Stretche Curd. This concept refers to a flexible and unique stretching process that is common to all cheeses of this family and gives a common identity to this diverse group. After creating the curd through the conventional process, the most important step is the thermo-mechanical treatment, during which the curd is stretched and heated in hot water, becomes plastic and takes the shape of mozzarella cheese [1]. Among all of cheese of this family, low-moisture and fat-free mozzarella are the largest part of consumption, used as a pizza topping. Although there is currently no defined international standard for low-fat cheese, the Codex International Commission considers a minimum of 50% fat reduction in dry matter to produce a low-fat cheese [2]. The fat in mozzarella cheese contributes to functions such as elasticity and smoothness by creating a lubricating effect during melting; But excessive consumption of fat in diet may contribute to the occurrence of some diseases such as cardiovascular diseases, obesity and diabetes. Therefore, todays there is a great interest to consumption of low-fat dairy products [3, 4, 5, 6, and 7]. On the other hand, cheese is an expensive product, through which have encouraged researchers and producers to find and introduce methods to improve the texture of this product and new solutions in this regard. Mozzarella textural characteristics including hardness, stickiness, springiness, cohesiveness, gumminess and chewiness are influenced by several factors such as fat, moisture, shelf life, cooking conditions, initial composition of milk, cheese calcium content and producing method but these characteristics improve, when the moisture and fat in the dry matter of mozzarella increases [8, 9, 10, 6]. However, the formation of the cheese structure in the cooking operation is directly influenced by cooking temperature and shear forces applied during the process of special thermo-mechanical operations and applying the shear module on curd [11]. In this regard, although some researchers such as Yu and Gunasekaran (2005), Mulvaney et al. (1997) and Banville (2016), proved that increasing the temperature and more intensity of thermo-mechanical operation causes an increase in mozzarella springiness, Merril et all (1994), found that pre-acidification of milk, lower pasteurization temperature and stretching the curd for 2 minutes in cooking water, led to a decrease in the hardness and elasticity of low-fat mozzarella [12, 13, 14, 15]. Mozzarella textural attributes can be measured by common methods such as texture profile analysis, compression and puncturing tests. But they cannot be used routinely in industry because of time-consuming, destructive and often experimental. They can also only be used to evaluate one sample. In other side, sensory evaluations depend on the panelists' sensory perceptions and are tedious, expensive and time-consuming [16, 17, and 18]. Therefore, new non-destructive methods, such as vibrational rheometers, visible/near/mid-infrared nuclear magnetic resonance spectroscopy and computer vision systems, are emerging to evaluate food properties. These non-destructive methods enable efficient online evaluation of food. Some of these non-destructive methods, including methods based on computer vision systems, such as hyperspectral imaging, have been tested to evaluate the texture of semi-hard cheeses during ripening [19, 20, 21]. In addition to providing chemical and molecular information (water, fat, protein, etc.), this method records the physical and morphological characteristics of food samples (color, size, shape, and texture) at the pixel level. In such a way that, in the light of infrared, the trace of these compounds can be recorded in relation to the specific characteristics of the food through identifying the molecular bands [22, 18, 23, 24]. The most widely used of hyperspectral imaging system in food analysis is in visible and near-infrared ranges of 400-1000 nm [25]. The hyperspectral imaging system using infrared is one of the most efficient modern methods that not only provides the spectral information, but also obtains the spatial data thanks to being equipped with a CCD camera [26]. Accordingly, Darnay et al. (2017) investigated the effect of transglutaminase enzyme on characteristics of semi-hard cheese by hyperspectral imaging technology by developing partial least squares regression and principal components regression following to selecting the most important wavelengths leading to predict textural characteristics by TPA [23].The hardness of mozzarella cheese also was estimated by partial least squares regression and artificial neural network by Vásquez et al [18].

Machine learning involves algorithms have the ability to learn from data without relying on explicit programming. Developing machine learning methods during the last decades following to the rapid analysis of hyperspectral images leading to creation of a spectral library in some cases the, it has been possible to apply the hyperspectral imaging system online and in real time [27, 28].

Since, there are rare studies on predictive modeling of textural properties in low-fat mozzarella cheese by non-destructive hyperspectral imaging using machine learning algorithms, in this research following to production of Low-fat mozzarella and investigating the effect of mechanical-thermal operations and process conditions on textural characteristics, prediction of these attributes including hardness, adhesiveness, springiness, cohesiveness, gumminess and chewiness evaluated by hyperspectral imaging through developing regression models.

2-Materials & Methods

2-1- Low Fat Mozzarella production

Cheese production according to modified method of Ah and Tagalpallewar (2017), MCMahon et al. (1996) and Jahani and Azar (2016) in three formulations, by addition of whey protein concentrate (0.5 g/kg; Lactomin 80 from the Lactoprot Co., Germany) as a fat substitute, sodium caseinate (0.1%) as an emulsifier and citric acid (20%) for pre-acidification of milk in 10 liters batches in Pegah dairy Co., Gorgan was performed [29, 9, 30]. Mozzarella curds were formed using a thermophilic starter for Pastafilata and Mozzarella cheeses, including "*Streptococcus thermophilus* and *Lactobacillus heloticus*" bacteria from Christian-Hansen, Denmark, and Calza Clemente microbial rennet enzyme based on *Mocor* mold, (Calza, Italy). Using a constant screw speed (8-10 RMP approximately), Half part of all curds were kneaded in hot water for 8-10 min [8, 31, 29], while the other part was formed for 2 min stretching in hot water to reach pH=5.1. Then, half of the 36 cheese samples were transferred to 4°C and the others were frozen at -18°C immediately after production and all the samples were maintained for 7 days.

2-2- Texture profile analysis (TPA)

According to modified method of Gimenez et *al.*, 2023, using a texture analysis in Gorgan university of agricultural sciences and Natural Resources (A TA.XT Plus (kg, Stable Microsystem, UK), textural properties of low-fat mozzarella as the real values for comparing to hyperspectral imaging method. After taking the Mozzarella cheeses out of 4°C and -18°C following to temperature balance to (25°C), three pieces of samples from different parts of the round cheese mold with the dimensions of 1.5 cm x 2.2 cm x 3.4 cm (length, width, thickness) were positioned under the spherical probe (36 mm in diameter) and compressed by 30% of their original height at a speed of 1 mm s^{-1}. Hardness (the peak force during the first compression cycle), cohesiveness (the ratio of the second positive bite area to the first positive bite area), adhesiveness (the negative force area for the first bite representing the work required to pull the plunger away from the sample), springiness (the height to which the sample returns)), gumminess (product of hardness and cohesiveness) and chewiness (product of gumminess and springiness) were obtained using the device software (Exponent Version 6.1.4.0). TPA was performed in three replicates [32].

2-3- Hyperspectral images acquiring

According to the method of Shan et al (2020), the spectral characteristics using a table-top visible-near-infrared hyperspectral imaging device equipped with a CCD camera with a speed of 100 frames per second (HSI-Vis-NIR-100fps model) located in the Knowledge based PartoAfzar Sanaat laboratory, Zanjan on the samples who got passed the TPA test were determined and stored in device software (LabView V8.6). The images stored inside the folder had two dimensions, where X is the first spatial dimension and λ is the spectral dimension. In these conditions, by moving the platform and recording successive images of the sample, the second spatial dimension, Y, was obtained, and thus a three-dimensional hypercube was prepared [19, 33, and 34].

2-4- Spectral Pre-processing

In order to extract the spectral data in the form of distinguishable wavelengths by algorithms, the region of interest was selected using Otsu's canny [10] edge detection algorithm, morphology and erosion technique [36] and contouring. Spectral data were considered as independent variable X and textural & functional characteristics as dependent variable Y [37, 18, 38, 39, and 40]. In order to noise reduction and scattering elimination, following to determining the latent variables, six pre-processing methods (smoothing with the Savitzky-Golay filter, first-order derivative with Savitzky-Golay, second-order derivative with Savitzky-Golay, Multiple Scattering Correction, Standard Normal Variable and a Second-order polynomial wavelength correction method), were put on competition to each other through developing a partial least squares regression model for all textural properties.

2-5- Development of regression models using machine learning methods

At first, the initial calibration models were created with raw spectrum and the accuracy of the models was estimated in predicting the textural and functional characteristics. After ensuring the appropriate performance of selected algorithms, feature selection methods (β regression, genetic algorithm, Iterative predictor weighting Partial Least Square (IPW-PLS), Sub-window permutation analysis Coupled with PLS (SwPA-PLS) and random forests) along with a PLSR model for each of the eight textural and functional characteristics were put into competition so that fitting to the models preferred as the optimal algorithms for selecting the effective wavelengths [41, 42, 34]. These processes were repeated for each textural and functional characteristic. Then, entering isolated wavelengths, several calibration models by machine learning methods (Multiple Linear Regression, Partial Least square Regression (PLSR), Support Vector Machine with linear kernel, Multilayer Perceptron Neural Network (MLPNN) and Majority Vote Regression Algorithm (VOTING) by integrating MLR, SVML and RF models were developed according to equation number (1). Before the development of calibration models, mozzarella samples were classified according to the spectral reflectance pattern based on process conditions using principal component analysis. In other words, to answer the question whether hyperspectral imaging has been able to create spectral separation based on the mentioned factors or not, its reflection diagrams were plotted based on wavelength for each of the mentioned variables using the Python module [43, 44, 45, 46, 47, 48, 17, 49, 50, and 51].

$$f(VR) = f_{MLR} + f_{SVML} + f_{RF} \qquad \text{Equation (1)}$$

2-6- Statistical analysis and validation of models

Since the samples were arranged based on the factorial method and the simultaneous effect of several independent variables on several dependent variables was considered, using completely randomized factorial design with GLM and univariate analysis through IBM SPSS Statistics. 26. Software, the data was analyzed and followed by comparing the means using the Least significant difference (LSD) at a significance level of α=0.05. After developing the calibration models, to validate the models using K-fold cross validation method, data were divided into two parts of training and testing, and then all models were trained. To this end, the validation was started by calculating the mean square of the error related to the test data and the second part was considered with 15 other random data as the test data, then the model was trained with the remaining 8 parts and the mean square of the error was calculated again for the second part. Then, the squared error was calculated for the whole set (k=10), while to acquire the total error of the model, the mean squared error obtained in each section was calculated [34, 52, 53]. Finally, after adjusting the hyper-parameters of the model, the following statistics were used to evaluate the efficiency of models.

2-6-1- Root-mean- squared error for prediction (RMSEP)

This statistic is used as an approximation of model's error in the predicted values compared to the actual measured values, which is calculated by the following equation:

$$RMSEP = \sqrt{\frac{\sum_{i}^{N} = 1(\widehat{y_i} - y_i)^2}{N}} \qquad \text{Equation (2)}$$

Where N is the number of samples, $\hat{y}_i$ is the predicted value of each parameter for the *i*th sample and y_i is the measured value for the *i*th sample.

2-6-2- Coefficient of determination

This statistic is utilized for evaluating the correlation coefficient between predicted values and actual values. The value of the coefficient of determination is between "0" and "1" and the closer it is to 1, it depicted that a higher percentage of data changes can be predicted by the regression model and a lower percentage by random errors (noise), which can be calculated by the following equation:

$$R^2 = 1 - (\frac{RMSE}{SD})^2 \qquad \text{Equation (3)}$$

Where *SD* shows the standard deviation. In this study, the coefficient of determination index was reported by R^2p value.

2-6-3- Residual predictive deviation (RPD)

The value of RPD is defined by the ratio of the standard deviation of the response variable to RMSEP or RMSECV. RPD between 1.5 and 2 means that model could have detected low and high variance of the response variable. A value between 2 and 2.5 indicates that better quantitative predictions could be possible and the one between 3 and 5 or higher corresponds to an appropriate and excellent prediction accuracy, respectively [52, 34]. This value can be calculated by:

$$\text{RPD} = \frac{SD}{RMSE_p} \qquad \text{Equation (4)}$$

3-Results and discussion

3-1- Variation of formulation effect on textural properties

The results of the different formulations effect on textural and functional characteristics of mozzarella cheese are depicted in Table 1. The results showed that hardness and chewiness were significantly different in all samples ($p<0.05$). But according to the Least significant difference (LSD), the average differences of the characteristics in all samples were not significant ($p>0.05$). Based on the difference in variety of formulation, fat had a determinative role in texture characteristics difference. In such a way that the low-fat control sample was showed the least adhesiveness while the high-fat control was illustrated the most, besides the high-fat sample containing acid (B) considered as the lowest degree of hardness; whereas the highest hardness value was related to control low-fat sample (C). There was no significant differences in gumminess ($p<0.05$) which was consistent with Esen et al., 2023 [54].

Table 1. The effect of different treatments on the textural and functional characteristics of mozzarella cheese

Treatments	Textural & Functional Properties					
	Hardness	Adhesiveness	Springiness	Cohesiveness	Gumminess	Chewiness
(A)	$4498.4^h \pm 612.58$	$187.78^a \pm 45.66$	$0.506^f \pm 0.05$	$0.301^f \pm 0.12$	$1439^g \pm 245.92$	$919.9^h \pm 217.95$
(B)	$1766.4^i \pm 140.85$	$181.14^b \pm 27.97$	$0.392^g \pm 0.01$	$0.231^g \pm 0.006$	$496.8^h \pm 31.38$	$192^i \pm 17.15$

(C)	13613.7c±1304.63	2.31g±0.20	0.748d±0.05	0.391d±0.20	4797.87d±337.48	3650.72f±428.11
(D)	11056.5f±962.26	31.32d±9.94	0.665e±0.26	0.48a±0.12	4282.63f±623.02	2351.65g±338.08
(E)	14584.4b±756.41	12.93e±0.70	0.838b±0.15	0.402c±0.20	6334.06c±464.85	5063.14b±475.49
(G)	11156.3e±830.4	9.62f±1.04	0.774c±0.29	0.447b±0.24	6397.36b±988.41	4321.73c±472.12
(J)	12775.1d±713.93	2.88g±0.24	0.845a±0.004	0.347e±0.16	4360.98e±71.15	3733.99d±66.42
(K)	9759.35g±726.49	39.83c±19.66	0.791b±0.20	0.394c±0.03	4346.23e±514.84	3691.24e±535.53
(L)	17459.5a±726.49	2.47g±0.24	0.837a±0.004	0.391d±0.23	7361.95a±218.39	5638.74a±177.63

Numbers with the same letters in each column have no significant difference at the 5% significance level (P<0.05). Adjusted R squared for univariate analysis in all variables= 0.964.

(A): Control High Fat; (B): Control Low Fat; (C): Control Low Fat; (D): Control Low Fat + Acid; (E): Control Low Fat + Acid + Caseinate; (G): Control Low Fat + Acid + WPC; (J): Control Low Fat + WPC; (K): Control Low Fat + WPC + Caseinate

In fact, since fat breaks the protein matrix through which plays a lubricating role, it creates a softer texture. This issue was consistent with To et al., 2020. They claimed that the injection of Co2 caused decreasing the pH up to 2.6, maintaining the moisture content and reducing the hardness of mozzarella cheese [55]. Moreover, aligned with the many other studies [15, 55, 4, 3, and 31] which have represented the addition of organic acids as one of the methods of modifying the structure and texture of low-fat mozzarella cheese, addition of citric acid reduced the hardness, springiness and cohesiveness of the samples. Because according to researchers, using acid caused a decrease in calcium and an increase in proteolysis during the storage period, and hence, it could make a decrease in the hardness of mozzarella cheese. In other words, the direct acidification of milk causes the separation of calcium and other minerals (phosphorus and magnesium) from the casein micelles, and this leads to the swelling and water absorption of the paracasein matrix after one day of cheese production. Addition of whey protein concentrate and sodium caseinate also caused a decrease in hardness, firmness, cohesiveness and chewiness. But the low-fat mozzarella produced by these compounds had a higher gumminess and adhesiveness. This issue was consistent with the research findings of Amador-Espejo et al., 2021; Abd Elkader et al., 2019; Ismail et al., 2011; Zisu & Sahh, 2005; Nateghi et al., 2015 [56, 57, 4, 59]. Because, addition of whey protein concentrate along with lubricant compounds improves the textural properties through increasing the moisture and lubricating or creamy texture.

2-3- The effect of changes in thermo-mechanical treatment and storage conditions on textural properties

The results of univariate analysis of variance showed that the effect of stretching time in hot water, storage temperature and type of formulation on all textural and functional characteristics of produced mozzarella was significant (P<0.05). So that by increasing the stretching time in hot water or the intensity of the thermo-mechanical operation, hardness, cohesiveness, springiness and chewiness were increased. Aligned with these findings, Kindstedt et al., 1992 by keeping the cooking temperature constant, proved that the hardness of mozzarella decreased at a lower screw speed level [60]. While Mulvaney et al., 1997 claimed that the intensity of the thermal process may enhance by increasing the screw speed, so that at a high speed and higher shear stress, the curd may collapse and therefore not have enough time to reach the desire temperature required for proper elasticity [13]. On the other hand, the results showed that freezing caused an increase in hardness, cohesiveness, and springiness due to structural damage in cheese. Since, samples that were harder had more coherent texture and a higher springiness, these findings confirmed the hardness results which were consistent with results of Tunik et al., 1991; Alinovi et al., 2020; Topcu et al., 2020; Esen et al., 2023 researches [61, 62, 63, 54].

3-3- Mozzarella cheese classification results based on spectral data

Looking for the spectral pattern affected by processes applied as independent variables, the reflectance average graphs in terms of wavelength were plotted (Figure 1). It was found that the process conditions, as they had a significant effect on the textural and functional characteristics, were able to distinguish the spectral profile precisely. This proved that spectra were able to estimate textural and functional characteristics consistent with Shan et al., 2020 findings who observed spectral differentiation based on the reflection intensity in processed cheese. [33].

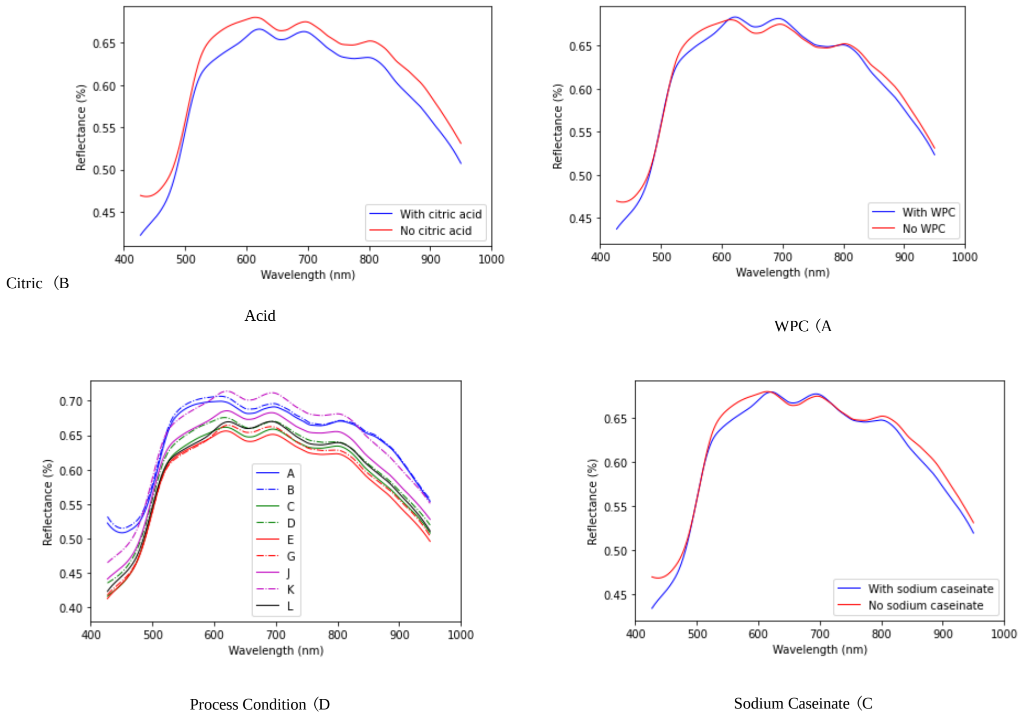

FIG 1. The effect of process conditions on the reflection pattern in mozzarella based on Hyperspectral imaging

According to the spectral separation observed, the results of mozzarella samples classification based on principal components analysis (PCA) showed that the classification based on fat had a suitable distribution as low-fat cheeses and high-fat are easily distinguishable (Figure 2); However, the classification based on the variety of formulation could not be easily separated due to the overlap of the trial related to the nature of the production and regulation of the formulation of samples in this research.

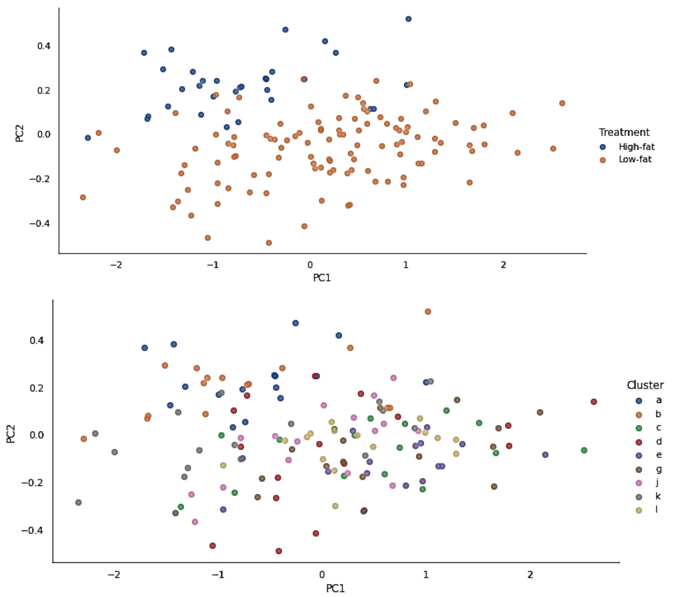

FIG 2. Mozzarella cheese classification results using PCA

3-4- Comparison of pre-processing methods in spectral data related to textural characteristics

The results of the pre-processing competition methods for all of textural properties based on the PLSR model are depicted in Table 2. The Savitzky-Goli smoothing method with a high-efficiency was preferred as the optimal method to reduce noise for prediction of hardness and springiness (R^2p=0.846, RMSE=2911.29) which was successfully overcomes the distortion of the raw spectrum. While the same filter along with the first derivative (SG_FD) was selected as preferred method for noise reduction of data related to adhesiveness. Similar to these findings, using the Savitzky-Guli filter and placing neighborhood points equal to three, Shafiee et al. (2016) detected the honey adulteration through developing a model and Hyperspectral imaging technique [64]. Similarly, Jajromi et al. (2015) used several pre-processing methods including Savitzky-Goley filter, multiple scatter correction, standard normal variable, first and second derivative by creating a PLSR model to predict soluble solids and lime acidity. They compared with each other and proved that the pre-processing methods have a high impact on explaining a model with high accuracy and precision in order to predict the quality of lemon juice [65].

Table 2. The optimal pre-processing selected method in textural properties of Mozzarella based on PLSR

Textural Properties	Selected Pre-Processing methods	Latent Variable	R^2c	RMSEc	R^2p	RMSEp
Hardness	SG_Smoothing	7	0.855	2867.115	0.846	2911.290
Adhesiveness	SG_FD	4	0.802	57.480	0.809	56.390
Springiness	SG_Smoothing	9	0.890	0.081	0.850	0.094
Cohesiveness	SNV-Detrend	4	0.644	0.076	0.654	0.071
Gumminess	SNV	9	0.842	1473.950	0.835	1446.520
Chewiness	MSC	12	0.920	836.013	0.817	1186.170

However, align with the results of Park et al., 2023; Zou et al., 2023, it was found that the multiple scattering correction (MSC) method removing the differences caused by the scattering effects enhanced the performance of the model by increasing the correlation between the spectral data and the response variables which was distinguished as the optimal method to reduce the noise related to the chewiness (R^2p=0.817, RMSE=1186.170), [66, 67]. This difference in light scattering and noise effects is related to the complexity of particle size in biological samples; from this as in point of view that, methods including MSC are able to remove scattering from the pure and desirable absorption spectrum [68]. Comparing the pre-processing methods, it was cleared that the standard normal variable method showed the highest efficiency in reducing the noise of the data related to the gumminess (R^2p=0.835, RMSE=1446.520). Although there are rare studies in this regard, similar to the findings of this study, researchers such as Priyashantha et al. (2020), using the standard normal variable method, estimated the ripening time of hard cheeses using a PLSR model and measure its efficiency by hyperspectral data analysis [20]. But based on the results of the PLSR model, the same method along with the second-order polynomial wavelength correction (Detrend) was the best option to reduce the noise in prediction of the cohesiveness; while other methods did not show proper performance. However, based on the results of the PLSR model, SNV along with the second-order polynomial wavelength correction (Detrend) was the best option to reduce the noise in the cohesiveness; while other methods did not present proper performance.

3-5- The results of developing calibration models to predict textural properties

In this study, after selecting the effective wavelengths for all of characteristics through feature selection algorithms, calibration models were developed using important wavelengths.

3-5-1- Hardness

The evaluation results of machine learning methods for predicting the hardness of mozzarella samples using isolated wavelengths are shown in Table 3. As a result of using ML methods, a model was obtained in the form of which the spectral pattern of the mozzarella cheese produced in this research well predicted the hardness of the cheese. Because as it is clear in table 3, all the machine learning methods have been able to predict the texture characteristic of hardness; But the model developed with the majority voting algorithm has shown the highest efficiency and the least error.

Table 3. Results of calibration models development on Mozzarella texture using Machine learning algorithms

Textural Properties	Selected wavelengths number	Feature selection algorithm	ML algorithms	R^2p	RMSEp	RPDp
Hardness	31	IPW-PLS	MLR	0.826	307.37	1.8
			PLSR	0.844	292.5	1.99
			SVML	0.841	295.7	1.92
			MLPNN	0.868	270.5	2.14
			RF	0.807	322.9	1.71
			VOTING	0.878	260.5	2.22
Adhesiveness	24	Genetic Algorithm	MLR	0.669	71.19	1.36
			PLSR	0.779	60.11	1.81
			SVML	0.746	63.85	1.7
			MLPNN	0.764	61.79	1.78

			RF	0.808	56.49	1.90
			VOTING	0.772	60.93	1.99
Springiness	25	Genetic Algorithm	MLR	0.802	0.106	1.79
			PLSR	0.821	0.102	1.97
			SVML	0.838	0.097	2.05
			MLPNN	0.848	0.094	2.12
			RF	0.725	0.123	1.67
			VOTING	0.826	0.1	1.96
Cohesiveness	32	β-Coefficient	MLR	0.581	0.076	1.2
			PLSR	0.661	0.07	1.35
			SVML	0.617	0.074	1.28
			MLPNN	0.66	0.07	1.34
			RF	0.655	0.071	1.34
			VOTING	0.7	0.067	1.91
Gumminess	22	SWPA_PLS	MLR	0.813	1530.67	1.8
			PLSR	0.814	1528.28	1.8
			SVML	0.815	1522.63	1.81
			MLPNN	0.793	1602.22	1.76
			RF	0.56	2177.16	1.22
			VOTING	0.81	1542.5	1.79
Chewiness	27	Genetic Algorithm	MLR	0.813	1198.4	1.79
			PLSR	0.819	1181.3	1.8
			SVML	0.822	1170	1.89
			MLPNN	0.84	1117.2	1.96
			RF	0.468	1817.2	1.14
			VOTING	0.81	1207	1.8

Most of the time, the majority voting algorithm is more accurate than the best classifier or regression algorithm. Because if all the algorithms have a weak learner (have performed only a little better than random guess), combining them together forms a strong learner [47]. According to the table, the model developed by this method has reported the highest RPD (RPD=2.22). It means that higher performance compared to other models has been presented for hardness prediction. Similar to these findings, Zhou et al. (2021) identified the corn seeds with using a convolutional neural network modeling and a majority vote algorithm at an accuracy higher than 98% [50]. Also, aligned with the current research, Alinovi et al. (2019) in determining the textural characteristics of process cheese using infrared

Fourier transform and least squares regression modeling, acknowledged that application of the infrared spectroscopy along with image processing were reliable methods for texture evaluation which can be used as a measuring tool for its quality control [62]. In addition, the results of this research were consistent with the findings of Vasquez et al. (2018), as well as Shan et al. (2020), who predicted cheese hardness with an accuracy of R^2=0.76 using the partial square regression model [18, 33].

3-5-2- Adhesiveness

According to the results mentioned in table 3 besides observing the obtained statistics (coefficient of determination prediction, Residual predictive deviation (RPD) and Root-mean- squared error for prediction (RMSEP), it was found that all models except for the MLR had a high prediction performance for adhesiveness . However, the models prepared by random forest algorithm, partial least squares regression and majority vote presented more suitable performance than others in predicting the texture characteristic of adhesiveness. There are very few studies regarding the prediction of the textural characteristic of adhesiveness in cheese or the use of the random forest algorithm in the estimation of food indicators using imaging; However, similar to the present study, Teixido-Orries et al. (2023), using the partial least squares regression method, quantified the amount of deoxylivanol by high-performance liquid chromatography and distinguished the contaminated oat successfully using random forest method with a high efficiency (77.8%) and introduced the hyperspectral imaging as a promising tool for detecting this poison in oat [69]. Align with this research, Pu e al. (b2023) presented a model using convolutional neural network and random forests with an optimal accuracy (R^2=86.11%) to predict the textural properties of beef [19].

3-5-3- Springiness

The results of using machine learning methods for developing models in predictability of the springiness showed that, all the models had an optimal performance in predicting mozzarella cheese springiness, while the multilayer perceptron neural network had the highest performance among the models. (Table 3), (RPD=2.12, R^2p=0.848 and RMSEp=0.094). It was claimed by researches that the multi-layer perceptron neural network has been an appropriate method to classify or predict the desired variable with an accuracy of over 90% using the data obtained from hyperspectral imaging. This is while in order to build a strong model, proper training is needed and it is necessary to have enough large amount of data [28]. In this situation, the aim of training is to minimize the errors. In this study, according to the appropriate number of spectral data, as it is clear from table 3, MLPNN with a small RMSEP, the highest RPD and a topmost R^2P have the highest efficiency to predict Mozzarella Cheese springiness. The results of this research were consistent with the findings of Ni et al. (2019). By optical fiber spectroscopy and comparing the algorithm of multilayer perceptron neural network and recurrent neural network with partial squares, they concluded that MLPNN could predict crispness of apple chips measured by texture analysis method with a much higher accuracy (99.9%) and effectively separate the important wavelengths. According to the table, following to MLPNN, the SVML model also showed the highest coefficient of determination and the lowest error which was represented the high performance for prediction of this feature. Nevertheless, kernel trick for strengthening the support vector machine method has been recommended by various researchers in the analysis of hyperspectral images [34, 71, 47, and 72]. Because it considers the spatial proximity as well as the spectrum to smooth the hyperspectral images. Thereby, the support vector machine will be able to provide better smoothing in the homogeneous region and preserve the details of the image, which in turn improves the resolution between groups. Similar to the method applied in the present study, Sahadevan et al. (2016) using a radial kernel on the support vector machine increased the accuracy of model more than 99% [71].

3-5-4- Cohesiveness

As it is clear from table 3, none of machine learning methods, except for the the majority vote algorithm (R2p=07, RMSEp=0.067 and RPDp=1.91), could not provide a model with a suitable performance for predicting the texture characteristic of cohesiveness. There are rare studies regarding predictive modeling of mozzarella cheese cohesiveness using machine learning and hyperspectral imaging methods. However, in consistent the results of this research, Shan et al (2020) predicted the cohesiveness measured by texture analysis method in processed cheese using partial least squares regression with a moderate accuracy of $R^2cv=0.677$[33]. It was found as well the majority voting algorithm generated by creating a function of MLR, PLSR and RF algorithms, provided a suitable performance compared to each of the algorithms itself in predicting the cohesiveness. This findings about the efficiency of the majority voting method were aligned with the observation of Zhou et al (2021) in applying the VOTING to separation of corn kernels [73].

3-5-5- Gumminess

The ML methods used, except for the random forests, provided a suitable model for predicting the characteristic of gumminess in low-fat mozzarella cheese, while support vector machine with linear kernel and partial square regression illustrated the higher efficiency respectively (Table 3). However, results in prediction of gumminess, by partial least squares regression model, were consistent with the findings of Shan et al. (2020) who predicted the gumminess by PLSR with an accuracy of $R^2=0.817$ [33]. On the other hand, performance of generated SVM model in gumminess prediction was in line with the results obtained from the research of Sahadevan et al. (2016) [71]. In addition, similar to the findings of this research, Zhang et al. (2022) in evaluation of texture characteristics in sheep meat, found that the use of the least squares support vector machine has excellent performance in predicting hardness and gumminess with RMSEp = 5.25 and 3.03, coefficient of determination of prediction = 0.986 and 0.984 as well. Similarly, Zhang et al. (2023), using this algorithm, developed a model to estimate the amount of volatile nitrogen in beef with appropriate accuracy [74]. However, Wu et al. (2014) using a model based on partial least squares failed to estimate the textural characteristics and especially the gumminess in pork accurately [27]; Still, they introduced hyperspectral imaging as a reliable and fast alternative to using traditional devices to measure the spatial distribution of texture profile analysis (TPA).

3-5-6- Chewiness

According to the table 3, all the machine learning methods, but the random forests, predicted the chewability of mozzarella cheese produced in this research; However, the perceptron multilayer neural network method and support vector machine with linear kernel showed more efficiency in comparison with other methods in predicting chewiness respectively. These results were in agreement with the findings of Shan et al. (2020) who predicted the chewiness of processed cheese with appropriate accuracy ($R^2=0.84$) by developing a partial least squares regression model and hyperspectral imaging [33]. Although there are very few studies on the prediction of this textural characteristic in cheese using hyperspectral imaging, the research outcomes of González-Martín et al. (2011) for chewiness, hardness and creaminess showed the high accuracy in predicting of sheep cheese quality using infrared spectroscopy and partial least squares regression algorithm [76].

4-Conclusion

Low-fat mozzarella cheese was produced using of fat substitutes, and the effect of thermo-mechanical treatment, storage conditions, and variation of formulation on textural characteristics (hardness, stickiness, ferrite, cohesion, gum state, and chewability) were evaluated. Destructive tests were carried out by texture analysis method and the results were analyzed in SPSS software. At the same time as performing the destructive tests, image acquisition of the same samples was implemented by a hyperspectral camera in the range of the near infrared reflection spectrum (400-1000 nm). Imreading the images by different Python software modules, the spectral data was extracted. In order to reduce noises, 6 pre-processing methods and to facilitate modeling and reduce data dimensions, 5 feature selection algorithms were put into competition using partial least squares regression for each of the textural properties and the important wavelengths for their prediction were isolated. Calibration models (multiple linear regression, partial least squares regression, support vector machine with linear kernel, multilayer perceptron neural network and majority voting algorithm) were developed and the efficiency of the models in predicting the features was determined based on the model statistics. TPA analysis results showed that, increasing the intensity of thermo-mechanical operations caused to increase the hardness, springiness, gumminess, chewiness and cohesiveness, while the adhesiveness was decreased ($P<0.05$). Fat content had a determinative impact on texture characteristics variations, while addition of acid, whey protein concentrate, and sodium Caseinate caused a decrease in hardness, springiness, cohesiveness, and chewiness. The results of classification of mozzarella based on spectral data through the principal component analysis (PCA) indicated that hyperspectral imaging is effective in classifying cheese based on fat content. Developing results of calibration models for predicting textural characteristics revealed that all machine learning methods predicted hardness with an appropriate accuracy; but the model developed with the majority voting algorithm with the least error showed the highest efficiency. Although none of the algorithms could predict cohesiveness precisely, the majority vote algorithm showed a higher efficiency in estimating it. While the multiple linear regression method could not predict the adhesiveness of cheese properly, other algorithms could overcome to predicting this characteristic of mozzarella with a high performance, while the best method concerned to the random forest algorithm. The model generated by the multi-layer perceptron neural network method illustrated the highest efficiency, RPD, R2p and a low RMSE in predicting springiness and chewiness. Whereas all the machine learning methods used in this study, except for random forests, were successful to predict the gumminess in low-fat mozzarella cheese, support vector machine method with linear kernel as the superior method with high performance for prediction of the this textural property was diagnosed. In short, in addition to affecting the moisture and fat content, the process conditions have a decisive role in textural and functional characteristics of mozzarella cheese due to their effect on the protein and fat structure. In such a way that, changing the optimal thermo-mechanical conditions, low-fat mozzarella cheese with more suitable textural characteristics can be produced. In such a way that, changing the optimal thermo-mechanical treatment, it could be possible to produced low-fat mozzarella cheese with more suitable textural characteristics. In other words, hyperspectral imaging along with machine learning methods was able to predict the textural characteristics of low-fat mozzarella cheese and act as a promising alternative method instead of destructive methods such as texture analysis.

7-References

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مقاله علمی_پژوهشی

پیش‌بینی ویژگیهای بافتی پنیر موزارلای کم چرب با استفاده از تصویربرداری فراطیفی به کمک روش‌های یادگیری ماشین

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با تغییر در شدت عملیات مکانیکی–حرارتی متفاوت، تنوع فرمولاسیون و شرایط نگهداری، ۳۶ نمونه پنیر موزارلا کم‌چرب تهیه و سختی چسبندگی، انسجام، فنریت، حالت صمغی و قابلیت جویدن آنها توسط تجزیه و تحلیل مشخصات بافت اندازه‌گیری و با استفاده از تجزیه و تحلیل تک‌متغیره در قالب فاکتوریل در نرم‌افزار SPSS با یکدیگر مقایسه شد. سپس تصویربرداری از همان نمونه‌ها با دوربین فراطیفی در محدوده ۱۰۰۰–۴۰۰ نانومتر با دوربین فراطیفی انجام و پس از پیش‌پردازش طیف‌ها و جداسازی طول موج‌های مؤثر به کمک الگوریتم‌های انتخاب ویژگی، مدلسازی با الگوریتم رگرسیون خطی چندگانه، رگرسیون حداقل مربعات جزئی، ماشین بردار پشتیبان با کرنل خطی، شبکه عصبی پرسپترون چندلایه، جنگل‌های تصادفی و الگوریتم رأی اکثریت در نرم‌افزار پایتون انجام و کارائی مدل‌های ارزیابی گردید. نتایج نشان داد که با تشدید عملیات مکانیکی–حرارتی، سختی، فنریت، حالت صمغی و قابلیت جویدن و انسجام افزایش و چسبندگی کاهش پیدا کرد ($P < ۰/۰۵$). افزودن اسید و جانشین‌شونده‌های چربی سبب کاهش سختی، انسجام، فنریت و قابلیت جویدن شده و حالت صمغی و چسبندگی را افزایش دادند. الگوریتم رأی اکثریت، بیشترین کارایی را در پیش‌بینی سختی (R^2p=۰/۸۷۸، RMSEp =۲۶۰۶/۵۲ و RPD=۲/۱۲) بروز داد و توانست انسجام موزارلا را با کارائی بالاتری نسبت به سایر الگوریتم‌ها پیش‌بینی نماید. رگرسیون خطی چندگانه در پیش‌بینی چسبندگی کارائی نداشت، اما روش جنگل‌های تصادفی با عملکرد بالا این ویژگی را پیش‌بینی نمود (R^2p=۰/۸۰۸، RMSEp =۵۶/۴۹، RPD=۱/۹۰). شبکه عصبی پرسپترون چندلایه با کمترین خطا، توانست فنریت (R^2p=۰/۸۴۸، RMSEp =۰/۰۹۴، RPD=۲/۱۲) و قابلیت جویدن (R^2p=۰/۸۴، RMSEp =۱۱۱۷/۲۱، RPD=۱/۹۶) موزارلا را با عملکرد مناسب پیش‌بینی نماید. تمام روش‌ها به جز جنگل‌های تصادفی توانستند با کارائی بالا حالت صمغی را پیش‌بینی کنند. در این مطالعه مشخص شد عوامل فرایند تأثیر معنی‌داری بر ویژگی‌های بافتی داشتند و روش تصویربرداری تصویربرداری فراطیفی یک روش جایگزین مناسب برای تخمین ویژگی‌های بافتی پنیر موزارلا تشخیص داده شد.