A MACHINE LEARNING METHOD FOR PREDICTION OF YOGURT QUALITY AND CONSUMERS PREFERENCES USING SENSORY ATTRIBUTES AND IMAGE PROCESSING TECHNIQUES

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ABSTRACT

Prediction of quality and consumers' preferences is essential task for food producers to improve their market share and reduce any gap in food safety standards. In this paper, we develop a machine learning method to predict yogurt preferences based on the sensory attributes and analysis of samples' images using image processing texture and color feature extraction techniques. We compare three unsupervised ML feature selection techniques (Principal Component Analysis and Independent Component Analysis and t-distributed Stochastic Neighbour Embedding) with one supervised ML feature selection technique (Linear Discriminant Analysis) in terms of accuracy of classification. Results show the efficiency of the supervised ML feature selection technique over the traditional feature selection techniques.

KEYWORDS

Food quality, Supervised feature selection, Yogurt preferences prediction, random forest classification

1. INTRODUCTION

Food quality assessment is taken from food attributes that fulfil the needs of the consumer, provide the user with the important nutrients and energy. Food quality and safety have attributes that play a fundamental role in choosing and accepting food products of the consumers, e.g., the nutritional added value and the sensory attribute. Sensory quality combines some specifications such as color, size, smell, shape, and taste, which can be evaluated by the senses of people [6]. People have a growth of interest in health awareness of consumption of probiotics in fermented foods such as yoghurt with probiotics. At the same time, dairy producers have a lot of the focus on consumer taste prediction for a new dairy product. [3, 18].

In the past, food sensory quality assessment was developed as one of the general techniques of sensory study. Moreover, sensory assessment was widely used in quality evaluation, product design in food companies to predict consumers liking of a new food product. Traditional methods like Principal Component Analysis [7] were used to analyze sensory data of food that is supplied by experts. This method can effeciently solve for some datasets, however sometimes it can lead to the loss of information. In this case, other methods were applied such as random forest, neural network, fuzzy logic and support vector machine to deal with uncertainty of sensory assessment. For example, [8] used random forest, [9] applied neural network, [10, 11] fuzzy logic was implemented for vital food products.

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Recently, some researches have approached data mining techniques for assessing the sensory quality of food products based on their physical and chemical composition. Cortez et al. [12] proposed a data mining method to predict the taste of white and red wines using support vector machines, multiple regression and neural network. The results show that the support vector machines method gives the highest accuracy. Debska et al. [13] proposed to apply the neural network to classify Poland's beer on the base of its chemical characteristics. Ghasemi-Varnamkhasti et al. [14] proposed to apply neural network model to assess the sensory properties of commercial non-alcoholic beer brands, and the result shows accuracy about 97%. Dong et al. [15] studied the application of partial least squares, genetic algorithm back-propagation neural network, and support vector machines to identify the relationship between flavor and sensory evaluation of beer. The results show that support vector machines gives the best accuracy (94%). Bi et al. [5] proposed a deep learning model based on autoencoder to extract yogurt features from the sensory attributes and these taken features are regressed with support vector machines analysis.

The previous researchers have demonstrated the importance of accessing data mining techniques in sensory evaluation and quality control of food products. However, the combination between data from sensory attributes and data from food's images was not enough investigated. Also, the choice of the feature extraction method that reduces the number of attributes and improves the accuracy of the classification for the sensory evaluation model was not tested and decided in previous researches.

In this paper, we combine two types of data to assess food quality: the sensory attributes and the color and texture features extracted from images of yogurt samples supplemented with some of probiotics and yeast strains.

The rest of the paper is organized as follows: Section 2 presents the data preparation. Section 3 presents the methodology. Section 4 presents the experimental results and gives a discussion on them. Section 5 concludes the work in the paper and suggests the future work.

2. MATERIALS PREPARATION AND PANELLISTS

Microbial strain collection: All the bacterial strains, yeasts, and were kindly obtained from microbiological resource centers (Cairo MIRCEN, Egypt).

2.1. Preparation of Probiotic Bacterial Strains

Each probiotic bacterial strain (*Bifidobacterium bifidum* DSM 20082, *Lactobacillus Plantarum* DSM 20174 and *Lactobacillus acidophilus* DSM 20079) was cultivated in De-Man-Rogosa-Sharpe broth (MRS). Then the bacterial suspension was adjusted in concentration 10^9 CFU/ml by using a spectrophotometer according to [4].

2.2. Preparation of nonviable yeast Strains

Each yeast strain (*Kluyveromyces lactis* CBS2359 and *Saccharomyces cerevisiae* ATCC 64712) was cultivated individually in Yeast Peptone Dextrose (YPD). Each yeast strain was used as nonviable strains by heating 10 min in an autoclave in starting concentration (10^9 CFU/ml) according to [4].

2.3. Yogurt sample Preparation

The yogurt was made from the total fat from the milk obtained at the dairy supermarket and then boiled for 20 minutes. In addition, that milk kept calling at 43ºC before adding yoghurt starter and the different type of M.Os treatment into the milk.

The 36 yogurt samples were prepared and divided into 6 groups according to the type of treatment M.Os (group 1 was *Bifidobacterium bifidum,* group 2 was *Lactobacillus Plantarum,* group 3 was *Lactobacillus acidophilus,* group 4 was *Kluyveromyces lactis*, group 5 was *Saccharomyces cerevisiae* and group 6 was a mix of all previous bacterial and yeast strains). Each group was stored under different conditions (different storage temperatures and storage times). The storage temperatures included low temperature (4ºC), room temperature (25ºC), and high temperature (38ºC). However, storage periods were classified in one day and two days.

2.4. Sensory Evaluation of yogurt sample

The panel persons of sensory evaluation included 80 members (40 in two days) from the Food Technology Department, and other departments, Arid Lands Cultivation Research Institute and Informatics Research Institute, City of Scientific Research and Technological Applications (SRTA-City).

The 36 yoghurt samples were detected for appearance, consistency, tenderness, flavor and overall acceptance according to scores from 1-7 where as 1= Very poor, 2= Poor, 3= Fair, 4=Medium, 5=Good, 6= Very good and 7= Excellent was the best score according to [4].
Figure 1 shows the preparation of the samples performed in labs

Figure 1. Samples Preparation

3. Methodology

3.1. Data Pre-processing

3.1.1. Color extraction

The images of the 18 samples were acquired in RGB coloured format and then converted to grayscale images. For each channel of the RGB images and the grayscale image, we calculated the mean value of all values ranging from 0 to 255 in the image, also the minimum value across the image and the standard deviation. In other words, three color features were calculated for each of the four images which gives 12 different values for color images for 18 images. Finally, we cluster the 18 samples by means of color features in 3 clusters using k-means clustering algorithm.

3.1.2.Texture extraction

The texture features of the 18 samples were extracted using LBP (local binary pattern). Local Binary Pattern (LBP) is a method that used to describe texture characteristics of the surfaces. By applying LBP, texture pattern probability can be summarised into a histogram. The 256 texture features resulted for each of the 18 samples were clustered in 3 clusters using k-means clustering.

3.2. Feature Selection Methods

Feature selection aims to reduce the number of features in a dataset by creating new features from the existing ones (and then discarding the original features). These new reduced set of features should then be able to summarize most of the information contained in the original set of features which are in our case four sensory attributes appearance, consistency, tenderness, flavour and two attributes extracted from the images describing color and texture

3.2.1.Principal Component Analysis

Principle Component Analysis (PCA) [1] is an unsupervised learning algorithm used as a common feature extraction method in data science. Technically, PCA finds the eigenvectors of a covariance matrix with the highest eigenvalues and then uses those to project the data into a new subspace of equal or less dimensions. PCA is able to do this by maximizing variances and minimizing the reconstruction error by looking at pair wised distances. In PCA, our original data is projected into a set of orthogonal axes and each of the axes gets ranked in order of importance.

3.2.2.Independent Component Analysis

ICA is an unsupervised learning algorithm used for linear dimensionality reduction method. It takes as input data a mixture of independent components and it aims to correctly identify each of them (deleting all the unnecessary noise). Two input features can be considered independent if both their linear and not linear dependance is equal to zero [2].

3.2.3.Linear Discriminant Analysis

LDA is a supervised learning dimensionality reduction technique and Machine Learning classifier. LDA aims to maximize the distance between the mean of each class and minimize the spreading within the class itself. LDA uses therefore within classes and between classes as measures. This is a good choice because maximizing the distance between the means of each class when projecting the data in a lower-dimensional space can lead to better classification results.

3.2.4.T-distributed Stochastic Neighbour Embedding

T-SNE is a non-linear dimensionality reduction technique, which is typically used to visualize high dimensional datasets. T-SNE works by minimizing the divergence between a distribution constituted by the pairwise probability similarities of the input features in the original high dimensional space and its equivalent in the reduced low dimensional space. T-SNE makes then use of the **Kullback-Leiber (KL)** divergence in order to measure the dissimilarity of the two different distributions. The KL divergence is then minimized using gradient descent.

3.3. Classification using Random Forest

Leo Breiman introduced the random forests in 2001[17]. The method builds a forest of uncorrelated trees using a CART like procedure. Random forests average multiple deep decision trees with the aim of reducing the variance [16].

In our work, we adopt the random forest to classify the sensory features into the seven grades given by the expert to assess the yogurt's quality.

3.4. The Evaluation Method

The framework of the sensory evaluation process is given by Figure 2

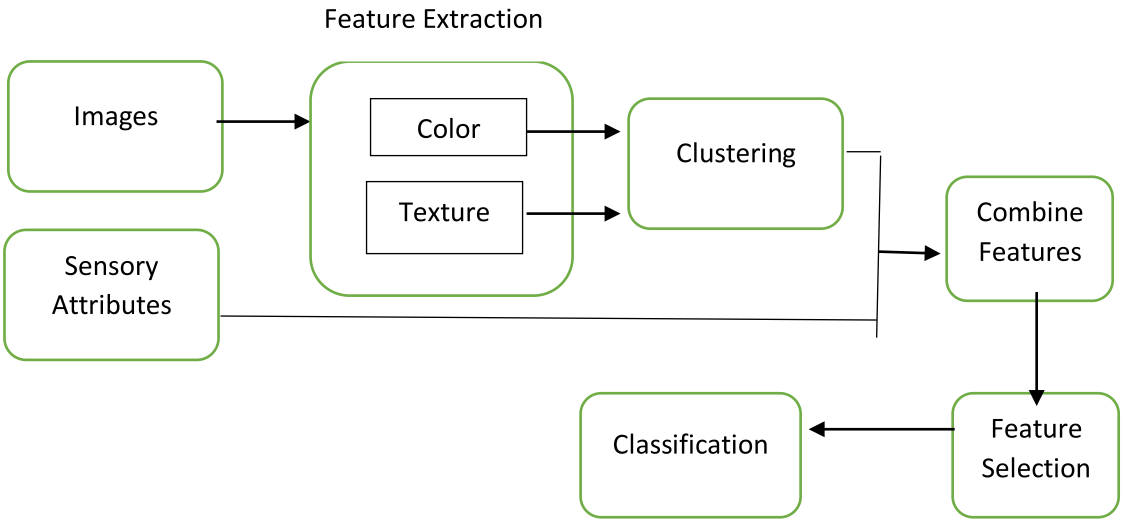

Figure 2. The sensory evaluation framework

4. Experimental Results and Discussion

4.1. Quality Metrics

The Confusion Matrix (CM) gives a comparison between the actual and predicted values to know the performance of a Machine learning classification. The accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of the dataset, i.e. the sum of the diagonal numbers in a confusion matrix divided by all numbers in the matrix

4.2. Results

In this section, we present the results of classification by comparing four feature selection techniques and the non-use of feature selection techniques. Table 1 shows the accuracy of classification without feature selection (FS) and with the use of the Principal Component Analysis (PCA) as feature selection technique and the Independent Component Analysis (ICA), the Linear Discriminant Analysis (LDA) and finally T-SNE

Table 1. The accuracy of classification with different types of feature selection

FS type	**Without FS**	**PCA**	**ICA**	**LDA**	**T-SNE**
Accuracy	0.56	0.54	0.53	**0.58**	0.52

Table 2.The confusion matrix of classification without FS

0	0	1	1	1	0	0
0	**4**	2	0	1	0	0
0	0	**12**	4	1	2	2
0	1	2	**18**	22	7	0
0	0	1	10	**54**	41	3
0	0	0	3	29	**98**	25
0	0	0	2	3	27	**55**

Table 3.The confusion matrix of classification with LDA

0	1	0	1	1	0	0
1	**5**	1	0	0	0	0
0	0	**12**	5	1	2	1
0	0	3	**21**	17	9	0
0	0	1	10	**57**	39	2
0	0	0	8	24	**97**	26
0	0	1	0	6	23	**57**

From Tables 1, 2 and 3, we can notice that using a supervised ML feature selection technique such as Linear Discriminant Analysis can improve the accuracy of the classification from 56% without feature selection to 58%. Also, the accuracy of the classification is not high and this opens the area of research and raises questions like: Are those sensory attributes sufficient to assess the product? Can the grading from 1 to 7 determine well the sense of human?

In sum, we can remark the importance of feature selection to improve the accuracy of classification and also the importance of the use of image features (color and texture) to define the sense of the product in a precise manner.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we presented a new framework to evaluate and predict the consumers' preferences for a dairy product (Yogurt) using sensory attributes and image analysis techniques. We select features by different feature selection techniques. We remark that the classification after LDA gets higher accuracy than all the other techniques. The supervised ML technique overcomes the other traditional techniques.

Future work will include the random forest regression techniques instead of classification. Acquiring data about taste, flavour, smell from persons seems to be easier when taking a percentage rather than a score from 1 to 7.

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