[1]László Sipos, [1]Viktor Losó, [1]Ákos Nyitrai, [1]Zoltán Kókai, [1]Attila Gere

Received: 2017. July – Accepted: 2017. October

Prediction of sensory preference by artificial neural networks, using sweet corn varieties as an example

Keywords: prediction, consumer preference, multi-layer feedforward neural network (MLFN), sweet corn, nutritional parameters of sweet corn, cluster analysis

1. Summary

According to our knowledge, there are only a few publications in available literature sources on the sensory characteristics and consumer preferences of sweet corn varieties. In our research, practical application of artificial neural networks (ANNs) is presented. In our study, 41 frozen sweet corn varieties were evaluated by a panel of expert sensory panelists (14 persons), by the method of profile analysis (MSZ ISO 11035:2001; ISO 13299:2003), on an unstructured scale of 0 to 100, then, in large-scale tests, 6 of the 41 varieties were evaluated by consumers (167 people) according to preference, on a structured scale of 1 to 9.

Artificial neural networks require large amounts of data, therefore, on the expert and consumer data for the 6 varieties, 1,000 Monte Carlo simulations were run. 80% of the resulting dataset was used to train the created neural networks, and 20% was utilized to test them. The best prediction was given by the 4-node multi-layer feedforward neural network (MLFN), the smallest residues were obtained in this case during the training and the test, which were also validated by predictions on random numbers and cross-checking. Preference values of the other 35 corn varieties were predicted by this model. The most preferred variety was 'Shinerock' (8.46), while the least preferred ones, according to the predictions, were 'Madonna' and 'Rustler', with and average preference value of 2.7 (on a scale of 1 to 9).

During the establishment of the artificial neural network model, product characteristics that are the main drivers of consumer acceptance were successfully identified: sweet taste, global taste intensity and juiciness. In general, it can be stated that prediction of the preference of different varieties is made possible by the validated product-specific artificial neural network presented.

2. Introduction and literature overview

For the development of artificial neural networks, revealing the analogy, the structure and functioning of the human nervous system was of key importance. Neural network programs were originally developed as a model for the nervous system, where signals coming from other neurons are collected by the inputs, summation is carried out by the processing unit (neuron), and then, depending on the result, the signal is transmitted by the outputs **[1]**, **[2]**, **[3]**, **[4]**, **[5]**. A breakthrough in the research of artificial neural networks was achieved by the work of Hopfield **[6]**, and Rumelhart et al. **[7]**, in which non-linear mapping was achieved by the dynamic modeling of neural network programs, as well as feedback between the outputs and the inputs. Artificial neural networks in today's

[1] Szent István University, Faculty of Food Science, Department of Postharvest and Sensory Evaluation

sense are network systems organized by the connection of simple processing units (neurons) capable of parallel operation, possessing learning and information recall algorithms.

Artificial neural networks are systems that learn from past experience, and are able to recall the things learned. Their main advantages are non-linearity, good fit, parallel calculations, high calculation speed and adaptability. The most important application areas are the identification of outliers, identification of the correlation between variables, space reduction, regression between nonlinear variables, modeling of complex relationships, classification and categorization **[8]**, **[9]**.

The most important parts of neural networks are the elements making up the network (neurons/nodes), network connections (structure/topology) and learning algorithms. The operating principle of ANN is based on the modeling of functional connection between the input and corresponding output variables: $y = f(x)$, where x and y are the input and output vectors, and the symbol f indicates that there is a functional connection. The signals received by the neurons are multiplied by the corresponding weighting factors, and then these are summed up. Next, the value of the output signal is calculated by the neuron, typically by a nonlinear transformation function – step, hyperbolic tangent, logistic, sigmoid, etc. These neuron units may be connected to the neurons of other layers, passing the information from one neuron to the next until the final output, where the input signal becomes an output signal **[10]**.

Determining the number of layers and neurons is particularly important, because it determines whether the network will be able to learn the relationships between independent and dependent variables. The number of hidden layers and the number of neurons in the hidden layers depends on the complexity of the classification task and the amount of data. In general, networks that contain one hidden layer and two hidden neurons cannot be trained to a satisfactory level of error. Any linear or nonlinear problem can be solved with the help of a hidden layer and a sigmoid activation function. The use of two or more hidden layers will unnecessarily increase training time. Usually, a few neurons are enough in a hidden layer. The number of branches (neurons) in the input layer is in accordance with the number of variables describing the subjects classified, while the number of branches in the output layer increases with the number of classes **[11]**, **[12]**, **[13]**.

Based on the learning methods of networks, we can distinguish between *supervised* and *unsupervised* networks. Based on the connections and structural system (topology) of supervised learning networks, they can be either *feedforward networks* or *recurrent networks*. In multi-layer feedforward networks, information flows forward in a way that neurons in the given layer do not receive a signal until it is produced by the units in the previous layer, so the output vector of each layer is also the input vector of the next layer. Unsupervised learning networks include Kohonen-based structures **[10]**. Practical application of neural networks consists of three main steps. The neural network is built up during the learning phase, the validation, with model indicators, of the neural network created is performed in the validation step, and the applicability of the neural network can be investigated by the testing step **[5]**, **[11]**.

In the following paragraphs, the most relevant nutritional, agrotechnical and breeding issues of sweet corn will be presented. Vegetables greatly contribute to the supply of vitamins and minerals for the human body, they affect carbohydrate and fat metabolism, and all other processes in the body that are related to their fiber content **[14]**. Compared to the average vegetable, sweet corn has a high energy content. Its nutritional significance is primarily due to its carbohydrate and protein content. It is characteristic of the carbohydrate profile of sweet corn varieties that the relative weight of the disaccharide sucrose, made up from a glucose and a fructose unit, is generally the highest (85%), followed by glucose (10%) and fructose (5%). Super-sweet varieties contain three to four times more sucrose, compared to normal sweet varieties. Glucose, as a simple sugar, is the direct energy source of the body, the energy-producing compound that can be utilized the fastest and due to this, its glycemic index is the highest among all carbohydrates. The sweetness of glucose is roughly three quarters of that of sucrose. Fructose can be found in most fruits and vegetables. Due to its slow utilization, it increases blood sugar levels more slowly, its glycemic index is the lowest among sugars and, besides, its sweetening ability is 1.2 to 1.8 times higher than that of sucrose, so to achieve the same sweetening effect, less fructose is needed **[15]**. Fast-frozen sweet corn provides valuable nutrients for consumers throughout the year. Nutritional values of sweet corn are generally calculated for 100 grams of kernels **[16]** (***Table 1***).

Agro-ecological conditions in Hungary are favorable for the growing of sweet corn, however, the effects of climate change cannot be ignored. The rates of processing of sweet corn produced in Hungary have been almost constant for years. 99% of sweet corn is processed industrially, two thirds of which is processed by the canning industry, and one third by the refrigeration industry as quick-frozen products. 1% of the harvest is consumed fresh. Sweet corn is one of the domestic industrial plants that are competitive on a global level. Over the past decade, Hungary has been among the first countries of the volume of quick-frozen sweet corn exported, however, it is important to stress that Chinese production and trade data are not included in international databases, or only as estimates **[17]**.

Varietal selection activities have typically been performed by international and domestic breeders with the considerations of cultivation and the processing industry in mind. At the same time, demands of the stakeholders of the sweet corn sector (growers, processors, merchants, consumers) are significantly different. The main goal of the cultivation of sweet corn is to increase profitability and, accordingly, the main considerations of growers are average yield per hectare, resistance to pests, planting period, ear yield, ear length, productivity, drought tolerance, stem strength, increase in kernel row number, ability to adapt to climate change, increasing crop safety, reducing ripening time. The most important consideration of processors is efficient processability: tenderness, homogeneity (ear straightness, kernel row straightness), kernel yield, shellability, increasing the efficiency of the machines used in technological processes. Currently, there are 10 to 15 varieties of sweet corn, optimized for industrial and cultivation properties, that are most popular in the processing industry. The above-mentioned properties are primarily genetically encoded in the genes of the varieties, however, these properties can be influenced by environmental conditions (ecological conditions, agrotechnical operations). The most important considerations of merchants are profit maximization and marketable product benefits: uniform color, kernel size, flavor and firmness characteristics. It is common practice in commerce that partners decide whether to buy the crops offered on the basis of sensory tests performed on samples sent by the supllier **[15]**.

3. Objective

Domestic research usually focused on processing industrial quality, plant and agronomic properties, as well as disease resistance **[18]**. No complex evaluation of the sensory properties of varieties in the national and international catalogs of varieties has been carried out. Even less is known about the sensory characteristics and consumer preferences of quick-frozen corn hybrids. No detailed investigations, focusing on consumer demand and broken down by variety, have been published so far. Therefore, our investigations were aiming to predict preference values, with the help of neural networks created on the basis of the expert sensory profiles of certain frozen sweet corn varieties and their consumer preference, the preference for other varieties.

4. Materials and methods

4.1. Sweet corn varieties

The subjects of the research were quick-frozen samples of sweet corn varieties. 41 sweet corn varieties were included in the research, and samples were designated by the names of the varieties. Over the years, some of the selected varieties have demonstrated their ability to grow continuously, however, most of them have a smaller share in the processing industry, and little is known about their sensory properties and popularity (***Table 2***).

Sample preparation was carried out in identical manner in each case (cooking time, container size, material, brand, hotplate size and temperature, water volume etc.). When serving the samples, the recommendations of Kilcast **[19]** were also taken into account, according to which, for better homogeneity, the serving samples were prepared were prepared by the same person. 100 g of the sample of the same temperature in identical containers were evaluated by each judge. In accordance with international practice, samples were encoded by three-digit numbers generated by a random number generator **[20]**. In the literature, different foods are used for flavor neutralization between the samples, depending on the nature of the product, in our test we used mineral water **[21]**.

4.2 Expert profile analysis method

The method of profile analysis is one of the most complex sensory tests, entirely (color, taste, aroma, consistency) characterizing the given food. Samples are evaluated by the panelists along sensory properties, with the help of scales. For classification, descriptive terms were defined by members of the sensory panel in two stages, first individually, and then through group work. In the case of this method, typically several properties are evaluated by the members of the sensory panel **[22]**, **[23]**.

Planning and execution of the experiment, determination of the number of products to be included and of the panelists, and the evaluation of the results were carried out in accordance with the relevant standards **[24]**, **[25]**. In our research, experimental samples were evaluated by the panelists using the ProfiSens sensory software developed by the Budapest University of Technology and Economics, Department of Biochemistry and Food Technology and Szent István University, Laboratory for Sensory Analysis. With the help of the software, by filling in a few dialog boxes, the evaluation sheet, the *kitchen list* and the sample codes for the distribution of the samples can be prepared. Accordingly, qualification was carried out through the following steps:

Panelists received a series of samples labeled with three-digit codes, and these were evaluated each attribute on scales. The 16 sensory attributes had been determined by the panel of expert panelists. Evaluation by the panelists was carried out on an unstructured scale of 0 to 100, the two extreme values of which were determined by consensus. To reduce the standard deviation of the given scores the scale was anchored, and the reference values of one of the corn varieties (*'Royalty'*) were determined for each property, which were as follows: yellow color (60), shade (85), kernel size (55), unevenness of kernel size (80), freshness (85), global smell intensity (70), cooked corn smell (85), sweet smell (70), consistency (75), juiciness (75), skin chewability (85), tenderness (45), global flavor intensity (40), sweet taste (35), cooked flavor (20), aftertaste (0).

Evaluation were carried out on computers in a local area network, in sensory booths separated from each other. After the evaluation, results for the individual samples and properties were read from the filled-in electronic evaluation sheets by the ProfiSens software. After statistical evaluation of the results, the profile diagrams of the varieties were obtained and, in addition to the average value and the standard deviation for each property, one-way analysis of variance was carried out, and in cases where there was a significant difference, *post hoc* tests were performed at two different probability levels (p=5% and p=1%) for each pair. Expert evaluations begin at 10 am on two consecutive days, so two repetitions were carried out. Members of the expert panel possessed „trained assessors" qualifications and experience (14 people). The people performing the evaluation had been members of the panel of the Laboratory for Sensory Analysis of Szent István University for several years, with extensive experience in the use of both the method and the software, and had been participating in similar tests and product-specific studies regularly **[26]**. Tests were carried out in the Laboratory for Sensory Analysis of Szent István University, established in accordance with international guidelines **[27]**.

4.3 Consumer preference testing

The 6 of 41 varieties to be tested by consumers were selected on the basis of the sensory profile characteristics of the varieties. For this reason, cluster analysis (*Agglomerative Hierarchical Clustering*, AHC) was carried out for the expert evaluation data performed earlier, using Euclidean distance and the Ward method. During clustering, results of the expert panelists were averaged, thus creating the input product property × variety matrix. The optimal cluster number was determined by the Silhouette index, which gave the highest value in the case of the six-cluster solution **[28]**. For each cluster thus obtained, the varieties that describe best the given cluster were determined by the *sum of ranking differences* (SRD) method **[29], [30]**. This way, the six "most average" varieties in the clusters (one for each cluster) were obtained. Sensory evaluation of the six samples obtained were carried out by the consumer panel.

The 6 samples were tested by by a consumer panel (167 people), who had received information only regarding the use of the scales and the software. They did not have any special qualifications, either practical or theoretical, related to the product, and the sensitivity of their senses had not been investigated either. Consumers provided answers regarding the global preference of the products on a 9-point, structured, continuously increasing scale (1=not at all, 2=very much not, 3=moderately not, 4=slightly not, 5=neutral, 6=slightly preferred, 7=moderately preferred, 8=very much preferred, 9=most preferred).

4.4 Artificial neural networks used

Our research was carried out using the Neural Tools ver. 5.5 software of the Palisade software family. During partitioning, the model was trained on 80% of the data of 1,000 Monte Carlo simulations, and starting data for the test runs were provided by the remaining 20%. For the optimization of the *multi-layer feedforward neural network* (MLFN) structure, the „Best Net Search" option was selected, which tests five nets with 2 to 6 nodes, and then selects the one giving the best prediction. The „Best Net Search" option of NeuralTools was developed to prevent overtraining. By default, „Best Net Search" starts to test a net with 2 neurons, which is typically too small to overtrain. With default settings, it will train nets with up to 6 neurons. If nets with 5 or 6 neurons are overtrained, it will appear in the results. The testing error of one of the nets with 2, 3 or 4 neurons will be the lowest.

5. Results

Using the „Best Net Search" setting, six MLFN configurations were tested by the software, until the configuration giving the best prediction was selected (***Figure 1***). In the case of consumers, best results were given by the 4-node MLFN (***Table 3***).

When developing the MLFN model, samples for training were selected at random. Residues of the model indicate how accurately consumer preference can be predicted, based on expert data. Minimum residues were given both during training and the test by the net consisting of 4 nodes. Validity of the neural network obtained was tested by predictions on random numbers, in addition to the interpretation of the residues. Based on the results thus obtained it was found that random numbers were predicted incorrectly by the network, no correlation was found between the data. In addition to the above, cross-checking of the model was also performed, based on which it showed no significant deviations. During the check, the net gave an accuracy value of 87%. based on this, the model was accepted, and the 4-node MLP model was used to predict the popularity of the other varieties, based on expert data.

According to the model developed, the most preferred variety on a 9-step scale was *'Shinerock'* (8.46), while the least preferred varieties were predicted to be *'Madonna'* and *'Rustler',* with average preference values of 2.7 (***Table 4***).

The order of importance of the variables that play a role in the structure of the nets was also given by the Palisade software during the training and testing of neural networks (***Figure 2***).

In the case of sweet corn varieties, during the search for the correlation between expert data and consumer preference data, the most important variables were found to be sweet taste (18%), global flavor intensity (14%) and juiciness (12%). This means that, based on the results of the network, higher preference scores were given by the consumers when evaluating juicy products with an intensive sweet flavor. Results support the conclusions of earlier studies **[31], [32], [33]**.

Results thus obtained were then compared to the initial clusters from which the neural network was built, following the selection of the „most average" varieties (representing the members of the cluster the most). It can be seen from the results of ***Table 5*** that the sweet taste intensities of the first two clusters have significantly higher values than the other clusters (there is no clear separation from cluster 5).

Similarly, higher values were also received by the first two clusters for global flavor intensity, however, clusters 3 and 6 also have high values, so they differ significantly from clusters 4 and 5, based on the results of the Tukey-HSD test. It is important to note that, during the evaluation of global flavor intensity, panelists perform the evaluation on the basis of total flavor intensity, and these flavors do not necessarily represent an advantage during consumer evaluation. Based on tenderness, in addition to the first two clusters, members of cluster 6 possess significantly higher values compared to the other clusters, so the clusters tested were divided into two groups (***Table 6***).

Results show that the first two clusters possess intensive global and sweet taste, and these were significantly tender products. Results are also reflected in the predicted consumer results, because the first two clusters received almost identical results, an average preference value of 6.8, based on the neural network. The average preference value of the third cluster was 5.2, largely due to its high (80) global flavor intensity value. The next group consists of the fourth and sixth clusters with average preference values of 4.0 and 4.3, respectively. Members of the sixth cluster possess higher tenderness and global flavor intensity values, while members of the fourth cluster have a mediocre tenderness value. The least preferred samples are contained in the fifth cluster, with low intensity values for all three product properties important for preference prediction.

6. Conclusions

The presented approach, which combines the artificial neural networks presented and Monte Carlo simulation proved to be suitable to predict consumer preference, based on expert sensory testing results. The advantage of this approach is that consumer tests requiring a lot of time, energy and expenditure can be successfully replaced by predictions based on expert data. The preference values of 36 sweet corn samples were successfully predicted on the basis of the consumer evaluation of six samples. During the development of the artificial neural network model, product properties that are the main drivers of consumer acceptance were successfully identified. These are, in the order of importance: sweet taste, global flavor intensity and juiciness. In the future, it would be advisable to extend our research to other horticultural and food products, or use it in the case of products for which consumer preference is not influenced by only a few, easily identifiable product characteristics. Another option is the creation of a software implementation simplifying calculation steps, thus testing and validation of networks, as well as the prediction of new date could be performed by a single software.

In summary, it can be concluded that validated product-specific artificial neural networks can make the determination of the most important sensory properties possible. As a result of the new approach, results will be more reliable, repetitions can be carried out more easily, tests can be reproduced better, overall creating a time- and cost-effective analytical system.

7. Acknowledgement

Emberi Erőforrások Minisztériuma

Our research and work was carried out with the support of the ÚNKP-17-4 New National Excellence Program of the Ministry of Human Capacities, the János Bolyai research scholarship, and grant no. OTKA K112547. We express our thanks for the support.

8. References

[1] McCulloch, W. S. and Pitts, W. H. (1943): A logical calculus of the ideas immanent in nervous activity. Bulletin of Mathematical Biophysics, 5, 115–137.

[2] Hebb, D.O. (1949): The organization of behavior: A neuropsychological theory. New York, John Wiley and Sons. 335.

[3] Rosenblatt, F. (1958): The perceptron: A probabilistic model for information storage and organization in the brain. Psychological Review, 65 (6), 386–408.

[4] Widrow, B. and Hoff, M.E. Jr. (1960): Adaptive Switching Circuits. IRE WESCON Convention Record. 96–104.

[5] Borosy, A. P. (2001): Mesterséges ideghálózatok. In: Horvay szerk. Sokváltozós adatelemzés (Kemometria). Budapest, Nemzeti tankönyvkiadó. 312–329.

[6] Hopfield, J. (1982): Neural networks and physical systems with emergent collective computational abilities, Proc. Natl. Acad. Sci. U.S.A., 79 (8) 2554–2558.

[7] Rumelhart, D.E. and McClelland, J.L., eds (1986) Parallel Distributed Processing, Explorations in the Microstructure of Cognition, MIT Press.

[8] Horváth G. (szerk.) (2006): Neurális hálózatok. Altrichter M., Horváth G., Pataki B., Strausz Gy., Takács G., Valyon J., Neurális hálózatok, Budapest, Panem Kiadó, 2006.

[9] Sipos László, Gere Attila, Kókai Zoltán, Szabó Dániel (2012): Mesterséges ideghálózatok (ANN) alkalmazása az érzékszervi minősítés gyakorlatában. 58, (1-2), 32-46.

[10] Marini, F. (2009): Artificial neural networks in foodstuff analyses: Trends and perspectives. A review. Analytica Chimica Acta, 635, 121–131.

[11] Debska B., Guzowska-Swider, B. (2011): Application of artificial neural network in food classification. Analytica Chimica Acta, 705, 283–291.

[12] NeuralTools Version 5.7 Manual (2010).

[13] Fu, LiMin (1994): Neural Networks in Computer Intelligence. McGraw-Hill, Inc. pp. 1-416.

[14] Székely Géza, Losó Viktor, Tóth Arnold: Nemzetközi és hazai zöldség-gyümölcsfogyasztás, módszertani kérdések- ÉVIK 2015/1

[15] Losó Viktor (2015): Gyorsfagyasztott csemegekukorica termékek komplex értékelése. Doktori Értekezés. Budapesti Corvinus Egyetem. 7-27.

[16] Bíró, Gy., Lindner K. (Szerk.) (1999): Tápanyagtáblázat: Táplálkozástan és tápanyagösszetétel, Budapest, Medicina Kiadó.

[17] Fodor, Z. (szerk.) (2016): Zöldség és gyümölcs ágazat helyzete Magyarországon. Budapest, FruitVeB Magyar Zöldség-Gyümölcs Szakmaközi Szervezet. 1-31.

[18] Orosz, F. (2009): Termesztéstechnológiai elemek hatása acsemegekukorica koraiságára. Doktori értekezés, Budapest. p. 1- 157.

[19] Kilcast, D. (2010): Sensory analysis for food and beverage quality control. Woodhead, Cambridge, UK.

[20] MSZ ISO 6658:2007 Érzékszervi vizsgálat. Módszertan. Általános útmutató

[21] Sipos, L. (2009): Ásványvízfogyasztási szokások elemzése és ásványvizek érzékszervi vizsgálata. Doktori értekezés. Budapesti Corvinus Egyetem. 80-102.

[22] Kókai, Z. (2003): Az almafajták érzékszervi bírálata. Doktori értekezés. Budapest: Budapesti Közgazdaságtudományi és Államigazgatási Egyetem, 35-59.

[23] Varela, P., Ares, G. (2014): Novel Techniques in Sensory Characterization and Consumer Profiling, CRC Press, pp. 9-41.

[24] MSZ ISO 11035:2001 Érzékszervi vizsgálat. A leíró kifejezések azonosítása és kiválasztása érzékszervi profilhoz többdimenziós eljárással

[25] ISO 13299:2003 Sensory analysis – Methodology – General guidance for establishing a sensory profile

[26] MSZ EN ISO 8586:2014 Érzékszervi vizsgálat. Általános útmutató a kiválasztott bírálók és az érzékszervi szakértő bírálók kiválasztásához, képzéséhez, valamint folyamatos ellenőrzéséhez

[27] MSZ EN ISO 8589:2015 Érzékszervi vizsgálatok. Általános útmutató a bírálati helyiségek kialakításához

[28] Chen G.X, Jaradat S.A, Banerjee N., Tanaka T.S., Ko M.S.H., Zhang M.Q. (2002): Evaluation and comparison of clustering algorithms in analyzing ES cell gene expression data. Stat Sin, 12:241–262.

[29] Héberger, K. (2010): Sum of ranking differences compares methods or models fairly. Trend. Anal. Chem. 29, 101–109.

[30] Héberger, K., Kollár-Hunek, K. (2011): Sum of ranking differences for method discrimination and its validation: comparison of ranks with random numbers. Journal of Chemometrics, 25, (4) 151–158.

[31] Gere, A., Losó, V., Tóth, A., Kókai, Z., Sipos, L. (2012): Kukorica fajták preferenciatérképezése szoftveres támogatással. Élelmiszervizsgálati Közlemények, 58, pp. 118-130.

[32] Gere, A., Losó, V., Radványi, D., Juhász, R., Kókai, Z., Sipos, L. (2013): Csemegekukorica fajták komplex értékelése. Élelmiszervizsgálati Közlemények, 59, pp. 120-134.

[33] Gere, A., Losó, V., Györey, A., Kovács, S., Huzsvai, L., Nábrádi, A. Kókai, Z., Sipos L. (2014): Applying parallel factor analysis and Tucker-3 methods on sensory and instrumental data to establish preference maps. Case study on sweet corn varieties. Journal of the Science of Food and Agriculture, 94, 15, pp. 3213-3225.