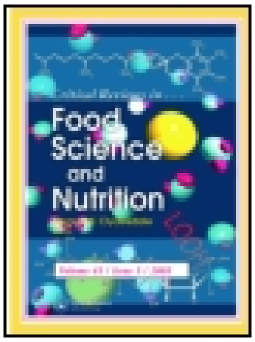

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A critical review on the use of artificial neural networks in olive oil production, characterization and authentication

I. Gonzalez-Fernandez, M. A. Iglesias-Otero, M. Esteki, O. A. Moldes, J. C. Mejuto & J. Simal-Gandara

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A critical review on the use of artificial neural networks in olive oil production, characterization and authentication

I. Gonzalez-Fernandez[a,b], M. A. Iglesias-Otero[a,b], M. Esteki[c], O. A. Moldes[b], J. C. Mejuto [b], and J. Simal-Gandara [d]

[a]DQBito Biomedical Engineering, Baiona, Pontevedra, Spain; [b]Department of Physical Chemistry, Faculty of Sciences, University of Vigo – Ourense Campus, Ourense, Spain; [c]Department of Chemistry, University of Zanjan, Zanjan, Iran; [d]Nutrition and Bromatology Group, Department of Analytical and Food Chemistry, Faculty of Food Science and Technology, University of Vigo – Ourense Campus, Ourense, Spain

ABSTRACT
Artificial neural networks (ANN) are computationally based mathematical tools inspired by the fundamental cell of the nervous system, the neuron. ANN constitute a simplified artificial replica of the human brain consisting of parallel processing neural elements similar to neurons in living beings. ANN is able to store large amounts of experimental information to be used for generalization with the aid of an appropriate prediction model. ANN has proved useful for a variety of biological, medical, economic and meteorological purposes, and in agro-food science and technology. The olive oil industry has a substantial weight in Mediterranean's economy. The different steps of the olive oil production process, which include olive tree and fruit care, fruit harvest, mechanical and chemical processing, and oil packaging have been examined in depth with a view to their optimization, and so have the authenticity, sensory properties and other quality-related properties of olive oil. This paper reviews existing literature on the use of bioinformatics predictive methods based on ANN in connection with the production, processing and characterization of olive oil. It examines the state of the art in bioinformatics tools for optimizing or predicting its quality with a view to identifying potential deficiencies or aspects for improvement.

KEYWORDS
Artificial neural networks (ANN); olive oil production; olive oil characterization; olive oil authentication

1. Artificial neural networks and its potential in olive oil production, characterization and authentication

Biological insights can be used to solve computational problems as a "translation" of biological phenomena into formal mathematical models. Most computational models inspired by biological systems contain special capabilities, which lead to ability to solve complex computational problems. *Artificial intelligence (AI)* is a term coined by John McCarthy in 1956, and can be defined as the application of computational systems to mimic human intelligence processes. This concept has evolved in parallel with definitions of human intelligence. Providing an exact, comprehensive definition for "artificial intelligence" is rather complicated owing to the linguistic, philosophical, economic, biological, mathematical and engineering nuances of the term.

Artificial intelligence has been mimicked in various ways for a variety of purposes. AI approaches include pattern recognition techniques, probability-based models, rule-based models, fuzzy logic systems, graph theory, non-linear dynamic algorithms and the most potentially successful predictive tool of this type: artificial neural networks. The model inspired by a biological system such as the brain and the nervous system has a particular capability named the learning ability. In addition to scientific curiosity, researchers try to pattern the brain when designing computational systems for many practical reasons. The brain presents many desired properties that may be hardly achieved in standard digital computational systems:

i) Fault tolerance and robustness: Specific nerve cells may die without affecting the functionality of the system; which means that the brain can tolerate damages which are not widespread;
ii) Ability to handle the inconsistent, noisy, or unreliable data: our daily experience shows that the brain is capable of reaching correct decisions, even when the relevant data are not fully reliable and complete;
iii) Computation in the brain happens simultaneously in different regions and is based on the local interaction between neurons connected to each other (parallelism);
iv) The brain does not contain a clock to synchronize the different computational processes however; it can handle the computation itself effectively (asynchronous); and
v) As the simpler organisms brain, the human brain, can adapt the organism's behavior to changing environments (learning ability); in contrast to computers, which have to be reprogrammed when computational challenges change.

Artificial neural networks (ANN) are computational models based on the structure and functions of the nervous system and

CONTACT J. Simal-Gandara jsimal@uvigo.es Nutrition and Bromatology Group, Department of Analytical and Food Chemistry, Faculty of Food Science and Technology, University of Vigo–Ourense Campus, Ourense, Spain.
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the brain. The brain is composed of a large number (about 10^{11}) of interconnected neurons; similarly, a neural net is a set of interconnected simple computational units. Using ANN has some advantages arising from their structure and special properties; ANNs are flexible, applicable to a variety of problems and situations, adaptable (*e.g.*, compatible with noise). ANNs have been successfully used for predictive purposes in the economic, marketing and financial (Chen, Leung, and Daouk 2003; Wang et al. 2012), industrial and manufacturing domains; It has also been deployed (Melin and Castillo 2007), in medical and pharmaceutical research (Chen et al. 1999; Sun et al. 2003) for physical–chemical characterization of properties and processes (Astray et al. 2013); in telecommunications (Kunz 1991); in environmental works (Iglesias-Otero et al. 2015); and for weather forecasting (Maqsood et al. 2005). The computing technologies in general, and ANN in particular, are also highly useful with a view to improving time- and cost-effectiveness in agro-food processes, and to authenticating agro-food products and especially olive oil.

ANNs constitute the most widely used bio-inspired model for characterizing and/or optimizing olive oil production, and for assessing quality and authenticity of the oil. In addition to general interests in artificial neural nets, more specifically they've grabbed the attention of those working on more complicated (in terms of learning or generalizing requirement, for instance) problems. An ANN consists of a large number of individual elements (viz., artificial neurons, which are assumed to be similar to natural neurons) working in parallel. Like the human brain, ANNs have the ability to "learn" thus, by using a significant enough data set in the form of input–output pairs, an ANN can provide a predicted output for new input data similar to the data sets used in the so-called "training process".

Artificial neural networks are intended to mimic the neural connection model of the human nervous system through the connection of neurons to one another in order to form layers and a series of mathematical functions providing the conversion of an input into an output that is the weighted sum of the outputs from the previous layer. As a result, the network output is a function of its inputs. During the "learning" or "training" process, the weighting parameters for the different nodes are modified so as to have the calculated output match the actual output, as precisely as possible. An ANN is thus a dynamic system. Furthermore, a collection of individual neurons, which are independently capable of data processing, creates neural network and the information handled by the whole network is distributed among the neurons. This feature would result in a highly robust system in which, changing the information stored in one element —or even suppressing that element— will have a little effect on the final output. This is not the case with other computational methods; where altering or suppressing a single factor can significantly affect the output.

Artificial neural networks can be developed by using commercially available software with a user-friendly interface providing multiple choices for data input and selection of parameter values for the learning process. Using powerful hardware also allows several learning processes to operate simultaneously. Additionally, new ANN does not need any especial programming language and existing libraries in C++ could be enough to develop this model. Table 1 summarizes the landmarks in the development of artificial intelligence and artificial neural networks.

Neural networks consist of layers or levels containing groups of neurons that use information from the same source. Layers are usually identified by the number of the belonging neurons (for example 3–3-5–1 ANN contains 3 neurons in the input layer, 1 in the output layer and the two intermediate layers contain 3 and 5 neurons, respectively). Neurons can be in either of two states depending on whether they are delivering an impulse to another neuron or not, namely, excited (active) or at rest. The difference is governed by activation values, which can be discrete or continuous. Following relation yields the state of a body of neurons in which $a_i(t)$ reflects the activate state of neuron I at a given point in time t.

$$A(t) = [a_1(t), a_2(t) \; ...a_i(t) \; ...a_n(t)]$$

The output neuron are returned by this function, known as transmit or activation function, applied to the value of other neurons. As a result, the activation state $a_i(t)$ is converted into an output form

$$x_j(t) = f_i[a_i(t)]$$

Therefore, the overall vector including all outputs is as follows:

$$X(t) = [f_1(a_1(t), f2(a_2(t) \; ..fi(a_i(t) \; ..f_n(a_n(t)]$$

Most of the artificial neural networks (Figure 1) operate as a multilayer perceptron (Figure 2), where each input variable is related to a variable in the next layer via appropriate coefficients (weights), the process repetition continues until the last (output) layer is reached. At this point, the resulting prediction is compared with the actual datum to adjust all weights over successive cycles, until the difference between the predicted and actual values falls below a pre-set level. Once all weights were adjusted, new input data would be employed to obtain refined predictions (output values) in the so-called "validation process".

ANNs are mainly appropriate to model non-linear problems; however, it should be noticed that ANNs contain a number of adjustable parameters makes them prone to overfitting which refers to start 'noise' fitting and thereby impairing its generalization accuracy that may finally result in worse predictive ability of a network. Non-linear regression is one of the most remarkable features of artificial neural networks, which most commonly used in olive oil characterization. For the present purposes, it is particularly useful for assurance and assessment of the oils quality with a protected denomination of origin, as well as regulation of the extraction and refining processes.

Since oil blends with a certified composition are difficult to obtain, data on mixtures can be computationally simulated from the experimental data in order to construct a model to examine a wide variety of possible experimental analytical inputs and assess the outputs. Therefore, a training set is selected as representative as possible. Then, the parameters would be optimized based on the comparison of the experimental outputs and the predicted ones;

Table 1. Landmarks in the history of artificial intelligence and artificial neural networks.

Year	Contributors	Landmark
1936	Alain Turing	Informatics is related to the human brain
1943	Warren McCulloch Walter Pits	Neural operation theory and a primitive neural network model
1949	Donnal Hebb	Neural pathways are strengthened each time they are used: two nerves fire at the same time, the connection between them is enhanced
1957	Frank Rosenblat	Development of one of the earliest types of neural networks: the Perceptron
1959	Bernard Widrow Marcian Hoff	ADALINE and MADALINE models were developed
1960	Stephen Grossberg	Development of Avalanche, a neural network for voice recognition and movement learning
1962	Bernard Widrow Marcian Hoff	New learning procedures were developed
1972	Teuvo Kohonen James Anderson	New network are developed: the neurons are supposed to activate a set of outputs instead of just one.
1975		First multilayered unsupervised network was developed
1980	Kunihiko Fukushima	Neocognitron, a neural network for visual pattern recognition
1982	John Hopfield	More useful machines were developed using bidirectional lines
	Douglas Reily Leon Cooper	“Hybrid network” with multiple layers, each layer using a different problem-solving strategy
		US-Japan conference on Cooperative/Competitive Neural Networks
1985		American Institute of Physics began what has become an annual meeting – Neural Networks for Computing
1986	David Rumelhart	Back propagation networks
1987		Institute of Electrical and Electronic Engineer’s (IEEE) first International Conference on Neural Networks
1988		International Joint Conference on Neural Networks
		INNS journal *Neural Networks* was founded
1989		Neural Networks for Defense Meeting
		Journal *Neural Computation* was founded
1990		US Department of Defense Small Business Innovation Research Program named 16 topics which specifically targeted neural networks
		IEEE Transactions on Neural Networks was founded.
1990		IEEE International Workshop on Cellular Neural Networks and their Applications
1990	Barak Pearlmutter	Dynamic recurrent neural networks
1991		First International Forum on Applications of Neural Networks to Power Systems
1991		IEEE First International Neural Networks Workshop for Signal Processing
1991	Hideyuki Takagi	Combining an artificial neural network (NN) and fuzzy reasoning
1992		International Workshop on Combinations of Genetic Algorithms and Neural Networks
1992	William Finnoff	Improving Model Selection by Nonconvergent Methods
1992	Linko, P.	Application of neural network modeling in fuzzy extrusion control.
1992	Shin-ichi Horikawa	Combination of fuzzy with back propagation algorithm.
1993		IEEE International Workshop on Neural Network Applications and Tools.
1993	Sushmita Mitra	Combination of fuzzy and MLP for classification and rule generation.
1993		The First New Zealand International Two-Stream Conference on Artificial Neural Networks and Expert Systems
1994		IEE Colloquium on Applications of Neural Networks to Signal Processing
1994		IEE Colloquium on Hardware Implementation of Neural Networks and Fuzzy Logic
1995		IEE Colloquium on Grounding Representations: Integration of Sensory Information in Natural Language Processing, Artificial Intelligence and Neural Networks
1996	Yun Li	Artificial evolution of neural networks and its application to feedback control
1995	J Zhang	Integration of artificial neural network (NN) with wavelet analysis
1996		International Workshop on Neural Networks for Identification, Control, Robotics and Signal/Image Processing
1997		IEE Colloquium on Neural Networks for Industrial Applications
1998		IEE Colloquium on Neural Networks in Interactive Multimedia Systems
2000	Rich Caruana	Improving the standard BP algorithm to overcome data over-fitting
2000		IEEE First Symposium on Combinations of Evolutionary Computation and Neural Networks.
2000		IEEE International Conference on Neural Network Applications in Electrical Engineering
2000	H. L Shashidhara	Combination of neural networks and wavelet analysis
2000		IEEE First International Conference on Intelligence Systems Design and Applications
2003		5th International Conference on Computational Intelligence and Multimedia Applications
2003	Y. Chtioui	Self-organizing map combined with a fuzzy clustering
2004	L. O. Odhiambo	Investigation of a fuzzy-neural network application in classification
2005		IEEE International Conference on Neural Networks and Brain
2008		IEEE First International Conference on Intelligent Networks and Intelligent Systems
2010		First International Conference on “Integrated Intelligent Computing”
2011		AIAA First International Conference on Artificial Intelligence, Soft Computing and Applications
2012		IAPR Workshop on Artificial Neural Networks for Pattern Recognition
2012		IEEE The World Congress on Computational Intelligence
2012		SCAI First International Conference on Soft Computing, Artificial Intelligence
2014		IEEE First International Conference on Networks & Soft Computing
2015		European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning
2016		The First International Conference on Neural Networks and Applications
2017		First International Conference on Information and Communication Technology for Intelligent Systems

finally neural networks provided an efficient model which led to estimated output values for totally external validation set by prediction errors that are far from the tolerance limits prescribed by the law.

With proper outputs encoding, the artificial neural network can be converted into a supervised classification tool, which is able to classify olive oils based on adulteration, geographical origin and the chemical compositions. Five major research lines

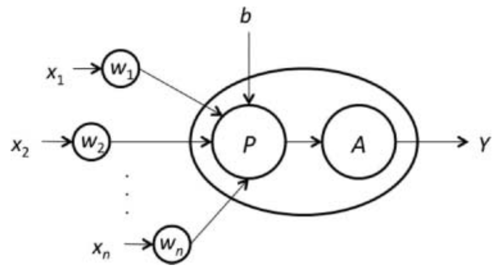

Figure 1. Scheme of a typical neural network. Reproduced from Moldes et al. (2017).

concerned with the use of ANN in connection with olive oil were identified:

- Application of ANN and olive oil production.
- ANN for characterizing olive oil and analyzing its composition.
- ANN for authentication: classification and detecting adulteration.
- Application of ANN in protected designations of origin.
- ANN and sensory devices for fingerprinting olive oil quality control.

2. Artificial neural networks in olive oil production

Olive (*Oliva europaea L.*) is an easily cultivated tree quite well adapted to the typical winter frosts of Mediterranean climate (minimum −10 °C) and to summer droughts, which are being increasingly longer. Its oil content differs among cultivars and ranges from 12 to 28%. Olive production can be as high as 22 000 kg fruit/ha (the weight of a single olive differs among varieties and typically ranges from 1 to 12 g). According to the International Olive Council -IOC- (http://www.internationaloliveoil.org) the major producers of olive are,, Spain (2.4 million ha), followed by Italy (1.4 million ha), Greece (1 million ha) and Portugal (0.5 million ha). In the last five years (2011/12 – 2015/16), the EU accounted for 70% of production, 56% of consumption and 66% of olive oil exports worldwide. Figure 3 shows the total production and exportation of olive oil by EU during last seven years. The main objective of the European's policy on olive oil is to maintain its position on the world market by encouraging the production of a high-quality product in favor of manufacturers, processors, traders and consumers. The increasing production of olive oil is due to an increase in global demand.

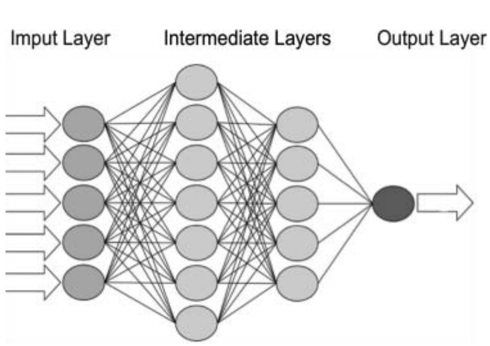

Figure 2. Scheme of a multilayer perceptron, the most widely used type of artificial neural network in bioinformatics prediction methods.

Olive farming provides an important source of employment in many Mediterranean rural areas, including many principal or part-time employer beside other dependent businesses such as tourism. Olive farming is also considered as an important part of local culture and heritage in many areas, and is being maintained and "valorized" through labelling schemes in some cases. Used cooking oil is one of the economical sources for biodiesel production. However, the products formed during frying, such as free fatty acid and some polymerized triglycerides, can affect the transesterification reaction and the biodiesel properties. Apart from this phenomenon, the biodiesel obtained from waste cooking oil such as olive oil gives better engine performance and less emission when tested on commercial diesel engines (Kulkarni and Dalai 2006). Waste cooking olive oil, which is much less expensive than pure vegetable oil may also be a promising alternative to vegetable oil for biodiesel production.

Olive oil can be obtained directly from olive fruit using only mechanical extraction, which can be consumed without further treatments. The production of virgin olive oil essentially includes three steps: grinding, shaking and separation (usually by centrifugation). Grinding olives releases drops of oil —which is largely present in mesocarp vacuoles— by destroying the structure and tissues of the fruit (Di Giovacchino et al. 2017). The drops are converted into a continuous oily phase (olive paste) by shaking under heating to decrease viscosity. After shaking, oil is extracted from the paste or separated by pressurization, percolation or centrifugation (Di Giovacchino et al. 2017). The pressurization and percolation treatments are now obsolete, where oil is largely extracted by centrifugation on a two- or three-phase centrifuge. In two-phase (oil and solid) centrifuges, the paste is supplied with no water and especially dry oil pomace (alperujo) is obtained as a result. In three-phase centrifuges, the mass (oil, water and pomace) is supplied with a large amount of water (1 liter per kilogram of olives). The increasing scarcity of water has led to a decline in the use of this technique. Additionally, adding water reduces the phenol content of the oil, and consequently its stability and healthiness. Inadequate washing can introduce earth or moisture odors, and too aggressive or fine grinding a burnt and/or metal taste besides giving rise to a more difficult shaking process. Moreover, the higher the temperature during shaking, the higher the quality of product and the greater yields. Finally, it is noteworthy that storage for a long time impairs the sensory quality of the oil.

Today modern olive mills extract VOO by means of centrifugation systems because they allow obtaining high-quality oils with less production cost. However, some bottles of VOO are still labelled with "cold pressed", which is an anachronistic and largely unregulated description for olive oil production process. Although centrifugation is a procedure that was set up in the 1960s, still there are studies on how to optimize parameters that are determinant of olive oil quality in terms of sensory characteristics. Thus, there is high interest in chemical changes of the oil occurring as consequences of crushing mechanism, malaxation time and temperature, kind of decanter centrifuge, and type of coadjuvant, among many others (Altieri and Esposito 2010; Moya et al. 2010; Veillet et al. 2009). The following information from these studies is assisting in the improvement

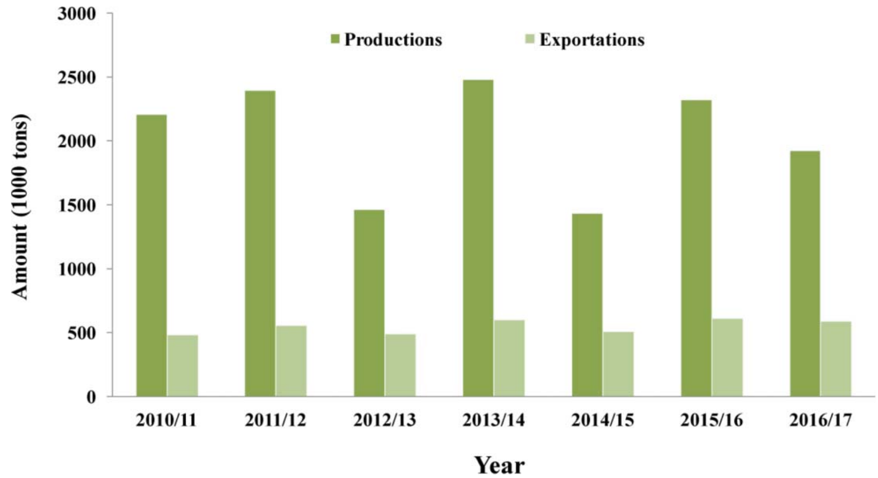

Figure 3. Total productions and exportations of olive oil in the last five years ($\times$ 10^3 t) by EU. Source: the International Olive Council –IOC.

of the manufacturing parameters which finally results in a better VOO sensory property and an optimum management of the olive by-products (García-González and Aparicio 2010). In order to characterize and optimize different steps of olive oil production, ANN techniques can be applied through developing the relationship between the input parameters and output variables.

Jiménez et al. (2008) used ANN to reduce fat content losses by determining the moisture and fatty acid contents of olive pomace from the first cold extraction; they adjusted some processing parameters including additives, dilution, temperature, mass flow and the position of the oil outlet in the centrifugation system. The system (a three-layer perceptron ANN) predicted moisture and fat content with 98.99 and 99.68% accuracy, respectively, and was used in combination with appropriate software to incorporate the ANN output into the oil production process.

Jiménez Márquez et al. (2009) deployed ANN for virgin olive oil production. They chose the olive fat and moisture contents, temperature, olive paste injection flow-rate, addition of micronized talc as adjuvants and the extent of paste dilution to predict the fat content of pomace dry matter and the moisture content of the resulting oil. The ensuing predictions were all more than 95% accurate and differed from the actual values by less than 1%.

Torrecilla et al. (2015) estimated photo degradation in olive oil during transportation and storage by UV/Vis absorption spectrophotometry and with ANN. Photo degradation of oil (largely photo-oxidation of its pigments and, especially, chlorophyll) impairs its attributes and degrades the quality. They used ANN to assess the influence of different steps in the processing, transportation and storage of oil from four varieties of olive oil.

Olive ripeness is considered as a substantial factor in oil quality; however, this is a subjective attribute rather than objective. Furferi, Governi, and Volpe (2010) used an artificial vision system in combination with three olive-related parameters (viz., oil, sugar and phenol contents) to develop an ANN whose predictions were highly correlated with the evaluation of a panel of expert tasters.

Faria Silva (2015) used ANN to assess the stability of olive oil in terms of auto-oxidation and photo-oxidation during processing at different levels of solar exposure and in two different types of packaging, tins and polyethylene terephthalate (PET) bottles. They examined changes in free fatty acid, peroxide, chlorophyll, phenol, tocopherol and squalene contents, and in color. The predictions of the ANN (a three-layer perceptron) were more than 90% accurate. Unlike tins, PET packages caused unwanted degradation of some components and detracted from the quality of extra virgin olive oil as a result.

Allouche et al. (2015) used ANN in combination with near-infrared spectroscopy to monitor olive fruit grinding in real time. They predicted several characteristic parameters for olives including stone/pulp mass ratio, extractability, oil and moisture contents, as well as other factors determinant of oil production process and quality, such as acidity, peroxide value, K_{232} and K_{270}, the presence of unwanted substances, pigments and polyphenols. The system finally provided real-time predictions approximately 90% accurate with substantial time and cost savings.

Gonzalez-Andujar (2009) developed an expert system to help farmers make scientific decisions as regards pests, weeds and plant diseases affecting olive growth. The system compared the contents of 150 photographs of olive trees using Boolean conditions. The system was given a performance score of more than 9 out of 10 by a number of agricultural experts.

Martínez Gila et al. (2015) used three different algorithms to correlate measurements made with a hyperspectral sensor with olive oil acidity, peroxide value and moisture in order to determine the optimum wavelength for characterization with a view to cost reduction. Table 2 shows other applications of ANNs in olive oil production and the corresponding schemes that were used.

3. Artificial neural networks for characterizing olive oil and analyzing its composition

The application of neural networks have been reported to be useful for predicting the chemical composition, consisting of minor and major components, and sensory properties of different olive oils. The major component is principally an oily fraction containing 98% oil in the form of triglycerides and free fatty acids. The remaining 2% is non-oily matter and includes

Table 2. Application of ANNs in olive oil production.

Approach	Architecture	Inputs	References
Optimization of the virgin olive oil elaboration process	MLP	Olive oil moisture (OM) and its total fat content (OF)	(Jiménez Marquez et al. 2009)
Automatic prediction of olive ripening index	FFBP-ANN	Chemical parameters including oil content, sugar content and phenol content	(Furferi, Governi, and Volpe 2010)
Proton transfer reaction— mass spectrometry (ptr-ms) headspace analysis for rapid detection of oxidative alteration of olive oil, Olive oil has been characterized by rapid proton transfer reaction—mass spectrometry (PTR-MS) headspace analysis without any concentration of the volatiles or pretreatment of the samples	MLP	Rapid proton transfer reaction-mass spectrometry (PTR-MS) headspace analysis	(Aprea et al. 2006)
Olive oil content prediction models based on image processing, In order to determine optimal harvest time, prediction models were developed to determine oil content based on quality features derived from known image processing algorithms.	MLP	Quality features such as size, shape, color, and texture which were derived from the Photographic images of the olives	(Ram et al. 2010)
Field determination of phenolic compounds in olive oil mill wastewater by artificial neural network, a new computerized approach to the determination of concentrations of phenolic compounds (catechol) is considered	BP-ANN	Current signals from amperometric detection of the laccase biosensor	(Torrecilla et al. 2008)
Predicting Oxidative Stability of olive oils Using Neural Network System and Endogenous Oil Components, Artificial Neural Network Systems (ANNW) to predict the stability of vegetable oil based on chemical composition was evaluated	BP-ANN	Fatty acid composition, free fatty acids, neutral lipids, phospholipids, glycolipids, tocopherols and tocotrienols, sterols, chlorophyll, carotenoids, metals, phenolic acids, and triglycerides	(Przybylski and Zambiazi 2000)
Prediction of gas-to-olive oil partition coefficients of organic compounds	MLP 5–5-1	The descriptors containing salvation connectivity index, hydrophilic factor, conventional bond-order ID number, dipole moment	(Golmohammadi, Konoz, and Dashtbozorgi 2009)
Estimation of the content of impurities in olive oil samples	MLP	Histograms of the channels of the Red–Green–Blue (RGB), CIELAB and Hue-Saturation-Value (HSV) color spaces	(Cano Marchal et al. 2013)

minor components that, however, contribute markedly to the properties of olive oil (Murkovic et al. 2004). Omega-6 and omega-3 fatty acids of olive oil are definitely more balanced than many other types of oily contents. Fatty acids present in olive oil are palmitic (C16:0), palmitoleic (C16:1), stearic (C18:0), oleic (C18:1), linoleic (C18:2), and linolenic (C18:3). Myristic (C14:0), heptadecanoic and eicosanoic acids are found in trace amounts. Scano et al. (1999), detected traces of 11-cis-vaccenic and eicosenoic acids by deploying ^{13}C-Nuclear Magnetic Resonance Spectroscopy.

The partial glycerides presence in olive oil is mainly the result of either the incomplete triacylglycerol biosynthesis reaction or hydrolytic. In virgin olive oil, concentration of diacylglycerols (DG) varies from 1 to 2.8% (Frega, Bocci, and Lercker 1993; Kiosseoglou and Kouzounas 1993). In the diacylglycerol fraction C-34 and C-36 compounds prevail (Frega, Bocci, and Lercker 1993). Monoacylglycerols are present in much smaller quantities (less than 0.25%) whereas 1-species are considerably higher than the respective 2-monoglycerides. Their ratio depends on oil acidity (Boskou 2006). Storage conditions could affect the distribution of fatty acids. 1,2-Diacylglycerols present in fresh oil tend to isomerize to the more stable 1,3-diacylglycerols. This rearrangement gives information about the age of the oil and storage conditions. The ratio of 1,3-/1,2-DG can be also considered as a useful criterion to monitor the olive oil quality (Pérez-Camino, Moreda, and Cert 2001).

Olive oil is known as a significant water-soluble vitamins (A, D, E and K) source (Visioli, Poli, and Gall 2002). Regarding applicable legislation (CE 2013), the quality specifications of olive oil are proposed to be the acidity, UV spectroscopic parameters (K_{270}, K_{232} and ΔK), peroxide value, alkyl esters and sensory properties. The olive oil quality is also strictly depends on several specific attitudes of the hydrophilic phenols including their antioxidant power and other properties that affect the healthy and sensory aspects of olive oil quality. Polyphenols are an important functional minor component of virgin olive oils that are responsible for the key sensory characteristics of bitterness, pungency, and astringency. Considering virgin olive oils, “polyphenol” mostly refers to hydrolysis products of oleuropein and ligustroside aglycons and related compounds (Paul Andrewes et al. 2003). These compounds are responsible for the oxidative stability of virgin olive oils and are associated with health benefits (Caponio, Gomes, and Pasqualone 2001; Leenen et al. 2002). Polyphenols also play an important role in the organoleptic properties of virgin olive oils and are commonly described as bitter and astringent. Less commonly, polyphenols are associated with pungency, that is, peppery, burning, or hot sensations (Tsimidou 1998).

The unique and delicate flavor of olive oil is attributed to a number of volatile components such as aldehydes, alcohols, esters, hydrocarbons, ketones and furans. The presence of flavor compounds in olive oil is closely related to its sensory quality. Hexanal, trans-2-hexenal, 1-hexanol, and 3-methylbutan-1-ol are the major volatile compounds of olive oil.

Obviously, this is the flavor components influencing the taste and aroma of olive, which are a function of olive cultivar, origin, ripeness stage of fruit, storage and planting conditions. The components octanal, nonanal, and 2-hexenal, as well as the volatile alcohols propanol, amyl alcohols, 2-hexenol, 2-hexanol, and heptanol, characterize the olive cultivar. The amount of volatile flavor components (e.g. aldehydes and esters) decreases over storage period. Phenolic compounds also have a significant effect on olive oil flavor. Hydroxytyrosol, tyrosol, which respectively present in olive oils of good and poor quality, caffeic acid, coumaric acid, and p-hydroxybenzoic acid influence mostly the sensory characteristics of olive oil. A wide variety of compounds such as pentanal, hexanal, octanal, and nonanal are formed by oxidation inside the fruit tissue in which 2-pentenal and 2-heptenal are mainly the representatives of the off-flavors (Kiritsakis 1998). The sensory properties of olive oil are assessed as the median of its strongest defect and that of the attribute "fruity". The minor components of the fraction accounting for 2% of the oil are crucial with a view to its authentication, characterization and origin identification.

Virgin olive oils, being mechanically extracted from olive fruits, retain volatile and non-volatile compounds, which are mainly responsible for their typical flavor that makes them highly appreciated by consumers not only in the countries of the Mediterranean basin where the olive oil production is concentrated. Even the healthy properties of olive oil such as its high nutritional power, excellent digestibility, high oxidative stability, strong capacity of prevention of heart and vascular troubles cannot completely explain the increased popularity of this product in countries where it was relatively underused. The large increase in the demand for high quality olive oils is thought to be related to their peculiar organoleptic characteristics that play an important role in human nutrition.

Torrecilla et al. (2008) used a three-layer ANN to predict the content in phenols (catechol) of olive oil. This network was applied to a biosensor measurement of the enzyme laccase. Their predictions were more than 99% accurate. Caciotta et al. (2016) developed a virgin olive oil quality assessment system, using the results of a tasting panel as the input data. The predictive system, which was based on a Kohonen network mimicking biological perception, was supposed to detect the basic flavors to be included on either negative or positive tasting attribute lists. Cancilla et al. (Cancilla et al. 2014) used an artificial neural network to relate chemical analyses of a series of olive oil samples to the results of their testing by an expert panel. The ANN processed six chemical parameters (viz., free acidity, peroxide value, the UV absorption parameters J232 and K268, and the contents in 1,2-diacylglycerol and pyropheophytins) to decide whether olive oil samples were of extra virgin or a lower grade.

García-Reiriz et al. (2008) developed an ANN-based tool for detecting malonaldehyde in olive oil. This compound, which results from the oxidation of fat, is known to be detrimental to health. By using various fluorimetric methods to analyze four different chemical reactions, these authors developed a method for detecting malonaldehyde while the analytical signal is nonlinear. This system could also be used for other compounds and reactions.

4. Artificial neural networks for authentication of olive oil: classification and detecting adulteration

Olive oil is classified according to the processes or treatments applied to olives in order to extract their juice:

- Virgin olive oil (VOO) is obtained by using a mechanical or physical procedure allowing olive juice to be extracted in a natural manner. VOO can be one of the following types:
  - Extra virgin olive oil (EVOO, acidity ≤ 0.8%), which is obtained from a single (monovarietal) or several (coupage) olive varieties, or even from oils from a specific geographic location (a Protected Designation of Origin, for example).
  - Virgin olive oil (acidity ≤ 2%) or lampante olive oil (acidity > 2%). The latter is produced by refining industries or for technical purposes.
- Refined olive oil, which is obtained by refining virgin olive oil. The process reduces acidity to below 0.3%. This olive oil production type does not let alterations in the initial glyceridic structure.
- Olive oil (acidity ≤ 1%), which consists of a mixture of refined olive oils and virgin olive oils other than lampante oil.
- Crude pomace oil, which is obtained by extracting olive pomace with an appropriate solvent.
- Refined pomace oil, which is a refined version of the previous one with acidity ≤ 0.3%. This type of olive oil does not lead to alterations in the initial glyceridic structure.
- Pomace oil (acidity ≤ 1%), which is a mixture of refined pomace oil and virgin olive oils other than those of the lampante type.

The most commonly used and heard of olive oil is the extra virgin. Extra virgin and the virgin olive oil are produced through a directly extraction method- including olive fruits grinding, which preserves the natural taste. The method for extracting the oil is known as "cold pressed," which keeps the oil from losing its flavor that can be changed when subjected to high temperatures. Extra virgin olive oil production is not involving any chemical treatments, which results in an organic olive oil. Virgin oil is also an indication that the oil is not refined, that they are of a higher quality and as mentioned above, retain their natural flavor. The other type is pure olive oil. However, the name can be misleading. Pure olive oil is actually a mixture of either extra virgin, virgin olive oil or refined ones. It is used mainly when extracted olive oil is of poor quality and the refining process helps it to have a better flavor. Many times, refined olive oil is used when frying as the taste is not really matter. A product labelled simply Olive Oil is nearly the same as something marked Pure Olive Oil on that is refined with lack of taste (https://www.thespruce.com/olive-oil-2355732).

Olive oil is a fine product with high nutritional value and significant health benefits. It is famous for its superior organoleptic characteristics (aroma and taste) beside its remarkable antioxidant properties. Olive oil has a relatively high commercial price because the cultivation of olive trees, harvesting of the olive fruits, and the oil extraction are hard to control and time-consuming tasks. Therefore, attempts to adulterate this commodity with less expensive materials, such as seed oils and/or olive oils of lower quality (refined olive oil), are by no means rare.

In the past decade, there has been an increasing interest in the classification of edible oils including olive oil as an alternative mean to examine authentication and to detect possible adulteration of EVOO with seed oils and/or olive oils of lower quality. Classification of various grades of olive oil has been carried out in several instances by using a variety of analytical techniques and chemometric procedures such as artificial neural networks model. The basis of neural networks for authenticity examination is based on their ability to identify the pattern and then the classification of the various components, which provides us the possibility to correctly determine which component belongs to which category. Generally, the category (*e.g.* production areas and the process of extracting olive oil) can be any subject that the neural network model may find its reliable varieties' patterns. Table 3 represents the main ANN approaches applied for authentication of olive oil in the last decades.

Aparicio et al. (2013) compared promising chromatographic, spectroscopic and trace analysis methods for authenticating olive oil. They reported that ANN could fulfil fast interpretation, which is required because data acquisition is currently so fast. Binetti et al. (2017) used ANN in combination with nuclear magnetic resonance spectra to classify oils obtained from different olive varieties harvested in two different seasons. Expandability of their results was limited by the fact that they only studied four olive varieties. Aroca-Santos (Aroca-Santos et al. 2016) developed a method for identifying and quantifying components in binary mixtures of refined olive oil and extra virgin olive oil (EVOO) from visible spectroscopy measurements. The system successfully predicted which EVOO variety was present in each sample and identified the presence of refined oil as adulterant. The method proved more expedition and cost-effectiveness than alternative characterization methods. Silva et al. (Silva et al. 2015) conducted a survey on the stability of extra virgin olive oil, which was kept in polyethylene terephthalate bottles and tinplate cans for 6 months both in dark and light conditions. Free fatty acids, peroxide value, specific extinction at 232 and 270 nm, chlorophyll, L^*C^*h color, total phenolic compounds, tocopherols and squalene were considered for the analysis. The physicochemical changes were evaluated using ANN considering different light exposure conditions and packaging material. The optimized parameters include 11 neuron inputs, 18 hidden neurons and 5 output neurons obtained by hyperbolic tangent and softmax activation functions. The five output neurons are equal to the number of possible categories coming from a combination of packing material conditions, and light exposure. The predicted physical-chemical changes showed very high compliance with experimental data (training set (>85%) and test set (>90%)).

Torrecilla et al. (2013b) proposed a method by which it is possible to classify virgin olive oils using the minimum experimental data based on the application of a multilayer perceptron (MLP). To validate the proposed model, 147 EVOO samples with two types of protected denomination of origin, were classified into four similar families. The classification was performed by reducing the size of the data dramatically, without an appreciable loss of information (less than 0.90%). Marchal et al. (2013) proposed a system based on computer vision and pattern recognition to classify the impurities content of olive oil samples in three sets, the results of which indicate the suitability of the process of separating olive oil after extracting from the paste. Several linear and non-linear feature extraction techniques were evaluated for ANNs model construction. The best result using ANNs was 82.38%, yielded by using principal component analysis (PCA) as data reduction and feature selection method.

5. Artificial neural networks and protected designations of origin

Traditionally, morphological and phonological traits are used to identify olive cultivars. Several researchers have found isozymes to be useful for cultivar identification and determining patterns of relatedness among cultivars. Pontikis et al. (Pontikis, Loukas, and Kousounis 1980) identified 27 olive cultivars, mostly of Greek origin, using 16 enzyme systems in pollen. Trujillo et al. (Trujillo and Rallo 1995) found that by using five pollen enzyme systems they could distinguish 134 of 155 cultivars. Ouazzani et al. (Ouazzani et al. 1993) distinguished 33 of 44 cultivars using 9 enzyme systems in leaf tissue. Although isozyme analysis has proved useful in olive, mainly due to the high level of isozyme polymorphism present in the species, direct analysis of DNA could considerably increase the number of markers produced. Furthermore, because isozymes are products of gene expression, differential expression by environment, tissue-specificity, and other factors is common and may make interpretation of results difficult. Random amplified polymorphic DNA (RAPD) analysis, first described by Williams et al. (1990) has proven to be a useful tool for genetic typing and mapping (Fabbri, Hormaza, and Polito 1995).

The previous knowledge of the structure of genetic diversity may be a help to make decisions on procedure management and breeding strategies for breeding program. Data on more of 500 cultivars of olive are stored in the World Germplasm Bank of the CIFA "Alameda del Obispo" in Cordoba, Spain (Belaj et al. 2002). Because the properties of each type of oil depend largely on the composition of its minor fraction (2% at most), olive varieties from some geographic regions are now under Protected Designations of Origin. Protected Designations of Origin (PDO) recognize extra virgin olive oil obtained from one or more specific olive varieties grown in an also specific area under strictly controlled conditions.

The quality and uniqueness of specific extra virgin olive oils (EVOOs) could be a function of different variables such as cultivar, environment and cultural practices. Consumers are also more and more oriented towards purchasing food products of a certified genuineness and geographical origin. Thus, the geographical identification becomes an instrumental tool to ensure the consumers' protection, particularly for extra virgin olive oil, the quality of which is highly related to the cultivars employed and to the environmental conditions of growth (Pafundo, Agrimonti, and Nelson 2005).

García-González et al. (2009a) reported an ANN-based method for identification of olive oils with a protected designation of origin (PDO) from Spain, Portugal and Italy. They used chemical characterization data obtained by gas chromatography and high-performance liquid chromatography as input variables, and the fatty acid contents of the oils as input data They also identified the particular PDO among the Spanish oil samples. Torrecilla et al. (2013a) developed an ANN system to

Table 3. Application of ANNs in olive oil authentication.

Approach	Architecture	Inputs	References
A classification tool for rapid assessment of the adulteration of virgin olive oils by other seed oils including soya, sunflower, peanut, corn or rectified olive oils using pyrolysis Mass Spectrometry	BP-ANN 150–8-1	Quantitative pyrolysis mass spectra	(Goodacre, Kell, and Bianchj 1993)
Classification of multicomponent analytical data of olive oils	BP-ANN Koh-ANN	fatty acid composition	(Zupan et al. 1994)
Classification of the source regions of olive oils based on the content of eight fatty acids.	RBFN	The data sets were electron ionization mass spectra for PCB compounds with chlorine atoms ranging from 1 to 9.	(Chuanhao and Harrington 1999)
Differentiation of adulterated and extra virgin olive oil	MLP 150–8-3	Pyrolysis mass spectra	(Alsberg et al. 1997)
Determination of olive pomace oil adulteration in extra virgin olive oil	MLP	Near-infrared, mid-infrared, and Raman spectroscopic data	(Yang and Irudayaraj 2001)
Commercial classification of olive oil of five of the most widespread cultivars (Carboncella, Frantoio, Leccino, Moraiolo, and Pendolino) from Sabina (Lazio, Italy)	BP-ANN 10–7-5	Fatty acids and sterol composition	(Bucci et al. 2002)
Classification of edible oils Based on total luminescence spectroscopy with pattern recognition, the method has been used to discriminate between four different types of edible oils, extra virgin olive, non-virgin olive, sunflower and rapeseed oils.	BP-ANN RBF-ANN	Excitation emission matrices of edible oils	(Scott et al. 2003)
A classification tool to authenticate Italian extra virgin olive oil varieties, they have investigated the possibility to resolve the composition of simulated binary mixtures of monocultivar olive oils	BP-ANN 6–10-5	12 variables including linolenic, palmitoleic, oleic, stearic, linoleic, stigmasterol, K_{270}, campesterol, acidity, palmitic, clerosterol, stigmastadienol	(Marini et al. 2004)
Classification of different edible vegetable oils including olive oil	Koh-NN	Fatty acid composition	(Brodnjak-Vončina et al. 2005)
Classification of Garda and not-Garda oils	CP-ANN	Electronic nose sensor signals, electronic tongue sensor signals, Chemical parameters including the free acidity (FA), the peroxide value (PV), the absorbances UV (K_{232}, K_{270}, and ΔK)	(Cosio et al. 2006)
A classification tool for detection of the presence of refined hazelnut oil in refined olive oil by fluorescence spectroscopy	MLP 4–3-1	Excitation-emission fluorescence spectra data (spectral range 300–500 nm of the excitation spectra at $\lambda_{em} = 655$ and spectral range 650 -900 of the emission spectra at $\lambda ex = 350$ nm)	(Sayago et al. 2007)
A classification tool for resolving binary blends of monocultivar Italian olive oils	BP-ANN 18–9-2	Chemical composition: acidity, palmitic acid (%), palmitoleic acid (%), stearic acid (%), oleic acid (%), linoleic acid (%), linolenic acid (%), cholesterol (%), campesterol (%), stigmasterol (%), clerosterol (%), β-sitosterol (%), sitostanol (%), $\Delta^{5,24}$-stigmastadienol, Δ^{7}-stigmastenol, Δ^{7}-avenasterol, trilinolein content (%), and UV extinction coefficient K_{270}	(Marini et al. 2007)
A classification tool for discriminating pure olive oil, pure hazelnut oil and mixture of olive oil adulterated with hazelnut oil to detect the presence of refined hazelnut oil in refined olive oil	CP-ANN	FT-MIR data	(Groselj et al. 2008)
Tracing the adulteration of olive oil	CP-ANN	FT-MIR data	(Groselj et al. 2008)
Classification of several olive cultivars from Trás-os-Montes region (northeast of Portugal)	MLP 10–10-8–6	Endocarp's quantitative biometrical data	(Peres et al. 2011)
Classification of the content of impurities of the olive oil samples	MLP	Histograms of the channels of the Red–Green–Blue (RGB), CIELAB and Hue-Saturation-Value (HSV) color spaces	(Cano Marchal et al. 2013)
Classification of 147 EVOO samples into four similar families. The oil samples employed came from two types of protected denomination of origin (PDO) oils and two non-PDO from the same Spanish province (Granada).	GNN 17–5-1 RNN 3–4-1	The employed data were acidity (as a percentage of oleic acid, %), peroxide index (meqO_2 per Kg oil), K_{232}, K_{270}, ΔK, moisture and volatile compounds (%), palmitoleic acid (%), palmitic acid (%), stearic acid (%), oleic acid (%), linoleic acid (%), linolenic acid (%), total unsaturated fatty acids/ total saturated fatty acids rate	(Torrecilla et al. 2013a)
Identification, quality control, traceability, and adulteration detection of extra virgin olive oils	LIBS-NN	Laser-induced breakdown spectroscopy (LIBS)	(Caceres et al. 2013)
A classification tool to discriminate packaging material in the light and dark	BFGS 11–18-5	FFA content, peroxide value, K_{232}, K_{270}, chlorophyll content, L^*, C_{ab}^*, h_{ab}^*, tocopherol content, squalene content, total phenolic content	(Silva et al. 2015)

classify olive oils with protected designations of origin by using two oils with a PDO and another two without any PDO, all from olives grown in the province of Granada, Spain. The ANN input variables included compositional parameters such as acidity, peroxide value, UV spectroscopic indices (K_{223} and K_{279}), the contents in oleic, linoleic and linolenic acid, and moisture. Reducing the amount of data used by 80%, made the oil identification protocol much easier and faster. The ensuing predictive model was accurate in more than 99% of cases. Table 4 summarizes the input variables used in ANN for characterizing olive oils over the period 2007–2017 and the variables provided by their prediction models.

6. Artificial neural networks and sensory devices for fingerprinting olive oil quality control

From a chemical point of view, a large number of different species characterizes food types and their qualitative difference is mainly based on differences in their taste and aroma. Detection of volatile compounds by human olfaction is very important in assessing the quality of foods. Accordingly, significant efforts have been made over the years to devise tools that operate on the basis of a similar principle. These systems would be in some cases a suitable alternative to conventional analyses of volatile compounds by traditional analytical techniques and sensory methods. Following publication of a basic article by Persaud and Dodds (1982), electronic nose has been developed for qualitative classification in various fields. Electronic nose is mainly known as a tool that contains a set of minor electronic chemical sensors in combination with an appropriate pattern recognition system that can recognize simple or complex odors (Gardner and Bartlett 1993).

It is noteworthy that the use of electronic nose in food analysis seems to have been applied more than other fields over the years. The main reason for the development of e-nose applications to food control is the food quality monitoring due to the rising levels of contamination in recent years. Moreover, the analysis of food flavor shows an opportunity to compare the electrical nasal performance with the analysis of people who use natural olfaction. Among the various e-nose uses in the food industry, the analysis of olive oil seems to be a promising program.

Many publications have reported different types of electronic nose to characterize the olive oil odor, so far. Along with the development of e-nose, deploying similar concepts in aqueous solutions was gradually increased. For example, "electronic tongue" or "taste sensor" was developed regarding the human sense of taste. Electronic noses have been studied much more than their wet chemical counterpart, but electronic tongues or flavor sensors are now commonly used methods and have grown very fast over the last few years due to their high potential (Winquist et al. 2005). Table 5 shows the researches about application of ANNs and electronic nose and tongue in olive oil analysis.

Table 4. ANN for traceability of olive oil.

Approach	Architecture	Inputs	References
Determination of the geographical origin of Italian extra virgin olive oil using pyrolysis mass spectrometry and artificial neural networks	MLP	Curie-point pyrolysis mass spectra	(Salter et al. 1997)
Classification of olive oils from nine different olive growing regions in Italy	FFNN	The content of eight fatty acids in 572 olive oils	(Kocjančič and Zupan 1997)
Authentication of virgin olive oils of very close geographical origins based on NIR spectroscopy	MLP	NIR spectrum	(Bertran et al. 2000)
High throughput flow ^{1}H NMR fingerprinting, for classification of geographic origin and year of production	PNN	^{1}H NMR fingerprints data	(Rezzi et al. 2005)
Identification of geographical origin of extra virgin olive oils by an electronic nose in combination with artificial neural networks	CP-ANN	Free acidity (FA), the peroxide value (PV), the absorbances UV (K_{232}, K_{270}, and ΔK), total phenol content based on HPLC determination	(Cosio et al. 2006)
A classification tool for geographical traceability of virgin olive oils	MLP	Complete chemical characterization of samples (64 compounds analyzed by GC and HPLC)	(García-González et al. 2009)
Identification of geographical origin of Spain, Italy and Portugal virgin olive oil using complete chemical characterization of samples (64 compounds analyzed by GC and HPLC)	MLP 7–5-3	64 chemical compounds obtained by GC and HPLC	(García-González et al. 2009)
Traceability of olive oil of Italy, Spain, France, Greece, Cyprus, and Turkey based on volatiles pattern using ANN	MLP	Gas chromatographic data obtained by head-space solid-phase microextraction (HS-SPME)-based sampling procedure, coupled to gas chromatography–ion trap mass spectrometry (GC–ITMS)	(Cajka et al. 2010)
Identification of geographical origin based on High resolution NMR characterization of olive oils	PNN	^{1}H NMR metabolic fingerprinting	(Mannina and Sobolev 2011)
Traceability of extra virgin olive oils of Spain, Italy, Greece and Argentina using Laser-Induced Breakdown Spectroscopy (LIBS) and Neural Networks	BP-ANN	Laser-Induced Breakdown Spectra	(Caceres et al. 2013)
Identification of geographical origin: distinguishing similar EVOO samples from four different but close origins in Spain	MLP	Acidity (%), peroxide index, K_{232}, K_{270}, ΔK, moisture and volatile compounds (%), palmitoleic acid (%), palmitic acid (%), stearic acid (%), oleic acid (%), linoleic acid (%), linolenic acid (%), total unsaturated fatty acids/total saturated fatty acids rate, monounsaturated fatty acids/polyunsaturated fatty acids rate, oleic/linoleic rate, oleic/linolenic rate and w-6 fatty acid/w-3 fatty acid rate of four EVOO types	(Torrecilla et al. 2013a)

Table 5. Application of ANNs and sensory devices for fingerprinting olive oil quality control.

Approach	Architecture	Inputs	References
Sensory Evaluation of virgin olive oils based on the volatile composition data	BP-ANN 114–7-1	Dynamic head-space gas chromatographic data	(Angerosa et al. 1996)
Electronic nose based on metal oxide semiconductor sensors and pattern recognition techniques: characterization of vegetable oils, they applied ANN to the signals generated by an electronic nose for the classification of vegetable oils	BP-ANN	The raw values of the sensor response, pattern of the volatile compounds present in the samples	(González Martín et al. 2001)
Electronic nose based on metal oxide semiconductor sensors as a fast alternative for the detection of adulteration of virgin olive oils, The system was comprising 12 metal oxide semiconductor sensors, and was used to generate a pattern of the volatile compounds present in the samples	BP-ANN	The raw values of the sensor response, pattern of the volatile compounds present in the samples	(Concepción et al. 2002)
An electronic nose for differentiation of Extra virgin olive (EVO) and Non-virgin olive oil (OI)	RBF-ANN 6–6-3	An array of partially selective piezoelectric quartz crystals (PZQ) sensors	(Ali et al. 2003)
Virgin Olive Oil Quality Classification Combining Neural Network and MOS Sensors, A model based on neural networks has been designed to detect lampante virgin olive oils	MLP 11–6-1	The response of 7 metal oxide sensors	(García-González and Aparicio 2003b)
An electronic nose and an electronic tongue to verify the geographical origin and the uniqueness of specific extra virgin olive oils	CP-ANN	Electronic nose sensor signals, electronic tongue sensor signals, Chemical parameters including the free acidity (FA), the peroxide value (PV), the absorbances UV (K_{232}, K_{270}, and ΔK)	(Cosio et al. 2006)
Quantification of Phenolic Compounds in olive oil mill wastewater by artificial neural network/ laccase biosensor, the developed a new computerized approach to the determination of concentrations of phenolic compounds (caffeic acid and catechol).	BP-ANN	Current signals from amperometric detection of the laccase biosensor	(José S. Torrecilla et al. 2007)
A sensor-software based on artificial neural network for the optimization of olive oil elaboration process, An artificial neural network (ANN) was built for real-time prediction of the moisture and fat content in olive pomace using two-phase olive oil processing.	FFBP-ANN	Technological variables including olive paste flow, olive paste temperature, coadyuvants addition, water dilution level, position of the exit of the oil in the 'horizontal centrifuge decanter', and the Wavelet pretreated near infrared spectra from the on-line scanned oils at the exit of the decanter.	(Jiménez et al. 2008)

Oliveros et al. (2002) have proposed an "electronic nose" to detect fraud in olive oil. The system, including 12 metal oxide semiconductor sensors, was used to produce a volatile compound pattern present in samples. The feature selection techniques were used to select a set of desirable diagnostic variables before using ANN as a supervised pattern recognition method. Very good results were obtained during differentiation of adulterated and non-adulterated olive oils, and even the type of oil was identified confidentially. Significant results have also been obtained regarding the rate of fraud. Garcia-Gonzalez et al. (2003) designed a model based on neural networks to detect lampante virgin olive oils, a kind of olive oil that cannot be consumed without the prior refining process according to the current rules of the European Communities. The response of 7 metal oxide sensors was analyzed for 114 samples of olive oil. The internal validity of the ANN was examined with a 4.5% error in validation set; the designed mathematical model was also validated using an external set of diverse varieties and geographical origins with 100% correct classification.

Cosio et al. (2006) used an electronic nose and tongue, in combination with multivariate analysis, to verify the geographical origin of specific extra virgin olive oils. The samples of olive oil belonging to a small production, located on Lake Garda (Northern Italy), which are distinct since 1998 as a European Protected Denomination of Origin. Free acidity, peroxide value, ultraviolet indices, and phenol content were also determined to be used as the input parameters. The dataset contains 36 Garda oil and 17 oils from other regions

The development of classification models in this work have been performed using Counter propagation ANN so as to be able to separate Garda olive oil from non-Garda ones. The procedure is as follows: first, by using all the chemical variables and sensor signals; second, by using electronic tongue sensors; finally, by using four selected electronic nose sensors. All the models have also been tested with 19 commercial olive oil samples. Neural networks provided very satisfactory results, which show that electronic noise may be considered as an appropriate tool for characterizing olive oil. These results show that how electronic nose and tongue, in combination with ANNs, could be a quick, inexpensive and efficient way to classify and characterize extra virgin olive oils from a restricted geographical origin.

7. Main conclusions on the state-of-the-art of artificial neural networks and olive oil

The olive growing sector is increasingly interested in optimizing production, transportation, packaging and quality analysis with a view to reducing costs and times. Bioinformatics and artificial intelligence tools can be especially useful for this purpose. In fact, artificial neural networks (ANN) can be used to process a wide variety of data from physical–chemical tests, macroscopic observations, specificities of the fruit grinding process, packaging material or even panel tasting to obtain highly accurate predictions as regards oil processing, adulteration and provenance.

Artificial neural networks, which are relatively affordable and easy to operate in real time, allow one to reduce the number of variables to be considered and hence processes to be simplified. In addition, ANN are highly flexible for adjustment to new situations. Effective guidelines or protocols are obviously needed to integrate existing knowledge on oil if ANN are to operate optimally. The olive growing sector has also used bioinformatics tools other than ANN, albeit much less often. Finally, ANN have also been used in connection with new devices for non-human testing (electronic noses and tongues, mainly).

ORCID

J. C. Mejuto http://orcid.org/0000-0001-8396-1891
J. Simal-Gandara http://orcid.org/0000-0001-9215-9737

References

Ali, Z., D. James, W. T. O'Hare, F. J. Rowell, and S. M. Scott. 2003. Radial basis neural network for the classification of fresh edible oils using an electronic nose. *Journal of Thermal Analysis and Calorimetry* 71:147–54.

Allouche, Y., E. López, G. Beltrán Maza, and A. Jiménez Márquez. 2015. Near infrared spectroscopy and artificial neural network to characterise olive fruit and oil online for process optimisation. *Journal of Near Infrared Spectroscopy* 23:111–21.

Alsberg, B. K., R. Goodacre, J. J. Rowland, and D. B. Kell. 1997. Classification of pyrolysis mass spectra by fuzzy multivariate rule induction-comparison with regression, K-nearest neighbour, neural and decision-tree methods. *Analytica Chimica Acta* 348:389–407.

Altieri, R., and A. Esposito. 2010. Evaluation of the fertilizing effect of olive mill waste compost in short-term crops. *International Biodeterioration and Biodegradation* 64:124–8.

Angerosa, F., L. Di.Giacinto, R. Vito, and S. Cumitini. 1996. Sensory Evaluation of Virgin Olive Oils by Artificial Neural Network Processing of Dynamic Head-Space Gas Chromatographic Data. *Journal of the Science of Food and Agriculture* 72:323–8.

Aparicio, R., M. T. Morales, R. Aparicio-Ruiz, N. Tena, and D. L. García-González. 2013. Authenticity of olive oil: Mapping and comparing official methods and promising alternatives. *Food Research International* 54:2025–38.

Aprea, E., F. Biasioli, G. Sani, C. Cantini, T. D. Märk, and F. Gasperi. 2006. Proton Transfer Reaction—Mass Spectrometry (PTR-MS) Headspace Analysis for Rapid Detection of Oxidative Alteration of Olive Oil. *Journal of Agricultural and Food Chemistry* 54:7635–40.

Aroca-Santos, R., J. C. Cancilla, E. S. Pariente, and J. S. Torrecilla. 2016. Neural networks applied to characterize blends containing refined and extra virgin olive oils. *Talanta* 161:304–8.

Astray, G., M. A. Iglesias-Otero, O. A. Moldes, and J. C. Mejuto. 2013. Predicting Critical Micelle Concentration Values of Non-Ionic Surfactants by Using Artificial Neural Networks. *Tenside Surfactants Deterg.* 50:118–24.

Belaj, A., Z. Satovic, L. Rallo, and I. Trujillo. 2002. Genetic diversity and relationships in olive (Olea europaea L.) germplasm collections as determined by randomly amplified polymorphic DNA. *Theoretical and Applied Genetics* 105:638–44.

Bertran, E., M. Blanco, J. Coello, H. Iturriaga, S. Maspoch, and I. Montoliu. 2000. Near infrared spectrometry and pattern recognition as screening methods for the authentication of virgin olive oils of very close geographical origins. *Journal of Near Infrared Spectroscopy* 8:45–52.

Binetti, G., L. Del Coco, R. Ragone, S. Zelasco, E. Perri, C. Montemurro, R. Valentini, D. Naso, F. P. Fanizzi, and F. P. Schena. 2017. Cultivar classification of Apulian olive oils: Use of artificial neural networks for comparing NMR, NIR and merceological data. *Food Chemistry*. 219:131–8.

Boskou, D., and American Oil Chemists' Society. 2006. *Olive oil: chemistry and technology*. AOCS Press, Champaign, Illinois, USA.

Brodnjak-Vončina, D., Z. C. Kodba, and M. Novič. 2005. Multivariate data analysis in classification of vegetable oils characterized by the content of fatty acids. *Chemometrics and Intelligent Laboratory Systems* 75:31–43.

Bucci, R., A. D. Magrí, A. L. Magrí, D. Marini, and F. Marini. 2002. Chemical Authentication of Extra Virgin Olive Oil Varieties by Supervised Chemometric Procedures. *Journal of Agricultural and Food Chemistry* 50:413–8.

Caceres, J. O., S. Moncayo, J. D. Rosales, F. Javier, M. De Villena, F. C. Alvira, and G. M. Bilmes. 2013. Application of Laser – Induced Breakdown Spectroscopy (LIBS) and Neural Networks to Olive Oils Analysis. *Applied Spectroscopy* 67:1064–72.

Caciotta, M., S. Giarnetti, F. Leccese, B. Orioni, M. Oreggia, C. Pucci, and S. Rametta. 2016. Flavors mapping by Kohonen network classification of Panel Tests of Extra Virgin Olive Oil. *Measurement* 78:366–72.

Cajka, T., K. Riddellova, E. Klimankova, M. Cerna, F. Pudil, and J. Hajslova. 2010. Traceability of olive oil based on volatiles pattern and multivariate analysis. *Food Chemistry*. 121:282–9.

Cancilla, J. C., S. C. Wang, P. Díaz-Rodríguez, G. Matute, J. D. Cancilla, D. Flynn, and J. S. Torrecilla. 2014. Linking Chemical Parameters to Sensory Panel Results through Neural Networks To Distinguish Olive Oil Quality. *Journal of Agricultural and Food Chemistry* 62:10661–5.

Cano Marchal, P., D. Martínez Gila, J. Gámez García, and J. Gómez Ortega. 2013. Expert system based on computer vision to estimate the content of impurities in olive oil samples. *Journal of Food Engineering* 119:220–8.

Caponio, F., T. Gomes, and A. Pasqualone. 2001. Phenolic compounds in virgin olive oils: influence of the degree of olive ripeness on organoleptic characteristics and shelf-life. *European Food Research and Technology* 212:329–33.

Cerrato Oliveros, M. C., J. L. Pérez Pavón, C. Garcıa Pinto, M. E. Fernández Laespada, B. Moreno Cordero, and M. Forina. 2002. Electronic nose based on metal oxide semiconductor sensors as a fast alternative for the detection of adulteration of virgin olive oils. *Analytica Chimica Acta* 459:219–28.

Chen, A.-S., M. T. Leung, and H. Daouk. 2003. Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index. *Computers & Operations Research* 30:901–23.

Chen, H. Y., T. C. Chen, D. I. Min, G. W. Fischer, and Y. M. Wu. 1999. Prediction of tacrolimus blood levels by using the neural network with genetic algorithm in liver transplantation patients. *Therapeutic Drug Monitoring* 21:50–6.

Chuanhao, W., and P. Harrington. 1999. Self-Configuring Radial Basis Function Neural Networks for Chemical Pattern Recognition. *Journal of Chemical Information and Computer Sciences* 39:1049–56.

Concepción, M. A., C. Oliveros, J. Luis, P. Pavón, C. G. Pinto, E. F. Laespada, B. Moreno Cordero, and M. Forina. 2002. Electronic nose based on metal oxide semiconductor sensors as a fast alternative for the detection of adulteration of virgin olive oils. *Analytica Chimica Acta* 459:219–28.

Cosio, M. S., D. Ballabio, S. Benedetti, and C. Gigliotti. 2006. Geographical origin and authentication of extra virgin olive oils by an electronic nose in combination with artificial neural networks. *Analytica Chimica Acta* 567:202–10.

Di Giovacchino, L., S. M. Preziuso, M. G. Di Serio, M. R. Mucciarella, G. Di Loreto, and B. Lanza. 2017. Double extraction of olive oil in large oil mills of Southern Italy: Effects on extraction efficiency, oil quality, and economy of the process. *European Journal of Lipid Science and Technology* 119:1600161.

Fabbri, A., J. I. Hormaza, and V. S. Polito. 1995. Random Amplified Polymorphic DNA Analysis of Olive (Olea europaea L.) Cultivars. *Journal of the American Society for Horticultural Science* 120:538–42.

Frega, N., F. Bocci, and G. Lercker. 1993. High-resolution gas-chromatographic determination of diacylglycerols in common vegetable oils. *Journal of the American Oil Chemists' Society* 70:175–7.

Furferi, R., L. Governi, and Y. Volpe. 2010. Author's personal copy ANN-based method for olive Ripening Index automatic prediction. *Journal of Food Engineering* 101:318–28.

García-González, D. L., and R. Aparicio. 2010. Research in Olive Oil: Challenges for the Near Future. *Journal of Agricultural and Food Chemistry* 58:12569–77.

García-González, D. L., and R. Aparicio. 2003. Virgin Olive Oil Quality Classification Combining Neural Network and MOS Sensors. *Journal of Agricultural and Food Chemistry* 51:3515–9.

García-González, D. L., G. Luna, M. T. Morales, and R. Aparicio 2009. Stepwise geographical traceability of virgin olive oils by chemical profiles using artificial neural network models. Eur. *Journal of Lipid Science and Technology* 111:1003–13.

García-Reiriz, A., P. C. Damiani, A. C. Olivieri, F. Cañada-Cañada, and A. Muñoz de la Peña. 2008. Nonlinear Four-Way Kinetic-Excitation−Emission Fluorescence Data Processed by a Variant of Parallel Factor Analysis and by a Neural Network Model Achieving the Second-Order Advantage: Malonaldehyde Determination in Olive Oil Samples. *Analytical Chemistry* 80:7248–56.

Gardner, J. W., and P. N. Bartlett. 1993. Design of conducting polymer gas sensors: Modelling and experiment. *Synthetic Metals* 57:3665–70.

Golmohammadi, H., E. Konoz, and Z. Dashtbozorgi. 2009. Prediction of gas-to-olive oil Partition Coefficients of organic Compounds Using an artificial neural network. *Analytical Science* 25:1137–42.

Gonzalez-Andujar, J. L. 2009. Expert system for pests, diseases and weeds identification in olive crops. *Expert Systems With Applications* 36:3278–83.

González Martín, Y., M. Concepción, C. Oliveros, J. Luis, P. Pavón, C. G. Pinto, and B. M. Cordero. 2001. Electronic nose based on metal oxide semiconductor sensors and pattern recognition techniques: characterisation of vegetable oils. *Analytica Chimica Acta* 449:69–80.

Goodacre, R., D. B. Kell, and G. Bianchj. 1993. Rapid Assessment of the Adulteration of Virgin Olive Oils by Other Seed Oils Using Pyrolysis Mass Spectrometry and Artificial Neural Networks. *Journal of the Science of Food and Agriculture* 63:297–307.

Groselj, N., M. Vracko, J. A. Fernández Pierna, V. Baeten, and M. Novi. 2008. The Use of FT-MIR Spectroscopy and Counter-Propagation Artificial Neural Networks for Tracing the Adulteration of Olive Oil. *Acta Chimica Slovenica* 55:935–41.

Iglesias-Otero, M. A., M. Fernández-González, D. Rodríguez-Caride, G. Astray, J. C. Mejuto, and F. J. Rodríguez-Rajo. 2015. A model to forecast the risk periods of Plantago pollen allergy by using the ANN methodology. *Aerobiologia* (Bologna). 31:201–11.

Jiménez, A., G. Beltrán, M. P. Aguilera, and M. Uceda. 2008. A sensor-software based on artificial neural network for the optimization of olive oil elaboration process. *Sensors & Actuators, B: Chemical*. 129:985–90.

Jiménez Marquez, A., M. P. Aguilera Herrera, M. Uceda Ojeda, and G. Beltrán Maza,. 2009. Neural network as tool for virgin olive oil elaboration process optimization. *Journal of Food Engineering* 95:135–41.

Torrecilla, J. S., M. L. Mena, P. Yáñez-Sedeño, and J. García. 2007. Quantification of Phenolic Compounds in Olive Oil Mill Wastewater by Artificial Neural Network/Laccase Biosensor. *Journal of Agricultural and Food Chemistry* 55:7418–26.

Kiosseoglou, V., and P. Kouzounas. 1993. The role of diglycerides, monoglycerides, and free fatty acids in olive oil minor surface-active lipid interaction with proteins at oil-water interfaces. *Journal of Dispersion Science and Technology* 14:527–39.

Kiritsakis, A. K. 1998. Flavor components of olive oil—A review. *Journal of the American Oil Chemists' Society* 75, 673–81.

Kocjančič, R., and J. Zupan. 1997. Application of a Feed-Forward Artificial Neural Network as a Mapping Device. *Journal of Chemical Information and Modeling* 37:985–9.

Kulkarni, M. G., A. K. Dalai. 2006. Waste Cooking OilAn Economical Source for Biodiesel: A Review. *Industrial & Engineering Chemistry Research* 45:2901–13.

Kunz, D. 1991. Channel assignment for cellular radio using neural networks. *IEEE Transactions on Vehicular Technology* 40:188–93.

Leenen, R., A. J. C. Roodenburg, M. N. Vissers, J. A. E. Schuurbiers, K. P. A. Mvan. Putte, S. A. Wiseman, and F. H. M. M. van de Put. 2002. Supplementation of Plasma with Olive Oil Phenols and Extracts: Influence on LDL Oxidation. *Journal of Agricultural and Food Chemistry* 50:1290–7.

Pérez-Camino, M. C., W. Moreda, and A. Cert. 2001. Effects of Olive Fruit Quality and Oil Storage Practices on the Diacylglycerol Content of Virgin Olive Oils. *Journal of Agricultural and Food Chemistry* 49:699–704.

Mannina, L., and A. P. Sobolev. 2011. High resolution NMR characterization of olive oils in terms of quality, authenticity and geographical origin. *Magnetic Resonance in Chemistry* 49:S3–11.

Maqsood, I., M. R. Khan, G. H. Huang, and R. Abdalla. 2005. Application of soft computing models to hourly weather analysis in southern Saskatchewan, Canada. *Engineering Applications of Artificial Intelligence* 18:115–25.

Marini, F., F. Balestrieri, R. Bucci, A. D. Magrı, A. L. Magrı, and D. Marini. 2004. Supervised pattern recognition to authenticate Italian extra virgin olive oil varieties. *Chemometrics and Intelligent Laboratory Systems* 73:85–93.

Marini, F., A. L. Magrì, R. Bucci, and A. D. Magrì. 2007. Use of different artificial neural networks to resolve binary blends of monocultivar Italian olive oils. *Analytica Chimica Acta* 599:232–40.

Martínez Gila, D. M., P. Cano Marchal, J. Gámez García, and J. Gómez Ortega. 2015. On-line system based on hyperspectral information to estimate acidity, moisture and peroxides in olive oil samples. *Computers and Electronics in Agriculture* 116:1–7.

Melin, P., and O. Castillo. 2007. An intelligent hybrid approach for industrial quality control combining neural networks, fuzzy logic and fractal theory. *Information Sciences* (Ny). 177:1543–57.

Moya, M., F. Espínola, D. G. Fernández, Ade. Torres, J. Marcos, J. Vilar, J. Josue, T. Sánchez, and E. Castro. 2010. Industrial trials on coadjuvants for olive oil extraction. *Journal of Food Engineering* 97:57–63.

Murkovic, M., S. Lechner, A. Pietzka, M. Bratacos, and E. Katzogiannos. 2004. Analysis of minor components in olive oil. *Journal of Biochemical and Biophysical Methods* 61:155–160.

Ouazzani, N., R. Lumaret, P. Villemur, and F. Di Giusto. 1993. Leaf Allozyme Variation in Cultivated and Wild Olive Trees. *Journal of Heredity* 84:34–42.

Pafundo, S., C. Agrimonti, and M. Nelson. 2005. Traceability of Plant Contribution in Olive Oil by Amplified Fragment Length Polymorphisms. *Journal of Agricultural and Food Chemistry* 53:6995–7002.

Paul, A., J. L. H. C. Busch, T. D. Joode, A. Groenewegen, and H. Alexandre. 2003. Sensory Properties of Virgin Olive Oil Polyphenols: Identification of Deacetoxy-ligstroside Aglycon as a Key Contributor to Pungency. *Journal of Agricultural and Food Chemistry* 51:1415–20.

Peres, A. M., P. Baptista, R. Malheiro, L. G. Dias, A. Bento, and J. A. Pereira. 2011. Chemometric classification of several olive cultivars from Trás-os-Montes region (northeast of Portugal) using artificial neural networks. *Chemometrics and Intelligent Laboratory Systems* 105:65–73.

Persaud, K., and G. Dodd. 1982. Analysis of discrimination mechanisms in the mammalian olfactory system using a model nose. *Nature* 299:352–5.

Pontikis, C. A., M. Loukas, and G. Kousounis. 1980. The use of Biochemical Markers to Distinguish Olive Cultivars. *Journal of Horticultural Science* 55:333–43.

Przybylski, R., and R. C. Zambiazi. 2000. Predicting oxidative stability of vegetable oils using neural network system and endogenous oil components. *Journal of the American Oil Chemists' Society* 77:925–32.

Ram, T., Z. Wiesman, I. Parmet, and Y. Edan. 2010. Olive oil content prediction models based on image processing. *Biosystems Engineering* 105:221–32.

Rezzi, S., D. E. Axelson, K. Héberger, F. Reniero, C. Mariani, and C. Guillou. 2005. Classification of olive oils using high throughput flow H NMR fingerprinting with principal component analysis, linear discriminant analysis and probabilistic neural networks. *Analytica Chimica Acta* 552:13–24.

Salter, G. J., M. Lazzari, L. Giansante, R. Goodacre, A. Jones, G. Surricchio, D. B. Kell, and G. Bianchi. 1997. Determination of the geographical origin of Italian extra virgin olive oil using pyrolysis mass spectrometry and artificial neural networks. *Journal of Analytical and Applied Pyrolysis* 40–41:159–70.

Sayago, A., D. L. García-González, M. T. Morales, and R. Aparicio. 2007. Detection of the Presence of Refined Hazelnut Oil in Refined Olive Oil by Fluorescence Spectroscopy. *Journal of Agricultural and Food Chemistry* 55:2068–71.

Scano, P., M. Casu, A. Lai, G. Saba, M. A. Dessi, M. Deiana, F. P. Corongiu, and G. Bandino. 1999. Recognition and quantitation of cis-vaccenic and eicosenoic fatty acids in olive oils by 13C nuclear magnetic resonance spectroscopy. *Lipids* 34:757–9.

Scott, S. M., D. James, Z. Ali, W. T. O'Hare, F. J. Rowell, X. Zhang, and Z. Hu. 2003. Total luminescence spectroscopy with pattern recognition for classification of edible oils. *Analyst* 128:966–73.

Silva, S. F., C. A. R. Anjos, R. N. Cavalcanti, and R. M. doss. Celeghini. 2015. Evaluation of extra virgin olive oil stability by artificial neural network. *Food Chemistry*. 179:35–43.

Sun, Y., Y. Peng, Y. Chen, and A. J. Shukla. 2003. Application of artificial neural networks in the design of controlled release drug delivery systems. *Advanced Drug Delivery Reviews* 55:1201–15.

Torrecilla, J. S., J. C. Cancilla, G. Matute, and P. Díaz-Rodríguez. 2013a. Neural network models to classify olive oils within the protected denomination of origin framework. *International Journal of Food Science and Technology* 48:2528–34.

Torrecilla, J. S., J. C. Cancilla, G. Matute, P. Díaz-Rodríguez, and A. I. Flores. 2013b. Self-organizing maps based on chaotic parameters to detect adulterations of extra virgin olive oil with inferior edible oils. *Journal of Food Engineering* 118:400–5.

Torrecilla, J. S., M. L. Mena, P. Yáñez-Sedeño, and J. García. 2008. Field determination of phenolic compounds in olive oil mill wastewater by artificial neural network. *Biochemical Engineering Journal* 38:171–9.

Torrecilla, J. S., S. Vidal, R. Aroca-Santos, S. C. Wang, and J. C. Cancilla. 2015. Spectroscopic determination of the photodegradation of monovarietal extra virgin olive oils and their binary mixtures through intelligent systems. *Talanta* 144:363–8.

Trujillo, I., and L. Rallo. 1995. Identifying Olive Cultivars by Isozyme Analysis. *Journal of the American Society for Horticultural Science* 120:318–24.

Tsimidou, M. 1998. Polyphenols and quality of virgin olive oil in retrospect. *Italian Journal of Food Science* 239;10:99–116.

Veillet, S., V. Tomao, I. Bornard, K. Ruiz, and F. Chemat. 2009. Chemical changes in virgin olive oils as a function of crushing systems: Stone mill and hammer crusher. *Comptes Rendus Chimie*. 12:895–904.

Visioli, F., A. Poli, and C. Gall. 2002. Antioxidant and other biological activities of phenols from olives and olive oil. *Medicinal Research Reviews* 22:65–75.

Wang, J. J., Jou. Wang, Z. G. Zhang, and S. P. Guo. 2012. Stock index forecasting based on a hybrid model. *Omega* 40:758–66.

Williams, J. G. K., M. K. Hanafey, J. Antoni Rafalski, and S. V. Tingey. 1993. Genetic analysis using random amplified polymorphic DNA markers. *Methods Enzymol* 218:704–0.

Williams, J. G. K., A. R. Kubelik, K. J. Livak, J. A. Rafalski, and S. V. Tingey. 1990. DNA polymorphisms amplified by arbitrary primers are useful as genetic markers. *Nucleic Acids Research*. 18:6531–5.

Winquist, F., R. Bjorklund, C. Krantz-Rülcker, I. Lundström, K. Östergren, and T. Skoglund. 2005. An electronic tongue in the dairy industry. *Sensors and Actuators B: Chemical*. 111–112:299–304.

Yang, H., and J. Irudayaraj. 2001. Comparison of near-infrared, fourier transform-infrared, and fourier transform-raman methods for determining olive pomace oil adulteration in extra virgin olive oil. *Journal of the American Oil Chemists' Society* 78:889–95.

Zupan, J., M. Novič, X. Li, and J. Gasteiger. 1994. Classification of multicomponent analytical data of olive oils using different neural networks. *Analytica Chimica Acta* 292:219–34.