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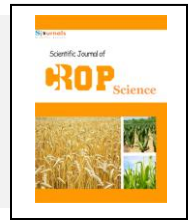

Review Article

Artificial neural networks in vegetables: A comprehensive review

S. Goyal
Member, IDA, New Delhi, India.

*Corresponding author; Member, IDA, New Delhi, India. Email: thesumitgoyal@gmail.com

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A B S T R A C T

Artificial neural networks (ANN) are implemented in a large number of applications of science and technology as the technique has become very popular and accepted tool for researchers and scientists. ANN renders realistic advantages such as real time processing, adaptability and training potential over conventional methodologies. In this communication an all inclusive review of ANN for predictive modeling, analysis that play crucial role in assessment of extensive range of vegetables, viz., asparagus, alfalfa sprouts, anise, basil, beans, beetroot, bell pepper, broccoli, cabbage, carrot, capsicum, celery, chickpea, chilli pepper, corn, cruciferous sprouts, cucumber, garlic, ginger, herb, jalapeno, lemon grass oil, lentils, maize, marjoram, mushroom, okra pods, onion, oregano, parsnip, peas, pepper, potato, potato chips, pumpkin, rhubarb, rosemary, soybean, spinach, thyme, turnip and walnut, has been discussed. The objective of this write-up is to provide all published literature related to ANN modeling in vegetables at one single stop, which would be very valuable for agriculturalists, academicians, researchers, scientists and students, so that they can follow a suitable methodology according to their exact requirements for conducting research.

1. Introduction

The development of computer technologies caused the appearance of the completely new analytic possibilities, basing on observations of natural processes, and in peculiarity on conclusions following with scientific researches relating the brain work investigations, what is described by the dynamically developing techniques of neuronal processing. Artificial neuronal networks (ANN) are able to operate both on gatherings of numeric data coming from experimental investigations, as well as on fuzzy sets, so characteristic for perception of human mind, being recently used in agricultural sciences (Boniecki, 2005). ANN models are mathematical and algorithmic software models inspired by biological neural network. An ANN model is an interconnected group of nodes, parallel to the vast network of neurons in the human brain. ANN model consists of interconnected group of artificial neurons and processes information using a connectionist approach to computation. In more practical terms, ANN models are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns inherent in data. The employment of ANN models is a method of data analysis that is designed to imitate the workings of the human brain. ANN models emulate the way in which arrays of neurons most likely function in biological learning and memory. It has been established that ANN has the ability to learn from examples and relearn when new data are utilized, hence effectively equipped for predicting the shelf stability and safety of food products (Vallejo-Cordoba et al., 1995).

2. Benefits of this study

In this review paper, every possible available literature related to use of ANN in vegetables is presented. Almost all vegetables are covered which have used ANN modeling directly or indirectly. This communication is first of its kind, which highlights the use of ANN modeling in vegetables and puts all literature at one single stop. The information delineated in this article is of great significance to agriculturalists, farmers, scientists, researchers, students, vegetable cultivators, food processing industry and regulatory agencies.

3. ANN in vegetables

ANNs are powerful tools for the automatic inspection of vegetables and fruits. Typical target applications of such systems include grading, quality estimation from external parameters or internal features, monitoring of fruit processes during storage or evaluation of experimental treatments. The capabilities of ANN system go beyond the limited human capacity to evaluate long-term processes objectively or to appreciate events that take place outside the visible electromagnetic spectrum. Use of the ultraviolet or near-infrared spectra makes it possible to explore defects or features that the human eye is unable to detect. Hyperspectral systems provide information about individual components or damage that can be perceived only at particular wavelengths and can be used as a tool to develop new computer vision systems adapted to particular objectives. In-line grading systems allow huge amounts of fruit or vegetables to be inspected individually and provide statistics about the batch. In general, ANN systems not only substitute human inspection but also improve on its capabilities. This work presents the latest developments in the application of this technology to the inspection of the internal and external quality of vegetables (Cubero et al., 2011). ANN modeling was used to predict the thermal conductivity of various fruits and vegetables, viz., apples, pears, corn starch, raisins and potatoes. ANN was also used to model the error between the experimental value and that of the theoretical model developed. Two separate networks were used to perform these separate tasks. The optimum configuration of the networks was obtained by trial and error basis using the multilayered approach with the backpropagation and Levenberg-Marquardt (LM) Methods used concurrently in the training of the networks. The results showed that these networks have the ability to model the thermal conductivity as well as to predict the model/experimental error accurately. The networks can then be used as correction factor to the model in a hybrid approach for obtaining better prediction of thermal conductivity than the model itself (Hussain and Rahman, 1999). The ANN multi-residue analysis method was successfully applied to the simultaneous determination of the three organ phosphorus pesticides residue in some vegetables samples (Li et al., 2007). With the help of neuronal models, it was possible to predict the expected crops yield on the basis of empirical data regarding crop yields in last summers (Boniecki, 2005). ANN was suggested for investigating prediction of physical properties of vegetables (Zenoozian, 2011). The published literature for vegetables using ANN methodology is alphabetically presented below:

3.1. Asparagus

An ANN was developed to predict the kinetics of ascorbic acid loss in green asparagus during thermal treatments and the model was trained using a backpropagation algorithm. The results indicated that the optimal ANN models consisted one hidden layer and the optimal number of neurons in the hidden layer was 24, 26, 26 and 18 for bud, upper, middle and butt segments of asparagus, respectively. The ANNs could predict the kinetic parameters of ascorbic acid degradation in asparagus with an Mean Square Error (MSE) of 1.3925 and Mean Absolute Error (MAE) 0.5283 for bud segment, MSE 2.4618 and MAE 0.6436 for upper segment, MSE 0.8985 and 0.4258 for middle segment and MSE 0.2707 and MAE 0.1883 for butt segment. In addition, the correlation coefficients between experimental k, t1/2 or D-value and predicted values were greater than 0.99 in all cases. Therefore, ANN offers a simple, quick and convenient means of the kinetic parameters prediction in green asparagus (Zheng et al., 2011a). ANNs with backpropagation algorithm were developed to predict the percentage loss of ascorbic acid, total phenols, flavonoid, and antioxidant activity in different segments of asparagus during water blanching at temperatures ranging from 65 to 95 °C as a function of blanching time and temperature. Results showed that the predicted values of the correlation coefficients between experimental and ANNs ranged from 0.8166 to 0.9868, suggesting ANNs as potential tool for the prediction of nutrient losses in vegetables during thermal treatments (Zheng et al., 2011b).

3.2. Alfalfa sprouts

A rapid method for the detection of Escherichia coli (ATCC 25922) in packaged alfalfa sprouts was developed. Volatile compounds from the headspace of packaged alfalfa sprouts, inoculated with E. coli and incubated at 10°C for 1, 2, and 3 days, were collected and analyzed. Uninoculated sprouts were used as control samples. An electronic nose with 12 metal oxide electronic sensors was used to monitor changes in the composition of the gas phase of the package headspace with respect to volatile metabolites produced by E. coli. The electronic nose was able to differentiate between samples with and without E. coli. To predict the number of E. coli in packaged alfalfa sprouts, an ANN was used, which included an input layer, a hidden layer, and an output layer, with a hyperbolic tangent sigmodial transfer function in the hidden layer and a linear transfer function in the output layer. The network was shown to be capable of correlating voltametric responses with the number of E. coli. A good prediction was possible, as measured by a regression coefficient (R^2 = 0.903) between the actual and predicted data. In conjunction with the ANN, the electronic nose proved to have the ability to detect E. coli in packaged alfalfa sprouts (Siripatrawan et al., 2006).

3.3. Anise

Mathematical model (MM) and ANN model for estimating the essential oil extraction yield from Anise, at high pressure condition, were used. The extractor modeled mathematically using material balance in both fluid and solid phases. The model was solved numerically and validated with experimental data. Since the potential of near critical extraction is of considerable economic significance, a multilayer feedforward neural network (FNN) was created for accurate prediction of the mass of extract at this region of extraction. According to the network's training, validation and testing results, a three layer neural network with fifteen neurons in the hidden layer was selected as the best architecture for accurate prediction of mass of extract from Anise seed (Shokri et al., 2011).

3.4. Basil

A Hybrid Neural Network (HNN) technique was applied for modeling slipped capital femoral epiphysis (SCFE) curves obtained from basil. A HNN was employed to estimate the parameters of the phenomenological model. A small set of SCFE data of each vegetable was used to generate an extended dataset, sufficient to train the network. Afterwards, other sets of experimental data, not used in the network training, were used to validate this approach. The HNN correlated very well with the experimental data and showed that the predictions accomplished with this technique may be promising for SCFE purposes. The study confirmed that HNN was successfully applied for modeling extraction curves from SCFE basil (Stuart et al., 1997).

3.5. Beans

A computer vision system (CVS) was created for the quality inspection of beans, based on size and color quantification of samples. The system consisted of hardware and software. The hardware was created to capture a standard image from the samples. The software was coded in MATLAB for segmentation, morphological operation and color quantification of the samples. For practical application of the software, a user-friendly interface was designed using MATLAB graphical user interface (GUI). Length and width of the samples were determined using this system. Then the results of the system were compared to the measurements obtained by a caliper. High correlations ($r = 0.984$ and 0.971 for length and width, respectively) were obtained between the results of the system and the caliper measurements. Moment analysis was performed to identify the beans based on their intensity distribution. Average, variance, skewness and kurtosis values were determined for each channel of red, green, blue (RGB) color format. ANNs were used for color quantification of the samples. Samples classified by human inspectors into five classes and twelve moment values of the 69 samples with their classes were used in the training stage of ANN. Testing of the ANN was performed with other 371 samples. The automated system was able to correctly classify 99.3% of white beans, 93.3% of yellow–green damaged beans, 69.1% of black damaged beans, 74.5% of low damaged beans and 93.8% of highly damaged beans. The overall correct classification rate obtained was 90.6% confirming the significance of ANN modeling (Kılıç et al., 2007).

3.6. Beetroot

A neural network technology with a Geographical Information System (GIS) was used to carry out land suitability analysis for beetroot. The suitability evaluation of beetroot (Beta Vulgaris) was based mainly on the methods described by the Food and Agricultural Organization (FAO). Study area of this research was in the upcountry of Sri Lanka. Soil properties, meteorological data, current land use and slope accessibility were considered as important factors to identify potential lands for beetroot. Average annual temperature and precipitation (1961-1990 data), topographic, soil and land use maps of the study area were used for the study. Crop requirement criteria were collected from a literature review and from the Department of Agriculture, Sri Lanka. Paper maps were scanned and screen digitized to prepare thematic layers (maps) and then converted to raster format and reclassified. Reclassified layers were converted to ASCII format. The LM algorithm was used to perform the ANN modeling. Finally, a suitability map was prepared according to the given criteria with four suitability categories; namely, highly, moderately, marginally and not suitable. According to the final suitability map of ANN modeling, 10.43%, 31.66% and 7.96% of lands fell respectively under highly, moderately and marginally suitable categories. The results revealed that there was no, “not suitable” land parcel in the present study area. According to the ANN modeling results, researchers concluded that there is moderate potential for growing beetroot in the upcountry of Sri Lanka (Jayasinghe and Yoshida, 2009).

3.7. Bell pepper

The effects of three different coatings (gum Tragacanth, sesame oil and gum Tragacanth–sesame oil), temperature and time on shelf life of bell pepper were investigated. Moisture reduction, shrinkage as well as firmness and colour changes were studied during 30 days at 4, 10, 15 and 23°C. Results of experiments indicated that bell peppers treated with gum Tragacanth at higher temperatures such as 10°C had good quality up to 30 days of storage. However, sharp changes in physicochemical characters were observed in bell peppers stored at 23 °C. In order to predict moisture reduction, shrinkage, firmness and colour changes genetic algorithm– ANN model was created. It was found that ANN with eight hidden neurons truly could predict the physicochemical changes of bell pepper during storage ($R^2 > 0.9598$) (Mohebbi et al., 2011).

3.8. Broccoli

Broccoli grading was studied based on computer vision and ANN. Broccoli images were captured and the five parameters of color and shape (b*, TCD, Hdeg, proportion of yellowness area, roundness) were extracted and calculated from those images by images analysis method such as background purification, color segmentation, gray transform etc. A new grading method was provided based on the results of image analysis. The five parameters used as input vector to establish the Backpropagation Neural Network (BNN) for improving prediction precision, and another four ANNs Probabilistic Neural Network, Self-Organizing Competition Neural Network, Learning Vector Quantization Neural Network and Self-Organizing Feature Map Neural Network were also used as classifier in MATLAB 7.0. The results showed that all the five neural networks could be used for broccoli grading with the forecasting accuracy at the range of 68.2-93.4%. The BNN was the best network with the forecasting accuracy of 93.4% (Tu et al., 2007). Hahn (1995;1996) used ANN to examine the properties of Broccoli grown in Scotland . Hosaka et al. (2012) predicted the degradation rate of broccoli by implementing ANN model.

3.9. Cabbage

ANNs are universal and flexible models for linear and non-linear systems. A study was conducted to modeling an ecosystem using ANN models and the conventional model, and assessing their effectiveness in the dynamic simulation of ecosystem. Elman ANN model, linear ANN model, and linear ordinary differential equation were developed to simulate the dynamics of Chinese cabbage growth system recorded in the field. MATLAB codes for these ANN models were given. Sensitivity analysis was conducted to detect the robustness of these models. The results showed that Elman ANN model could simulate the multivariate non-linear system at desired accuracy, indicating that sensitivity analysis is powerful to detect the robustness and stability of neural network models (Zhang et al., 2007). Hahn and Muir (1996) used ANN technique for identifying crop/weed discrimination in cabbage.

3.10. Carrot

Aghbashlo et al. (2011) studied the advantages of integrated response surface methodology (RSM) and genetic algorithm (GA) for optimizing ANN topology of convective drying kinetic of carrot cubes. A multilayer FNN trained by backpropagation algorithms was built to correlate output (moisture ratio) to the four exogenous input variables (drying time, drying air temperature, air velocity, and cube size). A predictive response surface model for ANN topologies was created using RSM. The response surface model was interfaced with an effective GA to find the optimum topology of ANN. The factors considered for building a relationship of ANN topology were the number of neurons, momentum coefficient, step size, number of training epochs, and number of training runs. A second-order polynomial model was developed from training results for MSE of 50 developed ANNs to generate 3D response surfaces and contour plots. The optimum ANN had minimum MSE when the number of neurons, step size, momentum coefficient, number of epochs, and number of training runs were 23, 0.37, 0.68, 2,482, and 2, respectively. The results confirmed that the optimal ANN topology was more precise for predicting convective drying kinetics of carrot cubes.

Kerdpiboon et al. (2006) used ANN analysis to predict shrinkage and rehydration of dried carrots, based on inputs of moisture content and normalized fractal dimension analysis ($\Delta D/D0$) of the cell wall structure. Several drying techniques were used including conventional hot air (HAD), low pressure superheated steam (LPSSD), and freeze drying (FD). Dried carrot sections were examined by light microscopy and the fractal dimension (D) determined using a box counting technique. Optimized ANN models were developed for HAD, LPSSD, HAD + LPSSD, and HAD + LPSSD + FD, based on 1–10 hidden layers and neurons per hidden layer. ANN models were then tested against an independent dataset. Measured values of shrinkage and rehydration were predicted with an $R^2 > 0.95$ in all cases.

Modeling and optimization of mass transfer during osmosis dehydration of carrot slices by neural networks and genetic algorithms was investigated by Mohebbi et al. (2011). Two paradigms of ANN, FNN and radial basis function neural networks (RBFNN) were applied and compared for modeling this process.

Erenturk and Erenturk (2011) analyzed drying kinetic of carrot considering different drying conditions. The drying experiments were performed at four levels of drying air temperatures of 60–90 °C, together with three levels of air flow velocities of 0.5–1.5 m/s, and also three levels of thickness 0.5–1 cm. Four different MMs available in the literature were fitted to the experimental data by researchers. Among the considered mathematical drying models, modified Page model, was found to be more suitable for predicting drying of carrot. In order to optimize MMs obtained by using regression analysis, genetic algorithm was used. In all stages of the mathematical modeling, genetic algorithms were applied. In addition, a FNN was employed to estimate moisture content of carrot. Backpropagation algorithm, the most common learning method for the FNN, was used in training and testing the ANN. Comparing the r (correlation coefficient), r^2 (coefficient of determination), χ^2, and sum of squares of the difference between the experimental data and fit values of the four models, together with the optimized model by using genetic algorithms and the FNN based estimator, it was concluded that the FNN represented drying characteristics of carrot better than the others.

3.11. Capsicum

Self-organizing and Kohonen ANN methodologies were used to study the results of random amplified polymorphic DNA and inter-simple sequence repeat analyses of genomic polymorphism in genus Capsicum. The results showed more than 90% accuracy, suggesting that the proposed approach proved efficient (Ruanet et al., 2005a; 2005b).

3.12. Celery

Łapczyńska-Kordon and Francik (2006) created a model based on ANN for description of changes in celery hardness during convection drying under forced air circulation conditions. The model was developed based on the tests. Celery samples in a form of cylinders in size of 10x10 mm were put to convection drying at temperatures 60 and 70°C. For creating the model a multilayer unidirectional ANN was employed, using a modified algorithm of backward error propagation for learning process. Networks with different architecture were analyzed in order to optimize actions of the network model. The analysis showed that the optimal network was the one with 3 neurons in layer 1, 3 neurons in layer 2, and 1 neuron in the output layer. The global relative error (GRE) between the values obtained from the experiments and from calculations was 28.7%.

3.13. Chickpea

Chickpea is one of the most consumed legumes in the world. The classification of chickpea based on the size and morphological properties is important for the market. The workers aimed to design and implement a computer vision system (CVS) integrated with ANN for quality evaluation of chickpeas based on their size, colour, and surface morphology. Their system was composed of a flat bed scanner for acquiring digital image and a software which was developed in MATLAB for image analysis. Physical properties (length, width and volume) of the samples of chickpeas as well as their colour properties and surface characteristics were determined by using the system, and results were validated. High correlations were found between the results from ANN-integrated CVS and those obtained by callipers or professionally trained inspectors based on the experiments. Overall, percentages of correct classification were determined as 95.4%, 87.6%, and 96.0% for colour, surface morphology, and shape evaluations, respectively. Results indicated that ANN integrated CVS can perform quality evaluation of chickpea (Çakmak and Boyacı, 2011).

ANN methods to predict the drying characteristics of agricultural products such as chickpea, hazelnut and bean were used. The ANN was trained using experimental data for three different products through the backpropagation algorithm containing double input and single output parameters. The results showed fairly good agreement between predicted results by using ANN and the measured data taken under the same modeling conditions. The mean relative error (MRE) and mean absolute error (MAE) obtained when unknown data were applied to the networks was 3.92 and 0.033, respectively, which were claimed to be very satisfactory (Topuz, 2011). Khazaei et al. (2008) used ANN technology for yield estimation and clustering of chickpea. Their ANN model predicted 90.3% of the yield data with relative errors ranging between ±5%.

3.14. Chilli pepper

Atas et al. (2010;2011;2012) conducted experiments for classification of aflatoxin contaminated in chilli pepper using ANN technique. They were of the opinion that chemical methods used for detection of aflatoxin contamination give accurate results, but they are slow, expensive and destructive. In their investigation, intensity histograms of hyper spectral images of chilli peppers were extracted under halogen illumination source and aflatoxin detection was made by ANN.

3.15. Corn

The Maryland Water Quality Improvement Act of 1998 requires mandatory nutrient management planning on all agricultural land in Maryland. Nutrient management specialists need simple and accurate estimation techniques to relate crop yields and nutrient utilization in the planning process. Therefore, a study was carried out by researchers to investigate, if ANN models could effectively predict Maryland corn yields for typical climatic conditions. Also, a multiple linear regression (MLR) model was developed to compare the effectiveness of ANN models. Results of their experiments revealed that ANN models consistently produced more accurate yield predictions than regression models. ANN corn yield models for Maryland resulted in r^2 and RMSEs of 0.77 and

1036 versus 0.42 and 1356 for MLR, respectively. Researchers found ANN to be a superior methodology for accurately predicting corn yields under typical Maryland climatic conditions (Kaul et al., 2005).

3.16. Cruciferous sprouts

Buciński et al. (2004) implemented ANN for prediction of antioxidant capacity of cruciferous sprouts. The aim of their work was to show that ANNs are a convenient tool for modeling the biological properties of cruciferous sprouts. Their results indicated that ANN modeling is acceptable for predictive analysis in cruciferous sprouts.

3.17. Cucumber

Water temperature is considered as one of the most important parameters, which influence the growth rate and development of sea cucumbers as well as their distribution within the pond environment. As the change process of water temperature is dependent on the complicated meteorological and geophysical conditions, ANN with specific features such as non-linearity, adaptively, generalization, and model independence might be a proper method for solving this problem. Therefore, researchers created a RBFNN model for water temperature prediction in sea cucumber aquaculture ponds and compared its results with 1-D vertical model to confirm the excellent predictive performance of optimized RBFNN model (Sun et al., 2012). In another study, based upon the combination of genetic algorithm and backpropagation ANN, a model to predict cucumber downy mildew was established. The hidden nodes in ANN and the weights were optimized. The result of training indicated that the prediction values approximate to the real values and the model is feasible in forecasting cucumber downy mildew because it takes the advantages of both traditional ANN and genetic algorithms, and gets rid of their defects (Changying et al., 2002). Drumm et al. (1999) analysed the ability of ANNs to predict the habitat preferences of the tropical sea cucumber (Holothuria leucospilota) in the reef-top ecosystem of Rarotonga, Cook Islands. Their findings suggested that ANNs combined with GIS provide an effective method for modeling spatial patterns in ecological data.

3.18. Garlic

Estimation of evapotranspiration (ET) is necessary in water resources management, farm irrigation scheduling, and environmental assessment. Hence, in practical hydrology, it is often necessary to reliably and consistently estimate ET. In a reported study, two artificial intelligence (AI) techniques including ANN and adaptive neuro-fuzzy inference system (ANFIS) were used to compute garlic crop water requirements. Various architectures and input combinations of the models were compared for modeling garlic crop ET. A case study in a semiarid region located in Hamedan Province in Iran was conducted with lysimeter measurements and weather daily data, including maximum temperature, minimum temperature, maximum relative humidity, minimum relative humidity, wind speed, and solar radiation during 2008–2009. Both ANN and ANFIS models produced reasonable results. The ANN with 6→6→1 architecture presented a superior ability to estimate garlic crop ET. The estimates of the ANN and ANFIS models were compared with the garlic crop ET (ETc) values measured by lysimeter and those of the crop coefficient approach. Based on these comparisons, the workers concluded that the ANN and ANFIS techniques are suitable for simulation of ETc (Abyaneh et al., 2010). In another investigation, Adaptive Neural Network based GA and Co-Active Neuro-Fuzzy Inference System inside ANN for estimation of garlic ET was created. For modeling from meteorological data including minimum and maximum temperature, minimum and maximum relative humidity, wind speed and sunshine hours and lysimeter data in climatology Station of Bu-Ali Sina University Agriculture Faculty during 2008-2009 for modeling were used. The garlic lysimeter ET maximum and average were 11.22 and 4.79 mmd-1, respectively. Results showed that Adaptive Neural Network based GA were more accurate than Co-Active Neuro-Fuzzy Inference System (Zare et al., 2011).

Zare et al. (2009) did assessment of ANN in prediction of garlic ET (ETc) with lysimeter in Hamedan. They developed an ANN model. Maximum and minimum air temperatures, maximum and minimum relative humidity values, wind speed and sunshine hours were used as the input layer data. The crop ET was measured using 4 lysimetres of 2×2×2m of the Bu-Ali Sina agriculture college's meteorology station during 2006-2008. Statistic indicators RMSE, MAE, STDMAE R2 were used for performance evaluation of the models. The results showed the more exact method concerned to the multilayer perceptron (MLP) model with the backpropagation algorithm. The 6→6→1 layout with LM rule and sigmoid function had the best topology of the model. The evaluation criteria were 0.088, 0.07 and 0.061 mm/day as well as 0.88, respectively. The results also showed that the average daily garlic ET were 8.3 and 6.5 mm based on the lysimeter ANN methods, respectively. Overall, evaluation of ANN results suggested that the errors of ANN were negligible. The ANN indicated high and low sensitivity to maximum air temperature and minimum relative humidity, respectively.

Abyaneh et al. (2011) determined the water requirement, single and dual crop coefficient of garlic using a drainage lysimeter. The lysimeter experiments were conducted during 2008–2009. According to the experimental results, garlic water requirements (ETC) in this period were 546.5 mm and 519.2 mm, respectively during the growing season. A reference ET (ET0) was simulated with ANN method during garlic growth season. Results showed that crop coefficient value (KC) in initial and final stages were 0.53, 1.4 and 0.3, respectively. The results were compared to the single and dual crop coefficients from the FAO-56 procedure. Results showed that maximum differences between ETC of single and dual KC values were observed at initial and final stages. The dual crop coefficient was observed to be more precise (RMSE= 38%), but the advantage of single crop coefficient was simpler for a user.

3.19. Ginger

Curcuma amada (Mango ginger) was dried at four different power levels ranging 315–800 W to determine the effect of microwave power on moisture content, moisture ratio, drying rate, drying time and effective diffusivity. A FNN using backpropagation algorithm was employed to predict the moisture content during microwave drying. It was found to be quite adequate for predicting the drying kinetics with R^2 of 0.985 (Izadifar and Abdolahi, 2006).

3.20. Herb

Multi-herb prescriptions of traditional Chinese medicine (TCM) often include special herb-pairs for mutual enhancement, assistance, and restraint. These TCM herb-pairs were assembled and interpreted based on traditionally defined herbal properties (TCM-HPs) without knowledge of mechanism of their assumed synergy. While these mechanisms are yet to be determined, properties of TCM herb-pairs can be investigated to determine if they exhibit features consistent with their claimed unique synergistic combinations. Workers analyzed distribution patterns of TCM-HPs of TCM herb-pairs to detect signs indicative of possible synergy and used AI methods to examine whether combination of their TCM-HPs are distinguishable from those of non-TCM herb-pairs assembled by random combinations and by modification of known TCM herb-pairs. Patterns of the majority of 394 known TCM herb-pairs were found to exhibit signs of herb-pair correlation. Three AI systems, trained and tested by using 394 TCM herb-pairs and 2470 non-TCM herb-pairs, correctly classified 72.1–87.9% of TCM herb-pairs and 91.6–97.6% of the non-TCM herb-pairs. The best AI system predicted 96.3% of the 27 known non-TCM herb-pairs and 99.7% of the other 1,065,100 possible herb-pairs as non-TCM herb-pairs. Researchers concluded that TCM-HPs of known TCM herb-pairs contain features distinguishable from those of non-TCM herb-pairs consistent with their claimed synergistic or modulating combinations (Ung et al., 2007).

3.21. Jalapeno

Jalapeno chili is grown extensively in Mexico, as it is one of the main vegetables consumed by the population, having also a high demand for exportation. Jalapeno chili classification is fundamental before arriving to the processing plants, grocery stores and supermarkets. A charge-coupled device camera imaged the product, which travelled through the conveyor belt, but it was very slow, so a laser scanning system was used to obtain the chili length in order to sort it by sizes. A brief study of the main chili features was carried out, before training a random backpropagation ANN classifier. It was noted that the best topology required to know only the chili width and length sorting up to five different sizes with accuracies over 94% (Hahn and Mota, 1997).

3.22. Lemon grass oil

Mishra et al. (2009) combined ANN and GA to predict and to maximize lemon grass oil production. Their best combinations could be assessed for N+P2O5+ZnSO4 (Kgha-1) as 89.03 + 60.00 + 40.65, 114.84 + 60.00+33.39, 120.00 + 54.84 + 42.10 and 120.00 + 60.00+45.00, respectively for maximum of oil production. They also identified the contribution of each nutrient combination.

3.23. Lentils

An MVS for color grading of lentils was developed using a flatbed scanner as the image gathering device. Grain samples belonging to different grades of large green lentils were scanned and analyzed over a two-crop season period. Image color, color distribution, and textural features were found to be good indicators of lentil grade. Linear discriminant analysis, k-nearest neighbors, and ANN based classifiers performed equally well in predicting sample grade. An online classification system was created with an ANN classifier that achieved an overall accuracy (agreement with the grain inspectors) of more than 90% (Shahin and Symons, 2006).

3.24. Maize

El-Sanhoty et al. (2006) applied ANN methodology to evaluate the lipid distribution of Bt-176 transgenic maize compared to that of conventional maize. The crude oil extracted from the grains of genetically modified maize (Bt-176), and nontransgenic maize was characterized in terms of the fatty acid, sterol, tocopherol distribution as well as the lipid classes and unsaponifiable level. The content of total lipids was within the range of 3.21–3.40% of grain dry matter. Fractionation of lipids into polar and nonpolar classes showed that the transgenic maize (Bt-176) contained more polar lipids than the control maize. In general, results obtained from lipid distribution analysis showed that except for a few minor differences, the grains of Bt-176 maize were comparable in composition to that of the control maize. On the other hand, the analytical data have been elaborated by supervised ANN pattern recognition technique in order to classify genetically modified maize (Bt-176) and conventional maize as well as to authenticate the origin of the samples.

In another study, Paul and Munkvold (2005) combined MLR and ANN modeling approaches to establish models to predict the severity of gray leaf spot of maize, caused by Cercospora zeae-maydis. In all, 329 cases consisting of environmental, cultural, and location-specific variables were collected for field plots in Iowa between 1998 and 2002. Disease severity on the ear leaf at the dough to dent plant growth stage was used as the response variable. Correlation and regression analyses were performed to select potentially useful predictor variables. Predictors from the best 9 of 80 regression models were used to develop ANN models. A random sample of 60% of the cases was used to train the ANN, and 20% each for testing and validation. Model performance was evaluated based on R^2 and MSE for the validation dataset. The best models had R^2 ranging from 0.70 to 0.75 and MSE ranging from 174.7 to 202.8. The most useful predictor variables were hours of daily temperatures between 22 and 30°C (85.50 to 230.50 h) and hours of nightly relative humidity ≥90% (122 to 330 h) for the period between growth stages V4 and V12, mean nightly temperature (65.26 to 76.56°C) for the period between growth stages V12 and R^2, longitude (90.08 to 95.14°W), maize residue on the soil surface (0 to 100%), planting date (in day of the year; 112 to 182), and gray leaf spot resistance rating (2 to 7; based on a 1-to-9 scale, where 1 = most susceptible to 9 = most resistant).

3.25. Marjoram

Sales predicting constitutes one of the stages in the distribution-production chain. It can bring much profit to a producer provided that it is carried out properly. There are many methods and models for constructing predictions. ANNs can reflect very complex functions because of their high adaptive properties. Their particular feature is non-linearity and easiness in constructing models. Analysts applied ANN to predict the sales volume for marjoram (Koszela et al., 2004).

3.26. Mushroom

The effect of different pre-treatments (osmotic dehydration and gum coating) on moisture and oil content of fried mushroom was investigated, and ANN and GA were applied for modeling of these parameters during frying. Osmotic dehydration was performed in solution of NaCl with concentrations of 5% and 10%, and methyl cellulose was used for gum coating. Either pre-treated or control samples were fried at 150, 170, and 190 °C for 0.5, 1, 2, 3, and 4 min. The results displayed that osmotic dehydration and gum coating significantly decreased (0–84%, depending upon the processing conditions) oil content of fried mushrooms. However, moisture content of fried samples diminished as a result of osmotic pre-treatment and increased by gum coating. An ANN model was developed to estimate moisture and oil content of fried mushroom, and GA was used to optimize network configuration and learning parameters. The developed GA–ANN, which included 17 hidden neurons could predict moisture and oil content with correlation coefficient of 0.93 and 96%, respectively. These results indicating that GA–ANN model provide an accurate prediction method for moisture and oil content of fried mushroom (Mohebbi et al., 2011).

3.27. Okra pods

An ANN model was applied to predict quality indices of okra pods after drying in a domestic microwave oven. The best possible ANN configuration was found to be a 3→6→4 structure with sigmoid transfer function. This optimal model was capable of predicting the total color change, browning index, coefficient of rehydration and bulk shrinkage coefficient with R^2 higher than 0.98 during training phase. The ANN model predicted quality indices better than the MLR model (Al-Sulaiman, 2011).

3.28. Onion

Tropea red onion (Allium cepa L. var. Tropea) is among the most highly appreciated Italian products. It is cultivated in specific areas of Calabria and, due to its characteristics, was recently awarded with the protected geographical indications (PGI) certification from the European Union. A reliable classification of onion samples in groups corresponding to “Tropea” and “non-Tropea” categories is now available to the producers. This important goal has been achieved through the evaluation of three supervised chemometric approaches. Onion samples with PGI brand (120) and onion samples not cultivated following the production regulations (80) were digested by a closed-vessel microwave oven system. ICP-MS equipped with a dynamic reaction cell was used to determine the concentrations of 25 elements (Al, Ba, Ca, Cd, Ce, Cr, Dy, Eu, Fe, Ga, Gd, Ho, La, Mg, Mn, Na, Nd, Ni, Pr, Rb, Sm, Sr, Tl, Y, and Zn). The multi-element fingerprint was processed using linear discriminant analysis (LDA) (standard and stepwise), soft independent modeling of class analogy (SIMCA), and backpropagation artificial neural network (BPANN). The cross-validation procedure showed good results in terms of the prediction ability for all of the chemometric models: standard LDA, 94.0%; stepwise LDA, 94.5%; SIMCA, 95.5%; and BPANN, 91.5% (Furia et al., 2011). In another study, moisture sorption isotherms of red onion slices were determined at 30, 40, 50, and 60°C using the standard gravimetric static method over a range of relative humidity from 0.11 to 0.83. The experimental sorption curves were fitted by seven empirical equations: modified Henderson, modified Chung–Pfost, modified Halsey, modified Oswin, modified Smith, modified BET, and GAB. Also, three types of ANN models: linear, multilayer perceptron, and RBFNN were developed and tested to predict the equilibrium moisture content of onion slices and the selected models were trained by using related algorithms. The modified Oswin model was found acceptable for predicting adsorption moisture isotherms and fitting to the experimental data, based on the R^2= 0.991, mean relative percent error (MRE=15.019), and standard error of estimation (SEE=1.371). Multilayer perceptron model with four layers (2→ 17→ 14→ 1) was selected as the best ANN configuration for estimation of onion slices’ equilibrium moisture content by considering R^2= 0.993 and good performance (Gazor and Eyvani, 2011).

Melin et al. (2007) performed experiments on real prices of green onion and tomato in the U.S. using modular ANN with fuzzy integration applied for time series forecasting. They implemented several ANN architectures to the problem of simulating and predicting the dynamic behaviour of complex economic time series. They also compared the simulation results with the traditional statistical model. The results suggested that real prices of green onion and tomato in the U.S. show complex fluctuations in time and are very complicated to predict with traditional statistical approaches.

Amiri et al. (2011) compared the ability of ANFIS, geostatistical models (ordinary kriging (OK), and Winter method for prediction of seasonality in prices of onions and potatoes in Iran over the seasonal period 1986-2001. Their results demonstrated that the best estimators in order are Winter method, ANFIS and geostatistical methods. Winter and ANFIS methods were good for predicting the prices while geostatistical models were not useful in this respect.

3.29. Oregano

ANN and MMs were developed to predict the supercritical carbon dioxide extraction of oregano bract essential oil. The extraction of essential oils using compressed carbon dioxide is a modern technique offering significant advantages over more conventional methods, especially in particular applications. The prediction of extraction efficiency is a powerful tool for designing and optimizing the process. Backpropagation learning algorithm, incorporating different training methods was applied. The required data were collected; pre-treating was used for ANN training. The accuracy and trend stability of the trained networks were verified according to their ability to predict unseen data. The LM algorithm was found to be the most suitable algorithm, with the appropriate number of neurons (i.e., ten neurons) in the hidden layer and a minimum average absolute relative error (ARE) (i.e., 0.019164). In addition, some excellent predictions with maximum error of 0.039313 were observed. The results demonstrated the ANN's capability to predict the measured data. The ANN model performance was also compared to a suitable MM, thereby confirming the superiority of the ANN model (Moghadassi et al., 2011).

3.30. Parsnip

In recent years, agricultural engineers working in research have been using modern modeling tools, such as ANNs, with increasing frequency. This tool, as a universal approximator together with computer image analysis is used to create empirical models that describe phenomena and processes involved in extracting and processing plant materials. ANNs are able to generalize from acquired knowledge, and this is an important feature when analyzing data involving a large range of factors to determine a given process. In a reported investigation, assessment and classification of dried parsnip was done using ANNs on the basis of digital photos. Obtained by the convection method, the dried parsnip was analysed and classified. The characteristic features were chosen, allowing classification according to quality. A number of generated ANNs were verified and validated (Koszela, 2012).

3.31. Peas

A study was planned to forecast maturity of green peas by applying ANN method. Maturity index (MI) is a key determinant of pea softness and ultimately retail value. Pea seed development goes through the optimal market stage for human consumption about a week before harvest. MI increases rapidly during the last 3–4 days prior to the optimal harvest, which is when there is a need for better forecasting capability. Extensive field sampling is currently used to track MI in each of the individual paddocks, though it has limited ability to predict MI more than a day ahead. Analysts developed an ANN model that complements field sampling by forecasting the MI trend several days ahead. It was built using historical harvest information along with weather and climate forecasts. They implemented and evaluated the ANN in a large pea growing region in Tasmania, Australia. The ANN produced an average error of 31.8 MI units when forecasting MI at harvest with a 7-day lead time versus the current manual method which produced an average error of 36.6 MI units for a lead time of 2 days. This means the ANN model provides the ability to not only harvest peas closer to their ideal MI but also plan harvesting and transport logistics with a much greater lead time (Higgins et al., 2010).

Use of hyperbolic and ANN models in modeling quality changes of dry peas in long time cooking has been reported (Xie and Xiong, 1999). Quality of dry peas cooked at 70°C, 80°C, 90°C and 100°C for up to 240 min was assessed using both sensory evaluation and instrumental measurement. The quality changes of the peas cooked at each temperature were modeled using the primary models, i.e. hyperbolic model and its two linear versions. Both Davey's modified Arrhenius model and ANN (1→9→16) model were used as secondary models to predict the parameters of the primary models from temperature. Compared to the first order reaction kinetic model the hyperbolic model and its two linear versions significantly improved the fitness to the experimental data. Among the three proposed primary models, the performance of the hyperbolic and second linear version models was similar and better than that of the first linear version model. For the full model prediction the performance of the ANN model was better than that of the Davey model.

Experimentally determined values for the degree of hydrolysis (DH) were used with ANN model to predict the tryptic hydrolysis of a commercially available pea protein isolate at temperatures of 40, 45, and 50 °C (Buciński et al., 2008). Analyses were conducted using the *STATISTICA ANN* software on a personal computer. Input data were randomized to two sets: learning and testing. Differences between the experimental and calculated DH% were slight and ranged from 0.06% to 0.24%. The performance of the educated ANN was then tested by inputting temperatures ranging from 35 to 50 °C. Very strong correlations were found between calculated DH% values obtained from the ANN and those experimentally determined at all temperatures; the R^2 varied from 0.9958 to 0.9997. The researchers claimed that the obtained results will be useful to reduce the time required in the design of enzymatic reactions involving food proteins.

Kinetic, ANN and fuzzy logic (FL) models were proposed to model the textural changes of dry peas cooked at 70, 80, 90 and 100 °C for up to 240 min (Xie et al., 1998). The results were compared to the first order kinetic and Rizvi and Tong (R-T) models. It was observed that the textural changes in cooked peas vs. time did not follow the first order reaction kinetic model. The ANN model consistently produced the best fit to the experimental data, and the first-order-reaction kinetic model the worst. The performance of the other three models, i.e., the proposed kinetic, fuzzy and R-T, varied. The models were also validated and a similar pattern was observed. Compared to the traditional kinetic models, the ANN and FL models were found more flexible to model textural changes of dry peas in long time cooking.

3.32. Pepper

To extend the shelf life of fresh cut fruits and vegetables, it is essential to develop models that can accurately predict their storage quality. In view of this, an ANN model based on backpropagation algorithm was developed to predict the storage quality (degree of yellowness, water loss, textural firmness and vitamin C content) of fresh-cut green peppers. The prediction accuracy of ANN was compared with that of MLR-based models. The RMSE, MAE, sum of squared residuals (SSR) and standard error of prediction (SEP) were used as comparison parameters. The results showed that the accuracy and goodness of fit of the storage quality parameters predicted by ANN were better than those predicted by MLR-based models. The RMSE, MAE, SSR and SEP values obtained from the former were much lower than those obtained from the latter (Meng et al., 2012).

A study was reported based on ANN modeling of fruit colour and crop variables to predict harvest dates of greenhouse-grown sweet peppers. Sweet peppers (Capsicum annuum L.) grown in the greenhouse have irregular yields. Modeling colouration of individual fruit could help growers predict the number of fully coloured peppers that will be ready to harvest within a routine harvest period. Researchers monitored the red, green and blue colour intensities of developing pepper fruit via digital image processing. These colour measurements together with crop phenology and environmental variables were used as inputs into ANN models to predict days-to-harvest (D-to-H) for individual fruit. Analysts concluded that ANN has potential to assist greenhouse operators to predict D-to-H of sweet peppers (Lin and Hill, 2007).

A FNN with LM training algorithm was developed to predict yield for supercritical carbon dioxide extraction of black pepper essential oil. Since yield of extraction strongly depends on five independent variables including residence time, supercritical carbon dioxide temperature and pressure, particle size and supercritical carbon dioxide mass flux per unit mass of substratum; these five inputs were devoted to the network. Different networks were trained and tested with different network parameters using training and testing data sets. Using validating dataset the network having the highest R^2 and the lowest MSE was selected. To confirm the network generalization, an independent dataset was used and the predictability of the network was statistically assessed. Statistical analyses showed that the ANN predictions had an excellent agreement ($R^2 = 0.9698$) with experimental data. Furthermore, a mass transfer based MM was developed for constant rate period and diffusion-controlled regime of supercritical carbon dioxide extraction. The proposed model was numerically solved using modified Euler's and finite difference methods. Comparing predicted results of the ANN model and the MM to experimental data indicated that the ANN model had better predictability than the MM (Izadifar and Abdolahi, 2006). Abdesselam and Abdullah predicted grading of pepper berries through the use of image processing and ANN modeling (Abdesselam et al., 2000). Also, ANN successfully predicted cuticle cracking in greenhouse peppers and tomatoes (Ehret et al., 2008).

3.33. Potato

To forecast site-specific early season potato yield in eastern Canada, ANN and MLR models were developed. Using data from several replicated on-farm experiments conducted over 3 years, model performance was evaluated for their capacity to forecast tuber yields 9, 10 and 11 weeks before harvest compared to SUBSTOR. A 3-input ANN using leaf area index (LAI) functions and cumulative rainfall yielded the most accurate estimations and forecasts of tuber yields. This ANN showed that tuber yield of contrasting zones was mostly a function of meteorological conditions prevailing during the first 5–8 weeks after planting. The ANN models were more coherent than MLR and SUBSTOR for two reasons: (1) the use of seasonal LAI directly as input rather than computed as an auxiliary variable and (2) the non-linearity of the modeling process resulting in more accurate estimation of the temporal discontinuities of potato tuber growth. This model showed potential for application in precision agriculture by accounting for temporal and spatial real-time climatic and crop data (Fortin et al., 2011). In a similar study, ANN and MLR were applied for modeling potato tuber growth and its in-field variations in eastern Canada. In addition to climatic inputs, the cumulative and maximal LAI were incorporated to account for in-field scale variability. Soil and genetic parameters were assumed to be integrated in LAI as suggested by earlier work. Each input and combination of inputs was evaluated from the changes they induced in MAE and RMSE. Results using data from several replicated on-farm experiments between 2005 and 2008 suggested that an ANN model using cumulative solar radiation, cumulative rainfall and cumulative LAI can adequately model site-specific tuber growth. The MAE of the retained model was 209 kg DM ha−1, which represents less than 4% of the mean final tuber yield for the 3 years of the study. Non-linear effects of explicative variables on tuber yield were attested by comparing the results of the ANN simulations to those of a MLR. The failure of MLR to simulate temporal discontinuities in tuber growth supported the use of a non-linear approach such as an ANN to model tuber growth (Fortin et al., 2010). An expert system for classification of potato tubers implementing ANN modeling showed encouraging accuracy of more than 96.22% (Ebrahimi et al., 2012). Using RGB images, ANN accurately predicted the leaf water of potatoes (Zakaluk et al., 2006).

The results of the application of two different approaches- parametric model (PM) and ANN for assessing economical productivity (EP), total costs of production (TCP) and benefit to cost ratio (BC) of potato crop have been compared. In this comparison, ANN model and Cobb-Douglas function as PM has been used. The ANN 8→6→12→1 topology with R^2=0.89 resulted in the best-suited model for estimating EP. Similarly, optimal topologies for TCP and BC were 8→13→15→1 (R^2=0.97) and 8→15→13→1 (R^2=0.94), respectively. The ANN approach allowed to reduce the average estimation error from -184% for PM to less than 7% with a +30% to -95% variability range (Zangeneh et al., 2011).

Drying kinetic of sweet potato was investigated considering different drying conditions. The drying experiments were performed at five levels of drying air temperature of 50-90°C, together with five levels of air flow velocities of 1.5-5.5 m/s, and also three levels of thickness of 0.5-1.2 cm. A predictive model using ANN was proposed in order to obtain on-line predictions of moisture kinetics during drying of sweet potato. A three-layer network with tangent sigmoid transfer function in hidden layer and linear transfer functions in the output was applied. A FNN with two hidden neurons was used. The best fitting with the training dataset was obtained with eight neurons in first hidden layer and four neurons in second hidden layer, which made possible to predict moisture kinetics (moisture content, drying rate and moisture ratio) with accuracy, at least as good as experimental error, over the whole experimental range. On validation dataset, simulation and experimental kinetics test were in good agreement. Comparing the R^2, MRE and standard deviation of % MRE (STD_R) using the developed ANN model. It was observed that the ANN could be applied for on-line state estimation of drying characteristics and control of drying processes (Singh and Pandey, 2011).

Discriminating between potato tubers and clods is the first step in developing an automatic separation system on potato harvesters. An acoustic-based intelligent system was developed for high speed discriminating between potato tubers and soil clods. About 500 kg mixture of potato tubers and clods were loaded on a belt conveyer and were impacted against a steel plate at four different velocities. The resulting acoustic signals were recorded, processed and potential features were extracted from the analysis of sound signals in both time and frequency domains. A multilayer perceptron ANN with a backpropagation algorithm was used for pattern recognition. Altogether, 17 potential discriminating features were selected and fed as input vectors to the ANN models. Optimal network was selected based on MSE, correct detection rate and correlation coefficient. At the belt velocity of 1 m s−1, detection accuracy of the presented system was about 97.3% and 97.6% for potatoes and clods, respectively. Increasing the belt velocity resulted in the reduction of detection accuracy and increase in the number of miss classified samples. By using this system, it is expected that a potato harvester may operate at a capacity of 20 ton hr−1 with the accuracy of about 97% (Hosainpour et al., 2009; 2011).

3.34. Potato chips

The ANN modeling approach was used to predict acrylamide formation and browning ratio (%) in potato chips as influenced by time*temperature covariants. A series of FNN models with backpropagation training algorithm were created. Among various network configurations, 4→5→3→2 configuration was found as the best performing network topology. Four neurons in the input layer were reflecting the asparagine concentration, glucose concentration, frying temperature, and frying time. The output layer had two neurons representing acrylamide concentration and browning ratio of potato chips. The ANN modeling approach was shown to successfully predict acrylamide concentration (R^2 = 0.992) and browning ratio (R^2 = 0.997) of potato chips during frying at different temperatures in time-dependent manner for potatoes having different concentrations of asparagine and glucose. The workers concluded that ANN modeling is a useful predictive tool which considers only the input and output variables rather than the complex chemistry (Serpen and Gökmen, 2007).

Quality of potatoes in chips industry is estimated from the intensity of darkening during frying. This is measured by a human jury, subject to numerous factors of variation. Gray level intensities were obtained for the apex, the center, and the basal parts of each chip using image analysis of frying assays. Investigators tested a feedforward ANN to associate these data with color categories. It behaved in good agreement with human estimations, obtaining correlation coefficients of 0.972 for training data and of 0.899 for validation data. A systematic study of the response of the model allowed understanding the criteria of evaluation used by the human operators (Marique et al., 2003).

3.35. Pumpkin

The experiments were conducted with the objectives to predict, using ANNs, the color intensity (ΔE), percentage of shrinkage as well as the Heywood shape factor, which is the representative of deformation of osmotically dehydrated and air dried pumpkin pieces. Several osmotic solutions were used including 50% (w/w) sorbitol solution, 50% (w/w) glucose solution, and 50% (w/w) sucrose solution. Optimum ANN models were established based on one to two hidden layers and 10–20 neurons per hidden layer. The ANN models were then tested against an independent dataset. The measured values of the color intensity, percentage of shrinkage, and the Heywood shape factor were predicted with $R^2 > 0.90$ in all cases, except when all the drying methods were combined in one dataset (Zenoozian et al., 2007).

Other investigation was planned with the aims to forecast the moisture content, product deformation and color changes (ΔE) of osmotically dehydrated pumpkin undergoing hot air drying via the use of combined wavelet transform (WT) ANN (Zenoozian and Devahastin, 2009). A multiple layer FNN was created to forecast the physical properties based on inputs of wavelet coefficients and drying time. Several pre-osmosed solutions were used including sorbitol, glucose and sucrose solutions. Optimized ANN models were created for sorbitol, glucose and sucrose solutions based on 1–2 hidden layers and 10–41 neurons per hidden layer. ANN models were then tested against an independent dataset. Measured values of moisture content, deformation, in terms of the so-called Heywood shape factor, and ΔE were predicted with $R^2 > 0.9957$ in all cases, except when pumpkin was osmotically dehydrated with glucose. The WT-ANN models were found to estimate the Heywood shape factor and ΔE with % MRE smaller than the ANN models alone in most cases.

3.36. Rhubarb

Rhubarb is one of the most widely used Chinese medicinal herbs in China. Fast and accurate identification of official and unofficial rhubarb samples is most critical for quality control of Chinese medicine production. In this study near-infrared reflectance (NIR) spectrometry and ANN were combined to develop classification models for identifying 52 official and unofficial rhubarb samples. The measured spectra were compressed by WT and then the ANN classification models were trained with the reduced-variables spectral data. The rate of correct classification was over 96% (Tang et al., 2004). In other study, NIR spectrometry and ANN were used for the quantitative prediction of four active constituents in rhubarb: anthraquinones, anthraquinone glucosides, stilbene glucosides, Tannins and related compounds. The near infrared spectra of the samples were acquired in 1100-2500 nm from powdered rhubarb samples. Four calibration models using RBFNN were set up to correlate the spectra with the values determined by high performance liquid chromatography. RMSEs of the models for the constituents studied were 2.572, 0.442, 2.794 and 9.438, respectively. The method is fast, and satisfactory results were obtained. The proposed method can be used for determining the active constituents in Chinese herbal medicine (Yu et al., 2007). Another report showed importance of ANN for the identification of rhubarb samples. A method by which discriminate official and unofficial rhubarb samples using three layer perceptron ANN was successfully applied to NIR data (Zhang et al., 2007).

3.37. Rosemary

For centuries, rosemary (Rosmarinus officinalis L.) has been used to prepare essential oils, which even now, are highly valued due to their various biological activities. Nevertheless, it has been noted that these activities often depend on the origin of the rosemary plant and the method of extraction. Since both of these quality parameters can greatly influence the chemical composition of rosemary oil, an original analytical method was developed where “dry distillation” was coupled to headspace solid-phase microextraction (HS-SPME), and then a data mining technique using the Kohonen self-organizing map algorithm was applied to the data obtained. The large dataset was then treated with a rarely used chemometric technique based on non-classical statistics. Applied to 32 rosemary samples collected at the same time from 12 different sites in the north of Algeria, this method highlighted a strong correlation between the volatile chemical compositions of the samples and their origins, and it therefore allowed the samples to be grouped according to geographical distribution. Moreover, the method allowed to identify the constituents that exerted the most influence during classification (Tigrine-Kordjani et al., 2007). Also, HNN technique was successfully applied for modeling extraction curves from SCFE rosemary oil (Stuart et al., 1997).

3.38. Soybean

Calibration equations for the estimation of amino acid composition in whole soybeans were developed using partial least squares (PLS), ANN, and support vector machines (SVM) regression methods for five models of NIR spectrometers. The effects of amino acid/protein correlation, calibration method, and type of spectrometer on predictive ability of the equations were analyzed. The performance of PLS and SVM was found to be significantly better than that of ANN (Kovalenko et al., 2006). ANN model could be applied to in-situ collected hyperspectral data for soybean LAI estimation with quite accurate prediction (Song et al., 2006). As per published report, ANN models proved to be a superior methodology for accurately predicting soybean yields under typical Maryland climatic conditions (Kaul et al., 2005).

3.39. Spinach

An attempt was made to retrieve the spinach crop parameters like biomass, leaf area index, average plant height and soil moisture content by using the X-band scattering coefficients with backpropagation ANN at different growth stages of this crop. The research confirmed the utility of backpropagation ANN in handling such a non-linear dataset. Different transfer functions, e.g., tansig, logsig and purelin were used and the performance of the ANN was optimized by changing the number of neurons in the hidden layers. The study suggested the need of critical analysis of the backpropagation ANN in terms of selection of the best transfer function and other network parameters for the better results (Prasad et al., 2012). In another study, a RBFNN was created for the retrieval of crop parameters of spinach. It was noted that retrieved parameters were so close to the experimental results that confirm the potential of RBFNN as estimator. The main advantages of RBFNN over other theoretical approaches are that it is less time taking and less complex approach (Pandey et al., 2010).

3.40. Thyme

Drying kinetics of thyme was analyzed considering different conditions: air temperatures between 40-80º C, and air velocity of 1 m/s. Eight different empirical models were fitted to the experimental data. Additionally, the dependence of the parameters of each model on drying temperature was determined, obtaining equations that allow the evolution of the moisture content to be estimated at any temperature. In addition, an ANN model was developed and compared with the empirical models; the ANN model predicted the moisture evolution more accurately (Rodríguez et al., 2011). The microwave drying kinetics of thyme leaves were modeled using ANN methodologies. Effects of microwave power output and sample mass on drying behavior, color parameters, rehydration characteristics and some sensory scores of thyme leaves were investigated. Within the range of the microwave power outputs, 180–900W, and sample amounts, 25–100g, moisture content of the leaves were reduced to 0.1 $\pm$ (0.01) from 4.05 kg water/kg dry base value. Drying times of the leaves were found to be varying between 3.5 and 15.5 min for constant sample amount, and 6.5 and 20.5 min for constant power output. Experimental drying data obtained were successfully modeled using ANN methodology. Statistical values of the test data were found to be 0.9999, 4.0937 and 0.025, respectively for R^2, mean absolute percentage error (MAPE) and RMSE. Some changes were recorded in the quality parameters; and acceptable sensory scores for the dried leaves were observed in all of the experimental conditions ($P<0.05$) (Sarimeseli et al., 2012).

3.41. Turnip

Generalized regression neural network (GRNN) and FNN were created to model squeezing of turnip. Francl (2004) observed that ANNs may extract previously undetected and possibly complex relationships, which can increase prediction accuracy.

3.42. Walnut

An acoustic-based intelligent system was developed for classifying of *sangi* and *kaghazi* genotypes of Iranian Walnuts. To establish the ANN models, a total of 4000 Walnut sound signals, 2000 samples for each genotypes were recorded. In creating the ANN models, several ANN architectures, each having different numbers of neurons in hidden layer were evaluated. The optimal model was selected after several evaluations based on minimizing the (MSE), correct detection rate (CDR) and correlation coefficient (r). Selected ANN for classification was of 47→18→2 configuration. CDR of the proposed ANN model for two walnut genotypes, *Sangi* and *Kaghazi* were 99.64 and 96.56, respectively. MSE of the system was found to be 0.0185 (Khalesi et al., 2004). In other study, an ANN model was used to predict removal efficiency of Lanaset Red (LR) G on walnut husk (*WH*). Effects of particle size, adsorbent dose, initial pH value, dye concentration, and contact time were investigated to optimize sorption process. Operating variables were used as the inputs to the constructed ANN to predict the dye uptake at any time as an output. Commonly used pseudo second-order model was fitted to the experimental data to compare with ANN model. According to error analyses and determination of coefficients, ANN was the more appropriate model to describe this sorption process. Results of ANN indicated that pH was the most efficient parameter (43%), followed by initial dye concentration (40%) for sorption of *LR G* on *WH* (Çelekli et al., 2011).

4. Conclusions

Due to their remarkable ability to learn from a set of examples and predict accurately, ANNs are being utilized more and more in agricultural sciences. This article highlighted the significant contribution of ANN technology in vegetable cultivation, packaging, processing, storage and transportation. This paper demonstrates how beneficial and promising ANN has become over a past decade for predictive analysis in vegetables. The review includes wide range of vegetables, viz., asparagus, alfalfa sprouts, anise, basil, beans, beetroot, bell pepper, broccoli, cabbage, carrot, capsicum, celery, chickpea, chilli pepper, corn, cruciferous sprouts, cucumber, garlic, ginger, herb, jalapeno, lemon grass oil , lentils, maize, marjoram, mushroom, okra pods, onion, oregano, parsnip, peas, pepper, potato, potato chips, pumpkin, rhubarb, rosemary, soybean, spinach, thyme, turnip and walnut. This is an all inclusive review reporting all the research related to applications of ANN in vegetables. According to this study, after extensive search of published literature, the following optimistic conclusion can be made: (i) ANN is fast, simple, reliable, accurate and low-cost method for predictive analysis and modeling in vegetables. (ii) ANNs are precious tools in reducing the workload of the scientists and researchers. (iii) ANN can analyze nonlinear multivariant data with high-quality performance, fewer variables, and shorter computation time.

References

Abdesselam, A., Abdullah, R. C., 2000. Pepper berries grading using artificial neural networks, In: Proceedings of the IEEE International Conference on TENCON, vol. 2, , pp. 153-159.

Abyaneh, H. Z., Nia, A. M., Varkeshi, M. B., Marofi, S., Kisi, O., 2010, Performance evaluation of ANN and ANFIS models for estimating garlic crop evapotranspiration, J. Irrig. Drain. Eng. 137(5) , 280-286.

Abyaneh, H. Z., Varkeshi, M. B., Ghasemi, A., Marofi, S., Chayjan, R. A., 2011. Determination of water requirement, single and dual crop coefficient of garlic ('Allium sativum') in the cold semi-arid climate, Aust. J. Crop Sci. 5(8), 1050.

Aghbashlo, M., Kianmehr, M. H., Nazghelichi, T., Rafiee S., 2011. Optimization of an artificial neural network topology for predicting drying kinetics of carrot cubes using combined response surface and genetic algorithm, Dry. Tech. 29(7), 770-779.

Al-Sulaiman, M. A., 2011. Prediction of quality indices during drying of okra pods in a domestic microwave oven using artificial neural network model, Afr. J. Agric. Res. 6(12), 2680-2691.

Amiri, A., Bakhshoodeh, M., Najafi, B., 2011. Forecasting seasonality in prices of potatoes and onions: challenge between geostatistical models, neuro fuzzy approach., Winter method, MPRA Paper No. 34093, Available online with updates at http://mpra.ub.uni-muenchen.de/34093.

Atas, M., Temizel, A., Yardımcı, Y., 2010.Classification of aflatoxin contaminated chili pepper using hyperspectral imaging and artificial neural networks, In: Proceedings of the 18th IEEE Conference on Signal Processing and Communications Applications (SIU), pp. 9-12.

Ataş, M., Yardimci, Y., Temizel A., 2012. A new approach to aflatoxin detection in chili pepper by machine vision, Comput. Electron. in Agric. 87, 129-141.

Ataş, M., Yardımcı, Y., Temizel, A., 2011. Aflatoxin contaminated chili pepper detection by hyperspectral imaging., machine learning, In: Proceedings of SPIE, vol. 8027, , pp.80270F-1.

Boniecki, P., 2005. The use of artificial neuronal networks of the RBF type for prediction of yield of chosen cereal plants, J. of Res. Appl. Agric. Eng. 50(2), 15-19.

Boniecki, P., 2005. Using of neuronal techniques in agricultural practice, J. Res. and Appl. in Agric. Eng. 50(2), 10-14.

Buciński, A., Karamać, M., Amarowicz, R., Pegg, R.B., 2008. Modeling the tryptic hydrolysis of pea proteins using an artificial neural network, LWT-Food Sci. and Tech. 41(5), 942-945.

Buciński, A., Zieliński, H., Kozłowska, H., 2004. Artificial neural networks for prediction of antioxidant capacity of cruciferous sprouts, Trends in Food Sci. 15(3),161-169.

Çakmak, Y. S., Boyacı, İ. H., 2011. Quality evaluation of chickpeas using an artificial neural network integrated computer vision system, Int. J. Food, Sci. Tech. 46(1), 194-200.

Çelekli, A., Birecikligil, S.S., Geyik, F., Bozkurt, H., 2011. Prediction of removal efficiency of Lanaset Red G on walnut husk using artificial neural network model, Bioresource Tech. 103(1), 64–70.

Changying, X. X. J., 2002. Application of the combination of genetic algorithm and artificial neural network to prediction of cucumber downy mildew, Trans. of the Chin. Soc. Agric. 4.

Cubero, S., Aleixos, N., Moltó, E., Gómez-Sanchis, J., Blasco, J., 2011. Advances in machine vision applications for automatic inspection and quality evaluation of fruits and vegetables, Food Bioprocess Tech. 4(4), 487-504.

Drumm, D., Purvis, M., Zhou, Q., 1999. Spatial ecology and artificial neural networks: modeling the habitat preference of the sea cucumber. Holothuria leucospilota) on Rarotonga, Cook Islands, in: 11th Annual Colloquium of the Spatial Information Research Centre, University of Otago, Dunedin, New Zealand.

Ebrahimi, E., Mollazade, K., Arefi, A., 2012. An expert system for classification of potato tubers using image processing and artificial neural networks, Int. J. of Food Eng. 8(4), 9.

Ehret, D. L., Hill, B. D., Raworth, D.A., Estergaard, B., 2008. Artificial neural network modelling to predict cuticle cracking in greenhouse peppers and tomatoes, Comput. Electron. Agric. 61(2), 108-116.

El-Sanhoty, R., Shahwan, T., Ramadan, M. F., 2006. Application of artificial neural networks to develop a classification model between genetically modified maize (Bt-176) and conventional maize by applying lipid analysis data, J. Food. Compos. Anal. 19(6), 628-636.

Erenturk, S., Erenturk, K., 2007. Comparison of genetic algorithm., neural network approaches for the drying process of carrot, J. Food. Eng. 78(3), 905-912.

Fortin, J. G., Ancti,l F., Parent, L. É., Bolinder, M.A., 2011. Site-specific early season potato yield forecast by neural network in Eastern Canada, Precision. Agric. 12(6), 905-923.

Fortin, J. G., Anctil, F., Parent, L. É., Bolinder, M. A., 2010. A neural network experiment on the site-specific simulation of potato tuber growth in Eastern Canada, Comput. Electron. Agric. 73(2), 126-132.

Francl, L. J., 2004. Squeezing the turnip with artificial neural nets, Phytopathology. 94(9), 1007-1012.

Furia, E., Naccarato, A., Sindona, G., Stabile, G., Tagarelli, A., 2011. Multielement fingerprinting as a tool in origin authentication of pgi food products: tropea red onion, J. of Agric., Food. Chem. 59(15), 8450-8457.

Gazor, H.R., Eyvani, A., 2011. Adsorption isotherms for red onion slices using empirical and neural network models, Int. J. Food. Eng. 7(6) DOI: 10.2202/1556-3758.2592.

Hahn F., Mota R., 1997. Nobel Chile Jalapeno sorting using structured laser and neural network classifiers, In: Proceedings of the Springer Berlin/Heidelberg on Image Analysis and Processing, , pp. 517-523.

Hahn, F., 1996. Neural networks using broadband spectral discriminators reduces illumination required for broccoli identification in weedy fields, In: Proceedings of International Society for Optics and Photonics on Aerospace/Defense Sensing and Controls, pp. 398-407.

Hahn, F., 1995. Broccoli/weed/soil discrimination by optical reflectance using neural networks, In: Proceedings of International Society for Optics and Photonics on OE/Aerospace Sensing and Dual Use Photonics, pp. 165-174.

Hahn, F., Muir, A.Y., 1996. Neural networks for crop/weed discrimination in different cabbage trials, In: Proceedings of the IEEE International 3rd Conference on Signal. Process, vol. 2, , pp. 1445-1448.

Higgins, A., Prestwidge, D., Stirling, D., Yost, J., 2010. Forecasting maturity of green peas: An application of neural networks, Comput. Electron. Agric. 70(1), 151-156.

Hosainpour, D. A., Komarizade, M. H., Mahmoudi, A., Shayesteh, M.G., 2009. High speed separation of potato and clod using an acoustic based intelligent system, J. Agríc. Sci. (university of tabriz), 19(2), 239-251.

Hosainpour, D. A., Komarizade, M. H., Mahmoudi, A., Shayesteh, M.G., 2011. High speed detection of potato and clod using an acoustic based intelligent system, Expert Syst. With. Appl. 38(10), 12101-12106.

Hosaka, A., Makino, Y. , Kawagoe, Y., Oshita S., 2012. Prediction of degradation rate of broccoli during storage by hyper spectral imaging, In: International Conference of Agricultural Engineering, Valencia, Spain, 8-12, , Abstract No. C-1164.

Hussain, M. A., Rahman, M. S., 1999. Thermal conductivity prediction of fruits and vegetables using neural networks, Int. J. Food. Prop. 2(2), 121-137.

Izadifar, M., Abdolahi, F., 2006. Comparison between neural network and mathematical modeling of supercritical CO< sub> 2</sub> extraction of black pepper essential oil, The J. Supercrit. Fluids. 38(1), 37-43.

Izadifar, M., Abdolahi, F., 2006. Comparison between neural network and mathematical modeling of supercritical CO< sub> 2</sub> extraction of black pepper essential oil, The J. Supercrit. Fluids. 38(1), 37-43.

Jayasinghe, P. K. S. C., Yoshida, M., 2009. GIS-based neural network modeling to predict suitable area for beetroot in Sri Lanka: towards sustainable agriculture, J. Dev. Sustain. Agric. 4(2), 165-172.

Kaul, M., Hill, R.L., Walthall, C., 2005. Artificial neural networks for corn and soybean yield prediction, Agric. Syst. 85(1) 1-18.

Kerdpiboon, S., Kerr, W.L., Devahastin, S., 2006. Neural network prediction of physical property changes of dried carrot as a function of fractal dimension and moisture content, Food. Res. Int. 39(10), 1110-1118.

Khalesi, S., Mahmoudi, A., Hosainpour, A., Alipour, A., 2011. Detection of walnut varieties using impact acoustics and artificial neural networks. ANNs, Mod. Appl. Sci. 6(1), p43.

Khazaei, J., Naghavi, M. R., Jahansouz, M. R., Salimi-Khorshidi, G., 2008. Yield estimation and clustering of chickpea genotypes using soft computing techniques, Agron. J. 100(4), 1077-1087.

Kılıç, K., Boyacı, İ. H., Köksel, H., Küsmenoğlu, İ., 2007. A classification system for beans using computer vision system and artificial neural networks, J. Food. Eng. 78(3), 897-904.

Koszela, K., 2012. Classification of dried parsnip using artificial neural networks, J. Res. Appl. in Agric. Eng. 57(1) 87-90.

Koszela, K., Boniecki, P., Weres, J., 2004. Neural predicting of the farm product distribution exemplified by the marjoram and carrot, J. of Res. and Appl. in Agric. Eng. 49.

Kovalenko, I. V., Rippke, G. R., Hurburgh, C.R., 2006. Determination of amino acid composition of soybeans (Glycine max) by near-infrared spectroscopy, J. Agríc. Food. Chem. 54(10), 3485-3491.

Łapczyńska-Kordon, B., Francik, S., 2006. Analysis of celery hardness during drying process, Inzynieria Rolnicza. Nr. 13 (88), 295-302.

Li, B., He, Y., Xu, C., 2007. Simultaneous determination of three organophosphorus pesticides residues in vegetables using continuous-flow chemiluminescence with artificial neural network calibration, Talanta. 72(1), 223-230.

Lin, W. C., Hill, B.D., 2007. Neural network modelling of fruit colour and crop variables to predict harvest dates of greenhouse-grown sweet peppers, Can. J. Plant. Sci. 87(1), 137-143.

Marique, T., Kharoubi, A., Bauffe, P., Ducattillon, C., 2003. Modeling of fried potato chips color classification using image analysis and artificial neural network, J. Food. Sci. 68(7), 2263-2266.

Melin, P., Mancilla, A., Lopez, M., Trujillo, W., Cota, J., Gonzalez, S., 2007. Modular neural networks with fuzzy integration applied for time series forecasting, Anal. and Des. of Intell. Syst. using Soft Comput. Tech. 217-225.

Meng, X., Zhang, M., Adhikari, B., 2012. Prediction of storage quality of fresh-cut green peppers using artificial neural network, Int. J. Food. Sci. Tech. 47, 1586–1592.

Mishra, K. K., Singh, B. K., Punhani, A., Singh, U., 2009. Combining neural networks and genetic algorithms to predict and to maximize lemon grass oil production, In: Proceedings of the IEEE International Joint Conference on Computational Sciences and Optimization, vol. 1, , pp. 297-299.

Moghadassi, A., Hosseini, S.M., Parvizian, F., Al-Hajri, I., Talebbeigi M., 2011. Predicting the supercritical carbon dioxide extraction of oregano bract essential oil, Songklanakarin J. Sci., Tech. 33.

Mohebbi, M., Akbarzadeh-T, M. R., Shahidi, F., Zabihi, S.M., 2011. Modeling and optimization of mass transfer during osmosis dehydration of carrot slices by neural networks and genetic algorithms, Int. J. Food. Eng. 7(2), DOI: 10.2202/1556-3758.1670.

Mohebbi, M., Amiryousefi, M. R., Hasanpour, N., Ansarifa,r E., 2011. Employing an intelligence model and sensitivity analysis to investigate some physicochemical properties of coated bell pepper during storage, Int. J. Food. Sci. Tech. 47(2), 299-305.

Mohebbi, M., Fathi, M., Shahidi, F., 2011. Genetic algorithm–artificial neural network modeling of moisture and oil content of pretreated fried mushroom, Food . Bioprocess Tech. 4(4), 603-609.

Pandey, A., Jha, S.K., Prasad, R., 2010. Retrieval of crop parameters of spinach by radial basis neural network approach using X-band scatterometer data1. Russ. Agríc. Sci. 36(4), 312-315.

Paul, P. A., Munkvold, G.P., 2005. Regression and artificial neural network modeling for the prediction of gray leaf spot of maize, Phytopathology. 95(4), 388-396.

Prasad, R., Pandey, A., Singh, K.P., Singh, V.P., Mishra, R.K., 2012. Retrieval of spinach crop parameters by microwave remote sensing with back propagation artificial neural networks, A comparison of different transfer functions. Adv. in Space Res. 50(3), 363-370.

Rodríguez, J., Cárcel, J., Clemente, G., Peña, R., Bon, J., 2011. Modeling drying kinetics of thyme (thymus vulgaris), In: III European Drying Conference EuroDrying, Palma (Mallorca).

Ruanet, V. V., Kochieva, E. Z., Ryzhova, N.N., 2005a. The use of a self-organizing feature map for the treatment of the results of RAPD and ISSR analyses in studies on the genomic polymorphism in the genus Capsicum L, Russ. J. . Genet. 41(2), 202-210.

Ruanet, V. V., Kochieva, E. Z., Ryzhova, N.N., 2005b. Kohonen network study of the results of RAPD and ISSR analyses of genomic polymorphism in the genus Capsicum L, Genet. 41(2), 269-278.

Sarimeseli, A., Coskun, M.A., Yuceer, M., 2012. Modeling microwave drying kinetics of thyme (thymus vulgaris l.) leaves using ann methodology., Dried Product Quality, J. of Food Process., Preservation. doi: 10.1111/jfpp.12003

Serpen, A., Gökmen, V., 2007. Modeling of acrylamide formation and browning ratio in potato chips by artificial neural network, Mol. Nutr. Food. Res. 51(4), 383-389.

Shahin, M. A., Symons, S. J., 2006. A machine vision system for grading lentils, Can. Biosyst. Eng. 43 (2001) 7-7.

Shokri, A., Hatami, T., Khamforoush, M., 2011. Near critical carbon dioxide extraction of Anise (< i> Pimpinella Anisum</i> L.) seed: Mathematical., artificial neural network modeling, The J. Supercrit. Fluids. 58(1), 49-57.

Singh, N. J. , Pandey R.K., 2011. Neural network approaches for prediction of drying kinetics during drying of sweet potato, Agric. Eng. Int.: CIGR J. 13(1), 1-7.

Siripatrawan, U., Linz, J. E., Harte, B. R., 2006. Detection of Escherichia coli in packaged alfalfa sprouts with an electronic nose and an artificial neural network, J. Food. Prot. 69(8), 1844-1850.

Song, K.S., Zhang, B., Wang, Z.M., Zhang, Y.Z., Liu, H.J., 2006. Soybean LAI estimation with in -situ collected hyperspectral data based on BP-neural networks, Scientia Agríc. Sinica. 6, 006.

Stuart, G., Machado, R., Oliveira, J. V. D., Uller, A. C., Lima, E. L., 1997. Hybrid artificial neural network applied to modeling scfe of basil and rosemary oils, Ciênc. Tecnol. Aliment. 17(4), 501-505.

Sun, M., Chen, J., Li, D., 2012. Water temperature prediction in sea cucumber aquaculture ponds by RBF neural network model, In: Proceedings of the IEEE International Conference on Systems and Informatics. ICSAI, pp. 1154-1159.

Tang, Y. F., Zhang, Z. Y., Fan, G. Q., 2004. Identification of official rhubarb samples based on NIR spectra and neural networks, Spectrosc Spect Anal. 24, 1348-1351.

Tigrine-Kordjani, N., Chemat, F., Meklati, B.Y., Tuduri, L., Giraudel, J.L., Montury, M., 2007. Relative characterization of rosemary samples according to their geographical origins using microwave-accelerated distillation, solid-phase microextraction and Kohonen self-organizing maps, Anal. Bioanal. Chem. 389(2), 631-641.

Topuz, A., 2010. Predicting moisture content of agricultural products using artificial neural networks, Adv. in Eng. Softw. 41(3), 464-470.

Tu, K., Ren, K., Pan, L., Li, H., 2007. A study of broccoli grading system based on machine vision and neural networks, In: Proceedings of the IEEE International Conference on Mechatronics and Automation, August. pp. 2332-2336.

Ung, C. Y., Li, H., Cao, W Z., Li, Y.X., Chen, Y. Z., 2007. Are herb-pairs of traditional Chinese medicine distinguishable from others? Pattern analysis and artificial intelligence classification study of traditionally defined herbal properties, J. of ethnopharmacology. 111(2), 371-377.

Vallejo-Cordoba, B., Arteaga, G.E., Nakai, S., 1995. Predicting milk shelf-life based on artificial neural networks and headspace gas chromatographic data, J. Food. Sci. 60, 885-888.

Xie, G., Xiong, R., 1999. Use of hyperbolic and neural network models in modelling quality changes of dry peas in long time cooking, J. Food. Eng. 41(3), 151-162.

Xie, G., Xiong, R., Church, I., 1998. Comparison of kinetics, neural network and fuzzy logic in modelling texture changes of dry peas in long time cooking, LWT-Food. Sci. Tech. 31(7), 639-647.
Yu, X. H., Zhang, Z. Y., Ma, Q., Fan, G. Q., 2007. Quantitative prediction of active constituents in rhubarb by near infrared spectroscopy and radial basis function neural networks, Guang pu xue yu guang pu fen xi= Guang pu, 27(3), 481.
Zakaluk, R., Ranjan, R.S., 2006. Artificial neural network modelling of leaf water potential for potatoes using RGB digital images: a greenhouse study, Potato. Res. 49(4), 255-272.
Zangeneh, M., Omid, M., Akram, A., 2011. A comparative study between parametric and artificial neural network approaches for economical assessment of potato production, Afr. J. Agric. Res. 6(13), 3061-3070.
Zare, A. H., Ghasemi, A., Bayat Varkeshi, M., Maroufi, S., 2009. Assessment of artificial neural network (ANN) in prediction of garlic evapotranspiration (etc) with lysimeter in hamedan, J. Water Soil. 23(3), 176-185.
Zare, A. H., Ghasemi, A., Bayat Varkeshi, M., Maroufi, S., 2011, Forecasting of garlic .allium sativum l. evapotranspiration by using multiple modeling, J. of Water and Soil Conserv .J. Agric. Sci. Nat. Resour. 18(2),141-158.
Zenoozian, M. S., 2011. Combined effect of packaging method and temperature on the leafy vegetables properties, Int. J. of Enviroment Sci. Dev. 2(2), 124-127.
Zenoozian, M. S., Devahastin, S., 2009. Application of wavelet transform coupled with artificial neural network for predicting physicochemical properties of osmotically dehydrated pumpkin. J. Food. Eng. 90(2), 219-227.
Zenoozian, M. S., Devahastin, S., Razavi, M.A., Shahidi, F., Poreza, H.R., 2007. Use of artificial neural network and image analysis to predict physical properties of osmotically dehydrated pumpkin, Drying Tech. 26(1), 132-144.
Zhang, W., Bai, C., Liu, G., 2007. Neural network modeling of ecosystems: A case study on cabbage growth system, Ecol. Mod. 201(3), 317-325.
Zhang, Z., Wang, Y., Fan, G., Harrington, P.D.B., 2007. A comparative study of multilayer perceptron neural networks for the identification of rhubarb samples, Phytochem. Anal. 18(2), 109-114.
Zheng, H., Fang, S., Lou, H., Chen, Y., Jiang, L., Lu, H., 2011a. Neural network prediction of ascorbic acid degradation in green asparagus during thermal treatments, Expert Syst. with. Appl. 38(5), 5591-5602.
Zheng, H., Jiang, L., Lou, H., Hu, Y., Kong, X., Lu, H., 2011b. Using neural networks to estimate the losses of ascorbic acid, total phenols, flavonoid, and antioxidant activity in asparagus during thermal treatments, J. Agric. Food Chem. 59 (2), 592-600.