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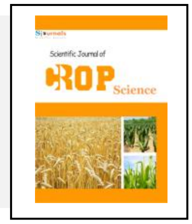

Review article

Predicting properties of cereals using artificial neural networks: A review

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A R T I C L E I N F O

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A B S T R A C T

This communication reports the use of artificial neural networks (ANN) in cereals and analyzes the major contribution of ANN in cereals (barley, corn, maze, oats, paddy, rice, rye and wheat) for prediction, forecasting, analysis and assessment, viz., cereal production; cereal yield; cereal quality; moisture; nitrogen and protein in cereals; water requirement of cereals; crop detection; monitoring and positioning; grain identification; grain quality; barley production; colour and tannin; rice husk; forecasting market share; deoxynivalenol content in grain, etc. This article would be very valuable for agriculturalists, cereal researchers, food scientists, nutritionists, academicians and students, so that they can follow a suitable methodology according to their exact requirements for conducting research.

1. Introduction

Artificial neural network (ANN) is a technique with flexible mathematical structure which is capable of identifying complex non-linear relationship between input and output data (Kashiri et al., 2012; Agrawal and Schorling, 1996; Basheer and Hajmeer, 2000; Krogh, 2008; Hassoun, 1995; Chiang et al., 2004; Wilamowski, 2003). ANNs rely on the inner structure of available datasets rather than on comprehension of the modeled processes between inputs and outputs. Therefore, ANNs have been regarded as highly empirical models with limited extrapolation capability to situations outside the range of the training and validation datasets (Mi et al., 2005). ANN and generic algorithms are two branches of artificial intelligence (AI) that can provide many benefits in engineering applications. The ANN technologies provide on-line capability to analyze many inputs and provide information to multiple outputs, and also, have the capability to learn or adapt to changing conditions (Abdelhay, 2002). In the past few years, ANNs have gained widespread acceptance for cereal grain classification and identification tasks. With the availability of different types of neural network architectures, the choice of the architecture for a particular task becomes crucial (Visen et al., 2002). The dynamic development of the information technology in the recent years resulted in the development of completely new computation possibilities, based on patterns taken from the observation of natural processes, and particularly of the work of the brain. The new methods, which have some features of AI, make it possible to build simulation models that perform the tasks assigned to them on the basis of patterns taken directly from the observation of the nature. Therefore, in the research of probabilistic empirical systems, it seems justified to use a complementary method of analysis of agricultural engineering problems and issues, which is represented by ANNs (Boniecki, 2004).

2. Significance of study

ANN is the scientific integration of the artificial neurons inspired by the biological neurons. ANN provides an alternative to the manual laboratory testing of agricultural products. ANN has a remarkable ability to predict and is replacing the process of manual testing of products in many industries. ANNs have many advantages over the conventional methods of testing, viz., they are fast, robust, low cost methods, and can model non-linear data types accurately and timely. The aim of this article is to provide insight into an area of ANN in cereals that may not have been previously appreciated, and the benefits of using ANN as a replacement for conventional methodologies of testing and report all published literature at one single stop. This communication would be very beneficial for agriculturalists, cereal researchers, scientists, academicians, students, food processing & nutrition industry and regulatory agencies.

3. Cereal grains

The development of non-destructive methods for the evaluation of cereal grain varieties has significant implications for the food processing industry (Zapotoczny, 2011). Grain yield is important for national economy, so it is necessary to predict grain yield (Yang and Zhongjian, 2011). ANN models have potential for prediction, classification, system modeling and image processing. Image analysis based on texture, morphology and colour features of grains is essential for various applications in wheat grain industry and cultivation (Pazoki and Pazoki, 2011). The ANN model helps the operator / farmer to decide the time of harvest. It also minimizes the post harvest grain losses by considering crop and machine parameters (Hiregoudar et al., 2011). ANN method is appropriate for grain monitoring, predicting grain yield, classifying aromatic and non-aromatic rice and providing feasible access to grain losses for paddy (Yang and Zhongjian, 2011; Tong et al., 2011; Jana et al., 2011). ANN is a powerful methodology that may describe the relationship between digestible amino acid contents and chemical composition of sorghum grain (Ebadi et al., 2011). Agricultural management specialists need simple and accurate estimation techniques like ANN to predict rice yields in the planning process (Ji et al., 2007). ANN has been applied in almost every aspect of agricultural science over past two decades, yet most applications are in the development stage (Bhotmange and Shastri, 2011; Goyal and Goyal, 2012a, 2012b; Goyal, 2013a, 2013b; Ebrahimi et al., 2012; Erenturk and Erenturk, 2007). The published literature for various cereals using ANN modeling is reported below.

4. Classification of cereal grains

Visen et al. (2002) hypothesized that robust specialist networks can be designed using a combination of simple networks having similar or different network architectures. To test this hypothesis, the classification accuracies of four simple network architectures, namely backpropagation network (BPN), Ward network, general regression neural network (GRNN) and probabilistic neural network (PNN) were compared with the accuracies given by specialist networks. Each specialist network was designed using a combination of five simple networks, each specializing in classifying one grain type. The grain types used in their study were Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats and rye. To evaluate the classification accuracy of the different ANN architectures, high resolution colour images of 7500 kernels (1500 kernels of each grain type) were taken for training and testing of networks. For each kernel, eight morphological features (namely, area, perimeter, length of major axis, length of minor axis, elongation, roundness, Feret diameter and compactness) and four colour features (namely, mean, median, mode and standard deviation of the grey-level values of the objects in the image) were extracted and used as input to the neural networks. Best classification accuracies (98·7, 99·3, 96·7, 98·4, and 96·9 for barley, CWRS wheat, CWAD wheat, oats and rye, respectively) were obtained using specialist PNN by researchers.

Paliwal et al. (2001) evaluated the most commonly used neural network architectures for cereal grain classification using the frequently used morphological features as inputs. An assessment of the classification accuracy of nine different ANN architectures was done by researchers to classify five different kinds of cereal grains namely, Hard Red Spring (HRS) wheat, CWAD wheat, barley, oats and rye. To evaluate the classification accuracy of the different ANN architectures, colour images of 7500 kernels (1500 kernels of each grain type) were taken. For each kernel, eight morphological features namely, area, perimeter, length of major axis, length of minor axis, elongation, roundness, Feret diameter and compactness were extracted and used as input to the ANNs. The networks were trained using 70% kernels for training and 20% kernels for validation of each grain type. Testing of the trained network was done on the remaining 10% kernels as well as the whole dataset. The classification accuracies were in excess of 97% for HRS wheat, CWAD wheat and oats. The classification accuracies for barley and rye were about 88%. The network required only four input features namely, Feret diameter area, minor axis length and compactness for classification. Analysts found GRNN architecture to be the least suitable for grain classification.

In another study taking same cereal grains, Paliwal et al. (2003b) compared the performances of a four-layer backpropagation ANN and a non-parametric statistical classifier for classification. A total of 230 features (51 morphological, 123 colour, and 56 textural) from the high-resolution images of kernels of the five grain types were extracted and used as input features for classification. Different feature models, viz., morphological, colour, texture, and a combination of the three were tested for their ability to classify these cereal grains. To make the classification process fast, the numbers of input features were reduced to 60 and 30. A set of features consisting of an equal number of morphological, colour, and textural features gave the best classification accuracies. The ANN classifier outperformed the non-parametric classifier in almost all the instances of classification.

Paliwal et al. (2004) used a flatbed scanner to identify and classify cereal grains for an inexpensive machine-vision system (MVS). Images of bulk samples and individual grain kernels of barley, CWAD wheat, CWRS wheat, oats, and rye were acquired and classification was done using a four layer backpropagation ANN. Classification accuracies in excess of 99% were obtained using a set of 10 colour and textural features for bulk samples. For single kernel images, a set of at least 30 features (morphological, colour, and textural) was required to achieve similar classification accuracies. Classification accuracies for single kernel samples varied between 96 and 99%.

Working further with the same cereal grains, Choudhary et al. (2008) classified cereal grains using wavelet, morphological, colour, and textural features of non-touching kernel images. A total of 51 morphological features, 93 colour features, 56 textural features, and 135 wavelet features were extracted from each kernel. Linear and quadratic statistical classifiers were used for classification using individual types of features and their combinations to find the best feature set and classification method for improved classification of cereal grains. Combining all morphological, colour, textural and wavelet features gave the best classification using the linear discriminant classifier with a classification accuracy of 99.4% for CWRS wheat, followed by 99.3%, 98.6%, 98.5%, and 89.4% for rye, barley, oats, and CWAD wheat, respectively.

Douik and Abdellaoui (2008) classified cereal varieties using wavelet techniques combined with multi-layer perceptron (MLP). Douik et al. (2010) focused on the classification of cereal grains using different classifiers combined to morphological, colour and wavelet features. The grain types used in their study were Hard Wheat, Tender Wheat and Barley.

Visen et al. (2004) compared two neural network architectures for classification of cereal grains. A digital image analysis algorithm was developed to facilitate classification of individual cereal grain kernels (barley, CWAD wheat, CWRS wheat, oats, and rye). A total of 230 features (51 morphological, 123 colour, and 56 textural) were extracted from 7500 high resolution colour images of each type of grain using the developed algorithm. A four-layer backpropagation neural network (BPN) and a specialist probabilistic neural network (SPNN) were evaluated for classification accuracies. The BPN used a sigmoid scaling function for input nodes and sigmoid activation function for nodes in the hidden layers. Five different data sets were used for training, testing, and validation. The

BPN based classifier outperformed the SPNN classifier for all grain types. Using various features models, the average classification accuracies for BPN were 96.4, 90.8, 98.0, 95.5, and 96.4% for barley, CWAD wheat, CWRS wheat, oats, and rye, respectively. For the SPNN classifier, the average classification accuracies were, 91.5, 84.7, 95.3, 88.4, and 93.3% for barley, CWAD wheat, CWRS wheat, oats, and rye, respectively.

Mohan et al. (2005) tested bulk samples of seven cereal grains for their reflectance characteristics using spectral wavelengths in the visible and the near-infrared (NIR) spectrum. The effect of moisture content, foreign material content and growing regions on the reflectance characteristics of CWRS wheat was determined. A classification accuracy of 99.5% was achieved by the linear parametric and BPN classifiers.

5. Crop detection and positioning

Development of an autonomous weeding machine requires a vision system capable of detecting and locating the position of the crop. It is important for the vision system to be able to recognize the accurate position of the crop stem to be protected during weeding. Several shape features of corn plants and common weed species in the location were extracted by means of morphological operations. Effective features in the classification of corn and weeds were analyzed using stepwise discriminant analysis. Among the seven features used in the analysis, four were sufficient to classify the two target groups of weeds and corn. These shape features were fed to ANN to discriminate between the weeds and the main crop. 180 images consisting of corn plants and four species of common weeds were collected from normal conditions of the field. Results showed that this technique was able to distinguish corn plants with an accuracy of 100%, while at most 4% of the weeds were incorrectly classified as corn (Kiani and Jafari, 2012).

6. Moisture and protein in cereals

Nonlinear ANN calibrations based on a large common European dataset consisting of approximately 4,000 samples in the training sets and 1,000 samples in the stop sets were used. The performance of these ANN calibrations was compared with Danish partial least squares (PLS) models for protein and moisture in cereals during the 1998 harvest in Denmark, and subsequently with PLS models based on the same European dataset. ANN models were more accurate than PLS and, unlike PLS, were linear and transferable up to 25% moisture. Investigators suggested that the improved performance of the ANN models is attributable to the modeling technique rather than the size and nature of the European dataset. The ANN models were also more stable as they required fewer bias adjustments or re-modeling over time compared with Danish PLS models (Buchmann et al., 2001).

7. Cereal grain quality

Egelberg et al. (1995) created a fully integrated instrument for cereal grain quality assessment. Colour video images of grains fed onto a belt were digitized and segmented into kernel entities. Feedforward ANN models with one hidden layer were trained with respect to desired features such as purity and flour yield. The resulting performance of ANN was better than manual human ocular inspection and alternative measuring methods.

8. Cereal grain identification

Algorithms were written to extract a total of 230 features (51 morphological, 123 colour, and 56 textural) from the high-resolution images of kernels of five grain types [barley, CWAD wheat, CWRS wheat, oats, and rye] and five broad categories of dockage constituents [broken wheat kernels, chaff, buckwheat, wheat spikelets (one to three wheat kernels inside husk), and canola (rapeseed with low erucic acid content in the oil and low glucosinolate content in the meal)]. Different feature models, viz., morphological, colour, texture, and a combination of the three, were tested for their classification performances using an ANN classifier. Kernels and dockage particles with well-defined characteristics (e.g., CWRS wheat, buckwheat, and canola) showed near-perfect classification, whereas particles with irregular and undefined features (e.g., chaff and wheat spikelets) were classified with accuracies of around 90%. The similarities in shape and size of some of the particles of chaff and wheat spikelets with the kernels of barley and oats affected the classification accuracies of the latter, adversely (Paliwal et al., 2003a).

9. Quantitative analysis for cereals

Eight cereal components (the concentration between 10-1~ 10-3), that is , protein (Pro), fat(Fat), leucine(Leu), isoleucine(Ile), valine(Val), threonine(Thr), phenylalanine(Phe) and lysine(Lys) were quantitatively analyzed by ANN. For the eight components the prediction coefficient of correlation (R^2) was: 0.969, 0.892, 0.897, 0.884, 0.970, 0,860, 0.854 and 0.899 (Ji and Yan, 1993).

10. Image analysis of bulk grain samples

Visen et al. (2004) established ANN models to acquire and process colour images of bulk grain samples of five grain types, namely barley, oats, rye, wheat, and durum wheat. The developed models were used to extract over 150 colour and textural features. A BPN based classifier was used to identify the unknown grain types. The colour and textural features were presented to the ANN for training purposes. Classification accuracies of over 98% were obtained for all grain types. Workers concluded that the results can be used to identify grain types when unloading railcars at a terminal elevator (grain handling facility).

11. Damaging process of cereal grains

Złobecki and Francik (2001) studied the damaging process of wheat grains using ANNs. Laboratory research, which provided the model basis, was affected for two types of grain stress: through random unsupported impacts inflicted on grains by a rotating arm, and - in a second experiment - loading the grains on support. The following variables were altered: energy, number of impacts and water-content in grains. Two models were developed, relying on feedforward three-layer ANN. The obtained results were verified by comparing the precision level of ANN with the existing empirical models. The comparative analysis of the relative error terms obtained showed that the values of error obtained for regression analysis were higher than the values obtained for ANN.

12. Whole grains

12.1. Amaranth

12.1.1. Quantitative prediction of synthetic food colours

Guo-qing et al. (2009) performed quantitative prediction on synthetic food colours by fluorescence spectroscopy and radial basis function neural network (RBFNN). Taking Amaranth as an example for sample solution of Amaranth with different concentrations, the fluorescence spectroscopy excited by the light with the wavelength of 400 nm was measured. The peak wavelength of Amaranth solution fluorescence spectroscopy was about 640 nm, and a non-linear relationship was observed between fluorescence relative intensity and concentration of solution. For each sample, 10 emission wavelength values were selected. The fluorescence intensity corresponding to the selected wavelength was used as the network characteristic parameters; a RBFNN was trained and constructed. The trained RBFNN was employed for predicting three kinds of samples of Amaranth solution concentration. The relative errors of prediction were: 4.60%, 4.71% and 5.94%. Their results suggested that the method is convenient, fast and of high accuracy. It is a new technique for the detection of synthetic food colour in food safety supervision and management.

12.1.2. Quantification of food colorants using a hand scanner

Kompany-Zareh and Farrokhi-Kurd (2005) developed a low-cost and reliable method employing a hand scanner for simultaneous colorimetric quantification of food colorant mixtures including amaranth, brilliant blue, and tartrazine. The appropriate instrumental conditions for measuring were selected using a genetic algorithm (GA) coupled with PLS regression. Using the conditions selected by GA, PLS and multiple linear regressions (MLR) were compared, and similar results for the two methods were obtained. Under the selected conditions for each of the colorants, ANN including three layers of nodes and Levenberg-Marquardt (LM) learning rule was employed by the researchers, which improved the results. The concentration ranges for the three colorants in the multivariate calibration models were 0.00–5.31mmol L^{-1} for amaranth, 0.00–1.85mmol L^{-1} for brilliant blue, and 0.00–21.57mmol L^{-1} for tartrazine. The minimum estimated relative standard error percentages (RSE%) for prediction of analytics in synthetic samples, using ANN with optimized parameters, were 16.8% for amaranth, 4.8% for brilliant blue, and 5.6% for tartrazine. A number of commercial food products were analyzed satisfactorily with the proposed method.

12.2. Barley

12.2.1. Identification of barley, corn and rye varieties

Cereal varieties are normally identified using time-consuming methods such as visual examination of either the intact grain or one-dimensional electrophoretic patterns of the grain storage proteins. A fast method for identification of both barley (Hordeum vulgare L.) and rye (Secale cereale L.) have been established. For barley, 95% of the mass spectra were correctly classified. However, the method was not useful in the classification of rye, due to the strong similarity between mass spectra of different varieties (Bloch et al., 2001).

Olszewski et al. (2008) applied an ANN methodology for automatic identification of the endpoint of drying barley in bulk. The usefulness of individual input variables characterising the process as well as their influence on the quality of the obtained model were analyzed. Analysts compared different topologies of the established models and found RBFNN as most suitable, thus they selected RBFNN for further experiments. The developed networks showed high R^2 values, ranging from 93.3 to 99.6%.

Nowakowski et al. (2011) implemented an ANN model for identification of mechanical damage to grain caryopses based on digital photographs. They selected a set of universal features that distinguish damaged and healthy caryopses. Researchers concluded that identification quality of multilayer ANN model is as good as a human expert.

Nowakowski et al. (2012) identified the malting of barley varieties using computer image analysis (CIA) and ANNs. They aimed to produce an identification model that allows for automatic recognition of malting barley varieties. Image analysis of samples of barley digital photographs allowed the extraction of the characteristics of varieties. Obtained characteristics from the images were used as learning data for ANN models. Workers concluded that ANN has identification abilities comparable to human experts.

12.2.2. Barley kernel identification

Szczypiński and Zapotoczny (2012) applied an algorithm for analyzing barley kernel images to evaluate cereal grain quality and perform grain classification. The input data comprised digital images of kernels obtained from an optical scanner. The algorithm identified individual kernels' smooth and wrinkled regions, described their orientation relative to the axis of symmetry, crease visibility and germ location. Workers were also able to determine the size of the wrinkled and smooth areas on a grain's surface, which allowed automatic grain classification and kernel quality assessment. Their proposed algorithm was tested using barley grain images, and validated by comparison with the evaluation results of a professional assessor. The validation of the algorithm confirmed that it is efficient and robust allowing accurate description of over 93% of kernel samples in comparison with the expert.

12.2.3. Recognition of environmental and genetic effects on barley

Gorodkin et al. (2001) aimed to find correlations between secondary metabolites and growth conditions of six varieties of barley. Using ANN methodology, it was possible for the analysts to classify chromatograms for which the varieties were fertilized by nitrogen and treated by fungicide. For each variety of barley, workers could also differentiate it from the others. Surprisingly, all these classification tasks could be solved successfully by a simple network with no hidden units. When adding to the methodology pruning of the network weights, investigators were able to reduce the set of peaks in the chromatograms and obtain a necessary subset from which the growth conditions and differentiation may be decided. Analysts found that it requires fewer information-rich peaks to perform the variety differentiation tasks than to recognize any of the growth conditions.

12.2.4. Estimating maze, wheat and barley yields

Askari and Khodadadi (2010) evaluated ANN techniques for estimating maze, wheat and barley yields. A variety of supervised feedforward ANNs, including several variations of backpropagation were selected for investigation of barley, maze and wheat yield prediction. The performance of ANN models were calculated by: mean absolute error (MAE), the root mean square error (RMSE) and the coefficient of determination (R^2). Input layer included soil chemical and soil physical properties as well as climatical and topography factors. ANN models with two hidden layer gave good accuracy between predicted and observed yield in training and validation.

12.2.5. Deoxynivalenol in barley seeds

Mateo et al. (2011) created MLP and RBFNN to predict deoxynivalenol (DON) accumulation in barley seeds contaminated with Fusarium culmorum under different conditions. Temperature (20–28°C), water activity (0.94–0.98), inoculum size (7–15 mm diameter), and time were the inputs, while DON concentration was the output. Researchers used dataset to train, validate and test many ANNs. Minimizing the mean-square error (MSE) was used to choose the optimal network. Single-layer perceptrons with low number of hidden nodes proved better than double-layer perceptrons, but the performance depended on the training algorithm. The RBFNN reached lower errors and better generalization than MLP-ANN, but they required a high number of hidden nodes. Accurate prediction of DON accumulation in barley seeds by F. culmorum was possible using MLP-ANNs or RBFNN. Bondalapati et al. (2009) also developed an ANN model that predicted the risk of economic DON accumulation in barley (>0.5 ppm) based on 5-day forecasted weather leading up to the date of heading.

12.2.6. Applying different inversion techniques to retrieve stand variables of summer barley

Vohland et al. (2010) planned a study for retrieval of state variables (LAI, canopy chlorophyll, water and dry matter contents) for summer barley from airborne HyMap data by means of a canopy reflectance model (PROSPECT + SAIL). Researchers applied three different inversion techniques to explore the impact of the employed method on estimation accuracies: numerical optimization (downhill simplex method), a look-up table (LUT) and an ANN approach. By numerical optimization (Num Opt), reliable estimates were obtained for LAI and canopy chlorophyll contents (LAI × Cab) with R^2 of 0.85 and 0.94, and RDP values of 1.81 and 2.65, respectively. Prediction accuracies generally decreased in the order Num Opt > LUT > ANN. This decrease in accuracy mainly resulted from an increase in offset in the obtained values, as the retrievals from the different approaches were highly correlated. The same decreasing order in accuracy was found for the difference between the measured spectra and those reconstructed from the retrieved variable values. The parallel application of the different inversion techniques to one collective dataset was helpful to identify modeling uncertainties, as shortcomings of the retrieval algorithms themselves could be separated from uncertainties in model structure and parameterization schemes.

12.2.7. Barley production

Ayoubi and Sahrawat (2011) designed ANN models to predict the biomass and grain yield of barley from soil properties; and the performance of ANN models was compared with earlier tested statistical models based on multivariate regression. Barley yield data and surface soil samples (0–30 cm depth) were collected from 1 m2 plots at 112 selected points in the arid region of northern Iran. ANN yield models gave higher R^2 and lower RMSE compared to the multivariate regression, indicating that ANN is a more powerful tool than multivariate regression.

12.2.8. Increasing barley grain yield

Gholipoor et al. (2013) optimized the effective components in conjunction with certain participant traits for increased barley Y using an ANN and a GA as an alternative procedure. Researchers carried out two field experiments at the Agriculture Research Station located in Gonbade Kavous (37°16' N, 55°12' E and 37 asl), Iran. Ten genotypes were grown in each experiment, and the Y and certain traits/components were measured. Among the components/traits, those with a significant direct effect and/or correlation with Y were selected as effective for the ANN and GA analysis. The results indicated that the remobilization of stored pre-anthesis assimilates to grain (R_1), crop height (R_2), 1,000-grains weight (R_3), grain number per ear (R_4), vegetative growth duration (R_5), grain-filling duration (R_6), grain-filling rate (R_7), and tiller number (R_8) were effective. The R^2 for the training and test phases was 0.99 and 0.94, respectively, which reveals the capability of the ANN models for predicting Y.

12.3. Grain

12.3.1. Grain quality

Pilarski et al. (2012) applied ANN models for the identification of physical parameters of grain quality regarding to malting barley. Miao et al. (2006) employed ANN analysis to evaluate the relative importance of selected soil, landscape and seed hybrid factors on yield and grain quality in two Illinois, USA fields. About 7 to 13 important factors were identified that could explain from 61% to 99% of the observed yield or quality variability in the study site-years. The response curves generated by the ANN models were more informative than simple correlation coefficients or coefficients in multiple regression equations. Investigators observed that hybrid was more important than soil and landscape factors for consideration in precision crop management, especially when grain quality was a management objective.

12.3.2. Varietal identification using morphometry of wheat grains

Dubey et al. (2006) grew three bread wheat varieties in different environments to create variation in the grain shape and sizes to cover the range of variations encountered in reality. Morphometric features of these grains were quantified using software named 'comprehensive image processing software'. Data on 45 morphometric features were used to train and test ANNs with different combinations of nodes and iterations. Best results were obtained with the resilient backpropagation architecture. Classification accuracy was about 88% for all the grains together and ranged from 84% to 94% for individual varieties. The results suggested that the ANN, combined with image analysis has excellent potential for wheat varietal identification.

12.3.3. Grain size

Miaoquan et al. (2002) highlighted an adaptive model of grain size, with the help of fuzzy ANNs, based on experimental results for Ti–6Al–4V titanium alloy with homogeneous deformation under various process technological parameters. Investigators obtained data of Teacher's samples from the experimental results. By the comparison of the calculated results with the experimental data of the Teacher's samples and the testing samples, analysts verified that the model can be applied to compute the grain size evolution during the deformation of Ti–6Al–4V titanium alloy.

Reddy et al. (2005) used ANNs, which are known for mapping non-linear and complex systems, to model the grain-refinement behavior of Al–7Si alloy. They created feedforward ANN models for the prediction of the grain size, as a function of Ti and B addition level and holding time during grain refinement of Al–7Si alloy. Comparison of the predicted and experimental results showed that the feedforward ANN models can predict the grain size of Al–7Si alloy with good learning precision and generalization.

Rashidi et al. (2009) developed feedforward multilayer ANN models to predict the dependence of the grain size of nano-crystalline nickel coatings on the process parameters namely current density, saccharin concentration and bath temperature. The process parameters were used as the model inputs and the resulting grain size of the nano-crystalline coating as the output of the model. The effect of the mentioned process parameters on the grain size of the deposited layer during the electroplating of nano-crystalline coatings from Watts-type bath was studied by workers using X-ray diffraction (XRD) technique. Comparison between the model predictions and the experimental observations predicted a remarkable agreement between them. The predictions of the model and sensitivity analysis showed that among the effective process parameters, the current density has the most significant effect and the bath temperature has the smallest effect on the resulting grain size.

Fratini et al. (2009) predicted the average grain size in friction stir welding (FSW) process using ANN technology. ANN structure was linked to a finite element (FE) model of the process to predict the average grain size values. The utilized net was trained starting from experimental data and numerical results of butt joints and then tested on further butt, lap and T-joints. The obtained results showed the capability of the ANN technique in conjunction with the FE tool to predict the final microstructure in the FSW joints.

Liu et al. (2011) predicted grain sizes of *as-cast mg-al-ca* alloys based on an ANN with parameter optimization. Rogiers and others (2012) compared two data-driven modeling methods *i.e.*, MLR and ANN that use the entire grain-size distribution data as input for K_s prediction. Analysts combined ANN models with generalized likelihood uncertainty estimation (GLUE) approach to predict K_s from grain-size data. The resulting GLUE-ANN hydraulic conductivity predictions and associated uncertainty estimates were compared with those obtained from the MLR models by a leave-one-out cross-validation. The GLUE-ANN ensemble prediction proved slightly better than MLR.

Asadi et al. (2012) forecasted the grain size and hardness of AZ91/SiC nanocomposite by ANN. Researchers added SiC nanoparticles to as-cast AZ91 magnesium alloy through friction stir processing (FSP) and an AZ91/SiC surface nanocomposite layer was produced. Experimental results showed that distribution of nanoparticles in the stirred zone (SZ) was not uniform and SZ was divided into two regions. In the ANN modeling, the inputs included traverse speed, rotational speed, and region types. Outputs were hardness and grain size. Investigators concluded that model can be used to predict hardness and grain size as functions of rotational and traverse speeds and region types.

De and Chakraborty (2012) investigated the feasibility of ANN based approach to estimate the values of mean grain size of seafloor sediments using four dominant echo features, extracted from acoustic backscatter data. The acoustic backscatter data were collected using a dual-frequency (33 and 210 kHz) single-beam, normal-incidence echo sounder at twenty locations in the central part of the western continental shelf of India. Statistically significant correlations were observed between the estimated average values of mean grain size of sediments and the ground-truth data at both the frequencies. Their results indicated that once a MLP is trained with backpropagation algorithm, the values of mean grain size can reasonably be estimated in an experimental area.

12.3.4. Moisture content of grain drying process using GA

Liu et al. (2007) optimized ANN topology for predicting moisture content of the grain drying process using GA. A structural modular ANN, by combining the backpropagation neurons and the RBFNN neurons at the hidden layer, was established to predict the moisture content of grain drying process. Inlet air temperature, grain temperature and initial moisture content were considered as the input variables to the topology of ANN. Analysts used GA to select the appropriate network architecture in determining the optimal number of nodes in the hidden layer of the ANN. The number of neurons in the hidden layer was optimized for 6 backpropagation neurons and 10 RBFNN neurons using GA. Simulation test on the moisture content prediction of grain drying process showed that the ANN optimized GA performed well.

12.3.5. Grain drying

Farkas et al. (2000a) modeled the moisture distribution in agricultural fixed-bed dryers using ANNs. Researchers studied ten different ANN topologies for modeling and the most appropriate one was selected for conducting experiments. Inlet and outlet air temperatures, absolute humidity and air flow were considered as the input variables to the layers of the drying bed. Some topologies included grain temperature for better performance. Randomly varying time series data simulating inlet conditions were used for training the ANN. The simulation of three scenarios corresponding to constant, slow and fast input dynamics were compared by them. Their results showed that moisture distribution in the drying bed could be well modeled using an ANN.

Farkas et al. (2000b) setup an ANN model in order to determine the relationship between the moisture distribution of the material to be dried and the physical parameters of the drying air temperature, humidity and air flow rate. Workers randomly changed input data, while output was generated by O'Callaghan's model based on the input specifically for barley. Analysts concluded that ANN could be an effective tool for modeling the grain drying process.

12.3.6. Starch amylose content versus total grain amylose content in corn

Campbell et al. (1999) investigated methods of improving a near-infrared transmittance spectroscopy (NITS) amylose calibration that could serve as a rapid, non-destructive alternative to traditional methods for determining amylose content in corn. Calibrations were developed using a set of genotypes possessing endosperm mutations in single- and double-mutant combinations ranging in starch-amylose content (SAC) from -8.5 to 76%, relative to a standard curve. The influence of three factors were examined including comparing calibrations made against SAC versus grain amylose content, developing calibrations using PLS analysis versus ANN. Researchers concluded that NITS may be useful to detect severe contamination during transport and storage of specialty grains or to aid breeders when selecting for amylose content from large numbers of grain samples.

12.3.7. Colour and tannin content in sorghum grain

Sedghi et al. (2012) studied the relationship between sorghum grain colour and tannin content using image analysis and ANN. Ahmadi and Azghadi (2012) collected and analyzed 33 phenotypes of sorghum grain differing in seed characteristics by Folin-Ciocalteu method. Analysts used CIA method to determine the colour characteristics of all 33 sorghum phenotypes. Two methods of MLR and ANN models were established to describe tannin content in sorghum grain from three input parameters of colour characteristics. Workers found CIA technique suitable to estimate tannin through sorghum grain colour strength. Therefore, the colour quality of the samples was described according three colour parameters: L* (lightness), a* (redness - from green to red) and b* (blueness - from blue to yellow. The developed MLR and ANN models showed a strong relationship between colour and tannin content of samples. The goodness of fit (in terms of R^2), which corresponds to training the ANN model, showed higher accuracy of prediction of ANN compared with the equation established by the MLR method (0.96 vs. 0.88). The ANN models in term of MS error showed lower residuals distribution than that of MLR model (0.002 vs. 0.006). The workers concluded that the platform of CIA technique and ANN-based model may be used to estimate the tannin content of sorghum.

12.3.8. Wheat grain varieties

Zapotoczny (2011) investigated 11 varieties of spring and winter wheat of different quality class. The investigator performed analysis on images acquired from a flatbed scanner interfaced to a PC and digitized kernel images at high resolution (2673 × 4031) with 24-bit depth and 400 dpi. Textures were computed separately for seven channels (R, G, B, Y, S, U, V) and results were examined with the application of ANN and discriminant analysis. His results showed accuracy of 100% for texture-based classification of 11 wheat varieties.

12.3.9. Rain fed wheat grain cultivars

Pazoki and Pazoki (2011) classified system for rain fed wheat grain cultivars using MLP-ANN. The study was done at Islamic Azad University, Shahr-e-Rey Branch, during 2010 on 6 main rains fed wheat cultivars grown in different environments of Iran. Workers used data of 6 colours, 11 morphological features and 4 shape factors for their study. The topological structure of MLP consisted of 21 neurons in the input layer, two hidden layers and 6 neurons (Sardari, Sardari 39, Zardak, Azar 2, ABR1 and Ohadi) in the output layer. Combination of 21→30→20→6 topology gave best performance with accuracy of 86.48%. Researchers concluded that ANN has excellent potential for rain fed wheat grain classification.

12.3.10. Sorghum grain for poultry

Sedghi et al. (2011) established ANN and regression models for estimating and modeling true metabolizable energy of sorghum grain for poultry. These models were established to describe the TMEn value of sorghum grain based on chemical composition of ash, crude fiber, CP, ether extract, and total phenols. A total of 144 sorghum samples were used to determine chemical composition and TMEn content using chemical analyses and bioassay technique, respectively. The goodness of fit in terms of R^2 values corresponding to testing and training of the ANN model showed a higher accuracy of prediction than the equation established by regression method. Their results suggested that the ANN model may be used to accurately estimate the TMEn value of sorghum grain from its corresponding chemical composition.

Ebadi et al. (2011) applied MLR and ANN approaches for predicting the true digestible amino acid (TDAA) contents of sorghum grain based on chemical composition. A precision-fed assay trial using cecectomized roosters was performed to determine the TDAA contents in 48 sorghum samples from 12 sorghum varieties differing in chemical composition. The input variables for both MLR and ANN models were CP, ash, crude fiber, ether extract, and total phenols, whereas the output variable was each individual TDAA for every sample. The results of study revealed that it is possible to satisfactorily estimate the TDAA of sorghum grain through its chemical composition. The chemical composition of sorghum grain seems to highly influence the TDAA contents when considering components such as CP, crude fiber, ether extract, ash and total phenols. The R^2 values for the ANN model corresponding to testing and training parameters showed a higher accuracy of prediction than equations established by the MLR method.

12.3.11. Sorghum soaking

Kashiri et al. (2012) evaluated efficiency of ANN technique for simulating the soaking behaviour of sorghum kernel as a function of temperature and time. Investigators studied soaking characteristics of sorghum kernel at different temperatures (10, 20, 30, 40 and 50 °C) by measuring an increase in the mass of sorghum kernels with respect to time. MLP-ANN was used to estimate the moisture ratio of sorghum kernel during soaking at different temperatures and a comparison was also made with the results obtained from Page's model. Workers used soaking temperature and time as input parameters and the moisture ratio was taken as output variable. Results showed that the estimated moisture ratio by MLP-ANN is more accurate than Page's model.

12.4. Rice

12.4.1. Delineating rice cropping activities from MODIS

Delineating rice cropping activities is important for crop management and crop production estimation. Chen et al. (2012) studied time-series MODIS data (2000, 2005, and 2010) to delineate rice cropping activities in the Lower Mekong countries. The data were processed using the wavelet transform and ANNs. The classification results assessed using the ground reference data indicated overall accuracy and Kappa coefficients of 83.1% and 0.77 for 2000, 84.7% and 0.8 for 2005, and 84.9% and 0.8 for 2010, respectively. Comparisons between MODIS-derived rice area and rice area statistics at the provincial level also reaffirmed close agreement between the two datasets ($R^2 \geq 0.8$). An examination of relative changes in harvested area revealed that from 2000 to 2010 the area of single-cropped rice increased 46.1%, while those of double- and triple-cropped rice were 20.1% and 25%, respectively.

12.4.2. Typhoon-induced losses to rice

Chang and others (2012) proposed a hybrid self-organizing radial basis (SORB) neural network for estimating economic losses of rice for the whole Taiwan as well as three sub-regions. The data sets of 143 typhoon events from 1961 to 2008 were collected and analyzed. Data included rice losses and typhoon-related meteorological factors. A number of different input combinations of meteorological and temporal variables were implemented to select the optimal network for predicting the losses, and a two-stage clustering method was used to explore the spatial classification of 15 counties in Taiwan into three sub-regions. The simulation results indicated that the constructed SORB network has great ability to capture the relationship between typhoon-related variables and rice losses.

12.4.3. Characteristics of rice straw

Chakraborty et al. (2012) investigated morphological and chemical characteristics of rice straw and acid-modified rice straw by scanning electron microscopy, surface area, and porosity analysis by the BET nitrogen adsorption method and Fourier transform infrared spectroscopy. Their results demonstrated that with increasing bed height and decreasing flow rate, the breakthrough time was delayed. In order to determine the most suitable model for describing the adsorption kinetics of Crystal violet in the fixed-bed column system, the Bed Depth Service Time, Thomas and ANN models were fitted to the experimental data. Workers carried out an extensive error analysis between the experimental data and data predicted by the models using the following error functions: R^2, average relative error (ARE), sum of the absolute error (SAE), and $\chi 2$ statistic test. Based on the values of the error functions, the ANN model was most appropriate for describing the dynamic dye adsorption process.

12.4.4. Grain yield

Moosavizadeh-Mojarad and Sepaskhah (2011) implemented ANN technique to predict rice grain yield under different water and nitrogen application. Grain yield was predicted based on five variables: nitrogen application rate, seasonal amount of applied irrigation water, plant population, and mean daily solar input before and after flowering. Furthermore, analysts compared ANN method with a very simple model (VSM) for prediction of rice grain yield. Workers considered two approaches for ANNs. In the first approach (local partitioning), rice grain yield and variable data from the south of Iran were used for training, and the network was then tested using independent data from the north of Iran. In another approach, the data for both experiments were mixed and randomized dividing was applied (stochastic partitioning). Their results showed that stochastic partitioning networks were more accurate than local partitioning networks. Comparison between ANN and VSM results suggested that using ANNs gives a more accurate prediction of grain yield. Therefore, researchers concluded that ANNs with stochastic partitioning of data is an accurate method to predict rice grain yield using readily available inputs.

12.4.5. Discriminating fungal infection

Liu et al. (2010) applied ANN and principal components analysis (PCA) techniques for discriminating and classifying different fungal infection levels in rice (Oryza sativa L.) panicles. Four infection levels in rice panicles were used in their study: no infection condition, light and moderate infection caused by rice glume blight disease, and serious infection caused by rice false smut disease. Hyperspectral reflectance of rice panicles was measured through the wavelength range from 350 to 2500 nm with a portable spectroradiometer in the laboratory. Researchers employed a learning vector quantization (LVQ) neural network classifier to classify healthy, light, moderate, and serious infection levels. Classification accuracy was evaluated using overall accuracy and Kappa coefficient. The overall accuracies of LVQ with PCA derived from the raw, inverse logarithmic, first, and second derivative reflectance spectra for the validation dataset were 91.6%, 86.4%, 95.5%, and 100% respectively, and the corresponding Kappa coefficients were 0.887, 0.818, 0.939 and 1. Their results indicated that it is possible to discriminate different fungal infection levels of rice panicles under laboratory conditions using hyperspectral remote sensing data.

12.4.6. Shelf life of packaged rice snacks

Siripatrawan and Jantawat (2009) established ANN models for shelf life prediction of two varieties of moisture-sensitive rice snacks packaged in polyethylene and polypropylene bags and stored at various storage conditions. The ANN model used to predict the shelf life was based on MLP with backpropagation algorithm. The performance of ANN was measured using R^2 = 0.23–0.28 and RMSE = 0.96–0.99. The ANN-predicted shelf lives agreed very well with actual shelf life data. ANN could be used as an alternative method for shelf life prediction of moisture-sensitive food products as well as product/package optimization.

12.4.7. Quantifying sub-pixel signature

Karkee et al. (2009) developed a method for quantifying sub-pixel land uses of individual rice types using ANN. Temporal patterns of normalized differential vegetation index (NDVI) depend on and result from the complex relationship between NDVI and cropping practice parameters associated with a pixel. In the case of a rice field, these parameters consist of the area fractions of different types of rice and their emergence dates. The data for this research were produced numerically using the soil–water–atmosphere–plant (SWAP) crop growth model. Crop area fractions within a pixel were predicted with an RMSE of 1.3% and an average estimated emergence date error of 4 days. Researchers concluded that ANN based approach was computationally very efficient and thus practical to apply to satellite imagery consisting of millions of pixels.

12.4.8. Leaf chlorophyll concentration

Liu et al. (2010) forecasted chlorophyll concentration in rice under heavy metal stress by applying backpropagation ANN system. Three experiment farms located in Changchun, Jilin Province, China with level II pollution, with level I pollution and with safe level were selected. Their results indicated that an optimum backpropagation ANN prediction model has 4→10→2→1 network architecture with gradient descent learning algorithm and an activation function including the sigmoid tangent function in the input layer, a hidden layer and sigmoid logistic functions in the output layer. The R^2 between the measured chlorophyll concentration and the predicated chlorophyll concentration was 0.9014, and the RMSE was 2.58.

12.4.9. Water requirements

Traore et al. (2010) evaluated the performance of a mixture PCA - ANN model for computing rice Crop-ET directly from temperatures data in Fada N'Gourma region located in Eastern Burkina Faso, Africa. From the statistical results, rice Crop-ET can be successfully computed by using PCA-ANN methodology, when only temperatures data are available in African semiarid environment. Researchers concluded that in poor data situation, Crop-ET direct computation can be rapidly addressed through PCA-ANN model for agricultural water management in African semiarid regions.

12.4.10. Estimation of rice neck blasts severity

Zhang et al. (2011) estimated rice disease using spectral reflectance, which is important to non-destructive, rapid, and accurate monitoring of rice health. The rice reflectance data and disease index (DI) were determined experimentally and analyzed by single wave correlation, regression model and ANN model. The results showed that raw spectral reflectance and first derivative reflectance (FDR) difference of the rice necks under various disease severities was clear and obvious in the different spectral regions. There was also significantly negative or positive correlation between DI and raw spectral reflectance, FDR. The ANN model provided better accuracy in retrieval of DI compared with the results from the statistic model.

12.4.11. Rice husk

Dahlan and others (2012) analyzed the application of response surface and ANN models in predicting and optimizing the preparation variables of RHA/CaO/CeO_2 sorbent towards SO_2/NO sorption capacity. The sorbents were prepared according to central composite design (CCD) with four independent variables (*i.e*. hydration period, RHA/CaO ratio, CeO_2 loading and the use of RHA_{raw} or pretreated $RHA_{600°C}$ as the starting material). The prediction of CCD experiment was verified by ANN models, which gave almost similar results to those determined by response surface models. The response surface models together with ANN models were then successfully used to locate and validate the optimum hydration process variables for maximizing the SO_2/NO sorption capacities.

12.4.12. Rice production

Routh and Huda (2011) predicted temperature for rice production in Dhaka, Bangladesh. Potential rise of global temperature due to climate change has huge impact on rice productivity and above all on food security. The study suggested that although weather prediction and meteorology is a very complex and imprecise science, ANN have shown that it has powerful pattern classification and pattern recognition capabilities, which can be used as a tool to get a reasonable accurate prediction of weather patterns.

12.4.13. Biophysical parameters

Yang et al. (2009) recorded hyperspectral reflectance (350 to 2500 nm) data at two different rice sites in two experiment fields with two cultivars, three nitrogen treatments and one plant density (45 plants m^{-2}). Stepwise multivariable regression (SMR) and RBFNN models were applied to compare their predictability for the leaf area index (LAI) and green leaf chlorophyll density (GLCD) of rice based on reflectance (*R*) and its three different transformations, the FDR (*D*1), the second derivative reflectance (*D*2) and the log-transformed reflectance (LOG). Analysts suggested that RBFNN may provide a useful exploratory and predictive tool for the estimation of rice biophysical parameters.

12.4.14. Discrimination of rice origin

Niu et al. (2010) used a total of twenty nine rice samples, including nineteen Xiang-shui rice samples and ten non-Xiang-shui rice samples. Researchers employed these samples to establish discrimination models with backpropagation ANN and least squares support vector machine (LS-SVM) based on the content value of B, Zn, Fe, Cu, Mn, Na, K, Mg and Ca determined by Inductively coupled plasma atomic emission spectrometry (ICP-AES). Accuracy of 100% for training set was achieved by LS-SVM, for test set the accuracy was only 90.91%. So the optimal result, the accuracy of 100% both for Xiangshui rice samples and for non-Xiangshui rice samples in test set was obtained by backpropagation ANN models with five nodes in hidden layer. Investigators provided a new discrimination method to discriminate rice from different geography origin, which is significant to detect and prevent fraud and adulteration.

12.4.15. Parboiled rice

Bualuang et al. (2011) predicted hybrid hot air-infrared radiation drying kinetics of Leb Nok Pattani parboiled rice using a mathematical model and ANN model. Researchers analyzed drying kinetics of parboiled rice considering different drying conditions. The drying experiments were performed at three levels of drying air temperatures of 60-100°C, two levels of infrared intensity of 5,118 and 7,678 W/m^2; air velocity was fixed at 1±0.2 m/s. The results between mathematical and ANN models were compared with the experimental data, which indicated that the prediction results of feedforward ANN model were in good agreement with the experimental results than empirical model. Thus, they concluded that the ANN model could be used for effective modeling of grain drying process.

12.4.16. Rough rice

Zhang et al. (2002) developed ANN model for rough rice drying to predict six performance indices: energy consumption, kernel cracking, final moisture content, moisture removal rate, drying intensity and water mass removal rate. Four drying parameters: rice layer thickness, hot airflow rate, hot-air temperature and drying time were taken as inputs for the ANN model. After evaluating a large number of trials with various ANN architectures, the optimal model was a four-layered backpropagation ANN, with 8 and 5 neurons in the first and the second hidden layers, respectively. The effectiveness of the proposed model was demonstrated using experimental data. The mean relative error (MAE) varied from 2·0 to 8·3% for six predictions with an average of 4·4%.

Amiri-Chayjan and Esna-Ashari (2010) compared mathematical models and ANN models for prediction of sorption isotherm in rough rice. Yong-Ni and others (2007) applied a new method for discrimination years of rough rice based on independent component analysis using visible/near infrared spectroscopy (Vis/NIRS). The Vis/NIR loading weight of rough rice with different years was obtained by using independent component analysis (ICA) and setting the wavelengths corresponding to the maximal correlation as the inputs of ANN. The outcome of study indicated that the result for discrimination years of rough rice was very good based on ICA method, and it offered a new approach to the fast discrimination years of rough rice.

12.4.17. Cooked rice texture

Sitakalin et al. (2001) highlighted the use of spectral stress strain analysis in combination with PLS regression and ANN to predict nine sensory texture attributes of cooked rice. The results showed that models calculated with ANN were significantly more accurate in predicting most of the sensory texture characteristics evaluated than the PLS models. Researches concluded that ANN models were more robust and discriminative than PLS models.

12.4.18. Drying of cooked rice

Ramesh et al. (2007) implemented commercially available neural networks software for prediction of processing parameters with reference to the product quality of the dehydrated cooked rice. The experimental results indicated good concurrence with the predicted data. Researchers used a small capacity vibro-fluidized bed drier for conducting the experimental studies. They concluded that trained model can be applied in a nonlinear model predictive scheme to control the product moisture content.

12.4.19. Predicting rice crop damage

Since the 1980s, incursions of greater flamingo (*Phoenicopterus ruber roseus*) in rice fields have been reported almost every year in the Camargue, south-eastern France, and more recently in Spain. Tourenq et al. (1999) assessed the performances of ANN system in predicting presence or absence of flamingo damages from 11 variables describing landscape features of rice paddies. The global matrix of 1978 records (276 with damage and 1702 without) for the 1993–1996 periods was used to determine the suitable parameters: number of hidden layer nodes and number of iterations. A classic multilayer feedforward ANN with backpropagation algorithm was used for experiments. Data from 1993 to 1996 were used to predict data for 1997 (73 fields with damage and 1905 without) and 1998 (88 with damage and 1890 without). Analysts concluded that ANN can be an alternative or a supplement to actual scaring methods in identifying potential damaged fields.

12.4.20. Italian rice varieties

Marini et al. (2004) applied a counterpropagation (CP) ANN system to classify 1779 Italian rice samples according to their variety, using physical measurements which are routinely determined for the commercial classification of the product. From the classification and prediction viewpoint, the optimal CP-ANN system was able to correctly predict more than 90% of the test set samples.

12.4.21. Rice yield

Samsudin et al. (2012) created hybrid integrating autoregressive integrated moving average (ARIMA) and ANN modes for forecasting rice yield times. Workers considered time series data of rice yield in Muda Irrigation area of Malaysia from 1995 to 2003 for their experiments. The results suggested that hybrid model can improve the forecasting performance of rice yields. A similar study was reported by Shabri and others (2009). They used 38 years of time series records for rice yield data in Malaysia from 1971 to 2008. Their results showed that the ANN model appears to perform reasonably well, and hence can be applied to real life prediction and modeling problems.

Ji et al. (2007) developed ANN and MLR models for predicting rice yield in Fujian province of China, which is a mountainous region, where weather aberrations such as typhoons, floods and droughts threaten rice production.

Models were created using historical yield data at multiple locations throughout Fujian. Field-specific rainfall data and the weather variables (daily sunshine hours, daily solar radiation, daily temperature sum and daily wind speed) were used for each location. Optimal learning rates were between 0·71 and 0·90. ANN models consistently produced more accurate yield predictions than MLR models. ANN rice grain yield models for Fujian resulted in R^2 and RMSE of 0·87 and 891 vs 0·52 and 1977 for MLR, respectively. Workers concluded that although it is more time consuming to develop ANN models than MLR models, but ANN models proved to be superior for accurately predicting rice yields under typical Fujian climatic conditions.

12.4.22. Rice tillering dynamics

Mi et al. (2007) tested the generalization ability of ANNs in predicting rice tillering dynamics. Investigators compared the performance of cross-validated ANNs with independent-validated ANNs, and found that neural networks were able to extrapolate and predict tillering dynamics if the data were within the range of inputs of the training set. The workers concluded that generalization of ANNs presented a wide spectrum of problems, and the proposed approaches were not confined strictly to modeling rice tillering dynamics but can be applied to other agricultural and ecological systems.

12.4.23. Rice nitrogen

Yi et al. (2007) applied MLR and ANN modeling methods for monitoring of rice N (nitrogen concentration, mg nitrogen g-1 leaf dry weight) status using leaf level hyperspectral reflectance with two different input variables, and as a result four estimation models were proposed. RMSE, REP (relative error of prediction), R^2, as well as the intercept and slope between the observed and predicted N were used to test the performance of models. Very good agreements between the observed and the predicted N were obtained with all proposed models, which was especially true for the R-ANN (artificial neural network based on reflectance selected using MLR) model. When researchers compared R-ANN model to the other three models, the R-ANN model improved the results by lowering the RMSE by 14.2%, 32.1%, and 31.5% for the R-LR (linear regression based on reflectance) model, PC-LR (linear regression based on principal components scores) model, and PC-ANN (artificial neural network based on principal components scores) model, respectively. Workers concluded that the ANN algorithm may provide a useful exploratory and predictive tool when applied on hyperspectral reflectance data for nitrogen status monitoring.

In another study, Yi et al. (2010) investigated a wide range of leaf nitrogen concentration levels in field-grown rice with the application of three fertilizer levels. Hyperspectral reflectance data of the rice canopy through rice whole growth stages were acquired over the 350 nm to 2500 nm range. Comparisons of prediction power of two statistical methods (linear regression technique (LR) and ANN), for rice N estimation (nitrogen concentration, mg nitrogen g−1 leaf dry weight) were performed using two different input variables (nitrogen sensitive hyperspectral reflectance and principal component scores). The results displayed very good agreement between the observed and the predicted N with all model methods, which was especially true for the PC-ANN model (ANN based on principal component scores), with RMSE=0.347 and REP=13.14%.

12.4.24. Pigment content in rice leaves

Chen et al. (2007) compared the predictive ability of the ANN models to that of the MLR models in estimating the content of pigments in rice leaves and panicles. Their results showed that all backpropagation ANN models gave higher R^2 and lower absolute errors (ABSE) and RMSE than the corresponding MLR models, in both calibration and validation tests. Also, significance tests by paired *t* tests and bootstrapping algorithms indicated that most of the backpropagation ANN models outperformed the MLR models. When trained by combination data that did not meet the assumption of normal distribution, the backpropagation ANN models appeared to not only have a better learning ability, but also had a more accurate predictive power than the MLR models. Researchers concluded that the estimation of leaf pigments was more accurate than that of panicle pigments, independent of which model was used.

12.4.25. Rice crop monitoring

Chen and McNairn (2006) established a rice crop monitoring system based on ANN classification. The system delineated rice production areas for one wet and one dry season, and was able to extract information on rice cultivation as a function of different planting dates. A minimum mapping accuracy of 96% was achieved for both seasons. This information was then used by workers in an ANN based yield model to predict rice yield on a regional basis for the wet season. When the yields, predicted by the ANN system were compared with government statistics, the result was a prediction accuracy of 94%.

12.4.26. Rice flour and rice starch

Ganjyal et al. (2006) modeled the selected properties of extruded rice flour and rice starch by creating ANN and regression models. Multiple input and multiple output (MIMO) models were developed to simultaneously predict five product properties or three product properties from three input parameters. They were extremely efficient in predictions with values of $R^2 > 0.95$. ANN models performed better than the regression models.

12.4.27. Forecasting market share

Apichottanakul et al. (2009) forecasted market share of Thai rice in the global market using ANN system. Researchers formed two models under two assumptions. First, the market share depending on exporting prices of rice of Thailand, Vietnam, India, USA, Pakistan, and China. Second, only the export prices of rice from Thailand, Vietnam, USA, and China were considered. Investigators used export prices as input parameters, while the market share of Thai's rice in the global market was the only output parameter of the models. Annual data from 1980 to 2005 was gathered from United States Department of Agriculture (USDA) and Food and Agriculture Organization (FAO) of the United Nations. The study reveled that the second model provided more promising results with the minimum mean absolute percent error (MAPE) of 4.69% and the average MAPE of 10.92%.

Co and Boosarawongse (2007) forecasted the Thailand’s rice export. Their results revealed that the Holt–Winters and the Box–Jenkins models showed satisfactory goodness of fit; the models did not perform as well in predicting unseen data during validation. On the other hand, the ANNs performed relatively well as they were able to track the dynamic non-linear trend and seasonality, and the interactions between them.

13. Conclusion

Cereals crops are grown and consumed worldwide. Therefore, cereals are one of the most dynamic areas of research in agricultural science. The literature search revealed that a lot of research has gone into using many ANN methods for predicting attributes and properties of cereals. Investigation shows that ANN systems are capable of replacing human expert because of their accuracy and robustness. A thorough review of published literature suggests that many ANN techniques have been compared with the conventional methods of prediction. ANN clearly emerged as a winner over these conventional techniques as ANN is simple to use, low cost tool, provides accurate and timely results. The consistency of results indicates that they are a suitable choice to classify cereals. It is expected that in future more and more concerned agriculturists, scientists and students would use these non-linear modeling tools for predictive assessment of cereals.

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