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Application of Artificial Neural Network in Predicting Crop Yield: A Review

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Abstract: Agricultural system is very complex since it deals with large data situation which comes from a number of factors. A lot of techniques and approaches have been used to identify any interactions between factors that affecting yields with the crop performances. The application of neural network to the task of solving non-linear and complex systems is promising. This paper presents a review on the use of artificial neural network (ANN) in predicting crop yield using various crop performance factors. General overview on the application of ANN and the basic concept of neural network architecture are also presented. From the literature, it has been shown that ANN provides better interpretation of crop variability compared to the other methods.

Key words: Artificial intelligent, artificial neural network, crop yield prediction.

1. Introduction

The vision of meeting world's food demands for the increasing population throughout the world is becoming more important in these recent years. Crop models and decision tools are increasingly used in agricultural field to improve production efficiency.

The combination of advance technology and agriculture to improve the production of crop yield is becoming more interesting recently. Due to the rapid development of new higher technology, crop models and predictive tools might be expected to become a crucial element of precision agriculture [1].

There are a lot of factors influencing crop productions, either directly or indirectly which affected the crop performance. Most of the factors that normally highlighted in researches are soil factors, such as pH, available nutrients, texture, organic matter content and soil-water relationships. There are also other factors highlighted in researched, e.g., weather and climatic factors including temperature, rainfall and light intensity; crop and cultivar; postharvest handling and storage; fertilizer applications and cultural practices [2]. These factors have formed a complex system for agriculture since it always deals with a large set of data for each problem it faced with. Agronomists and scientists still have doubt in finding a really suitable tool to review the available datasets based on current knowledge. Until today, a lot of approaches and modelling techniques have been in existence. Most of them represent the data based on probabilities, which then are estimated by training and presented using algorithm by a human classifier [3]. Crop modelling was initially viewed as a tool to understand the performance of complex systems such as external factor like weather condition towards crop yield, at once helped us to understand the qualitative links between processed and crop performance [4]. For a number of years, the most crop models which were based on linear method were constructed from either linear or multiple linear regression or correlation analysis. These procedures assume a linear relationship

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between variables and crop production. However, these techniques were neither sufficient nor comprehensive enough to really show the interactions of parameters and crop yield. These complex situations need non-linear approaches such as neural network, fuzzy logic or Bayesian classification, etc., to overcome the drawbacks of linear methods.

Most farmers were relied on their long-terms experiences in the field [5] on particular crops to expect a higher yield in the next harvesting period. Shearer et al. [1] had listed two important steps to predict crop performance. First was by using traditional approach of mathematical models and the second was on the application of artificial intelligent for the prediction of crop response.

A prerequisite of intelligent system has brought artificial neural network (ANN) to become a new technology which provides assorted solution for the complex problems in agriculture researches. Since it can solve many problems that linear system is incapable to resolve, ANN becomes crucial especially in innovating and developing better products for society. Though there are many types of ANN, this paper only presented the most commonly used type of ANN, which is the multilayer feed-forward network. The basic principle of ANN architecture, application of ANN in predicting crop yield by using various types of crop performance factors as the input parameters, guidelines for selecting ANN method and future development and current trends in the application of ANN to predict yield will also be presented. At the end of the paper, a brief conclusion is doted.

2. ANN Architecture

The ANN was pioneered more than 40 years ago and nowadays, there has been a great interest in neural network since an artificial network shares some of the physical and behavioral aspects of a biological one [3]. The ANN structure which is parallel system is based on human brain's biological neural process used to solve complex problems where it tries to imitate into mathematical models [6]. A few authors [1, 3, 7] had briefly discussed about the architecture of ANN.

Typically, a minimum of three layers which are the input layer, the hidden layer and the output layer is required to develop an ANN system (Fig. 1). The number

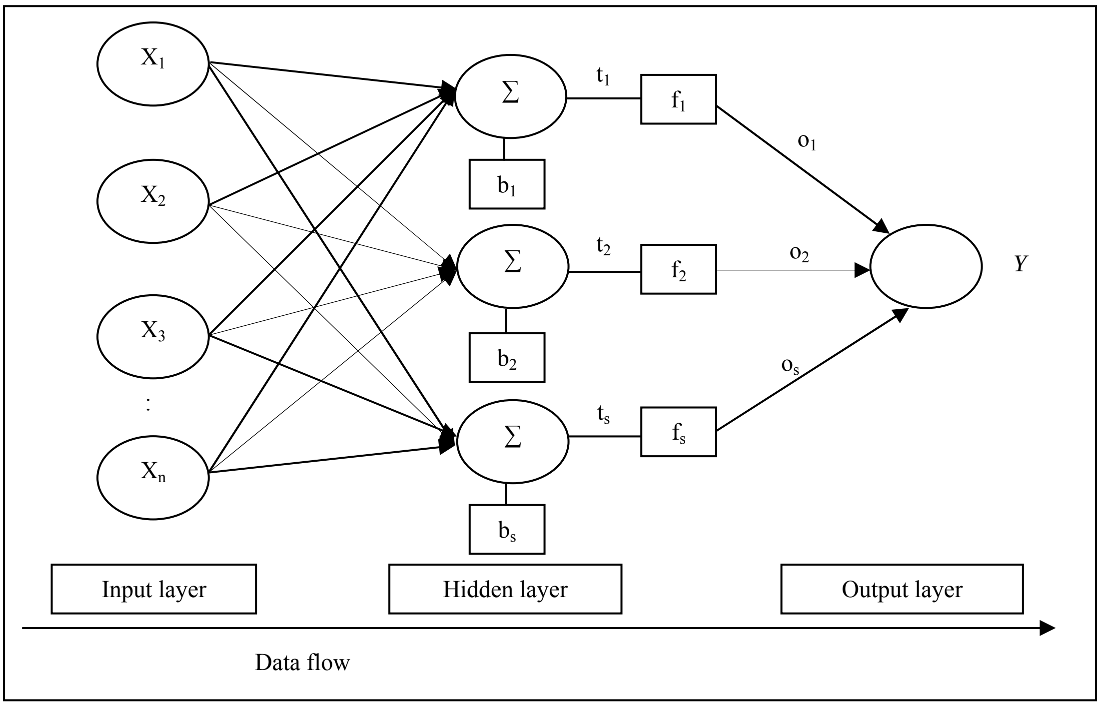

Fig. 1 Layers and connection of a feed-forward back propagation ANN.

of hidden nodes which are depending on specific problem of the study which can easily extend to more hidden layers. The input contains nodes that correspond to input variables while the output contains nodes that correspond to output variables [7].

The input layer is used to distribute the inputs to a number of hidden layers, and the output of which is connected to an output layer, where the outputs of units are connected to the inputs of the next via connection weight [3]. In simpler way, the weighted connections allow data to move between layers through it, where the node accepts data from previous layer and calculates a weighted sum of all its net inputs:

$$t_i = \sum_{j=1}^{n} (w_{ij} x_j + b_i) \qquad (1)$$

where, n is the number of inputs, w is the weight of connection between node i and j, x is the input from node j, and b_i is a bias. In order to calculate the node output o_i, a transfer function f_i is then applied to the weighted value:

$$o_i = f_i(t_i) \qquad (2)$$

The most popular transfer or activation function is sigmoidal function [3, 7] for the hidden and output layers. Input layer commonly uses a linear transfer function to pass the information to hidden layers [7].

The dataset then can be “learnt” by training [3]. According to Alvarez [8], the learning process can be defined as “a process which consists in adjusting the weights associated to the transfer functions between neurons comparing ANN output with observed data”. The most common training method is back-propagation (BP). The BP method is used to train the feed-forward neural network to minimize the error [1] where in this training the error represents the difference between calculated output and the target value [9]. However, a large networks which used too many nodes will become over-trained, causing it to memorize the training data resulting in poor predictions [10] and consumes a lot of memory [1]. The process is repeated until either a specified error limit is achieved or the total number of training cycles (epochs) has been completed.

3. ANN in Predicting Crop Yield

Presently, ANN has become a well-liked method to most authors because of its ability of prediction, forecasting and classification in biological science fields. Although regression model consumes more time to be developed, an ANN model can produce more consistent yet accurate crop yield prediction rather than regression models [7]. Since there are a lot of factors which influence crop production, the use of ANN in predicting crop yield using direct and indirect factors will be presented.

3.1 ANN in Environmental Factors

Agricultural plants such as paddy, corn, soybean and wheat have strong response to their environment to determine the yield at the end season. The environment factors such as temperature, photoperiod and water stress [11] are among the most important factors that control plant development, growth and yield [12].

Ushada and Murase [12] used ANN to explain the relationship between input parameters and output parameters for moss (*Rhacomitrium canescens*) growing system. Moss is a non-vascular plant which is used as an active greening to ease the urban heat island effect. Three cardinal temperature, i.e., minimum temperature, T_{min}, maximum temperature, T_{max}, and optimum temperature, T_{opt}, were used as input variables, in addition to ambient temperature T. This model produced six output parameters which were heat unit accumulation, relative rate of growth, leaf area index, moss high, moss mass and temperature stress factor. At the end of the testing, this model successfully explained the relationship between inputs and outputs with a low learning error of 6.96×10^{-2}.

Kaul et al. [7] also stated that ANN produces better results than traditional statistical methods when predicting soybean yield. A research which was conducted by Bandel and Hagel in Maryland Agronomic Soil Capability Assessment Program (MASCSP) showed that ANN gave excellent result of coefficient of determination for yield rather than using multiple linear regressions. The average of coefficient of determination using multiple linear regression and ANN were $r^2 = 0.55$ and $r^2 = 0.72$, respectively.

O'Neal et al. [13] designed a fully connected back-propagation ANN to predict maize yield with five data coding schemes at three scales using local crop-stage weather data and yield data from 1901 to 1996. Sensitivity analysis also has been done to compare testing errors for nets having various number of hidden nodes and training cycles and various levels of earning rate. Overall, the best version of the networks came out with root means squared testing error of 10.5% which was better than quadratic regression (12.2%).

There are also many publications of ANN models which focused on prediction of agricultural crops focused on environmental factors. Zhang et al. [11] developed a feed-forward back-propagation neural network with three layers. The model used three photoperiod factors (planting date, maturity group and normalized growth stage) as inputs to predict the date of specific growth stage. Morimoto et al. [14] used two environmental factors which were rainfall data and sunshine duration to identify the changes of sugar and acid citric contents in Satsuma mandarin using ANN. The result later was used to make a scheduled watering system to maximize sugar content and minimize citric acid in Satsuma mandarin yield.

3.2 ANN in Soil and Soil-Plant Hydrology

Drummond et al. [15] applied a feed-forward neural network to estimate nonlinear relationship between soil parameters and crop yield. The dataset is not only reasonably accurate but also at the same time, the model retained good generalization characteristics. Although the model tended to overestimate low yielding points while underestimating the higher yielding ones, the estimated yield maps generated by neural network method tended to be very similar to the actual yield map.

Kitchen et al. [16] used ANN and also considered a few analyses procedures such as correlation analysis and regression analysis, to analyze the relationship of apparent soil electrical conductivity (EC_a) profile and topographic measures to grain yield for three contrasting soil-crop systems. From the study, it has been found that ANN were able to provide most accurate empirical model of the data and it fitted the yield data to soil and topographic characteristics very well. Another example of ANN prediction model has been done by Ezrin [17] who used EC_a data from two consecutives harvesting systems of paddy yield in Malaysia. There are four standard methods of prediction model which has been used to identify the relationship between EC_a and yield. From the result, it has been shown that ANN is more reliable to be used to generate predicted rice yield map rather than other methods. Although boundary-line analysis approach was found to be a very promising technique to relate rice yield with EC_a data, with coefficient of determination $r^2 = 0.47$, however, ANN approach was consistently superior to the other techniques and produced minimal root mean square error (RMSE) in both seasons.

The application of ANN to estimate water uptake by plant roots has been developed by Qiao et al. [18]. A total of seven factors were used as input parameters which were soil moisture, electrical conductivity (EC) of the soil solution, potential evapotranspiration, atmospheric humidity, air temperature, plant shoot height and diameter while root water uptake rates at different depth in the soil profiles were taken as the outputs. The model was trained and tested using feed-forward three layers neural network model. This model effectively came out with a small relative error, which was less than 17%.

3.3 ANN in Sensing Technologies

Sensing technologies have become important for site specific management in agriculture. A lot of sensing systems have been developed such as in yield mapping and prediction, irrigation control, etc., using diverse types of sensors and instruments such as field-based electronic sensors, spectroradiometers, machine vision, airborne multispectral and hyperspectral remote sensing, satellite imagery, thermal imaging, etc. [19]. These technologies provide a broad usage in measuring variety factors such as crop nutrient, water content as well as soil properties.

Uno et al. [20] developed a yield prediction model using statistical and ANN techniques where the model was used to predict corn yield from compact airborne spectrographic image data. Although the study came out with no clear difference between ANN and stepwise multiple linear regression models, it was concluded that ANN has high potential to be used in yield prediction.

Ye et al. [21] conducted a study on citrus orchard in Japan using an Airborne Imaging Spectrometer for Application (AISA) Eagle system to obtain hyperspectral image of study area for three consecutive months. A back-propagation neural network was applied to relate the average canopy reflectance to citrus yield for individual trees where average canopy reflectance of 31 selected tree samples was extracted using ERDAS Imagine 8.6 software. About 10,000 experiments of neural network training were carried out and the results show that models with hyperspectral data in May predicted citrus yield more accurately rather than in April and June. These results show that ANN also has potential to predict yield using airborne hyperspectral remote sensing.

Fertilization application especially nitrogen [22] plays a big role to increase crop yield, but excessive nitrogen leads to nitrogen leaching occurred in the field. Thus, Noh et al. [23] used a machinery-mounted multispectral imaging sensor (MIS) to detect maize nitrogen stress level by capturing crop canopy reflectance in three different channels. The canopy reflectance in red (R), green (G) and near infrared (NIR) channels of the MIS sensor were used as input variables in three layers (input, hidden and output) ANN model. The output was the estimation of soil plant analysis development (SPAD) reading. This reading was commonly used to assess maize nitrogen stress level. The results of coefficient of determination and RMS error are 0.89 and 2.52, respectively. The results successfully prove that ANN model can give faithful estimation on maize nitrogen deficiency in real-time.

Parpinello et al. [24] used an electronic nose (based on chemical gas-sensor array technology) with combination of ANN to estimate the headspace of apricot fruits during ripening in order to classify 10 different commercial cultivars. Llobet et al. [25] also had used the electronic nose sensor to analyze the state ripeness of bananas, while Green et al. [26] used spatial analysis neural network (SANN) algorithm consisted of four layers to relate winter wheat yield to topographic attributes from processed spatial yield data.

3.4 ANN in Biomass Factor

Chtioui et al. [27] designed generalized regression neural network (GRNN) for leaf wetness prediction model which later compared the result obtained with multiple linear regression (MLR). Leaf wetness is predicted based on temperature, relative humidity, wind speed, solar radiation and precipitation in order to warn of disease in agricultural crop which would affect crop yield production sooner or later. In this study, spring wheat (*Triticum aestivum* L.) was used as experiment plant. Average absolute error tested by GRNN was low (0.0491 for training set and 0.0894 for test set) rather than using MLR (0.1300 for training set and 0.1414 for test set).

Rahman and Bala [28] designed ANN models trained by back propagation consisted of four-layered networks with two hidden layers consisted of nine and five neurons to predict jute production using field experiments of biomass such as leaf area index (LAI) and dry matter weight (DMW) in Bangladesh. The models successfully predicted jute production accurately and could be used at different locations.

3.5 ANN in Controlled Environment

ANN models also have been applied in controlled environments like greenhouse [29-31] and glasshouse [32]. Similar to the outside environment, greenhouse is also classified as complex system [33] since it always deals with environmental factors such as temperature, humidity, radiation intensity and carbon dioxide concentration for optimization of plant growth and production [12].

Apart of the above factors, In et al. [34] used a neural network to develop a vase life prediction model of cut roses grown in greenhouse. With three input variables of 11 environmental parameters, 10 at harvest morphological parameters and eight physiological parameters, the network contained 29, 26 and one units of input, hidden and output layer, respectively. The data were measured during harvesting time until time of flower auction before the flowers were transferred to a new controlled room. The temperature of the room was fixed to 25 °C with 10 $\mu mol/m^2 \cdot s$ and humidity at 50%. A good result was obtained to predict and guarantee a vase life of cut roses production ($r^2 = 0.886$, RMSE = 1.126).

4. Guidelines for Selecting ANN Method

An ANN approach has some natural capabilities that are lacked in other programming techniques and traditional analysis. The ability of ANN to predict and work as approximator without the need to specify a particular function has become the big advantages compared to multivariate statistics [9]. According to Sass [35], there were six criteria that needed to be taken before someone decided to apply ANN approach in their research problem: (1) the performance at presently statistical model needs to be improved; (2) the programming is too complicated which normal analysis cannot be done by computer or the algorithm is neither exist nor satisfactory; (3) there are available historical data that could be trained as a pattern matcher; (4) the problem leads to discrete set of predefined answers; (5) there are experts on certain problems but it consumes a lot of time to reach the answers; (6) there is a large amount of machine-readable data which need to be analyzed with no solution for it.

Learning rate has to be small enough to ensure convergence of weight values but large enough to make computing time reasonable. Constant learning rate is not advisable, because the error will not converge to minimum smoothly. When the error is increased or decreased by small amount, the learning rate can be adjusted to decrease or increase. Generally, the learning rate initially started at 0.2 but finally reduced to 0.01.

Although ANN has the ability to handle quantitative and qualitative data which are difficult to handle with conventional simulation methods, and also can be used to model a complicated problem in agriculture which consists of linear and non-linear responses, it also has some disadvantages [36]. Some of these drawbacks include the need of many representative data to be trained in general manner. This is because it is a mainly data driven type of model. Furthermore, elementary reliance between ecological factors may sometimes appear because of its compensating behavior and also it is hard to dig out new knowledge from trained networks as opposed to other modeling approach [36]. ANN can give better predictions compared to regression models, however, it is also applicable only to the condition for which problem it was developed [7].

Until today, ANN model still remains as a black box especially when it comes to identify causal-effective relationship between input and output. With large number of hidden layers and nodes, the training time will increase and lead to overfitting of networks. Sometimes, it comes out with hardly interpretation results. Therefore, when traditional methods to analyze problems are appropriate, ANNs may not need to be used.

5. Future Developments and Current Trends in the Application of Neural Network to Predict Yield

Compared to the earlier stages in agricultural modelling, the limitation of mathematical approaches and lack of computer software are not a big setback anymore. Everything becomes possible and it is easier to deal with a bulk of data and build including handling very complex models for very complex systems. With the current knowledge and technology that we gained, the only problem is to find the most suitable method and approach concerning the specific problem and the actual data situation.

Thus, future developments of ANN in predicting crop yield are needed to better focused on current research in order to see at what extend that this approach can go further in precision agriculture. It remains unknown whether ANN is applicable for different intended goals such as to optimize agriculture productivity, minimize the use of natural or man-made resources and also reduce harmful environmental impacts. Furthermore, the factors affecting yield may be different from year to year.

Current trends in crop yield prediction can be found to focus on soil characteristics parameters, electrical conductivity (EC_a) and genotype of seed which affected crop growth and yield performances. The past decades of observational papers have shown that these focus points were related to yield but less attention was given whether those properties were really influencing those crop's yield or not. Lately, the trend is toward a greater interpretation of the relationship between these properties to a crop's yield at a specific location and point in time. With the existence of ANN, more predictions and interpretations of achieving higher yield can be realized.

The number of research papers on application of ANN in predicting crop yield has increased enormously during recent years. Huang et al. [37] were summarized that among 348 papers and reports reviewed, modelling and prediction using ANN applications was about 43.97% solving about 22.7% crop problems. Most applications of ANN in agricultural and biological engineering have been accomplished using multilayer feed-forward ANN and trained by back-propagation algorithm [37].

Sensitivity analysis must be conducted to detect the robustness of every ANN model because different choices of function and parameters in ANN models would influence the performance of simulation [38]. Generating guidelines for predetermining optimal ANN structures and training algorithms should be thought in order to get an effective research. Additional research topics in crop yield productions must be considered from time to time to improve agricultural managements and precision agriculture.

However, at this time, no further research is conducted to evaluate thoroughly the effectiveness of neural network prediction model from a holistic perspective of environment, crop productivity and economical impacts. This task remains as a future goal for agronomist and scientist in order to meet world's future food demands. More researches towards dynamic modelling of precision farming in agriculture using neural networks are needed in the future.

6. Conclusions

The complexity of agricultural system which deals with so many factors affecting the crop yield needs a non-linear method to interpret the relationships between these factors and crop performances. Thus, a linear method such as linear regression is insufficient to show the interactions of the factors and crop yield. The combination of artificial intelligent and agriculture is and will become a more interesting area of research in the near future.

In a real sense, neural networks are one of the best solutions in search for a few agriculture problems, especially when it comes to predict crop yield. A conclusion has been made that ANN has better explained yield variability rather than other methods [7]. Undeniably, the application of ANN to precision agriculture plays a crucial role in future evaluation of the concept of precision agriculture as a sustainable means of meeting world's food demands. However, further research about the ANN impacts towards crop yield production must be conducted to ensure sustainability of future food needs.

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