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Artificial Neural Networks in Mexican Agriculture, A Overview

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ABSTRACT

Mexican agriculture has become polarized over the years and large properties have been created commercial farms that dominate the sector and on the other hand, the small properties that still exist persist. The main source of income for small farmers in the country. The former are able to take advantage of the fact that trade barriers have been reduced and that exports, especially to the United States, have increased.Despite higher production, agriculture has decreased in the percentage of Mexico's GDP.Faced with this situation, the use of new technologies in small and large scale agriculture is of colossal importance, meanwhile applying this technologies to agriculture would help explode productivity in the Mexican countryside, an important role in this situation is the artificial neural networks.The objective of this work is to know the current state of the applications of the artificial neural networks.in agriculture of the country.In Mexico the applications artificial neural networks.in agricultureare little used, despite their benefits for automation.In the review carried out of the applications of artificial neural networks in Mexican agriculture.

Keywords: *Agriculture ,Mexico, Artificial Neural Networks.*

INTRODUCTION

Mexican agriculture has become polarized over the years and large properties have been created commercial farms that dominate the sector and on the other hand, the small properties that still exist persist. The main source of income for small farmers in the country. The former are able to take advantage of the fact that trade barriers have been reduced and that exports, especially to the United States, have increased.Despite higher production, agriculture has decreased in the percentage of Mexico's GDP. The share of GDP that corresponds to agriculture, forestry and fisheries is reduced from 8% of the nation's GDP in 1990 to 5.4% of Mexico's GDP in 2006, with a growth rate of only 1.6% .In 2010, the structure of GDP and agricultural workers in agriculture, forestry and combined fisheries were valued at 3.8% of the total value of GDP, employing 5,903,300 or 12.5% of the labor force. Currently, young people from rural areas migrate to cities and other countries, mainly to the USA, which is why it is important to promote technologies that automate the farming of small properties,like artificial neural networks.

The status of the automation in Mexican greenhouses and perspectives for the future and also suggests the use of new technologies &mechatronics to automate and increase the productivity of agriculture, animal production and beekeeping (Negrete, 2015;2016; 2017a; 2017b; 2017c).

Faced with this situation, the automation of small and large scale agriculture is of colossal importance, Negrete(2018),meanwhile applying mechatronic and others technologies to agriculture would help explode productivity in the Mexican countryside, an important role in this situation is the systems.

The objective of this work is to know the current state of the applications of the Artificial Neural Network in agriculture of the country.

Artificial neural networks are used for crop selection and crop yield prediction as well as for crop disease prediction.Cáceres(2017).Also Artificial neural networks (ANN) are used to handle experimental data, and their benefits have been more and more recognized in various fields of technology and science (such as biology, ecology, physics, chemistry, agronomy,

economy, medicine, mathematics and computers science). Thanks to their ability to tackle complex calculation issues, they are progressively applied to solve practical problems. The main advantage of ANNs is the fact that task-solving is done by putting forward input signals stimulating network capability to learn and recognize patterns. Sometimes ANN is preferred over complex algorithms or rule-based programming for solving various tasks.Samborska (2014)

Definitions

In computing, a neural network is a program or system which is modelled on the human brain and is designed to imitate the brain's method of functioning, particularly the process of learning.www.collinsdictionary.com

Materials and Methods

Asystematic and thorough search was conducted for data collection in printed data bases, Internet, journals scientific, graduate and postgraduate university thesis, newspaper articles, etc.

Literature Review

Table1. *Applications of artificial neural networks systems in world agriculture*

Author and year	Description	country	
Sathiesh(2016)	Smart Autonomous Gardening Rover with Plant Recognition using Neural Networks	India	
VIEIRA(2011)	evaluate the performance of artificial neural network for poultry preslaughter mortality prediction.	Brazil	
Snehal(2014)	Agricultural Crop Yield Prediction Using Artificial Neural Network Approach	India	
Gaurav (2014)	Classification of Agricultural Pests Using DWT and Back Propagation Neural Networks	India	
Martínez(2013)	Artificial neural network based model to calculate the environmental variables of the tobacco drying process	Colombia	
Rocha (2012)	Develop an Artificial Neural Network that estimate the irrigation time and to contrast the results with the management based on a volume balance method on a watermelon field.	Brazil	
Sartoin(2014)	Development of a multilayer artificial neural network system in reconfigurable device,withthe function of identify deficiency of the Potasium macronutrient by soybean leaf.	Brazil	
Pandey(2017)	Application of artificial neural networks in yield prediction of potato crop	India	
Cárdenas(2008)	Recognition of lactation pattern curves through neural networks and discriminate analysis, during the first third of lactation in dairy cows from the IX Región.	Chile	
Figueroa (2016)	Identification of the state of maturity of fruits with artificial neural networks		
Binoti(2016)	Estimation of fuel comsumption in agricultural mechanized operations using artificial neural Networks	Brazil	
Xue(2014)	Crop Yield Forecasting Using Artificial Neural Networks.		
Trajkovics (2012)	Forecasting of reference evapotranspiration by artificial neural networks		
Helio(2014)	Estimation of inside-bark diameter and heartwood diameter for Tectona grandis Linn. trees using artificial neural networks.		
Silveira(2013)	Soil prediction using artificial neural networks and topographic attributes		
Waidyarathne(2014)	A computational modelling attempt to classify a plant disease using visual symptoms to ease crop management programmes. Weligama coconut leaf wilt disease (WCLWD), a phytoplasma-borne coconut disease characterised by three foliar symptoms (flaccidity (bending of leaflets), yellowing and marginal necrosis) found in Sri Lanka, was used to demonstrate its applicability.	Sri Lanka	
Amraei(2017)	Machine vision and artificial neural Network(ANN)procedures were used to estimate live body weight of broiler chickens	Greait Bretain	
Bashish(2011)	Developed Neural Network classifier that is based on	Jordan	

	statistical classification perform well in all sampled types of leaf diseases and can successfully detect and classify the examined diseases with a precision of around 93%.		
Bennedsen(2007)	Artificial neural networks and principal components were used to detect surface defects on apples in near-infrared images. Neural networks were trained and tested on sets of principal components, derived from columns of pixels from images of apples acquired at two wavelengths (740 nm and 950 nm).	USA	
Elnesr(2017)	An artificial neural network predictor model was developed based on the data from the well-tested model HYDRUS 2D/3D. The simulation data grid from HYDRUS was converted to simpler 3-variables vectors of wetting ellipses.	Saudi Arabia	
Dutta(2017)	An artificial neural network (ANN) was used toanalyze photometric features extracted from the digitized imagesof leaves from in vitro-regenerated potato plants for noninvasiveestimation of chlorophyll content. A	India	
Wang(2008)	An image-based walk-through system was developed in this study for pig liveweight approximation without having to restrain the pig to a certain area for stationary imaging. A protocol was developed to automatically screen and select the images captured for image processing. The artificial neural network technique was used in this study to correlate a multitude of physical features extracted from the walk-through images to pig liveweight in an attempt to improve the accuracy of liveweight approximation.		
Barth(2017)	A current bottleneck of state-of-the-art machine learning methods for image segmentation inagriculture, e.g. convolutional neural networks (CNNs), is the requirement of large manuallyannotated datasets on a per-pixel level.Was investigated how related syntheticimages can be used to bootstrap CNNs for successful learning as compared to other learningstrategies.		
Ovando(2005)	Work models based on neural networks of the backpropagation type were developed in order to predict the occurrence of frosts from meteorological data such as temperature, relative humidity, cloudiness and wind direction and speed.	Argentina	
Oppenheim(2017)	Presents a potato disease classification algorithm which leverages these distinct appearances and the recent advances in computer vision made possible by deep learning. The algorithm uses a deep convolutional neural network training it to classify the tubers into five classes, four diseases classes and a healthy potato class.		
Glezakos(2010)	Genetic algorithms and multilayer neural networks are applied to plant virus identification. The initial data set is derived via a well known prototype method, which uses specially designed biosensors to monitor the virus reactions. Several techniques have been introduced for preprocessing the plant virus waves.		
Martí(2009)	Presents the application of artificial neural networks (ANNs) for the estimation of two relevant variables of irrigation engineering: reference evapotranspiration and integrated emitter local losses.	Spain	
Fitz(2012)	Proposes a neural network predictive control approach for optimizing water and energy usage in a naturally ventilated and fog cooled greenhouse while providing a near-optimum and uniform environment for plant growth.	USA	
Alipour(2013)	The greenhouse conditions were controlled by using artificial neural network (ANN). First, an experimental greenhouse was built and equipped with control instruments. Then by using electronic sensors, some climatic parameter data (temperature, humidity, carbon	Iran	

	dioxide and light index) were measured and saved during five minute periods. In the next stage, three types of ANN including feed forward neural networks with multiple delays in the input, two-layer neural network with a feedback from hidden layer and input delay and three-layer neural network with two feedbacks from hidden layers and input delay were trained by 66% of the recorded data, and were evaluated by using the remaining data. The three-layer neural network with two feedbacks from hidden layers and input delay was able to better predict humidity and light index of the greenhouse with MSE,s of 0.025 and 0.032, respectively		
Singh(2017)	Develop an Artificial Neural Network (ANN) model for prediction of oneday ahead mean air temperature and relative humidity of greenhouse located in the sub-humid sub-tropicalregions of India	India	
Patil(2007)	Study included an auto regressive (AR) model with an external input (ARX), an auto regressive moving average model with an external input (ARMAX) and a neural network auto regressive model with an external input (NNARX). External and internal climatic data recorded over a year were used to build and validate models for simulating environmental conditions inside the greenhouse. The variables measured to estimate the greenhouse internal climate included external temperature, solar radiation, relative humidity and cloud cover.		
Uchida(2004)	An NNARX system is proposedfor modelling the internal greenhouse temperature as a function of outside air temperature and humidity, global solar radiation and sky cloudiness. The models show a good performance over a complete year using only two training periods, 1 week in winter andone in September. Finding the balance between the number of neurons in the hidden layer of the NNARX system and the number of iterations for model training is found to play an important role in obtaining this goodperformance.	Belgium	
Manonmani(2018)	In the present work, the approximation capability of a neural network is used to model and control sufficient growth conditions of a GHS. An optimal neural network-based non-linear auto regressive with exogenous input (NARX) time series model is developed for a GHS. Based on the NARX model, two intelligent control schemes, namely a neural predictive controller (NPC) and non-linear auto regressive moving average (NARMA-L2) controller are proposed to achieve the desired growth conditions such as humidity and temperature for a better yield.		
He(2010)	A back propagation neural network (BPNN) based on principal component analysis (PCA) wasproposed for modeling the internal greenhouse humidity in winter of North China. Theenvironment factors influencing the inside humidity include outside air temperature andhumidity, wind speed, solar radiation, inside air temperature, open angle of top vent and sidevent, and open ration of sunshade curtain, which were all collected as data samp	China	
He(2007)	The adequacy of improved back propagation (IBP) neural network to model the inside airtemperature and humidity of a production greenhouse as a function of outsideparameters including temperature, relative humidity, wind speed, and solar radiationwas addressed. To avoid standard BP algorithm's shortcoming of trapping to a localoptimum and to take advantage of the genetic algorithm (GA)'s globe optimal searching, a new kind of hybrid algorithm was formed based on the IBP neural network and GA. BPneural network was improved by adding the inertia impulse and self-adaptation learningrate to	China	

	lessen convergence vibration and increase the learning speed. Then the initializedweights and thresholds of IBP neural network were optimized with GA. Through carryingout the experiments, the specimen data were collected on half-hourly basis in agreenhouse.		
Bisi(2016)	Information and Communication Technologies (ICT) has provided access to data and information, specially with the advent of the Internet, and this led to changes in society. In this context, this paper aims to demonstrate how data can assist agriculture in control of production, using the data available in government databases. Therefore, we carried out a literature search about the subject and made a data collection on government databases. The completion of the crossing of data using the computation model of artificial neural networksshowed that data can aid in the prediction of agricultural production.	Brazil	
Borges(/2017)	Develop artificial neural networks for the estimation of tractor fuel consumption during soil preparation, according to the adopted system. The multilayer perceptron network was chosen. As input data: the soil mechanical penetration resistance, the mobilized area by implements, the working gear and the tractor engine speed. The number of layers and neurons varied to form different architectures. The adjustment was verified based on various statistical criteria.	Brazil	

Neural Network in Mexican Agriculture

Garcia (2017). Applied Bayesian regularized neural networks (BRNN) and classification trees to predict iron deficiencies based on SPAD-502 readings that estimated the greenness index in common bean leaves. An experiment was carried out with eight treatments at different levels of Fe concentration in the nutrient solution (0, 20, 40, 60, 80, 100, 150 and 200 %). For seven weeks, the average Green index measurements of the three leaflets of five replicates corresponding to the eight treatments were taken, and the collected data were used to adjust the statistical models mentioned above. With BRNN, the correlation between observed and predicted values was 0.77 for the training data set and 0.54 - 0.71 for the test data. In the case of classification trees, in the training stage, the percentage of correct classifications was 56.25 %, and when the validation procedure was carried out, it decreased almost 30 %. Thus for this type of research, the use of BRNN constitutes a valuable tool for the prediction of early deficiencies of Fe in common bean crop.

Trueba(2014) Proposed a methodology to identify hydric erosion using a digital image analysis. The proposed methodology consists of using a backpropagation artificial neural network as pixel classifier using the Levenberg-Marquardt training algorithm. The network is capable of identifying white tepetate with an error of 2.5%; tepetate in transition from white to yellow with 16%; trees with 13.5%, and soils covered with arvenses with 7.1%. For yellow tepetates, the error was up to 3560%; the same trend was observed in the identification of gullies.

Berra V.E.(2017)Perform, a revision of the techniques occupied in the agriculture of precision is carried out, specifically the techniques of lineal analysis of data and the classification of soils, by means of the neural networks for the taking of decisions, the investigation was focused in two basic techniques, historical data analysis and image analysis, for the classification by Kilo grams and images, making a comparison of the results of the neural networks used.

Cervantes(2011) Present a literature review on artificial neural networks for reference evapotranspiration estimating and related variables, including: theory and artificial neural networks foundations and backpropagation algorithm, some similarities and differences between traditional statistical models and artificial neural networks, applications of artificial neural networks in reference evapotranspiration estimating and variables

associated with the prospects of artificial neural networks in agroclimatic variables prediction.

Sállago(2012)Built to model the rate of foliar photosynthesis of tomato plants, grown under greenhouse conditions using artificial neural networks, using as input variables: temperature, relative humidity, vapor pressure deficit and concentration of carbon dioxide (CO2) of the air, and photosynthetically active radiation. The experiment was conducted during 2009 in an experimental greenhouse of the Autonomous University of Querétaro, Mexico. The equipment used was the PTM-48M phyto-monitoring (Daletown Company, Ltd), to record CO2 exchange on the leaves, and weather variables. In order to remove the sensor noise in the measurements, the Savitzky-Golay filter was used. Different configurations for back-propagation networks were evaluated, with 4 layers and 10 neurons in the first hidden layer, 15 in the second one and 10 more in the third one, which produced the best statistical indices on the test data: coefficient of determination, R2= 0.9756 and mean square error, MSE= 0.8532. Taking the best ANN predictions, we performed a static optimization, linking two climatic variables with the rate of photosynthesis, using three-dimensional graphics, to show strategies for maximizing the rate of photosynthesis.

Trejo(2009) Analyzes an energy consumption predictor for greenhouses using a multi-layer perceptron (MLP) artificial neural network (ANN) trained by means of the Levenbergh-Marquardt back propagation algorithm. The predictor uses cascade architecture, where the outputs of a temperature and relative humidity model are used as inputs for the predictor, in addition to time and energy consumption. The performance of the predictor was evaluated using real data obtained from a greenhouse located at the Queretaro State University, Mexico. This study shows the advantages of the ANN with a focus through analysis of variance (ANOVA). Energy consumption values estimated with an ANN were compared with regression-estimated and actual values using ANOVA and mean comparison procedures. Results show that the selected ANN model gave a better estimation of energy consumption with a 95% significant level. The study resents an algorithm based in ANOVA procedures and ANN models to predict energy consumption in greenhouses.

CONCLUSIONS

In the review carried out the applications of neural networks to agriculture is very limited, but in the country is really minimal because there are only two revision works and only four of applications of neural networks to agriculture in the country, a very depressing since these have very varied applications, which should motivate researchers of the universities and institutes whose lines of research include engineering and agriculture, such as the National Institute of Forestry, Agricultural and Livestock research, the Postgraduate Collegue, the Autonomous Agricultural university Antonio Narro, the University of Guanajuato, the Faculty of Higher Studies of Cuauhtitlan of the National Autonomous University of Mexico, among others.to conduct research in this regard.

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