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USING ARTIFICIAL NEURAL NETWORKS MODELS FOR PREDICTING WHEAT YIELD PRODUCTIVITY

[56]

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ABSTRACT

Artificial intelligent provides diverse solutions for the complex problems in agriculture research. The study aimed to use three models of artificial neural networks (Feed Forward Neural Network (FFNN), Generalized Regression Neural Network (GRNN) and Radial-Basis Neural Network (RBNN)) in the field of wheat yield prediction. 27-year data for the period (1986-2012) were utilized to improve the models and four-year data (2013 and 2016) were used to estimate the models, to compare their outputs with the measured data. Prediction data was not entered in the process of building neural network models. The results showed that the optimal configuration of the FFNN model consists of 40 neurons in the hidden layer (8-40-1). The Tan Sigmoid activation function was used in both the hidden layer and the output layer using all of these models (anterior neural feeding network and the regression neural network and radial base neural network) in the 4-year wheat yield forecast field for production (2013-2016) by applying 8 input parameters that were result of NMMS (8.6%, 7.6% and 15.7% resp.), To find that FFNN and GRNN provide the best result from BRNN because while the information set was large or in a wide range, then the range data ranges from -1 to +1 (normalization data) , GRNN gives better outcomes after the information or sample data were in large range.

Keywords: Wheat yield, Forecast, Artificial neural networks, Feed-forward Back propagation.

INTRODUCTION

Crop yield Forecast could also be an active area of current research interest and had been so later the 1980s. Though, within the initial days the operate was ordinarily associated with the research of linear systems models then was only related with the linear relationships between the numerous agricultural parameters. Consequently, most of the predictable or traditional models are not capable operate good for they were not able to efficiently arrangement with the matter and non-linear environment of the data, **(Jiang et al 2004).** Crop Imitation patterns were programmed statements of crop growing, progress, and yield, imitated including calculated equations as purposes of soil specifications, weather and executive processes **(Hogenboom et al 2004)**. Fundamentally, yield prediction models were often divided keen on two categories; statistical display and crop simulation display, **(Safa et al 2004)**. Considered as composite models that usage many differing kinds of data and distrust strongly on computer design to imitate the expansion of wheat as within the CERES **(Brooks et al 2001 and Bannayana et al 2003)**. While simulation and statistical displays had developed toward enhanced well crop prediction displays, they were immobile non adept really through a complicated data fixed. Also, forms established on Intelligent Systems (ISs) procedures were skilled toward amaze this restriction. This kind of procedure be able to create suitable outcomes with influencing basic and simple or complicated information which they do in competitively with the more complicated models. The foremost common ISs procedure which has been expended on behalf of crop or wheat forecast exhibits was Artificial Neural Networks (ANNs) (Shearer, *et al*., 2000). The importance of wheat assembly was replicated inside modern food safety debt review amid the Department for Environment, Food and Rural Affairs (DEFRA) which resolved that crops, and exactly wheat, were the various statistics within limiting worldwide food obtainability, **(F.a.R.A. Dep. for Environment, 2010)**. During this procedure, the multilayer perceptron was possibly the foremost normally exploited algorithm with the planning of neural networks for its ability to allow information that was imperfect, accurate or polluted through noise **(Mas and Flores, 2008)**. The multilayer perceptron holds a non-limited statistical display of nonlinear regression which mostly usages one hidden layer to fully split the important unnecessary alongside which the extent of multinational of hidden units was constant **(Foody, 2000)**.

MATERIALS AND METHODS

The main purpose of this article was to study changed ANN procedure in developing wheat prediction. There are many kinds of neural networks. Then the elementary ethics were exact relevant. All neuron inside the network can obtain input signals, for processing and transmission of the output signal. Each neuron was linked to minimum one neuron, and all linking was estimated by an actual number, and the coefficient of weight, which indicates the degree of significance of a join in the neural network. Assuming, the neural network was a common estimating force, i.e., it could realign irrational mapping of one vector area over alternative vector area. The foremost advantage of neural networks was feature, which could utilization a few unknown previously hidden information in the data (but it was not able to extract it). The procedure of "capturing" unknown information was named "learning the neural network" or "training the neural network". Three different neural FFNN, GRNN and RBNN to predict wheat yield. FFNN: including the various networks, the feed forward neural networks or Multi-Layer Perception (MLP) were the utmost utilized in engineering sciences. MLP networks were usually arranged into three layers of neurons, the supposed multilayer assembly:

- Input layer: its neurons similarly named nodes or treating units lead the display inputs.

-Hidden layer(s) (one or more layers): Its nodes relate the inputs with weights that are converted through the learning procedure.

-Output layer: This layer provided the estimations of the network, **(Reza Ghodsi et al 2012)** .In these networks, the output was purpose of the linear mixture of hidden component's stimulations; each one is a non-linear function of the weighted summation of the inputs: $\hat{\mathbf{Y}} = \mathbf{f}(\mathbf{X}, \boldsymbol{\theta}) + \boldsymbol{\epsilon}$

Where: x is the vector of cooperative variables, ε is the random error element.

f (x, θ) = ŷ is the unlimited function for measurement and prediction from the obtainable data. Deliberate MLP with three layers and one output. The network depends on the keep forming:

$$\hat{Y} = \mathbf{F}(\boldsymbol{u_0} + {}_{j=1}^{m}\boldsymbol{H}\,(\boldsymbol{\lambda}+_j\mathbf{n} \quad {}_{i=1}\,\boldsymbol{X_i\theta_{ij}})\boldsymbol{u_j})$$

Where:

Ŷ: Network output,

F: Output component activation function,

H: Hidden component activation function,

n: number of input component s, m: number of hidden component s,

xj: input vector for component j (xij = i the input to the j component),

θij: weight from component layer i to hidden component j,

u_0: output bias,

λj: hidden component s biases (j = 1 . . . m),

uj: weights from hidden component j to output (j = 1 . . . m)

The GRNN was convenient to determination a diversity of problems as prediction, management, create procedure modelling or general development potencies, **(Qeethara et al 2013, Neves and Vieira 2006)**. General regression neural network does not assume reiterative training method as in back-propagation method, **(Specht, 1991)**. The GRNN was consumed for estimation of permanent variables, as in normal regression procedures. It was linked to the radial base purpose network and was recognized by a normal statistical procedure named kernel regression. By explanation, the regression of dependent variable y dependent on x estimations the extremely workable value for y, organized x and a training set. The regression method will establish the estimated value of y, which minimizes the mean-squared error. GRNN is a method for estimating the linkage Probability Density Function (PDF) of x and y, organized only a training set. For the PDF is attained from the data with no concepts suitable its procedure, the system was absolutely common. Additionally, it is consistent; that is, as the training set size established massive, the estimation error set almost zero, with just minor restrictions on the function. In GRNN, instead of training the weights, one logically stipulates to wij the target value promptly from the training set linked with input training vector i and component j of its adapting output vector . GRNN was created on the following formula (Kayaer and Yildirim, 2003).

$$\boldsymbol{E}[\boldsymbol{y} \mid \boldsymbol{x}\,] = \frac{\int_{-\infty}^{\infty} \boldsymbol{y}\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})\boldsymbol{dy}}{\int_{-\infty}^{\infty} \boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})\boldsymbol{dy}}$$

Where: y is the output of the estimator, x is the estimator input vector, E(y/x) is the expected value of output, created the input vector x, and $f(x, y)$ is the linkage possibility degree function (pdf) of x and y. The function value is adapting optimally as follows:

$$y_j = \frac{\sum_{i=1}^{n} h_i w_{ij}}{\sum_{i=1}^{n} h_i}$$

Where: wij is the target output adapting to input training vector xi and output j; $hi = \exp[-Di^2/(2\sigma^2)]$ is the output of a hidden layer neuron; $Di^2 = (x - ui)^T(x - ui)$ is the squared distance between the input vector xi and the training vector ui; and σ is a constant functioning the amount of the perceptive area. The main change between GRNN and RBNN neural networks is the method that the weights wij, are recognized. Instead of training weights, the GRNN gives the target value correctly to the weights, wij, from the training set associated with input training vector and a component of its equivalent output vector. The RBNN network normally take three layers: an input layer, a hidden layer by a non-linear RBF activation function and a linear output layer. Consider the hidden layer has i neurons, and i the neuron revolves at c_i with its chosen value w_i. The input canister be shaped as a vector of real numbers $x \in R^n$, the output of the network is then a scalar function of the input vector $\phi: R^n \rightarrow R$, estimated by:

$$\varphi(x) \frac{\sum_{i=1}^{I} \omega_i \rho(\| x - c_i \|^2)}{\sum_{i=1}^{I} \rho(\| x - c_i \|^2)}$$

Where: $\rho(\|x - c_i\|^2) = \exp(-\beta_i \|x - c_i\|^2)$. Mention that the output $\phi(x)$ assumed input x is the weighted mean of w_i among weight $\rho(\|x - c_i\|^2)$. The cost function is described by the resulting quadratic formula:

$$C = \frac{1}{2n} \sum_x \| y(x) - \varphi(x) \|^2 \stackrel{\text{def}}{=} \frac{1}{n} \sum_x C_x$$

The limitations w_i, c_i, β_i are chosen by decreasing C.

Data set and evaluation

In this research, employed 8 foremost components as inputs(maximum temperature (Tmax), main temperature (Taver), minimum temperature (Tmin), Rain (R), Potential Evapotranspiration (PET), dew point data (DP), wind speed (WS) and irrigation requirement (IR)). Climbed all data from standard agricultural meteorological stations of the Agricultural Research Center in the tests station of Sakha Province, Kafer el Shikh Governorate, Egypt, at latitude 31° 5\ 12\\ N, and longitude 30°56\ 49\\ E, and mean altitude 2m above sea level. These data contain of 31 years from 1986 to 2016. The wheat yield data was used as the target output data was indicated in terms of tone and carries to the same period as the weather data. There were other factors which will assume the wheat yield and these involved; soil condition, effect of pests or plant diseases and so on these parameters are difficult to get clamp of and they are not ordinarily used to predict wheat yield, so do not involved such variables in calculations. Consumed MATLAB neural network toolbox to build this ANN feed forward back propagation model. Annual data for 27 years from 1986 to 2012 were utilized in this study. To predict wheat production, Artificial Neural Networks (ANN) procedures were examined for evaluating the data. The data set was then divided into training set (70%), validation set (15%) and testing set (15%). Wheat production for the years 2013- 2016 used in simulation for three artificial neural networks (ANN). This evaluation was organized by using four statistical indices: determination coefficient (R^2), Root Mean Square Error (RMSE) and the ratio between average predict wheat yield values and observed wheat yield values correlation coefficient (R). The R^2 measures the degree to which two variables were linearly joined and should optimally be one. The Normalized Root Mean Square Error (NRMSE) as a percentage it gives a suggestion of the relative variance between the results of the simulation models and the observations. Can be observed as simulation (modeling) was excellent if it was smaller than 10% statistical indicator, and good if between 10% and 20%, medium quality if between 20% to 30% and bad if it was greater than 30%These indices described as follows:

$$R^2 = \frac{[\sum(P_i - P)(O_i - O)]^2}{\sum(P_i - P)^2 \sum(O_o - O)^2}$$

$$RMSE = \left[N^{-1} \sum_{i=1}^{N} (P_i - O_i)^2 \right]^{0.5}$$

$$R = \frac{P}{O}$$

$$\text{NRMSE} = \frac{RMSE}{O} \times 100$$

Where: N is the number of observations, P_i is the predicted (using the ANN and conventional methods), O_i is the observed wheat production, P and O are the average value for P_i and O_i.

RESULTS AND DISCUSSION

Feed Forward Neural Network (FFNN)

To make feed forward neural network MLP which had been shown to be applicable at exchange with either linear or nonlinear data. **Karpov et al (2020), LiMin Fu (2003) and Tetko et al (2008)** revealed that there were a lot of traditions in which to create the number of neurons in the hidden layer and usually the optimum number was established by trial and error. Investigated with 10, 15, 20, 25, 30, 35, 40, 45 and 50 hidden neurons and the results were evaluated to establish the best performance. By working MATLAB expended newff function and treating one hidden layer. In input layer were utilizing 8 input limits as input vectors and output appears in output layer. Tansig function had been added as transfer function in hidden layer for it was extremely capable transfer function for non-linear realistic usage data. The Levenberg-Marguardt (trainlm) training algorithm was extreme for training for this algorithm was extremely valuable than others training algorithm in recognize to time and memory utilities in implementation. **Table 1** showed that the results when FFNN was involved with 1 hidden layer and a Learning Rate (LR) of 0.25. The neurons in the hidden layer were adapted from 10 to 50. The best neural network with (8-40-1). **Fig. 1** with a testing R^2 of 0.99.and RMSE of 0.003659. **Fig. 2** showed that the outdo validation working was accomplished 0.0019577 at 2 epoch and the diagram rapidly drops it shown the well brought-up accomplishment. **Fig. 3** shown the training established, validation set, testing set and all common set shapes, resp. and shown that the relationship between output value and the target value, it was almost accomplished 0.99012. It means it was best attained at 99% with target value.

Table 1. Comparisons for all hidden layer on number of neuron influence

No. of	Training		Validation		Testing		All	
neurons	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
10	0.941388	0.154222	0.811451	0.045785	0.976171	0.121665	0.949138	0.137299
15	0.945877	0.149461	1	2.01E-08	0.951848	0.192228	0.946931	0.146926
20	0.746452	0.320007	0.999999	0.001148	0.996916	0.04777	0.820397	0.277842
25	0.904622	0.191168	0.999385	0.018021	0.979066	0.106692	0.918922	0.168433
30	0.954344	0.122016	0.99832	0.042243	0.991318	0.080886	0.96991	0.108173
35	0.962903	0.130874	0.995458	0.050889	0.972053	0.14302	0.965652	0.120138
40	0.976157	0.09884	0.990271	0.081993	0.999973	0.003659	0.980332	0.085967
45	0.974089	0.095471	0.992809	0.017096	0.768038	0.269945	0.954242	0.123322
50	0.956678	0.139733	0.978514	0.096912	0.999989	0.002471	0.962081	0.128245

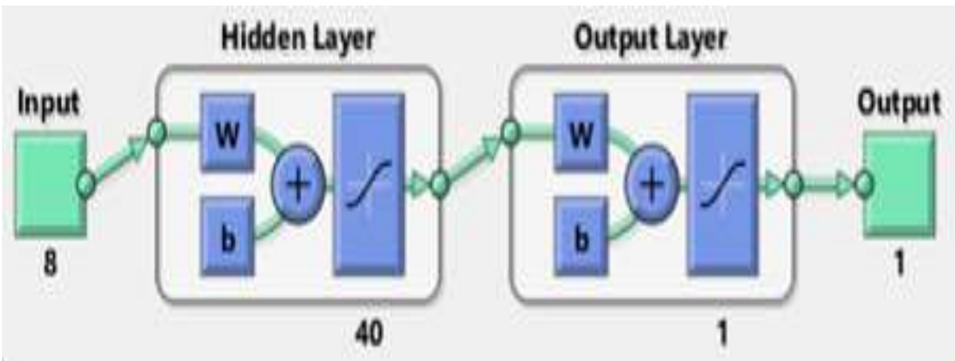

Fig. 1. The best Feed Forward Neural Network Assembly.

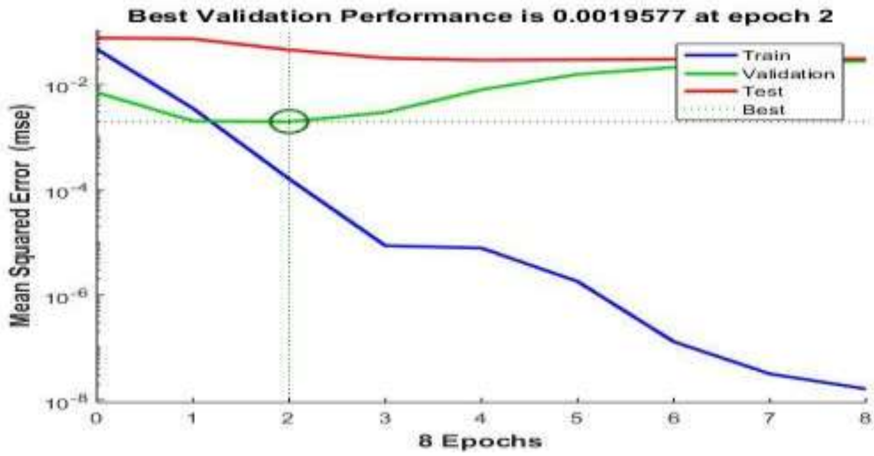

Fig. 2. Validation performance index graph in MSE.

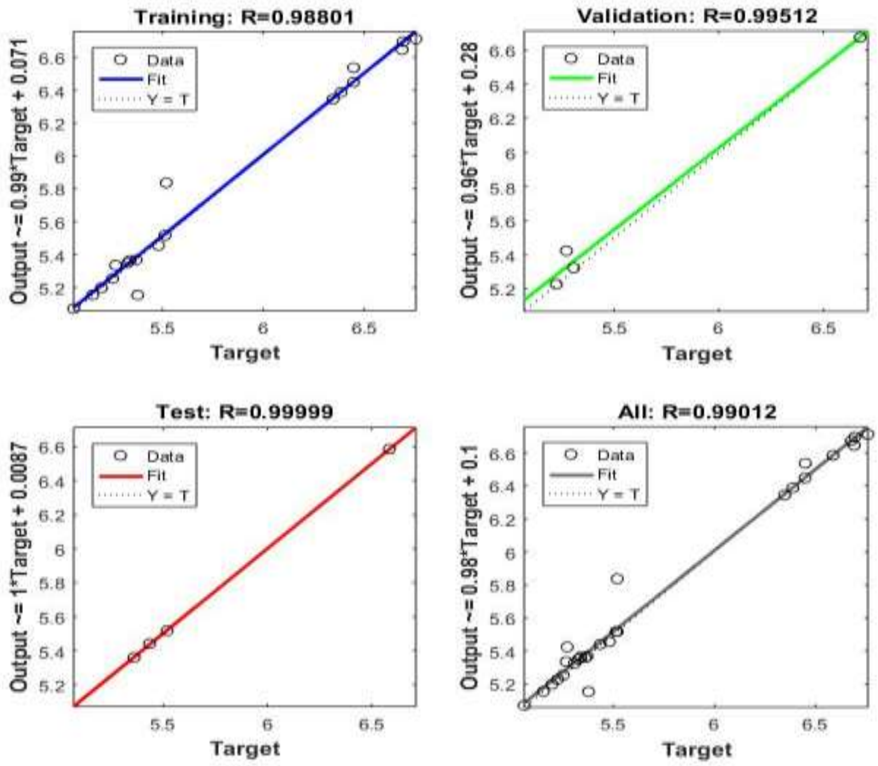

Fig. 3. The training, validation, testing and all normal traditional.

Generalized Regression Neural Network (GRNN)

Generalized regression neural networks were a variety of radial basis network that is a lot reduced for function estimation. GRNNs can be designed very quickly GRNN (P, T, SPREAD) takes these inputs, P- R*Q1 matrix of Q1 input vectors. T- S*Q2 matrix of Q2 target class vectors. SPREAD - Spread of radial basis functions, default = 1.0 and incomes a new generalized regression neural network. The larger SPREAD was the glibber the function estimate will be. To fit data carefully, exploited a SPREAD smaller than the typical distance among input vectors. To fit the data extra easily expended a larger SPREAD.GRNN creates a two-layer network. The first layer had radbas neurons, establishes weighted inputs by dist and obtain input through net product. The second layer has purlin neurons, estimates weighted input beyond normal product and obtain inputs through net summation, unique the first layer had biases. **Fig. 4** shown generalized regression neural network assembly.

Fig. 5 shown regression with R=1 by GRNN showed that generalized regression gives data matching inaccuracy as 100 % and it was more correct than FFNN.

Radial Foundation Neural Network

Radial base networks can be employed to assessment operates. RBNN extremely quickly outlines a radial basis network among zero error on the outline vectors. RBNN (P, T, and SPREAD) incomes two or three views, P-R*Q matrix of Q input vectors. T- S*Q matrix of Q target status vectors. SPREAD - of radial basis functions, default = 1.0 and incomes a new perfect radial basis network. The better that SPREAD, was the tenser the function assessment will be. As well significant a reportage can make numerical efforts. RBNN establishes a two-layer network. The first layer had radbas neurons, and estimates its weighted inputs among DIST, and it achieve input among net product. The second layer had purlin neurons and analyzes its weighted input among dot product, and it achieve inputs among net summation. Individually layers had likings. RBNN feeds extra data fitting accuracy than FFNN and GRNN deprived of error. **Fig. 7** shown regression chart in among output and target estimates among 100%.

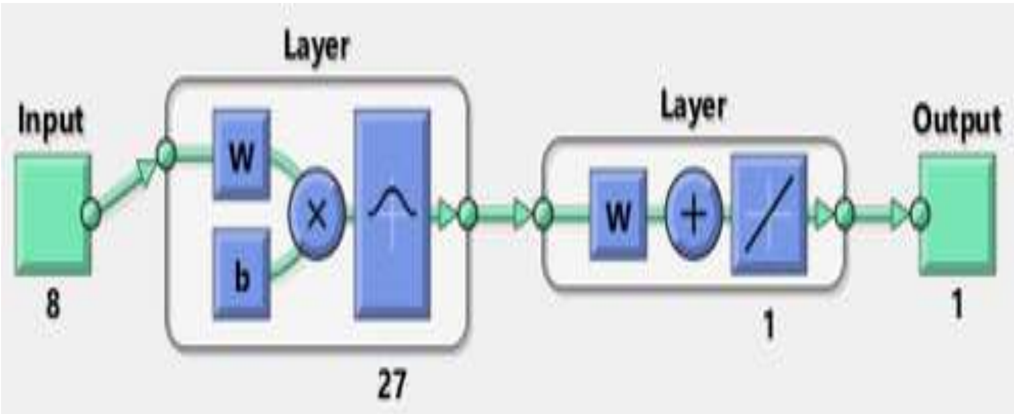

Fig. 4. Generalized Regression Neural Network Structure

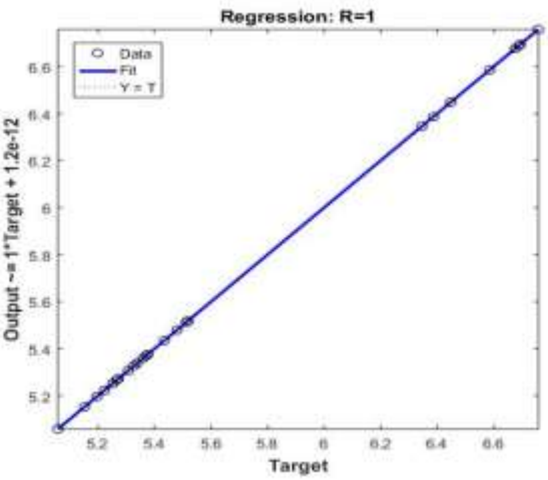

Fig. 5. Regression scheme in amongst Output and Target rates by GRNN display

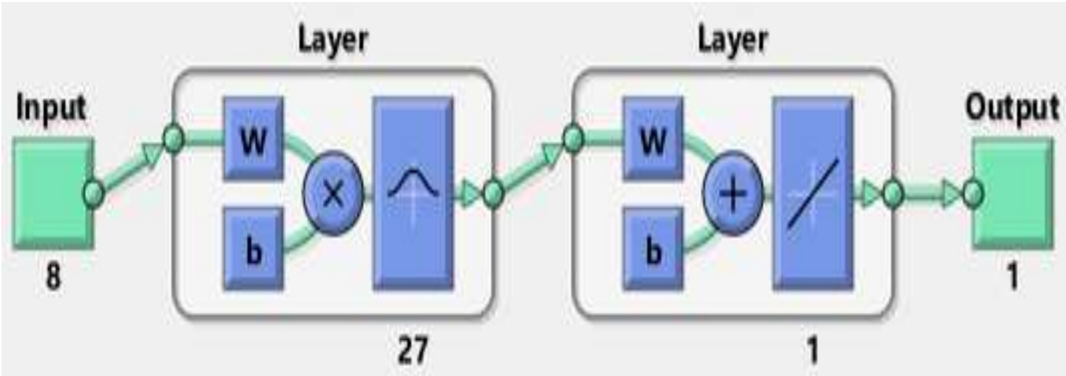

Fig. 6. RBN Network Structure.

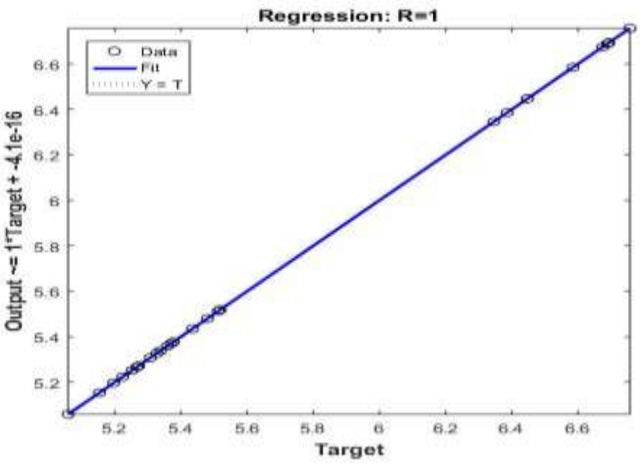

Fig. 7. Regression scheme in among Output and Target estimates by RBNN display

Comparison Analysis In Between All Three Models

All three types attain unique regressions FFNN realizes 99%, GRNN observes 100 % and RBNN obtains 100%. Utilizing all these types for wheat prediction for 4 years productions (2013-2016) by employing 8 parameters inputs NRMSE 8.6%, 7.6% , 15.7% resp. and found that FFNN and GRNN network supply outdo effect than RBNN network for GRNN network keeps well result while the data organized were great or in a comfortable range, the data range was in among -1 to +1 (normalization data) GRNN supplies more satisfactory result when data will in varied range or on bulky samples data. GRNN arranges batter function estimate than RBNN.

CONCLUSIONS

The research assessment in concerning MLP, GRNN and RBNN in the field of wheat yield forecast. The forecast was worked utilizing the climate variables namely; Rain (R), maximum temperature (Tmax), mean temperature (Taver), minimum temperature (Tmin), potential evapotranspiration (PET), dew point data (DP), wind speed (WS) and irrigation requirement (IR) for wheat. Data of historical 31 years (1986 to 2012) were collected from standard agricultural meteorological stations of the Agricultural Research Center in the tests station of Sakha Province, Kafer el Shikh Governorate, Egypt, Data of 27 years for the period (1986-2012) were retained to develop the models and the data of four years (2013 and 2016) were expended to evaluate the models, to compare their outputs with the data measured these data did not affect in the process of building neural networks models. Results discovered that the ideal conformation for the FFNN model involved of one layer (8-40-1). The hidden layers had 40 nodes in the hidden layer for the ANN model. Hyperbolic tangent transfer function was engaged in hidden and output layers of the ANN display. The learning rate and the momentum parameter were 0.005 and 0.9 resp. for the ANN model. Iterations were 1000 epochs during training process for the ANN model. The outcome represented that GRNN extant well forecast outcomes as competed to FFNN and RBNN.

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إستخدام نماذج الشبكات العصبية الاصطناعية للتنبؤ بإنتاجية القمح

[56]

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الموجـــــــــــز

تهدف الدراسة إلى إستخدام ثلاث نماذج للشبكات العصبية الاصطناعية (الشبكة العصبية للتغذية الأمامية (FFNN) والشبكة العصبية للانحدار (GRNN) والشبكة العصبية للأساس الشعاعي (RBNN)) في مجال التنبؤ بمحصول القمح. تم التنبؤ باستخدام متغيرات المناخ وهي: الأمطار (PRE)، درجة الحرارة القصوى (TMX)، درجة الحرارة المتوسطة (TAVG)، درجة الحرارة الدنيا (TMN)، والبخر نتح المرجعي (PET)، درجة حرارة نقطة الندى (DP)، سرعة الرياح (WS) والاحتياجات الاروائيه للقمح (IR). تم جمع البيانات من السنوات الـ 31 الماضية (1986 إلى 2016) من محطات الأرصاد الجوية الزراعية القياسية لمركز البحوث الزراعية في محطة اختبارات سخا، محافظة كفر الشيخ، مصر. تم استخدام بيانات 27 سنة للفترة (1986–2012) لتطوير النماذج واستخدمت بيانات الأربع سنوات (2013 و2016) لتقييم النماذج، لمقارنة مخرجاتها مع البيانات المقاسة ولم يتم إدخال بيانات التنبؤ في عملية بناء نماذج الشبكات العصبية. أظهرت النتائج أن التكوين الأمثل لنموذج FFNN يتكون من 40 عقدة في الطبقة المخفية (8–40–1). تم إستخدام دالة التفعيل Tan Sigmoid في كل من الطبقة المخفية وطبقة المخرجات وبإستخدام جميع هذه النماذج (شبكة التغذية العصبية الأمامية والشبكة العصبية للانحدار والشبكة العصبية للأساس الشعاعي) في مجال التنبؤ بمحصول القمح لمدة 4 سنوات للإنتاج (2013: 2016) من خلال تطبيق 8 معلمات مدخلات كانت نتيجة جذر متوسط مربع الخطأ المعاير (NRMSE) 8.6٪، 7.6٪ و 15.7٪ على التوالي، نجد أن شبكة FFNN و GRNN توفر أفضل نتيجة من شبكة BRNN لأن شبكة GRNN تقدم أفضل نتيجة عندما تكون مجموعة البيانات كبيرة أو في نطاق واسع.