

Utilization of Artificial Neural Networks (ANNs) for Predicting Traits and Protein Content in Maize Crops

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Abstract

Improving maize production is an important step in reducing agricultural costs. This study aimed to use artificial neural networks to simulate grain yield, protein ratio, and 1000-grain weight of maize. A field experiment was conducted at the Agricultural Research Station, College of Agriculture, University of Basrah, Garmat Ali area, to demonstrate the effect of irrigation water salinity and nitrogen and potassium fertilization on crop traits, including grain yield, 1000-seed weight, and protein ratio, of maize using Artificial Neural Networks (ANNs). Three levels of irrigation water salinity (1, 4, and 8) dS⁻¹ were used, four levels of nitrogen fertilizer (0, 60, 120, and 240) kg N ha⁻¹ in the form of urea (46% N), three levels of potassium fertilizer (0, 80, and 160) kg K ha⁻¹ in the form of potassium sulfate (52% K₂O) were used, and one level of phosphate fertilizer (60) kg P ha⁻¹ in the form of high-phosphorus NPK was also added. ANN yielded highly reliable results for predicting grain yield, protein ratio, and 1000-grain weight under the influence of irrigation water salinity and nitrogen and potassium fertilization. The neural network using the Levenberg-Marquardt training algorithm demonstrated the best prediction ability for grain yield (R²= 0.99992, MSE= 0.00014571), protein ratio (R²= 0.9992, MSE= 0.00055522), and 1000-grain weight (R²= 0.99994, MSE = 0.00010432).

Keywords: ANNs, yield traits, protein ratio, prediction, maize crop.

I. Introduction

Maize (*Zea mays* L.) is an important and strategic grain crop, it is widely cultivated worldwide and ranks second after wheat in terms of cultivated area, estimated at approximately 177 million hectares, and first in terms of grain production, which reached 970 million tons (USDA, 2016). Maize grains are characterized by their high content of carbohydrates, essential minerals, dietary fiber and a protein content of up to 9%, in addition to vitamins A, C and D, which makes them an important source of energy (IITA, 2009).

Today, the world has begun to use intelligent computations such as Artificial Neural Networks (ANNs) and fuzzy adaptive network inference systems in forecasting. This can contribute to improving the accuracy of forecasting and analysis in various areas of agricultural operations. These intelligent methods allow for learning from available data and gaining experience through analysis and inference of complex patterns and nonlinear relationships. ANNs are based on their analogy to the neural networks in the human brain. They consist of processing units connected together

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in multiple layers. These units use complex mathematical functions to process incoming signals and generate outputs associated with the prediction. (Simon, 2012).

Numerous studies have employed artificial neural networks (ANNs) in agricultural fields to predict various traits under investigation. These studies have demonstrated remarkable success and high reliability in prediction (Almaliki et al., 2019; Alzoubi et al., 2019; Almaliki and Monjezi, 2021; Salim et al., 2021).

Al-Bayati (2006) explained that salinity negatively impacts crop growth, in addition to its impact on photosynthesis, it disrupts nutritional balance and reduces the number of dividing cells, leads to a reduction in growth indicators and crop components, such as soluble and insoluble carbohydrates, and a decrease in protein content. This is due to a decrease in enzyme activity, in addition to shrinkage of chloroplast membranes and a decrease in their numbers.

Grattan (2002) reported that the ratio of decrease in maize yield increases with increasing irrigation water salinity, reaching 100, 90, 75, and 50%, with increasing critical irrigation water salinity limits (1.1, 1.7, 2.5, and 3.5 dS m⁻¹), Dehghan and Naderi (2007) demonstrated that when irrigated with water with a salinity of 8.0 dS m⁻¹, maize yield and 1000-grain weight decreased by 38.7%, compared to treatments irrigated with water with a low salinity of 2.0 dS m⁻¹, nitrogen fertilization has been shown to have an effect on maize yield.

Shah *et al.* (2018) demonstrated superiority in 1000-seed weight and grain yield in maize when using two nitrogen levels (100 kg N ha⁻¹ and 250 kg N ha⁻¹). The 250 kg N ha⁻¹ level (294 gm and 431 kg ha⁻¹), respectively, compared to the 100 kg N ha⁻¹ level, which gave the lowest values for the aforementioned traits, (232 gm and 3515 kg ha⁻¹), respectively. The results of Hafez and Abdelaa (2015) showed that when using four levels of nitrogen fertilizer (60, 90, 120, and 150 kg N ha⁻¹), the 150 kg N ha⁻¹ level achieved the highest protein content in the grains, amounting to 10.15%, while the 60 kg N ha⁻¹ level gave ha⁻¹ The lowest protein ratio was 9.04%.

Ngosong *et al.* (2022) observed that when potassium fertilizer was applied, the 120 kg K ha⁻¹ level significantly outperformed the 1000-grain weight and grain yield traits, reaching 682 gm and 11.8 ton ha⁻¹, compared to the control treatment, which yielded the lowest values for these traits, reaching 320 gm and 7.5 ton ha⁻¹, respectively. Ghosh (2016) found that when adding two levels of potassium fertilizer (40 and 120 kg K ha⁻¹) to maize, the 120 kg K ha⁻¹ level recorded the highest protein content, reaching 10.40%, while the 40 kg K ha⁻¹ level yielded the lowest, reaching 9.50%.

This study aims to demonstrate the efficiency of Artificial Neural Networks (ANNs) in predicting maize crop productivity.

II. Materials and Methods

The agricultural experiment was conducted at the University of Basrah's Agricultural Research Station, College of Agriculture, located in the Garmat Ali area. The area lies at longitude E 40°44'47 and latitude N 44°33'30, at an elevation of 3 m above sea level and 9.78 km from the center of Basra city, for the 2024 agricultural season.



The experiment included three factors:

Factor 1: Irrigation water salinity levels (1, 4, and 8) dS⁻¹.

Factor 2: Nitrogen fertilizer levels (0, 60, 120, and 240) kg N ha⁻¹.

Factor 3: Potassium fertilizer levels (0, 80, and 160) kg K ha⁻¹.

A single level of phosphate fertilizer (60) kg P ha⁻¹ was added to the entire field.

The first factor, represented by the salinity levels of irrigation water (1, 4, and 8), was prepared based on the salinity of the river water by diluting or increasing its concentration with drainage water to the desired levels. This was done using the following equation according to Ayers and Westcot (1985):

$$EC_i = (EC_a + a) + (EC_b (1 + a))$$

EC_i: electrical conductivity of the irrigation water to be achieved (ds/m)

EC_a: electrical conductivity of the tap water (ds/m)

a: proportion of tap water in the mixture

EC_b: electrical conductivity of the tap water (ds/m)

Considering that the Leaching Requirement (LR) is 20%, the total irrigation water quantity is calculated using the Du Plessis equation:

$$V_i = FC / 1 - LR$$

V_i: Irrigation Water Volume

FC: Field Capacity

The electrical conductivity of the tap water was 1.01 dS⁻¹

The electrical conductivity of the drainage water was 8.05 dS⁻¹

The water was mixed in 1000-liter tanks.

Table (1) Mixing ratios for irrigation water.

EC _i ds/m	Mixing ratios		EC _b	EC _a
	a	b		
4.10	0.12	0.88	8.05	1.01



The properties of irrigation water were estimated in the laboratories of the College of Agriculture, University of Basrah, included the hydrogen ions (pH), electrical conductivity (Ec), positive ions (Ca, Mg, Na, and K), and negative ions (SO₄, Cl, HCO₃, and CO₃) according to Richard (1954) (Table 2).

Table (2) Chemical properties of irrigation water.

Items	Irrigation levels			Units
	1	4	8	
Ec	1.01	4.10	8.05	dS m ⁻¹
pH	7.02	7.11	7.32	---
Ca	720.70	880.80	1121.10	mg. L ⁻¹
Mg	1098.00	414.80	732.00	
Na	62.31	102.21	126.40	
K	3.29	16.61	33.31	
SO ₄	1595.50	2803.10	6677.30	
HCO ₃	73.33	80.00	100.00	
CO ₃	0	0	0	
Cl	2299.20	999.00	899.70	
B	2.62	6.05	8.67	

The land was prepared for cultivation by plowing it twice perpendicularly, smoothing it and leveling it. Samples of silty clay soil were collected from the fields of the Agricultural Research Station, College of Agriculture, University of Basrah, from a depth of 0-30 cm and mixed to form a composite sample. They were air dried, ground and sieved through a sieve with a 2 mm opening for the purpose of conducting the incubation experiment. A portion of it was used to estimate the initial properties of the soil (Table 2) as described in Black (1965) and Page *et al.* (1982).

Table (3) Chemical and physical properties of soil.

Items	Unit	Value
pH	--	7.82
E.C	dS m ⁻¹	4.00
carbonate minerals	gm kg ⁻¹	359.00
CEC	Cmol +kg-1	26.73
Organic mater	gm kg ⁻¹	2.62
Available Nitrogen		20.19
Available Sulfur		0.62
Available Phosphorus		9.40
Available Potassium		92.73
Ca ⁺² Soluble	mmole L ⁻¹	9.70
Mg ⁺² Soluble		4.32
Na ⁺ Soluble		19.92
K ⁺ Soluble		1.07



HCO ₃ ⁻ Soluble		1.05
SO ₄ ⁻² Soluble		7.46
Cl ⁻ Soluble		26.67
CO ₃ ⁻² Soluble		0.00
Sand	%	11.20
Clay		54.60
Silt		34.20
Texture		Silty clay

The experiment was designed according to a Block Design (RCBD), with three factors and three replicates. The land was divided lengthwise into three blocks, each containing nine holes, and each block containing four experimental units. Each experimental unit was 3.5 m in area, with a distance of 0.5 m between each hole and 0.5 m between each unit. Thus, the total number of experimental units was 108 (3×4×3×3) (salinity level× nitrogen fertilizer level× potassium fertilizer level× replicate). An irrigation system was installed for three irrigation water tanks according to the aforementioned levels. Treatments were randomly distributed. A local variety of maize was then planted on March 1, 2024, in a single row opposite each dotted hole, with the distance between holes being 0.25 m. Each hole contained 5-6 plants. The number of plants in each experimental unit was 108. 14 plants and fertilizers were added by making a slit in the soil next to the irrigation pipe and nitrogen fertilizer levels were added in the form of urea fertilizer (46% N) and urea was added in two batches, the first before planting and the second one month after planting, as for the potassium fertilizer levels (52% K₂O).

After harvest, the ear weights of five plants were taken, and the grain yield was calculated based on the grain weight of the 3.5 m² experimental unit. The weight was then converted to (tons ha⁻¹). The weight of 1000 grains after being removed from the ear of the plants within the 3.5 m² experimental unit was calculated. The protein ratio was calculated using the formula N%× 6.25, as stated in A.O.A.C. (1975). The results were analyzed using artificial neural networks to predict maize yield based on variables including fertilizer, soil characteristics, and irrigation water quality. ANN models will be developed using the backpropagation algorithm using MATLAB (Mathworks, Inc.). In general, an ANN has three layers: an input layer, a hidden layer, and an output layer. The available data is typically divided into three randomly selected subsets, including 70% of the dataset is for training, 15% for model validation, and 15% for testing.

III. Results and Discussion

Using Artificial Neural Networks (ANNs) to Predict Grain Yield:

The results demonstrated the high predictive power of the Levenberg-Marquardt algorithm, which provides significant predictive power for grain yield. ANNs performed best, with R² and MSE values of 0.99992 and 0.00014571, respectively. The regression plots represent the relationship between the actual and predicted grain yield values using the ANNs in the training sets, with a correlation coefficient of 0.99993 (Figure 1-a). The validation correlation coefficient was 0.99994 (Figure 1-b), while the test correlation coefficient was 0.99996 (Figure 1-c). Figure 1-d also shows the convergence of the total scattered data on a unit slope line, which represents the good performance of the optimal model. The correlation coefficient value was 0.99993. Figure (2) shows the differences in MSE for the training, validation, and test samples and the number of cycles. After cycle 27, it was observed that the neural network



performed best, yielding the lowest MSE value of 0.00014571. In general, these results demonstrate that the ANNs model successfully learned from the training dataset and was therefore able to achieve healthy grain yield results, using the linear equations listed on the vertical axis of Figures (1-a, b, c, d).

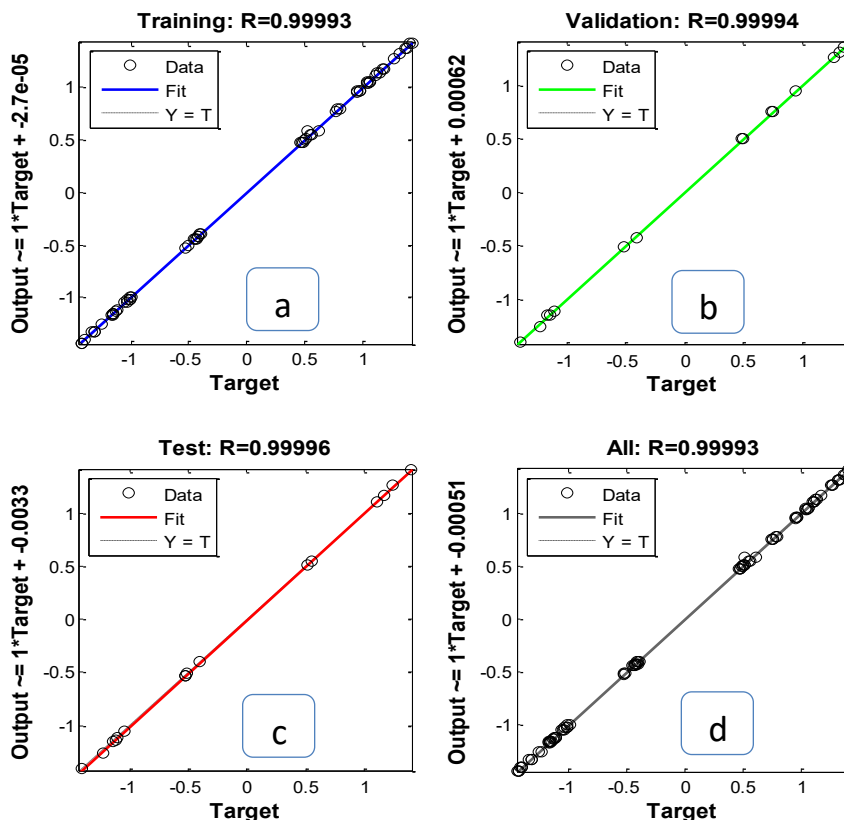


Figure (1-a,b,c,d) ANNs model for predicting grain yield using Levenberg-Marquardt training algorithm.



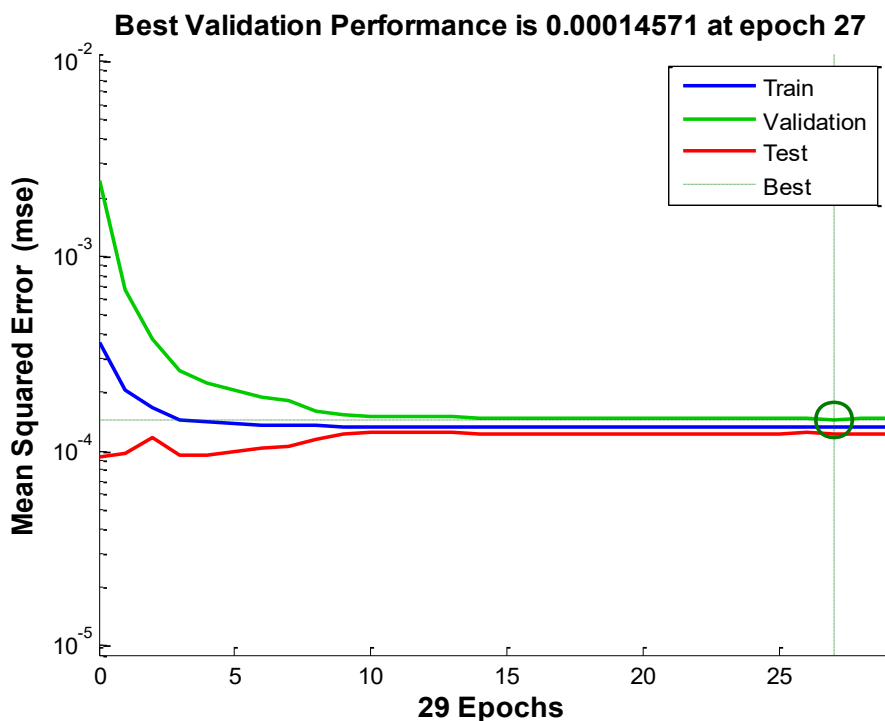


Figure (2) Result of regression to train the artificial neural network on MSE of grain yield.

Using Artificial Neural Networks (ANNs) to Predict Protein %:

Prediction results using the Levenberg-Marquardt algorithm demonstrated the ability to accurately predict protein ratios. It performed best with an R2 and MSE of 0.9992 and 0.00055522, respectively. The regression plots represent the relationship between the actual and predicted protein values using the ANNs in the training set, with a correlation coefficient of 0.99982 (Figure 3-a), while the validation correlation coefficient was 0.9997 (Figure 3-b). In the test, the ANNs achieved good prediction performance with a correlation coefficient of 0.99968 (Figure 3-c). Figure 3-d also shows the excellent fit of the sparse data on a unit slope line, which in turn represents the model's best performance, with a correlation coefficient of 0.99978. Figure (4) shows the differences in the MSEs of both the training and validation samples used in the network. We note that after round 7, the neural network achieved its best performance, achieving an MSE value of approximately 0.00055522. Thus, we find that the network successfully learned from the input training data and was then able to provide the correct results for the protein ratio, according to the equations shown on the vertical axis of Figures (3-a, b, c, d).



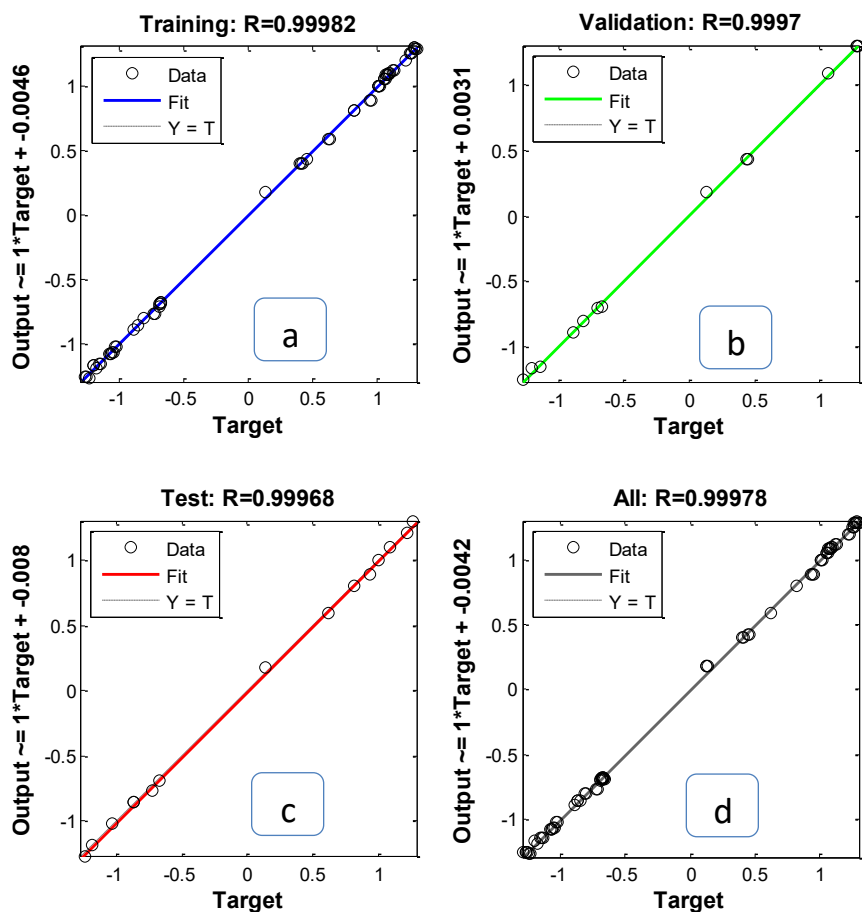


Figure (3-a,b,c,d) ANN model for predicting protein ratio using Levenberg-Marquardt training algorithm



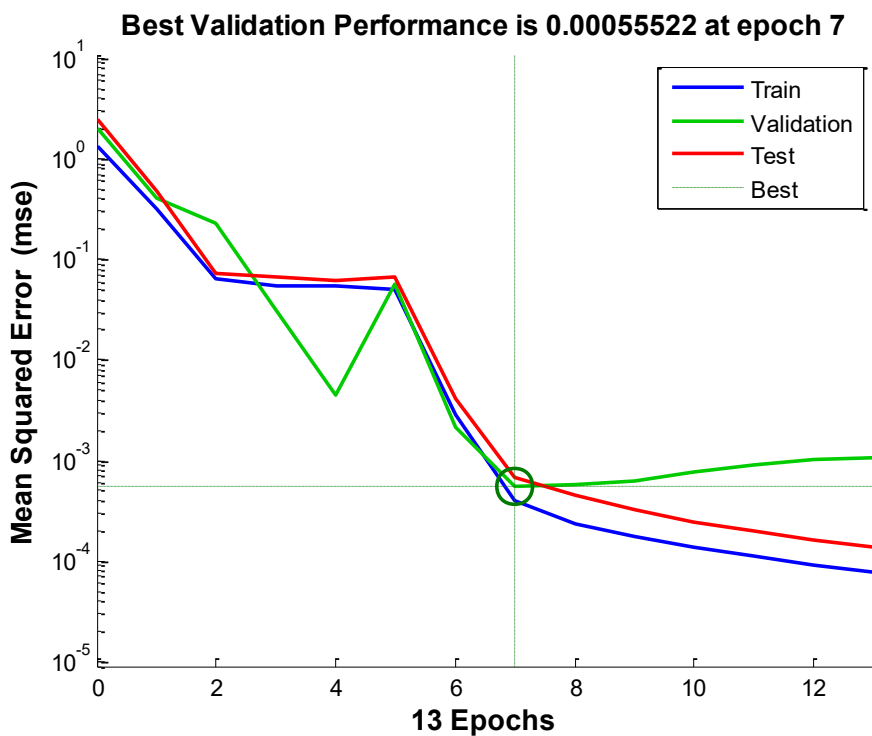


Figure (4) Regression result for training the artificial neural network on the MSE of the protein ratio.

Using Artificial Neural Networks (ANNs) to Predict the Weight of 1000 Grains:

The results demonstrated a high estimate for predicting the weight of 1000 grains using the Levenberg-Marquardt algorithm. It achieved the best performance with R2 and MSE values of 0.99994 and 0.00010432, respectively. The regression plots represent the relationship between the actual values and the values predicted by the ANNs in the training set, with a correlation coefficient of 0.9999 (Figure 5-a). The validation correlation coefficient was 0.9999 (Figure 5-b). For the test, the ANNs achieved the best prediction performance with a correlation coefficient of 0.99997 (Figure 5-c). Figure 5-d also shows the high convergence of the scattered data on the unit slope line, which represents the desired performance of the model, with a correlation coefficient of 0.9999. Figure (6) also shows the differences in the MSEs of both the training and validation samples used in the network. We note that after cycle 19, the neural network achieved its best performance, with an MSE value of approximately 0.00010432. Thus, we conclude that the network was able to successfully learn from the input training data and was then able to correctly interpolate the weight of 1000 grains, as shown in the vertical axis of Figures (5-a, b, c, d).



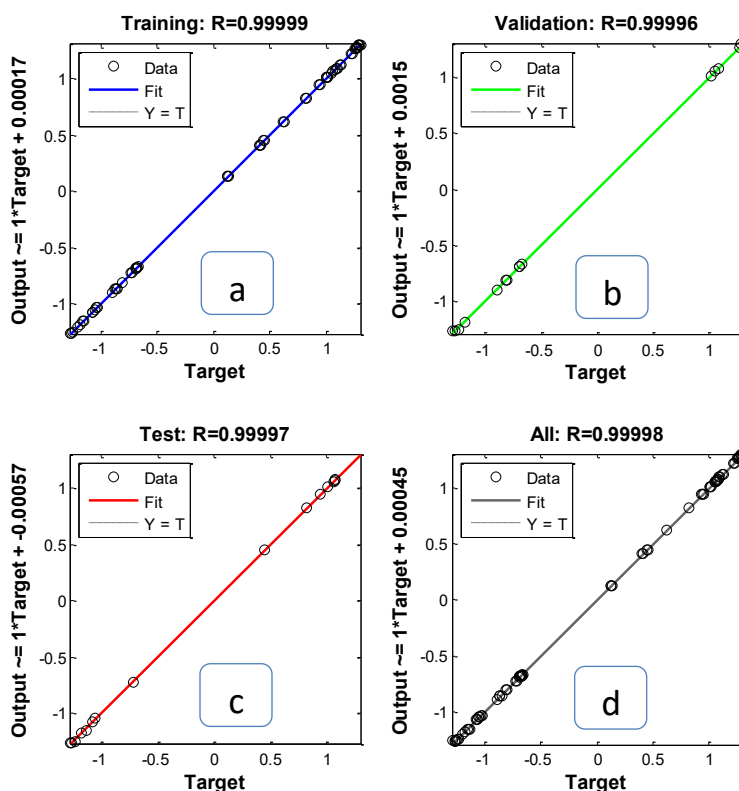


Figure (5-a,b,c,d) ANNs model for predicting the weight of 1000 grains using the Levenberg-Marquardt training algorithm.



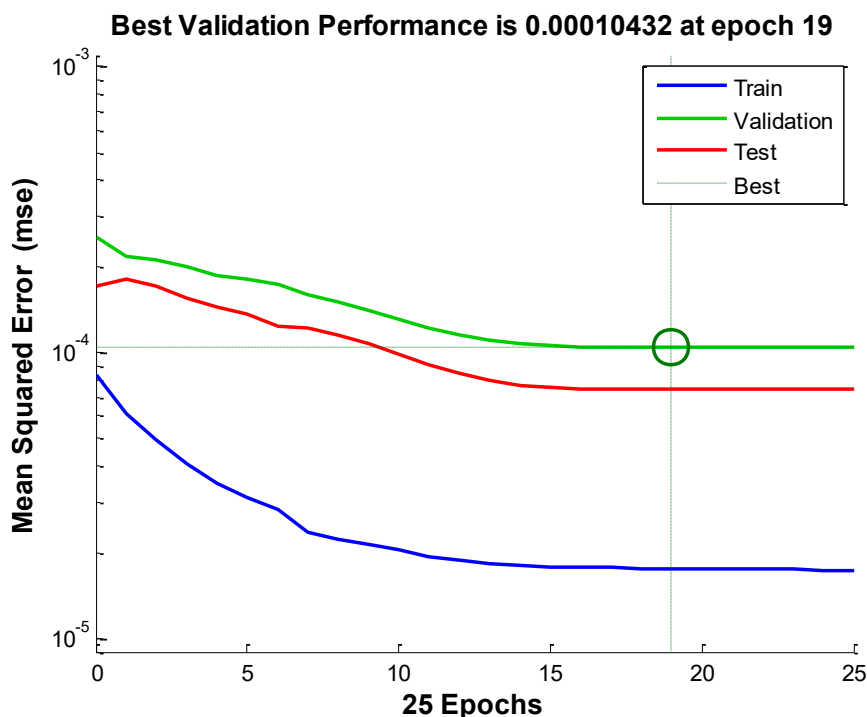


Figure (6) Result of regression to train the artificial neural network on the MSE of the weight of 1000 grains.

Conclusions:

High irrigation water salinity reduced maize (*Zea mays* L.) grain yield, while high levels of nitrogen and potassium fertilization significantly improved grain yield, including total yield, 1000-grain weight, and protein ratio in grain, of the three factors studied, irrigation water salinity had the greatest impact on yield, followed by nitrogen fertilization and then potassium fertilization. The use of Artificial Neural Networks (ANNs) also yielded high accuracy in predicting maize grain yield.

IV. References

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