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Predicting and Optimizing Tillage Draft Using Artificial Network Technique

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Abstract: Tillage as one of the agricultural practices consumes the largest amount of energy, which reflects on the total production cost. The artificial neural network (ANN) technique was utilized in the current study to optimize the performance of the tillage process. The ANN-modeled multilayer perceptron network with a backpropagation learning algorithm and momentum term was used by the PYTHON program. The ANN inputs were: the implement type, soil texture, moisture, bulk density, width, speed, and depth. The draught was the output (kN). Five layers composed the ANN model's optimal configuration (13-64-16-4-1). The linear and rectified linear units (ReLU) functions were utilized with hidden layers and the output layer, respectively. Momentum term and learning rate were 0.00003 and 0.9 respectively. The iteration number was 1000 epochs and stopped at 290 epochs. The coefficient of determination in the test datasets was high (0.92) while the difference between actual and predicted output was low (2.08). Bulk density and depth were the main determinants of the draft. The evaluation of the developed model for chisel, moldboard, and disk plow gave satisfactory results of 0.985, 0.924, and 0.917. In comparison to the ANNs, the regression model's correlation coefficient for predicting draught force was the lowest (0.373).

1 Introduction

The technique of mechanically modifying soil to create conditions that will promote seed germination and crop growth is known as tillage (Abdallah 2015). It is considered the most important agricultural process since it consumes the largest amount of energy in all yield production activities, so it represents a large part of the cost of production (Janulevičius et al 2019). The easiest approach to figure out how much energy a tool needs to operate is to analyze the draft needed to pull it because this force is usually used to measure and evaluate the energy requirements of tillage equipment. This force is determined by the following variables: soil conditions (such as moisture content and texture), tool parameters (such as cutting depth, cutting angle, and cutting sharpness), and operating parameters (such as the forward speed of the tools) (Grisso et al 2015).

Several scholars have employed a range of techniques to predict draft force, including conceptual, experimental, and numerical techniques (Al-Janobi et al 2020). On the other hand, the Multiple Linear Regression (MLR) technique is simple to use since it could be utilized to infer the draught and energy needs of tool plowing based on the quantity and quality of the data (Aboukarima 2013). Due to the linear nature of the interactions between the parameters, regression models might not provide reliable forecasts in some complicated cases, like nonlinear data. Regression models have other drawbacks, such as the requirement to fulfill regression assumptions, and many linear relationships amongst dependent and independent variants, which makes them ineffective (Ul-Saufie et al 2011). Regression models are less flexible and difficult to employ, but the ANN model is more accurate (Noor et al 2016).

In recent years, a variety of sectors have often employed machine learning techniques due to the development of high-performance computing (Hong et al 2020). Artificial Neural Networks (ANNs), one of the many machine learning techniques, are particularly good for nonlinear mapping, adaptive learning, and environmental problem prediction since they don't rely on statistical assumptions about the distribution of the data. Therefore, they have done well in recent studies (Valipour et al 2013, Valipour 2016).

To get around some of the shortcomings of existing numerical and analytical approaches in physical and dynamic modeling, ANN-proposed models have recently gained a lot of popularity. In many fields like finance, medicine, physics, engineering, geology, and hydrology, ANN models have been employed to successfully simulate the complicated nonlinear interactions between inputs and outputs (Saleh and Ayman 2013).

The key benefits of ANNs are their capability to deal with big data sets, their capability to find potential relations between predictor variables, and their ability to discern the complicated nonlinear connection between dependent and independent variables (Saluja et al 2013).

A number of models of artificial neural networks have been created to address issues in agriculture (Erzin et al 2010). Rahmán et al (2011) created an ANN model to forecast a tillage tool's energy needs based on laboratory data. The input parameters to train and test the ANN model were the forward speeds, depths of plowing, and moisture content. The output factor was the measured energy requirements of the tillage implementation. The results indicated that the difference between the measured and expected energy requirements was minimal.

Abьaspour-Gilándeh et al (2020) showed that the rigid tine chisel cultivator's drafting force can be predicted by the ANN model. Moisture content, depth of plowing, speed, and cone index of soil were utilized as the network's input parameters to forecast the draft force. The outcomes demonstrated that the ANN technique was more perfect for forecasting the draught force than the linear regression method.

In Iran, to forecast the geographical distribution of land companies, Taghizadeh-Mehrjardi et al (2015) examined the six mining data methods. These models include random forests, artificial neural networks, decision tree modeling, logistic regression, k nearest neighbor, and support vector machines. The outcomes demonstrated that, when compared to the other models, the decision tree and artificial neural network models provided the best accuracy.

The objectives of this research are 1- To utilize an ANN approach to predict the tillage draft force and calculate the required energy according to the input parameters; 2- To obtain the optimal required conditions to optimize the performance of the plowing process and 3- To compare the performance of the ANN technique with regression models in prediction of draft force.

2 Materials and Methods

To accomplish these objectives, the data related to the draft requirements were collected from previous research studies. The ANN was trained and tested by dividing the data into three sets. Then the ANN performance was compared with the regression models.

2.1 Data collection

For developing the models, the researcher gathered a huge quantity of data associated with draft requirements of plowing implements under varied operation and soil conditions collected from previous research studies. There are several reports related to chisel plow (Grisso et al 1996, Al-Suhaibani and Ghaly 2010, Aboukarima 2016, Nassir et al 2016b, Shafaei et al 2017), moldboard plow (Rashidi et al 2013, Al-Suhaibani et al 2015, Nassir et al 2016a, Muhsin 2017, Himoud 2018, Al-Janobi et al 2020), disk plow (El-Shazly et al 2008, Olatunji et al 2009, Okoko 2018, Nkakini et al 2019), rotary plow (Kheiralla et al 2003), subsoiler plow (Askari et al 2017), chisel, moldboard, and disk plow (Al-Suhaibani and Al-Janobi 1997, Naderloo et al 2009, Al-Hamed et al 2014), moldboard, disk and rotary plow (Kheiralla et al 2004) chisel and moldboard plow (Khadr 2008, Askari and

Khalifahamzehghasem 2013), and moldboard and disk plow (Alele et al 2018). The collected data included 667 data points that rely on field experiments.

The following were used as inputs to the models: implement type (chisel, moldboard, disk, rotary, and subsoiler plow), the particle size distribution of soil (sand %, silt %, and clay %), the moisture content (%), the bulk density (g/cm^3), depth (*cm*), speed (km/h), and width (m). The output was the draft (kN).

2.2 Programming language and dividing data

PYTHON (IDE: Jupyter with Gui Interface) was used to create the models to optimize the performance of the tillage process through artificial network technique and compare their performance with regression models. It is considered one of the scientific programming languages at present time and it is an open-source language. According to Ayer et al (2014), and Ozgur et al (2017), within the community of data analysts, Python is now considered to be crucial.

The cross-validation strategy was used in this study's stopping concept to avoid overfitting. Training, validation, and test subsets are therefore created from the database. The network weights in the training set are updated. A cycle or epoch is a single trip through a group of training samples, as well as the accompanying modification of the weights. The validation set error is tracked during this process. As the optimal point of generalization, the training is considered complete once the difference between the observed and predicted value starts to rise on the validation sample. The networks are then given test data to evaluate their performance (Erzin et al 2010). The collected data were split randomly into 3 sets: a training, a validation, and a testing sample each comprising 60%, 20%, and 20%, respectively.

2.3 Machine learning regression models

Many different disciplines employ machine learning, a kind of artificial intelligence, to find solutions to issues. Because of this, an understanding of numerous disciplines, including probability, statistics, computational complication, information theory, psychology, neurology, and control theory, is necessary for using machine learning algorithms (Silva et al 2020). Therefore, this study used ANN and compared their performance with DTR, RFR, GBR, SVR, and MLR to optimize the performance of the tillage process.

2.3.1 Comparison models

This section involved the DTR, RFR, GBR, SVR, and MLR models using the same datasets to compare their results with the outcomes of the ANN model. A brief description of the five models will be provided in the following paragraphs.

2.3.1.1 Decision tree regression (DTR)

A regression tree analysis is performed when the required expected value is numeric. In a DTR, the top node is called the root node, which represents the decision to be made. The factors influencing the choice to be made are represented by the internal nodes (also called decision nodes). The tree is divided into subdivisions, and in each subdivision, a binary test is run by asking questions for each feature value to create branches that predict and provide the expected value. Each branch also serves as a test result indicator, and each leaf is referred to as a node. Consequently, a data set with known and observed values must be present to create a classification or regression decision (Gelfand et al 1991).

The most important factor for constructing a decision tree is the max_depth. The optimal value for this parameter was estimated by a trial and error approach. Therefore, the value of this parameter in this study was 30.

2.3.1.2 Random forest regression (RFR)

RFR has many advantages, such as being insensitive to noise or over-fitting and handling many features without deleting a feature (Belgiu and Drăguţ 2016, Shah et al 2019).

To configure an RFR, two parameters must be determined: n_estimators (the tree number) and the max_depth. For this study, the optimal values for the n_estimators, and max_depth were estimated by a trial and error approach. Finally, the tree's number is 1000, and the maximum depth for each tree is 7.

2.3.1.3 Gradient boosting regression (GBR)

The advantages of GBR were demonstrated by Díaz et al (2019): low prediction errors and good stability. RFR, two parameters must be determined:

The parameters that must be determined to configure a GBR are the learning rate, the tree number, and the max_depth. These hyperparameters of the GBR model were estimated by the trial and error approach. Therefore, in this research, the learning rate, the number of trees, and the maximum depth are 1.5, 2000, and 17, respectively.

2.3.1.4 Support vector regression (SVR)

According to Mountrakis et al (2011), SVR's capacity to predict with high accuracy even with a limited number of training data is its key benefit. The kernel, which establishes the model's kernel functions, is the most crucial SVR hyperparameter. The *radial basis function* (RBF) was found as the kernel function since it was discovered to be effective, and precise for regression situations (Ramedani et al 2014).

The SVR model is configured by two hyperparameters: Epsilon (ε) and the regulation parameter (C). The ideal values of these parameters were optimized by utilizing a trial-and-error approach. Therefore, in this study, epsilon and regulation parameters are 1 and 100000, respectively.

2.3.1.5 MLR

A Single of the first statistical techniques, linear regression (LR), is still used widely in the academic world, particularly for evaluating the efficacy of recently developed predicting tools. As an extension or simplification of the LR model, MLR is utilized to analyze the connection between the dependent factor and the independent factors (Ul-Saufie et al 2011).

The goal of regression modeling is to construct a statistical function that explains the correlation between input and output parameters using some independent measurements, as many problems in engineering and science turn around the connection among two or more factors. Thus, the MLR is a very important LR method to determine the best correlation between the response factor and many independent factors, in contrast to the normal LR analysis (Shabani and Norouzi 2015, Akán et al 2015).

2.3.2 ANN

ANN is an application of artificial intelligence (Al-Hamed et al 2013). It is a computer program that is designed to mimic how the human brain processes information (Adisa et al 2019).

Fig 1 illustrates a simple example of an ANN, where each node receives inputs X_1, X_2, X_3……..X_n and for each connection, the input is connected with a weight W_{in} indicating the strength of the joining (Ozgur et al 2011).

Every input in a neuron is multiplied by the weight associated with it. B_i is a bias, a form of the weight connection that is added up to the sum of the inputs and the weights corresponding, and has a constant nonzero value (Cirak and Demirtas 2014) as shown in Equation 1:

$$\boldsymbol{u_i = \sum\nolimits_{j=1}^{n} WijX_j + b_i} \qquad \textit{(1)}$$

The sum u_i is transferred utilizing activation function $f(u_i)$ for getting the unit activation(output), as shown in Equation 2 (Cirák and Demirtás 2014):

$$\boldsymbol{y_i = f(u_i)} \qquad \textit{(2)}$$

Activation functions enable the creation of nonlinearity in neural networks, which elevates the network above linear variation in importance. The extremely common training strategy for the multilayer perceptron is the back-propagation algorithm (BP), which lowers the error for a certain training pattern (Al-Janobi et al 2020). Therefore, the activation movement is guided from the layer of input to the layer of output through the layers hidden for a given input pattern. Then, the errors are calculated in the layer of output. The back-propagation technique is used to reduce the error by correcting the weights (Cirak and Demirtas 2014). It is very important in the backpropagation algorithm to determine the optimal learning rate (η) to achieve convergence as it determines the length of the steps to correct the network's weights and biases (Abbaspour-Gilandeh et al 2020). Additionally, BP employs a gradient descent method that converges gradually. The performance of the conventional backpropagation technique is improved by the gradient descent with momentum term (GDM). Moreover, the momentum term promotes learning, stabilizes convergence, and prevents local minima.

The network is trained by adjusting weights and biases. Thus, this method is performed using a variety of training patterns as well as iteration numbers (Cirak and Demirtas 2014). The goal of the learning method is to define the ideal values of weights as well as biases which give the proper outputs to the inputs. Then, the network's predicted value is compared with the actual output to calculate the error. An ANN may carry out a variety of complicated activities, including prediction, identification, forecasting, modeling, control, and optimization, once it has learned a pattern. (Panchal and Panchal 2015, Karsoliya, 2012).

The ANN modeling multilayer perceptron with a backpropagation learning technique was selected for this investigation. The trial and error method was employed to select factors like the hidden layers number, the nodes number in every layer hidden, the activation type in each layer, the learning rate, MT, and the iterations number to find the best network configuration for the selected network.

The ideal structure was found utilizing three layers hidden the first, second, and third layers contain 64, 16, and 4 neurons, respectively as shown in **Fig 2**. The rectified linear unit (ReLU) was utilized in the layers hidden along with the linear function in the layer of output. According to (Hara et al 2015) the ReLU is the most frequently used transfer function. As it is a linear function that allows unimpeded backpropagation as well as rapid convergence of ANNs. The best value for the learning rate was 0.00003 and MT was 0.9. The number of iterations was 1000 epochs and stopped at 290 epochs by using early stopping.

2.4 Performance evaluation

The efficiency of the ML regression algorithms was assessed using the mean square error (MSE), the root means square error (RMSE), and the determination coefficient (R2) among the actual and expected values (Williams and Ojuri 2021).

The MSE calculates the mean squared variation between the value of the actual and its prediction value. Where the mean squared error was calculated for models during training, validation, and testing. Equation (3) is used to calculate MSE:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad (3)$$

The RMSE among observed and expected values are calculated using Equation (4):

$$RMSE = \sqrt[2]{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \qquad (4)$$

The R^2 indicates the ratio of the total variance in the expected value that is described by the various independent factors. Thus, the R^2 value rises as the error decreases. The value of the determination coefficient varies between 1 and 0. When the value of R^2 is close to 1, it indicates a suitable and acceptable model, but when the coefficient of determination value is close to 0, it indicates an inappropriate model. The R^2 is calculated from Equation (5):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (5)$$

Somewhere y_i are the observed values, $\hat{y}_i$ are the predicted values for the dependent variable and $\bar{y}$ is the mean value for the actual value. The overall number of data is *N*.

3 Results and Discussion

3.1 ANN technique

In this investigation, the best architecture of the ANN was found in the form of 13-(64-16-4)-1 which, produced lower MSE, RMSE, and higher R^2 as shown in **Table 1**. The MSE error of the network with epochs is shown in **Fig 3**. The results showed that the best consequence was accomplished at 290 epochs, which achieved a minimum MSE of 0.6 and 1.92 during the training and the validation process, respectively. Therefore, the ANN was capable of generalizing between inputs and output reasonably well.

Fig 4 shows the importance of every input and its influence on the draft. The outcomes demonstrated that, in comparison to the other features, the bulk density had the biggest contribution to the draught prediction, which contributed about 29%, followed by the depth which contributed about 19%.

After training and testing the ANN, the optimum conditions for optimizing the performance of the tillage process were obtained which are the use of a disk plow, the soil type is clay loam, the moisture content is 14.69%, the depth is 10 cm, the speed is 2.38 km/h, the bulk density is 1.5 g/cm3 and the width of the plowing is 1.73 m which gave a minimum draft value of 1.378 kN. Thus, this result will change as the data size increases for the same number of inputs. Then, we can use the model to forecast any plow's draught and energy requirements under different conditions.

To validate the performance of the created ANN-model to expect draft, (Hemeda et al 2017, Azimi-Nejadian et al 2019, Al-Dosary et al 2020) data were used. The results showed that the developed ANN model gave satisfactory results for plows, as the value of the R^2 were 0.985, 0.924, and 0.917 for the chisel, moldboard, and disk plow, respectively. **Fig 5** illustrates the actual and predicted draft relationship for evaluating the developed ANN-model.

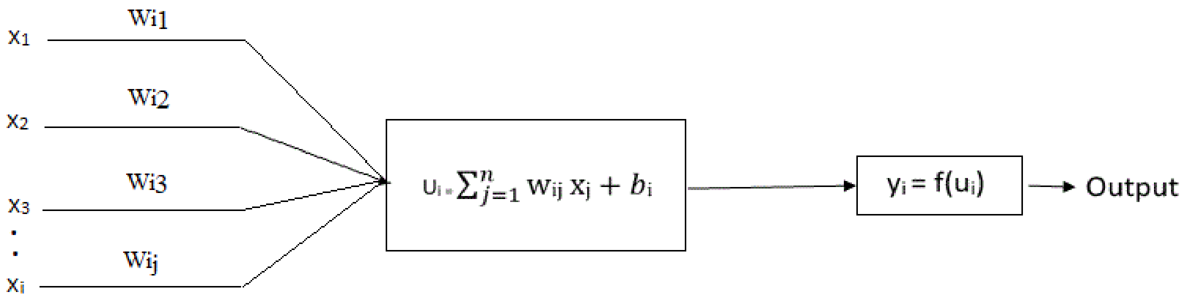


Fig 1. Artificial neural network structure (Cirak and Demirtas 2014)

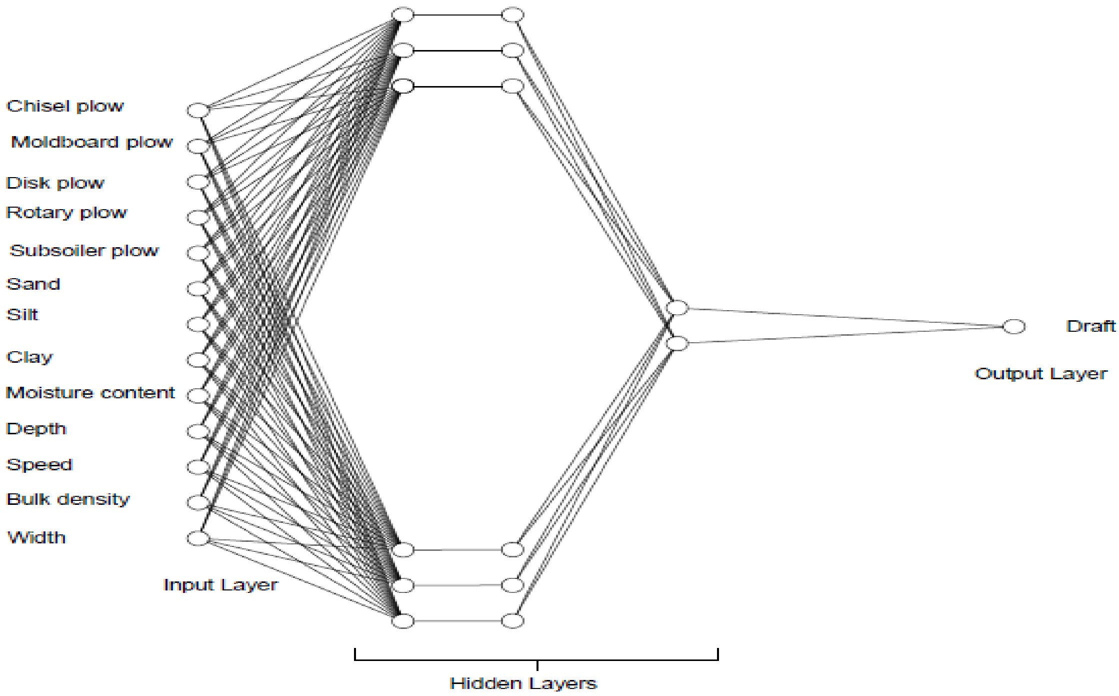


Fig 2. The architecture of the developed ANN in this study

Table 1. Result of the best structure of the ANN model

Model	Training Dataset			Validation Dataset			Testing Dataset		
	MSE	RMSE	R^2	MSE	RMSE	R^2	MSE	RMSE	R^2
ANN	0.6	0.77	0.977	1.92	1.39	0.931	2.08	1.44	0.923

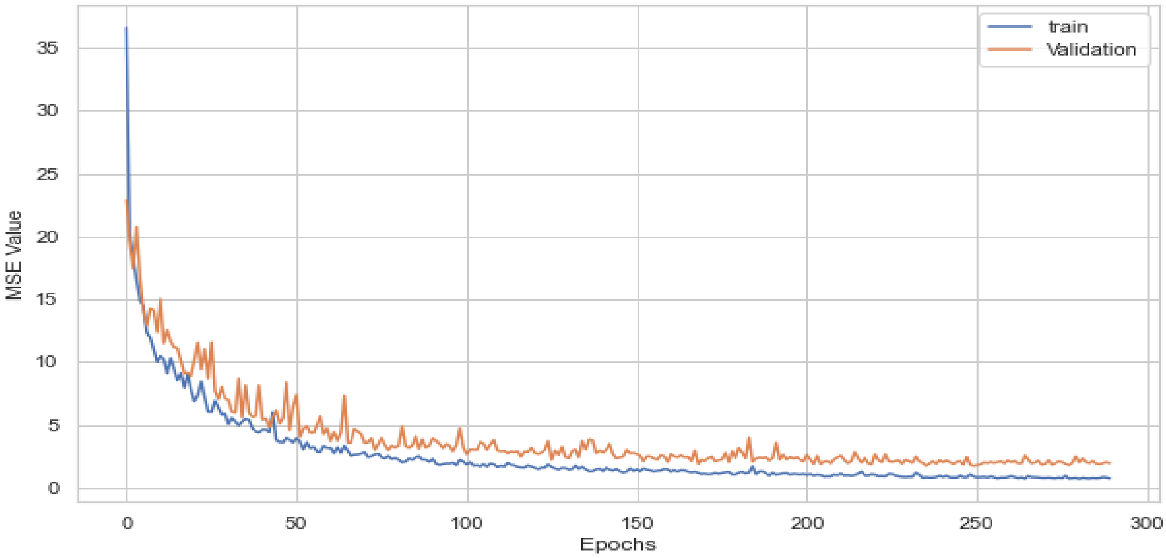


Fig 3. The influence of epochs on the MSE for trained networks

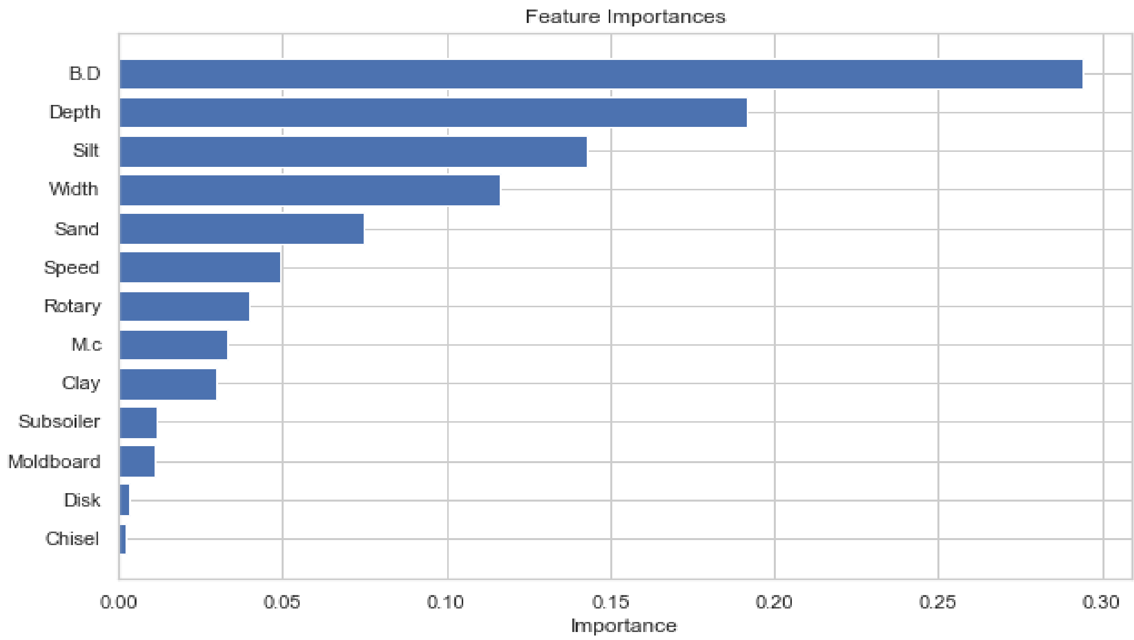
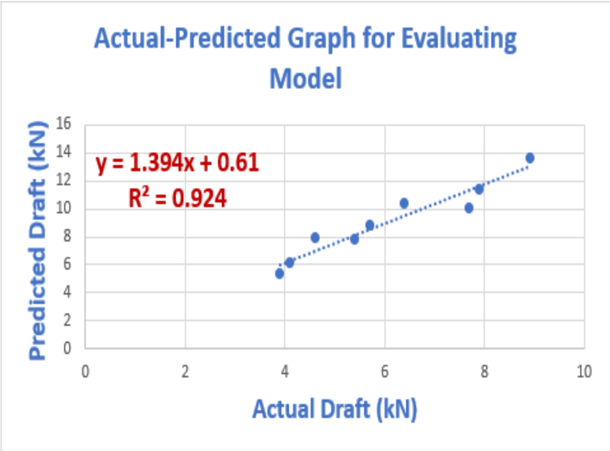
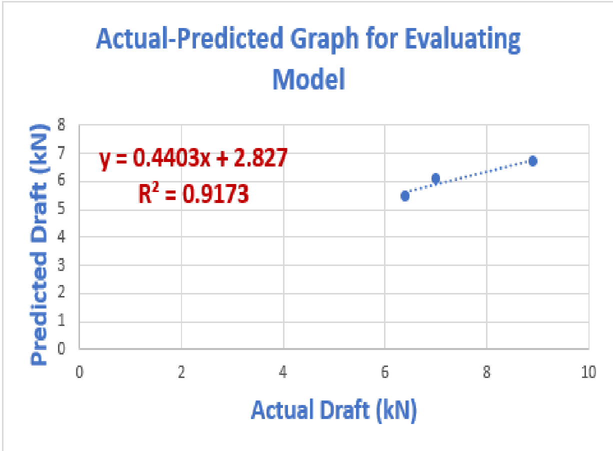


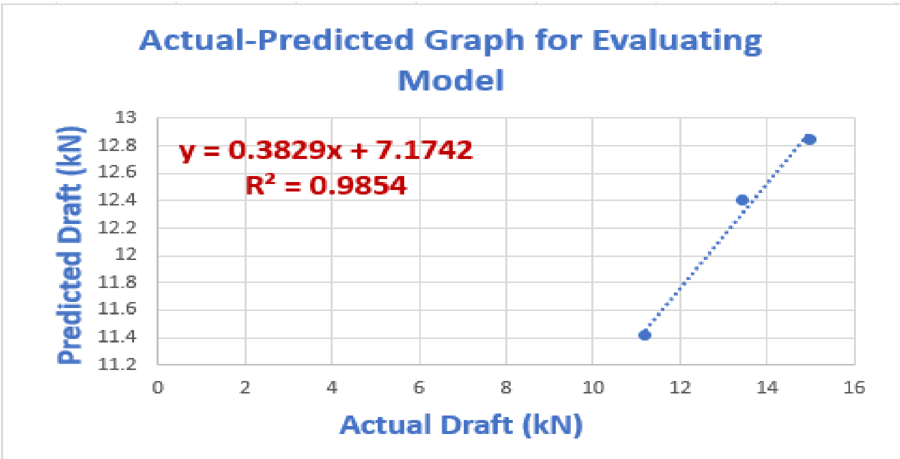
Fig 4. Importance of inputs and their influence on the draft



(a)



(b)



(c)

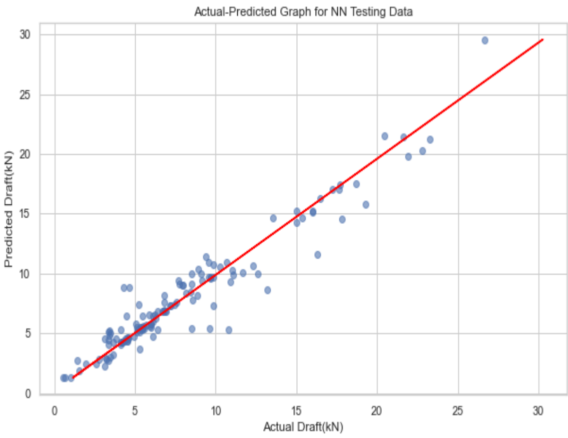
Fig 5. The actual and predicted draft relationship for evaluating the developed ANN-model. (a) moldboard plow, (b) disk plow, (c) chisel plow

3.2 Results from ANN Model and Results from Regression Models

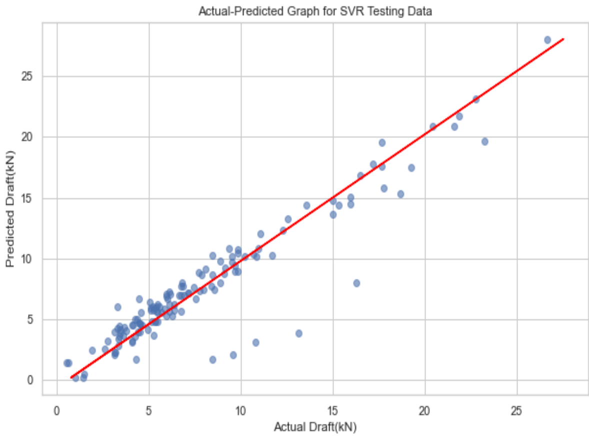
Table 2 and Fig 6 compare the ANN-model performance with five regression algorithms in the testing, validation, and training datasets. The outcomes show that the ANN-model achieved the highest performance as shown in **Table 2**, (MSE = 2.08, RMSE = 1.44, R^2 = 0.923), followed by the SVR model (MSE = 3.3, RMSE = 1.82, R^2 = 0.878), RFR model (MSE = 3.79, RMSE = 1.95, R^2 = 0.86), DTR model (MSE = 5.81, RMSE = 2.41, R^2 = 0.785) and GBR model (MSE = 9.17, RMSE = 3.03, R^2 =0.661) in the testing datasets. Also, in the validation dataset, the ANN achieved the highest performance (MSE = 1.92, RMSE = 1.39, R^2 = 0.931). In contrast, the MLR model had the lowest performance (MSE = 16.96, RMSE = 4.12, R^2 = 0.373).

Table 2. Performance comparison of the ANN-model and five regression algorithms

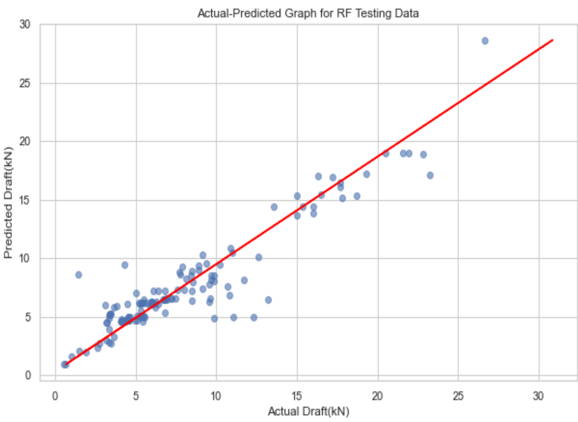
Models	Training Dataset			Validation Dataset			Testing Dataset		
	MSE	**RMSE**	**R^2**	**MSE**	**RMSE**	**R^2**	**MSE**	**RMSE**	**R^2**
ANN	0.6	0.77	0.977	1.92	1.39	0.931	2.08	1.44	0.923
SVR	0.59	0.77	0.978	2.45	1.56	0.912	3.3	1.82	0.878
RFR	1.47	1.21	0.944	5.41	2.33	0.806	3.79	1.95	0.86
DTR	0.07	0.26	0.997	5.38	2.32	0.807	5.81	2.41	0.785
GBR	0.07	0.26	0.997	6.88	2.62	0.753	9.17	3.03	0.661
MLR	11.78	3.43	0.551	17.43	4.18	0.373	16.96	4.12	0.373



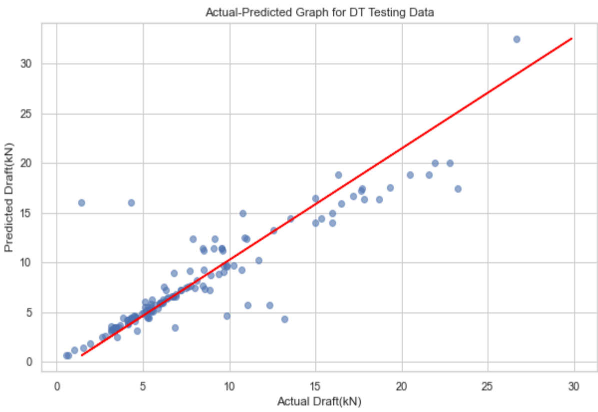
(a)



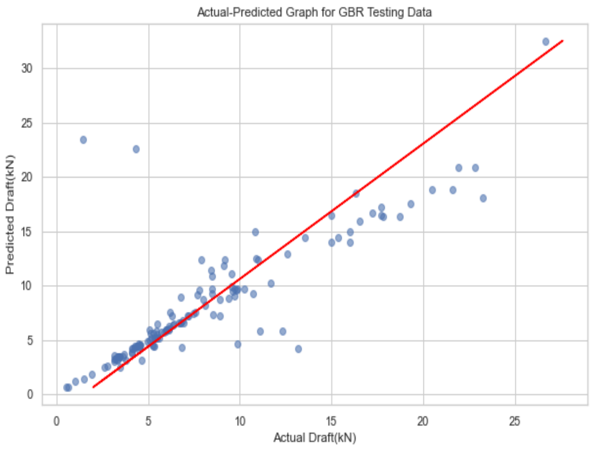
(b)



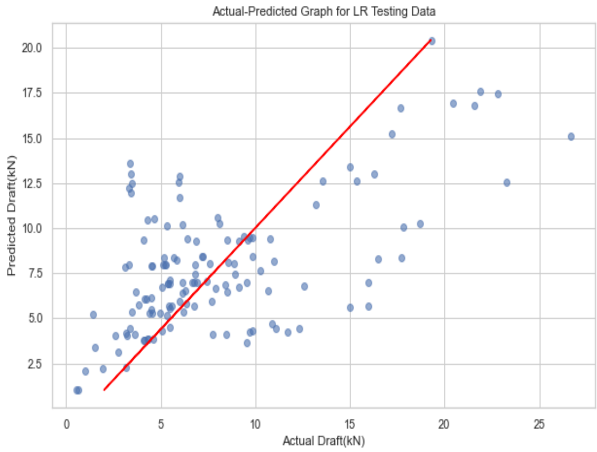
(c)



(d)



(e)



(f)

Fig 6. Comparison of the actual and the predicted draft in the testing data for the models. (a) ANN, (b) SVR, (c) RFR, (d) DTR, (e) GBR, (f) MLR

4 Conclusion

The ANN modeled multilayer perceptron with a backpropagation learning technique and momentum term was selected in this study to forecast the draught force of the plowing implements, calculate the required energy according to the input parameters and obtain the optimal conditions required to optimize the performance of the plowing process using PYTHON software. The inputs to the ANN were: implement type (chisel, moldboard, disk, rotary, and subsoiler plow), the particle size distribution of soil (sand %, silt %, and clay %), the moisture content (%), the bulk density (*g/cm*^{3}), depth (*cm*), speed (km/h), and width (m). The output was the draft (kN). The results showed that the optimal architecture to ANN was (13-64-16-4-1) consisting of 5 layers, The rectified linear unit (ReLU) was utilized in the layers hidden and the linear function in the layer of output, and the learning rate and MT were 0.00003 and 0.9 respectively and the number of iterations were 1000 epochs and stopped at 290 epochs by using early stopping. the ANN gave the highest performance (R^2=0.923) and minimum error (MSE=2.08). The optimum conditions for optimizing the performance of the tillage process were obtained After training and testing the ANN. In addition, the ANN was compared with regression models, the outcomes illustrated that the ANN achieved the highest performance compared with these models.

Recommendation

- The Artificial Neural Network model can be employed to resolve some agricultural problems.
- Using the Python programming language to solve the draft model of tillage implements.
- The ANN model can be relied on to predict the draft and calculate the amount of energy required to optimize the performance of the tillage process compared to regression models.

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