Predictive analysis of chopping length of a forage machine using Artificial Neural Network (ANN) in MatLab

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Abstract: In this work, Chopping Length (CL) of a multi-forage machine was predicted using Artificial Neural Network (ANN), in order to improve on the overall performance of the Forage Machine (FM). Data was imported from the experiment carried out on FM after chopping Guinea Grass (GG), Siam Weed (SW) and Maize Stover (MS). The data were cleaned to remove monotonous (similar) numbers and outliers. The data were split into two sets (Training and testing sets) and ANN algorithm was used to create the model. Network building (Multi-Layered Perceptron), training, predictions, evaluations and improvement were done using MatLab of R2013a model. The results revealed that GG, SW and MS has a predictive CL of 3.1, 2.5 and 3.5 cm respectively. The coefficients of determination (R^2) for training (43.9%, 95.9%& 29.88%), validation (99.79%, 18.8%& 92.14%) and all data (31.78%, 66.09%& 29.27%) gave a low error of ANN model. The Mean Square Errors (MSE) obtained are 0.84, 2.06 and 0.076 for GG, SW and MS respectively. But the MSE of MS gave the smallest error and the best fitting pattern whose average experimental data was the same with the predictive data obtained from ANN model. The ANN performance for GG, SW and MS are 3.72, 0.47 and 0.47 with epoch number of 2, 6 and 7 respectively. The CL obtained using ANN were within the international chopping length standard of 2 – 4 cm for FM.

Keywords: ANN, forage machine, machine learning, MatLab

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1 Introduction

Machine learning (ML) deals with pattern recognition couple with computational learning model in imitation intelligence (II) or artificial intelligence (AI) (Britannica, 2024). ML can be used in different contexts as predictive modelling and often employed in several industrial works and as computing jobs where algorithms designing and programming are clearly unseen. This study focuses on how machine (Software) can recognize patterns for a predictive modelling through artificial neural network (ANN). Neural networks are made up of basic parts that run in parallel and these components are inspired by biological nerve systems. The connections between the components, govern the network function in major part, just as they do in nature. The purpose of ANN is to train a neural network (neurons) to execute a certain function by altering the values of the connections (weights) between its members. Neural networks are often

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altered, or trained, such that a certain input result will deliver a specific goal output. The network is then changed based on a comparison of the output and the target, until the network output matches the target. In supervised learning, numerous of these input/target pairings are often utilised to train a network (Howard and Mark, 2004). As a principle in ANN, stimulus (input variables, “FEATURES”) are trained to attain observable output usually called “Desired Reponses” (Wunderlich, 2021). ANN mimics the behaviour of human brain (Haykin, 2009) and may be classified into two types and its classification depends on the number of layer involved during analysis. An ANN with one hidden layer has been termed “Shallow ANN”while the ANN with multiple layers (Figure 1) has been called a“Deep ANN” (Wunderlich, 2021). Deep ANN has input layer, hidden layer and output layer (Al Shamisiet al., 2011) as presented in Figure 1. Al Shamisiet al. (2011) have used ANN model to predict global solar radiation after training weather elements such as temperature, average wind speed, amount of sunshine, average relative humidity and solar radiation for Al Ain city in United Arab Emirate. The used of ANN model to explore the outcome of temperature and volume fraction of nanoparticles on the heat conductivity of graphene oxide was examined by Tian et al. (2021). Kartal and Kaptan (2024) used ANN to observe the effect of processing parameters on surface roughness during machining of aluminum alloy. Akhgar et al. (2019) used an ANN model to predict the heat conductivity of a substance by dividing his data into three part to train, validate and test. Esfeet al. (2018) opined an ANN model with experimental data to look into Nusselt number and the fall of pressure water-based tin oxide in nanofluids. However, this study predictively examined the chopping length of a forage machine in three forages using ANN model.

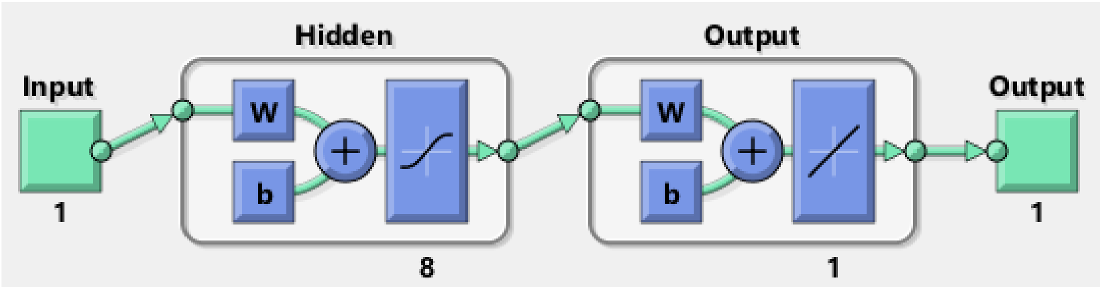

Figure 1 Multiple layer ANN patterns

Table 1 Sample data used for prediction

S/N	GG (cm)	SW (cm)	MS (cm)	Weight	MC
1	2.7	4.3	6.9	3.0	27.7
2	7.7	2.3	7.4	2.0	7.4
3	2.6	4.3	2.8	2.0	7.4
4	5.7	2.5	5.0	2.0	27.7
5	9.0	2.3	3.3	2.0	47.9
6	1.9	4.2	5.3	1.3	13.3
7	3.6	2.7	2.0	1.0	27.7
8	4.5	4.1	4.5	1.0	27.7
9	2.2	1.3	2.7	2.0	27.7
10	3.8	2.2	1.4	1.3	13.3
11	3.8	3.6	1.9	2.7	13.3
12	1.6	2.3	5.5	1.3	42.0
13	2.1	2.9	2.4	2.0	27.7
14	1.5	2.1	2.6	3.0	27.7
15	1.7	3.4	4.3	2.7	42.0
16	1.8	1.2	1.7	2.0	27.7
17	1.8	2.6	4.0	1.3	42.0
18	4.2	2.5	2.6	2.7	42.0
19	4.2	1.3	1.8	2.0	47.9
20	3.6	1.6	1.1	2.7	13.3

2 Materials and methods

2.1 Data collection and preparation

In carrying out predictive analysis using ANN, sample data were collected, cleansed and arranged in matrix language that MatLab will understand. Because MatLab understands and reads data arranged in vector and matrix formats. The data used (Table 1) in this study was imported from the experiment carried out on forage chopper chopping length performance evaluation at the Department of Agricultural and Environmental Engineering, University of Ibadan, Nigeria (7.4433° North latitude and 3.9003° East longitude). Collecting and preparing sample data is the initial phase in designing ANN models (Al Shamisiet al., 2011). The data collected were measured in cm with 20 samples each from Guinea Grass (GG), Siam Weed (SW) and Maize Stover (MS) forages as presented in Table 1.

2.2 Data cleaning

Data cleaning was done using Word Excel of version 2013 in order to remove monotonous (similar data) numbers and outliers. Monotonous numbers are corrected by taking the average of the neigbouring data together with the data to be corrected.

2.3 Data preparation

After cleaning has been done, two sets of data were inputted into MatLab namely; Output data (actual chopping length, Table 1) and target (weight, Table 1).

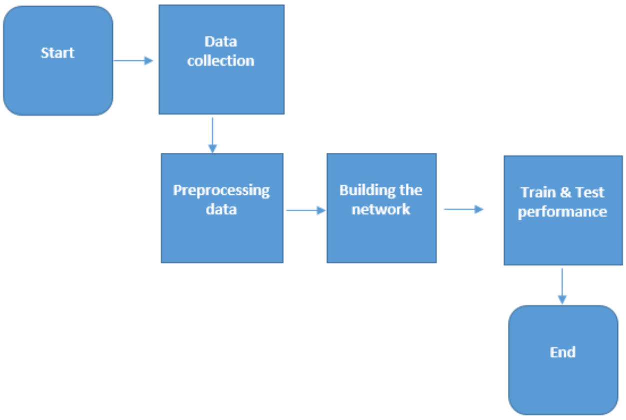

Figure 2 Flow chart for ANN model design steps

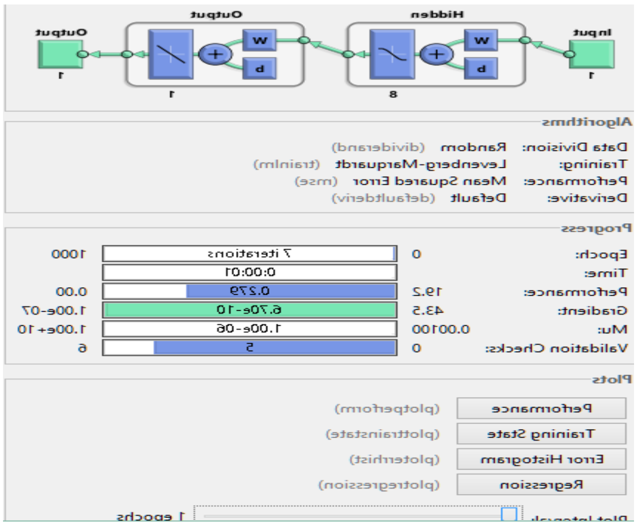

Figure 3 Test performance out

2.4 Artificial neural network models designing and programming

2.4.1 ANN models designing

ANN design entails data collection, preprocessing data, building the network, train, and test performance of model as indicated in the flow chart in Figure 2. The algorithm used to create model was ANN. Network building (Multi-layered perceptron, MLP), training, predictions, evaluations and improvement were done using MatLab software of R2013a model and Excel 2013 model. Screen captions of the MLP ANN training windows obtained using the “nntraintool” graphic user interphase (GUI) toolbox in MATLAB was presented in Figure 3.But both the called functions and GUI were used one after the order during the analysis.

2.4.2 Programming and coding into M-file of MatLab

MatLab is a programming language used by engineers and scientists that can be expressed in matrix and array mathematics using the right syntax directly (MathWorks, 2024) as illustrated in Figure 4. While the M-file coding was illustrated in Figure 5.

```
Command Window
  Toolbox Path Cache read in 0.56 seconds.
MATLAB Path initialized in 5.75 seconds.
>> X = [100 200 300; 10 20 30; 1 2 3]

X =

   100   200   300
    10    20    30
     1     2     3
```

Figure 4 MatLab command window

```
GGT  =[3 2.5 2 2.5 2 1.3 1.15 1.5 2.0 1.3 2.7 1.3 1.65 3.0 2.7 2.4 1.3 2 2.4 2.35];
GGout = [6.9 7.4 2.8 5.0 3.3 5.3 2.0 4.5 2.7 1.4 1.9 5.5 2.4 2.6 4.3 1.7 4.0 2.6 1.8 1.1];
net = feedforwardnet(8);
net = train(net,GGT,GGout);
view(net)
y = net(GGT);
perf = perform(net,y,GGout);
plotregression(GGout,y,'Weight')
```

Figure 5 Code written in M-file of MatLab

3 Results and discussion

3.1 Data presentation

The initial data collected was presented in Table 1 while Table 2 revealed the cleansed data that was used for actual prediction in order to avoid repetition of data. This section presents the superlative results obtained for the multi-layer perception (MLP) ANN model in chopping lengths of GG, SW and MS.

3.2The prediction of guinea grass chopping length

The predictive chopping lengths obtained after training and testing for GG were presented in Table 3. The mean predicted chopping length was 3.1 cm and the mean actual chopping length was 3.5 cm with residual value of 0.4 cm. The predictive chopping length was in line with the international chopping length of 2 - 4 cm. The training regression analysis between the output and target (weight of forage) was 44% (Figure 6) and this shows that the trained data are not well fitted. Although, the trained regression coefficient obtained was not too strong but the validation regression coefficient of determination was as high as 99.79%. Esfeet al. (2018) also observed similar regression coefficient of 99.98% when they used ANN model for their study. This reveals a higher validation and a reduced mean square error (MSE) as shown in Figure 7. The best validation performance value was 0.84 (MSE). Similar work was carried out by Al Shamisiet al. (2011) but they did not consider the epoch function and they used climate data. But Esfeet al. (2018) developed similar reality. The green circle in Figure 7 represents the point of reference (Epoch 2). This means that all the data that fall below this point of reference are good to make decision. The epoch represent one complete pass (Forward & backward pass as one pass) of the entire training dataset through the learning algorithm. Figure 7 shows that the dataset has been exposed 7 complete times during ANN training. Table 4 shows that there no significant difference between the actual (*X*) and predicted (*Y*) chopping lengths of GG ($p>$ 0.05). This is an indication of a good predictive chopping length. The trend pattern was indicated in Fig. 8 and the pattern of actual and predictive chopping lengths seem to be normalised toward the end of the graph than at the beginning. The purpose of the prediction is to optimise process, reduce costs and improve the overall performance of the machine.

Table 2 Cleansed data sample

S/N	GG (cm)	SW (cm)	MS (cm)	Weight	MC
1	2.7	3.3	6.9	3.0	27.7
2	7.7	2.3	7.4	2.5	7.4
3	2.6	4.3	2.8	2.0	7.4
4	5.7	2.5	5.0	2.5	27.7
5	9.0	2.4	3.3	2.0	47.9
6	1.9	4.2	5.3	1.3	13.3
7	3.6	2.7	2.0	1.15	27.7
8	4.5	4.1	4.5	1.5	27.7
9	2.2	1.3	2.7	2.0	27.7
10	3.8	2.2	1.4	1.3	13.3
11	3.8	3.6	1.9	2.7	13.3
12	1.6	3.0	5.5	1.3	42.0
13	2.1	2.9	2.4	1.65	27.7
14	1.5	2.1	2.6	3.0	27.7
15	1.7	3.4	4.3	2.7	42.0
16	1.8	1.2	1.7	2.4	27.7
17	1.8	2.6	4.0	1.3	42.0
18	4.2	2.5	2.6	2.0	42.0
19	4.2	1.9	1.8	2.4	47.9
20	3.6	1.6	1.1	2.35	13.3

Table 3 Prediction of GG chopping length

S/N	*X* =Actual	*Y* = Predicted	Residual	MSE	R	Performance
1	2.7	2.70	0.0	0.84*	0.44	3.72
2	7.7	4.50	3.2			
3	2.6	2.61	0.0			
4	5.7	4.50	1.2			
5	9.0	2.61	6.4			
6	1.9	3.16	-1.2			
7	3.6	3.78	-0.1			
8	4.5	3.37	1.1			
9	2.2	2.61	-0.4			
10	3.8	3.16	0.7			
11	3.8	2.73	1.0			
12	1.6	3.16	-1.6			
13	2.1	-0.49	2.6			
14	1.5	2.70	-1.2			
15	1.7	2.73	-1.0			
16	1.8	4.29	-2.5			
17	1.8	3.16	-1.4			
18	4.2	2.61	1.6			
19	4.2	4.29	-0.1			
20	3.6	3.79	-0.2			
Mean	3.5	3.1	0.4			

Note: *MSE is Adequate

Table 4 t-Test: two-sample assuming equal variances

	X =Actual	Y = Predicted
Mean	3.496667	3.09699936
Variance	4.13274033	1.16844269
Observations	20	20
Pooled variance	2.65059151	
Hypothesized mean difference	0	
Df	38	
t Stat	0.77629642	
P(T<=t) one-tail	0.22118964*	
t Critical one-tail	1.68595446	
P(T<=t) two-tail	0.44237928*	
t Critical two-tail	2.02439416	

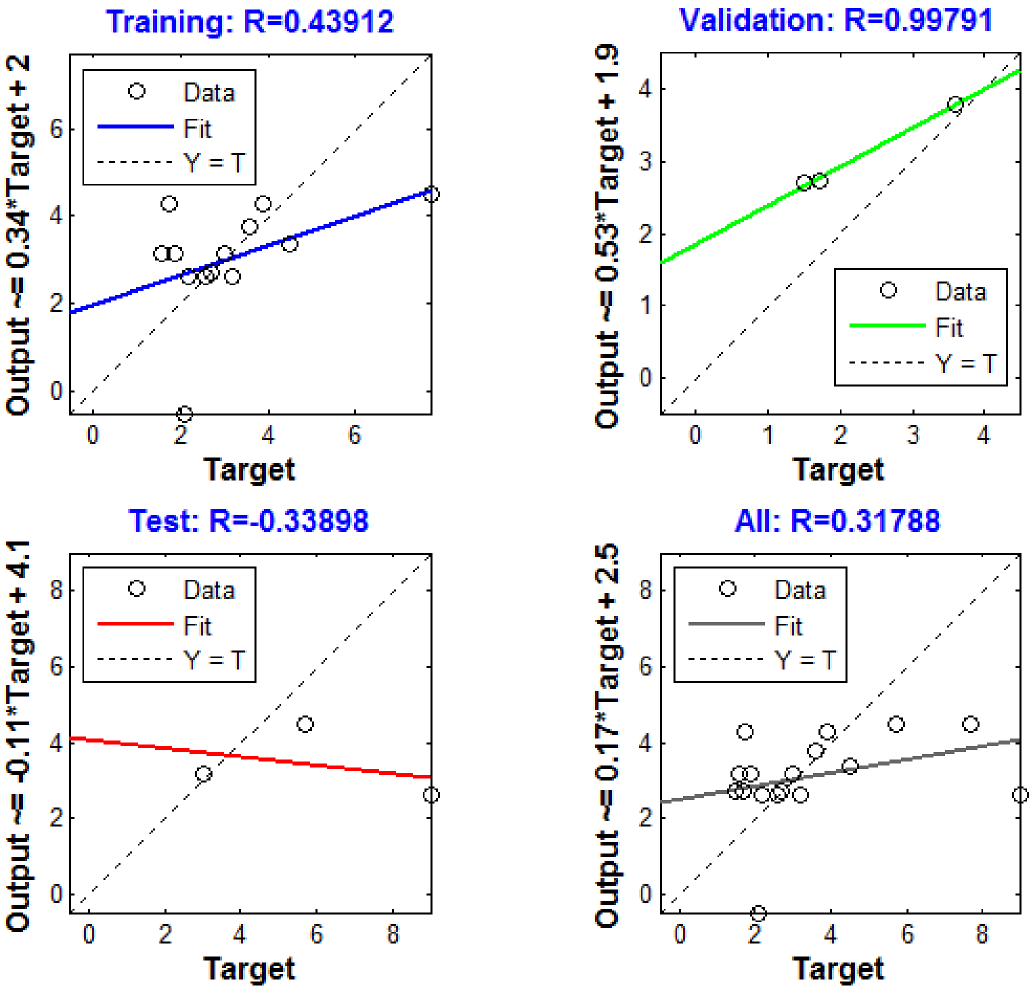

Figure 6 Regression analysis between the output and target trained

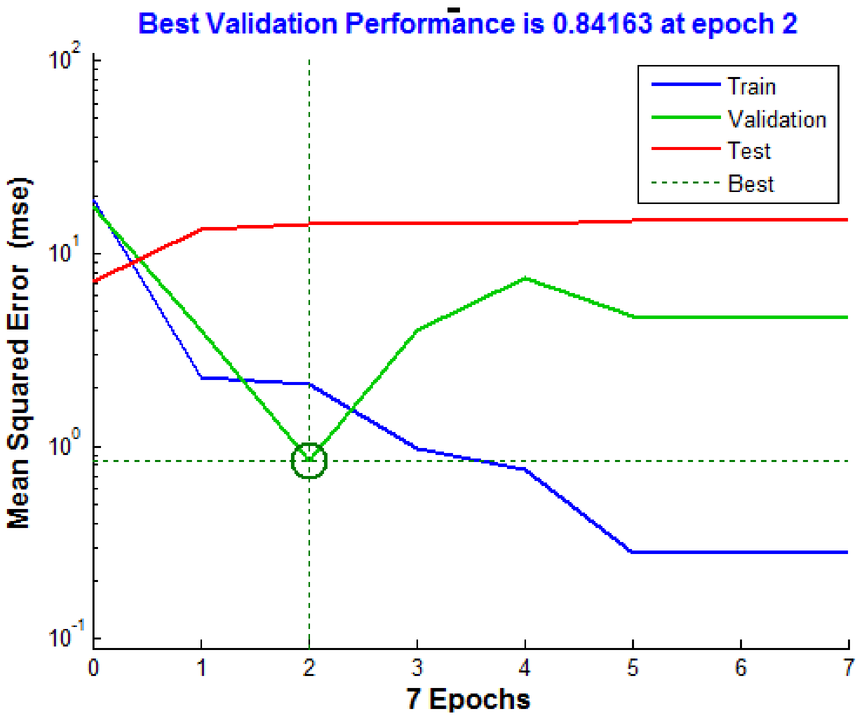

Figure 7 Performance of the training

Note: *Not significant

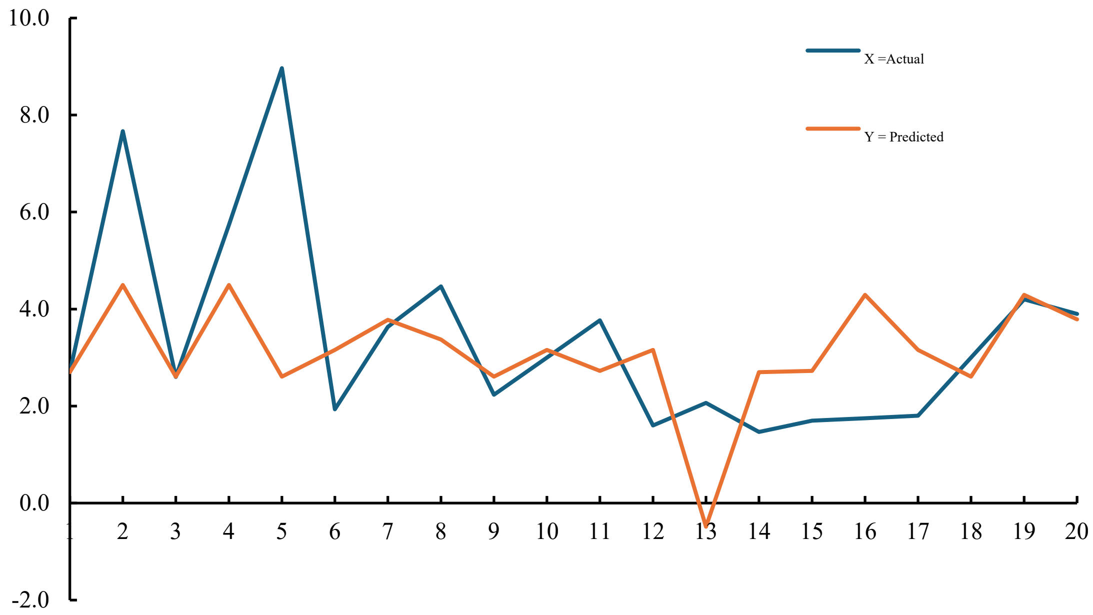

Figure 8 Trend between predicted and actual

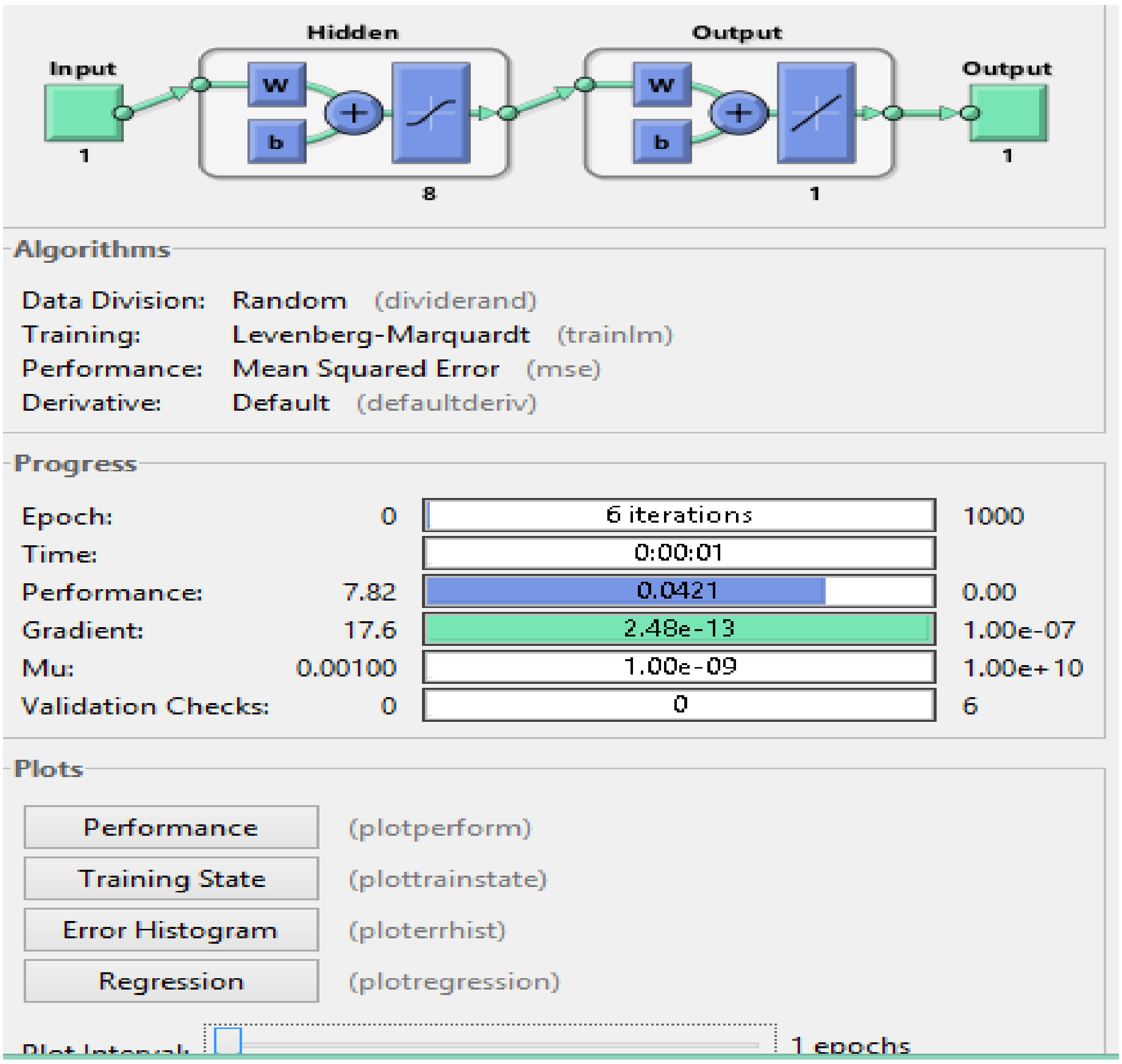

Figure 9 GUI performance evaluation of Siam weed chopping length

Table 5 Prediction of SW chopping length

S/N	*X* =Actual	*Y* = Predicted	Residual	MSE	R	Performance
1	3.3	2.1	1.2	2.06*	0.959	0.47
2	2.3	2.4	-0.1			
3	4.3	2.4	1.9			
4	2.5	2.4	0.1			
5	2.4	2.4	0.0			
6	4.2	2.6	1.6			
7	2.7	2.7	0.0			
8	4.1	4.1	0.0			
9	1.3	2.4	-1.1			
10	2.2	2.6	-0.4			
11	3.6	3.6	0.0			
12	3.0	2.6	0.4			
13	2.9	2.9	0.0			
14	2.1	2.1	0.0			
15	3.4	3.6	-0.2			
16	1.2	1.5	-0.3			
17	2.6	2.6	0.0			
18	2.5	2.4	0.1			
19	1.9	1.5	0.4			
20	1.6	1.6	0.0			
Mean	2.7	2.5	0.2			

Note: *MSE is not Adequate

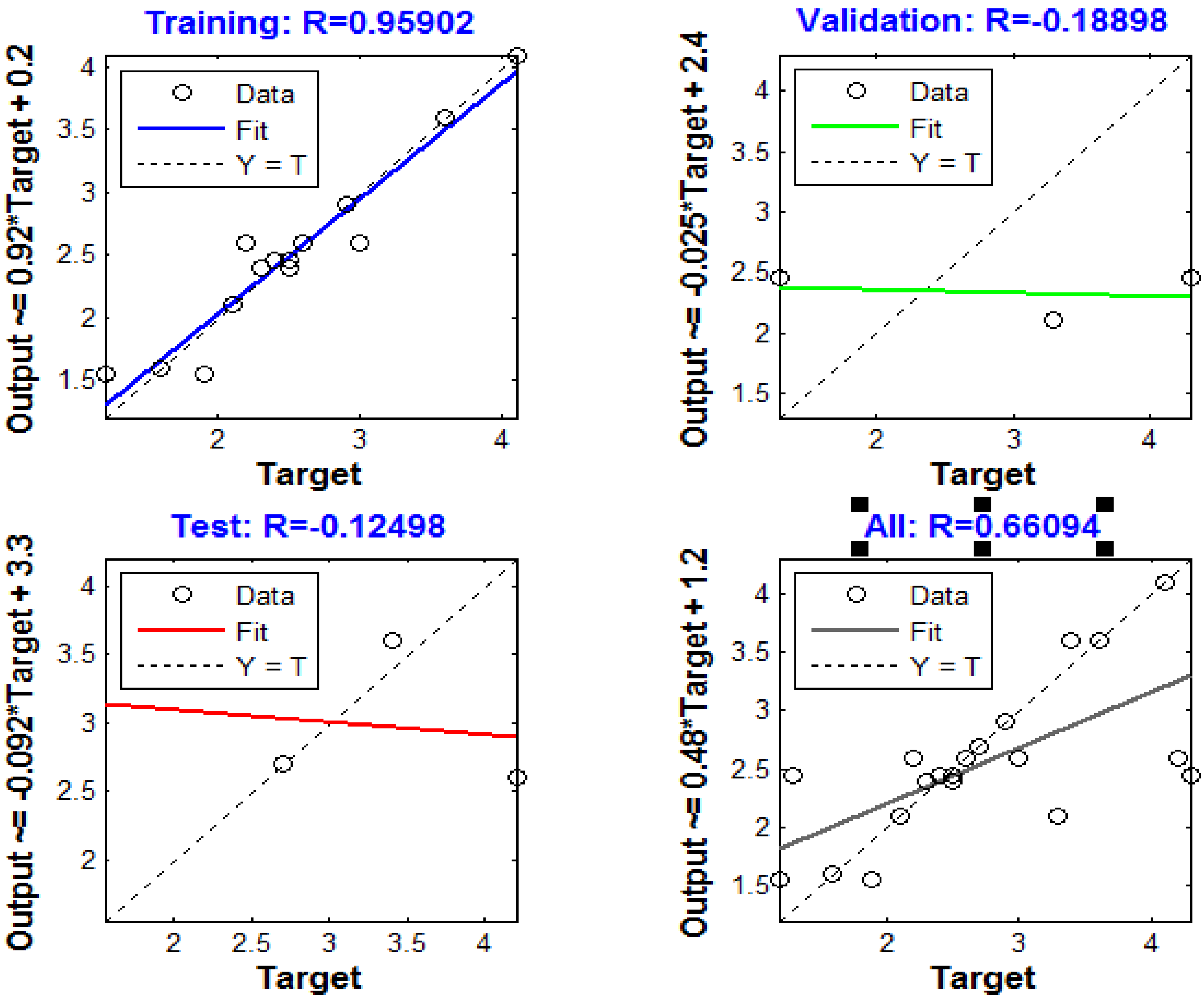

Figure 10 Regression analysis of SW chopping length

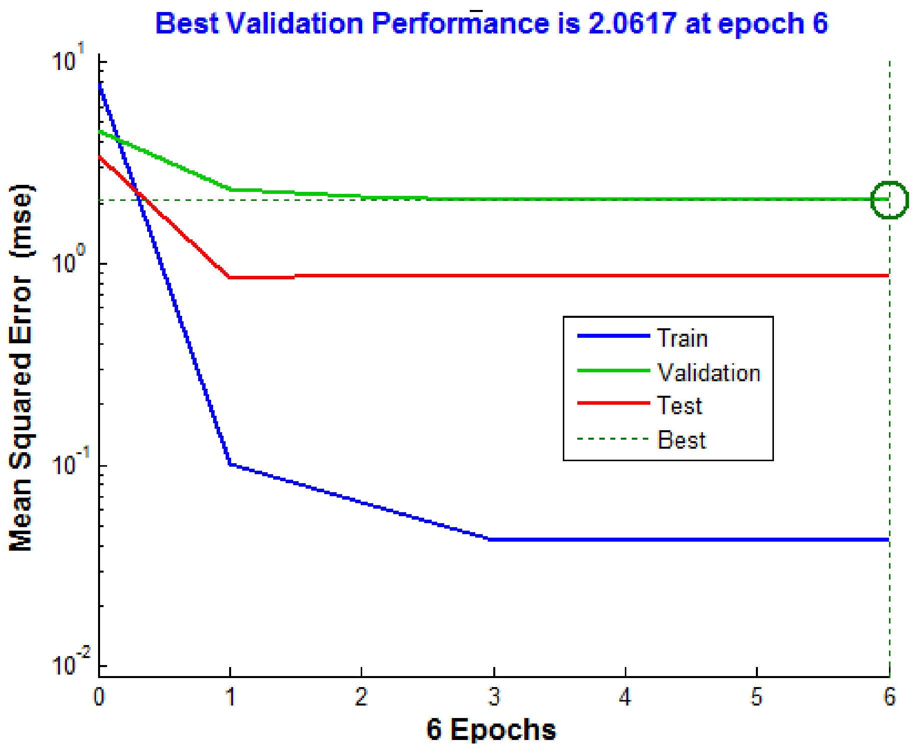

Figure 11 Performance of trained data using Siam weed chopping length

Table 6 t-Test: two-Sample assuming equal variances

Statistics	X =Actual	Y = Predicted
Mean	2.703334	2.539785
Variance	0.818702	0.429034
Observations	20	20
Pooled Variance	0.623868	
Hypothesized Mean Difference	0	
Df	38	
t Stat	0.654786	
P(T<=t) one-tail	0.258275*	
t Critical one-tail	1.685954	
P(T<=t) two-tail	0.51655*	
t Critical two-tail	2.024394	

Note: *Not Significant ($p > 0.05$)

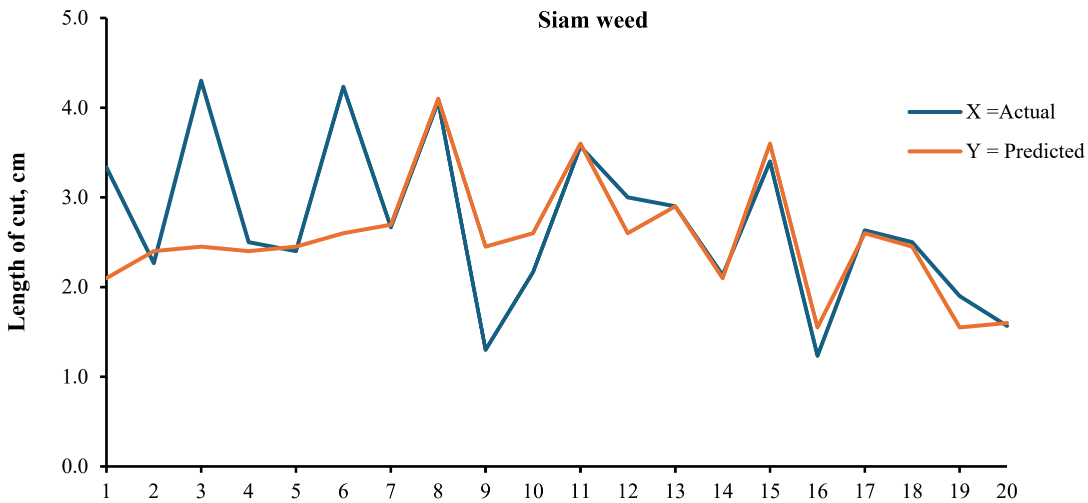

Figure 12 Trend between predicted and actual chopping length of SW

3.3 The prediction of Siam weed chopping length

The chopping length ofSWin Table 2 was entered into MatLab M-file in row matrix and the coded program was reprocessed to give the GUI in Figure 9. The figure was used to perform other analysis. However, the predictive chopping lengths obtained after training and testing for SW were presented in Table 5. The mean predicted chopping length was 2.5 cm and the mean actual (experimental) chopping length was 2.7 cm with residual value of 0.2 cm. This was in line with international standard of chopping length of 2 - 4 cm. The training regression analysis between the output and target (weight of forage) was 95.9% (Figure 10). This is an indication of a strong relationship between the target and the output and that the data are well fitted better than GG and this shows that a low error occur and ANN model was completed with high correctness. But a poor validation regression coefficient of 0.1889 (18.89%) and high MSE of 2.06 were observed as indicated in Figure 11. The overall regression coefficient (R) of 0.66049 made it better than the performance of GG chopping length. Because the model performance, is subject to the higher values of R, and lower values of MSE as observed also by Sultana et al. (2022).

The epoch function in Figure 11 shows that the chopping lengths are outside the reference point. This is an indication that the forward and backward pass of the dataset through the algorithm has zero exposure time during the ANN training. Table 6 shows the test of independence sample t-test between the actual and predicted chopping length of SW. The result revealed that no significant difference occurs between the actual (X) and predicted (Y) chopping lengths of SW. This shows that the p-value obtained was higher than 0.05 i.e. p = 0.258275. This is an indication that the predictive chopping length is not statistically different from the actual chopping length. The trend pattern was within the stipulated standard for chopping length for both the actual and predictive chopping lengths seem to be normalised at the beginning and toward the end of the graph (Figure 12). This pattern can be used to predict future performance of the machine with different target set.

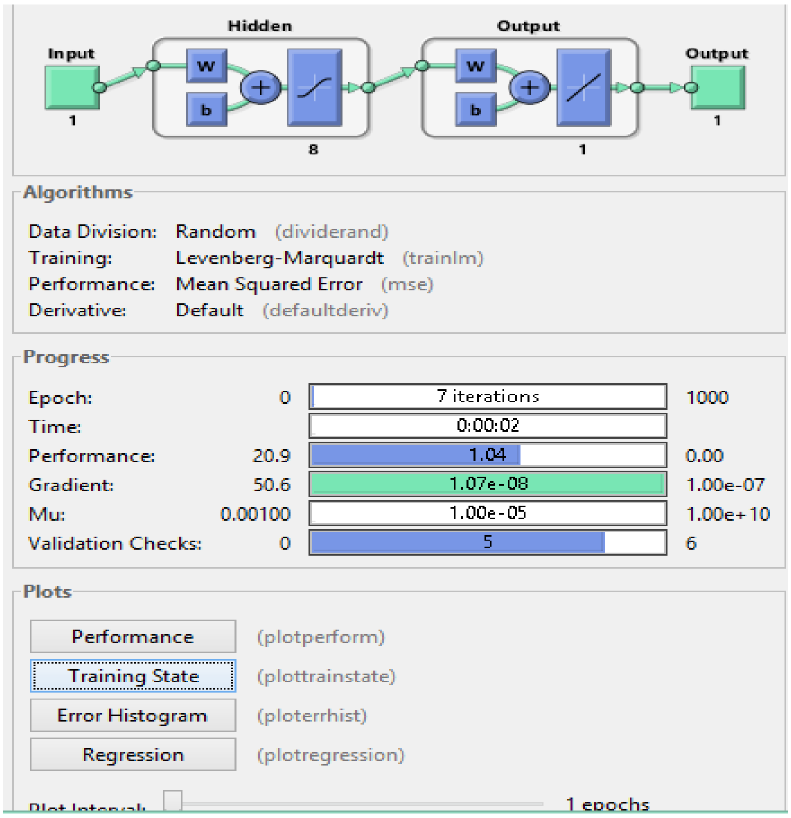

Figure 13 GUI output performance of MS chopping length

3.4 Prediction of maize stover(MS)chopping length

The GUI output in Figure 13 after running the code written in MatLab to predict MS chopping length was achieved. The GUI was used to analyse the performance, training, and validation checks of MS chopping length. The result of the predicted chopping length of MS was presented in Table 7. The predicted chopping length has an average length of 3.5 cm and actual (experimental) chopping length of 3.5 cm. The prediction of MS chopping length was so accurate to the extent that the experimental average chopping length was the same with the predicted chopping length (Table 7). This shows that ANN model used for this analysis has a very low error. Because the MSE and coefficient of determination (R) are used to analyse the predictive performance of ANN model. The coefficients of determination for training, validation, test and All are 0.2988, 0.9214, 0.8485 and 0.2927 respectively as indicated in Figure14. This shows that the training coefficient of determination has 29.88% with a very good validation checks of 92.14% and the test coefficient of determination is adequate at 84.85%. These variables (training, validation, test and all data) and optimisation data are usually tested during ANN model analysis as seen in results obtained by Çolak (2021) and Sultanaet al.(2022). The high values of R in validation and test regression analyses showed that, the predictive chopping length of MS has a low error. However, the prediction process is said to be better in MS than in GG and SW because MS predicted chopping length has the lowest MSE of 0.076028 as revealed in Figure 15 and Table 9. The green circle in Figure 15 represents the point of reference (Epoch 2). This means that all the data that fall below this point of reference are good to make decision. The epoch represent one complete pass of the whole training dataset through the learning algorithm. Table 8 revealed that the predicted chopping length of the forage machine is not significantly different from the actual chopping length. Because the *p*-value (0.474726) obtained was greater than 0.05 error margin. The patterns seen in Figure 16 is an evidence that the average chopping length of the actual (experimental) chopping length should not be different from that of the predicted ones. The patterns look alike in attributes. This shows that the points in the predicted chopping length are in perfect agreement with the experimental chopping length. This findings was in line with the discovery of other researchers (Sultanaet al., 2022; Huang et al., 2021) who validates that the points in output (predicted) data obtained from ANN model are in line with experimental data. In this, one could say that forecasting of chopping length is possible using weight as target and MS as testing sample.

Table 7 Prediction of MS chopping length

S/N	X =Actual	Y = Predicted	Residual	RMSE	R, %	Performance
1	6.9	7.0	-0.1	2.06*	95.9	0.47
2	7.4	2.7	4.6			
3	2.8	2.9	-0.1			
4	5.0	2.7	2.3			
5	3.3	2.9	0.4			
6	5.3	3.6	1.7			
7	2.0	2.0	-0.1			
8	4.5	2.3	2.2			
9	2.7	2.9	-0.2			
10	1.4	3.6	-2.3			
11	1.9	6.5	-4.7			
12	5.5	3.6	1.9			
13	2.4	2.4	0.0			
14	2.6	7.0	-4.4			
15	4.3	6.5	-2.3			
16	1.7	1.4	0.3			
17	4.0	3.6	0.4			
18	2.6	2.9	-0.3			
19	1.8	1.4	0.3			
20	1.1	1.3	-0.2			
Mean	3.5	3.5	0.0			

Note: *MSE is Adequate

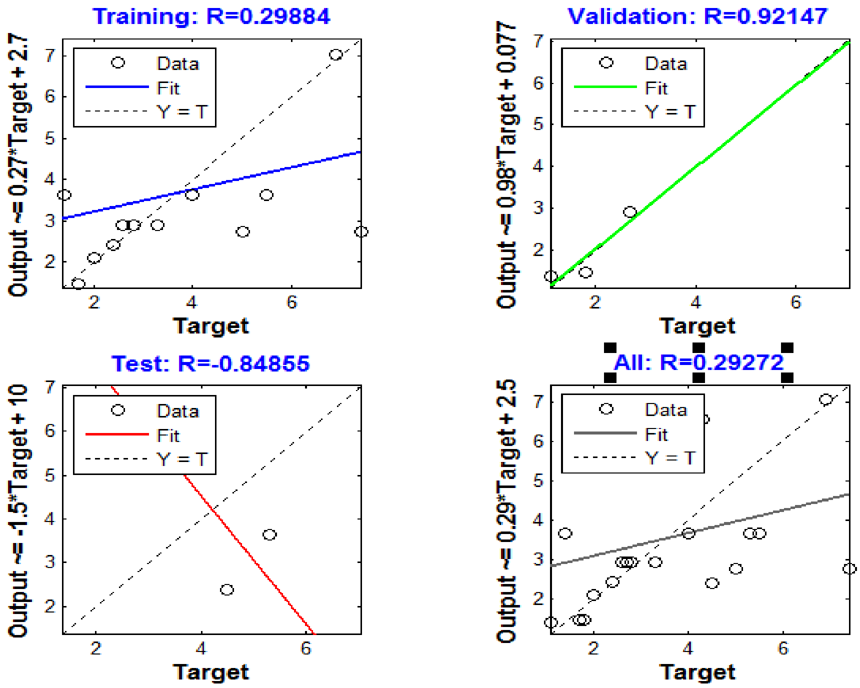

Figure 14 The regression analysis of MS chopping length

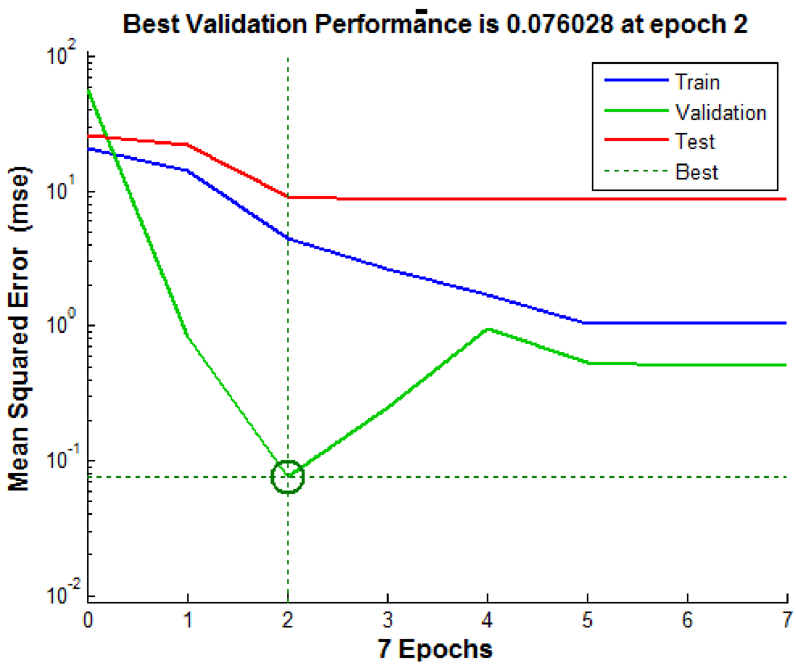

Figure 15 Performance of trained data using maize stover (MS) chopping length

Table 8 t-Test: two-sample assuming equal variances

Statistics	X =Actual	Y = Predicted
Mean	3.463333	3.500196
Variance	3.319989	3.353827
Observations	20	20
Pooled Variance	3.336908	
Hypothesized Mean Difference	0	
df	38	
t Stat	-0.06381	
P(T<=t) one-tail	0.474726*	
t Critical one-tail	1.685954	
P(T<=t) two-tail	0.949453*	
t Critical two-tail	2.024394	

Note: *Not significant (P > 0.05)

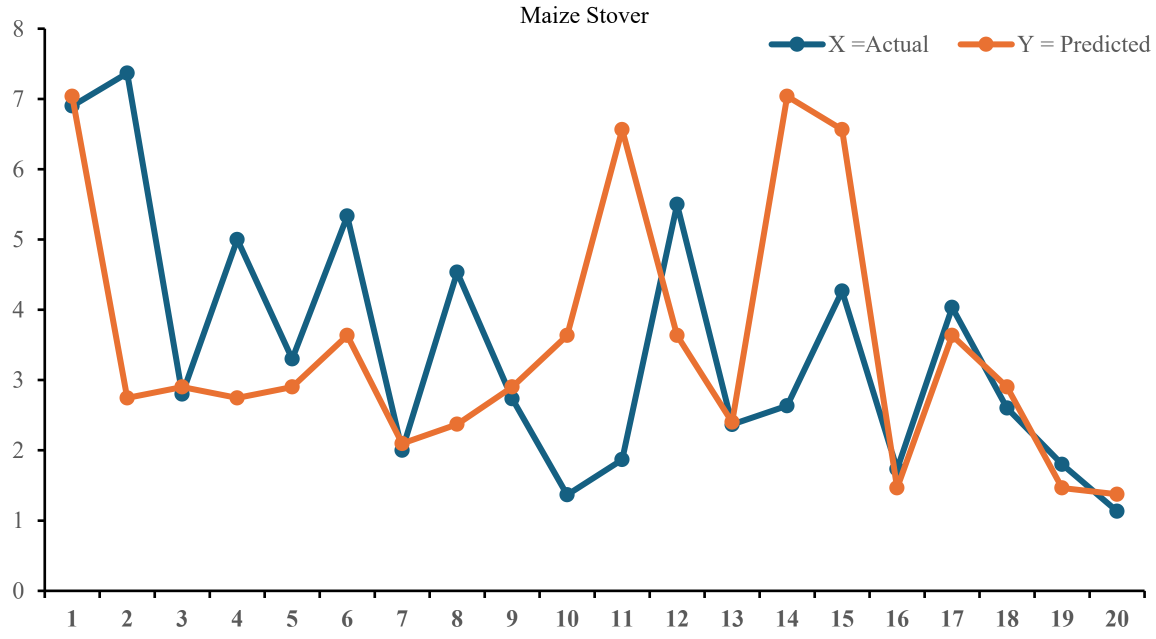

Figure 16 Trend between predicted and actual chopping length of maize stover

3.5 Comparison the three sampled forages

The chopping length of GG, SW and MS were subjected to the same training conditions. However, they all have good experimental data (3.5, 2.7 and 3.5 cm) and adequate predictive data (3.1, 2.5 and 3.5 cm). But SW has the best coefficient of determination (*R*) in training, GG has the best *R*-value in validation and SW has the best *R*-value in all data. More so, MS has the lowest error in ANN model and the highest epoch number as presented in Table 9.

Table 9 Comparison among the chopping lengths of GG, SW and MS

Parameters compared	GG	SW	MS	Best
Average actual length, cm	3.5	2.7	3.5	All
Average predicted length, cm	3.1	2.5	3.5	All
***R*-value (Training)**	0.439	95.9	29.9	SW
***R*-value (Validation)**	99.8	18.8	92.1	GG
***R*-value (All)**	31.8	66.1	29.3	SW
MSE	0.84	2.06	0.076	MS
Epoch number	2	6	7	MS
Performance value	3.72	0.47	0.47	

4 Conclusion

The following conclusions were made due to the observations made in this study;

1. ANN model can be used to predict chopping length of forage machines.

2. All the forages used have good predictive chopping lengths that are within international standards for forage machines

3. The coefficients of determination (*R*) for training (43.9%, 95.9% and 29.9%), validation (99.8%, 18.8% and 92.1%) and all data (31.8%, 66.1% and 29.3%) gave a low error of ANN model.

4. The MSE obtained are 0.84, 2.06 and 0.076 for GG, SW and MS respectively. But the MSE of MS gave the smallest error and the best fitting pattern whose average experimental data was the same with the predictive data obtained from ANN model.

ANN model is therefore, recommended for use to forecast and improve the performance of forage machines.

References

Akhgar, A., D. Toghraie, N. Sina, and M. Afrand. 2019.Developing dissimilar Artificial Neural Networks (ANNs) to prediction the thermal conductivity of MWCNT–TiO2/water–ethylene glycol hybrid nanofluid. *Powder Technology*, 355: 602–610.

Al Shamisi, M. H., A. H.Assi, and H. A.N.H. Hejase. 2011. Using MATLAB to develop Artificial Neural Network models for predicting global solar radiation in Al Ain City–UAE. In *Engineering Education and Research Using MATLAB*, ed. A. H. Assi, ch. 9, 220-238. London, UK: IntechOpen Limited.

Britannica. 2024. Neural Network. Accessed at: www.britannica.com/technology/neural-network Accessed on 01 June 2024.

Çolak, A.B. 2021. An experimental study on the comparative analysis of the effect of the number of data on the error rates of Artificial Neural Networks. *International. Journal of Energy Resources*,45(1):478–500.

Esfe, M.H., A.A. Nadooshan, A. Arshi, and A. Alirezaie. 2018.Convective heat transfer and pressure drop of aqua based TiO2 nanofluids at different diameters of nanoparticles: Data analysis and modeling with Artificial Neural Network. *Physical E: Low-dimensional Systems and Nanostructures*, 97: 155–161.

Haykin, S. 2009.*Neural Networks and Learning Machines*. 3rd ed.New Jersey: Pearson Education, Inc.

Howard, D., and B. Mark. (2004, January 1). Neural Network Toolbox for use with MATLAB. The MathWorks 2024. Inc. Mail 3 Apple Hill Drive Natick, MA 01760-2098.

Huang, X., C. Cheng and X. Zhang. 2021. Machine learning and numerical investigation on drag reduction of underwater serial multi-projectiles. *Defence Technology*, 18(2): 229-237.

Kartal,F.,and A. Kaptan.2024. Artificial Neural Network and multiple regression analysis for predicting abrasive water jet cutting of Al 7068 aerospace alloy. *Sigma Journal of Engineering and Natural Science*, 42(2): 516 – 528.

MathWorks. 2024. Mathematics Graphics Programming. Published by The MathWorks, Inc. 1994-2024. Available at:www.mathworks.com/products/matlab.html. Accessed 31 May 2024.

Sultana, P., A.K.Dey,and D. Kumar. 2022. Empirical approach for prediction of bearing pressure of spread footings on clayey soil using artificial intelligence (AI) techniques.*Results in Engineering*, 15: 100489.

Tian, S., N.I. Arshad,D.Toghraie,S.A. Eftekhari,and M. Hekmatifar.2021. Using Perceptron Feed-Forward Artificial Neural Network (ANN) for predicting the thermal conductivity of graphene oxide–Al2O3/water–ethylene glycol hybrid nanofluid. *Case Studies in Thermal Engineering*, 26: 101055.

Wunderlich, J. 2021. Artificial Neural Network (ANN). Class Lecture and suggested semester project option. Available at:https://users.etown.edu/w/wunderjt/Neural%20Network%20MATLAB%20toolbox%201.pdf. Accessed 5 May 2024.