

Comparative Analysis of Artificial Neural Network Algorithms for Prediction of FL305DMY in Murrah Buffalo

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Abstract

In the present study, first lactation records of 301 Murrah buffaloes were collected at Indian Veterinary Research Institute, Izatnagar. The first lactation 305-day milk yield (FL305DMY) of Murrah buffaloes was predicted using three different Artificial Neural Network (ANN) algorithms and their performance was compared. Performance of each algorithm was evaluated and compared on the basis of coefficient of determination and Root Mean Square Error (RMSE). In the study two different input sets were used to predict the milk yield. First input set consisted of four test day milk yields record along with Age at first calving (AFC) and Peak yield (PY) and second input set consisted of four monthly milk yields record, AFC and PY. ANN was trained using three algorithms that were Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG). Each algorithm was compared using four different training-test data sets (66.66:33.33, 75:25, 80:20 and 90:10). BR achieved highest accuracy of 81.98% with lowest RMSE value of 16.13 % for input set-1 and 78.33% accuracy with RMSE value of 16.89 % for input set-2. Higher accuracy and lower RMSE value for BR algorithm clearly indicates it outperform SCG and LM algorithm. Hence, for prediction of FL305DMY in Murrah buffaloes by ANN should be done using BR algorithm as it shows better accuracy than LM and SCG algorithm.

Keywords: Artificial Neural Networks, Bayesian Regularization, Murrah Buffalo, Test Day Milk Yields

Introduction

Dairy cattle breeding programs are primarily based on milk yield and its composition. Farmer's incomes are dependent on milk production and its composition. The accurate amount or proper forecasting of milk yield is crucial to their economy (Fernandez *et al.*, 2007) for better resource allocations. 305-day milk yield is an important basis for the selection and elimination of cows during the production process and for individual genetic evaluation. Sires are generally evaluated on the basis of 305-day or less milk yield of their daughters which ultimately leads to improved generation interval, lower genetic gain per unit of time and less numbers of daughters per sire due to smaller herd size. Early milk yield prediction could help the farmer to decide whether to keep cows for breeding or cull it to manage its economic losses early in the lactation. Further, it also helps farmers to manage resource allocation on feed and fodder of individual animal or a herd (Khan *et al.*, 2005). Early prediction will help in early identification of bulls of with good characters and sooner the semen collection can be started and the further dissemination of semen in cows can be done (Sharma *et al.*, 2007).

In most of the developing countries recording systems is very weak and its accuracy is also questionable. Under field conditions its very tedious job to collect and record the milk yield daily, so it led to search for alternatives for this problem. And therefore, for milk yield prediction part lactation and test day milk yield can be used (Gandhi *et al.*, 2009; Raja, 2010; Dongre *et al.*, 2012). Test day milk yields which will not only reduce the cost of recordings and also the time taken for recording. Test day milk yields and part lactation are also accurate as farmers pay more attention if he has to record the yield on specific days or for a period. Sample collected will also be less as compared to daily sampling. Further, more accurate information we receive more accurate will be prediction, lesser will be expenditure. The technological developments in field of artificial intelligence, block chain, cloud technologies and data science (ABCD technologies) are going to transform the practice of traditional dairy farming into smart dairy farming (Ruhil *et al.*, 2019). The latest challenge in dairy farming which is in focus and also an important aspect in dairy farming is to achieve animal health and welfare in best possible standards keeping in mind the high-performance potential of animals. To meet these challenges faced by the farmer's introduction of technological advancement are necessary in animal sciences. The Artificial Neural Networks (ANNs) is one of the advanced computing methods used mainly for classification and prediction. ANN is multi layer connected neural network which looks like a web. A basic ANN unit consists of input layer, hidden layers and output layer. Each layer has neurons or nodes which are interconnected to each other in the next layer. Each node in hidden layer has some weight and bias values connected to them. ANN is non linear technique which can take any type of input. It has gained popularity in the field of artificial intelligence.

As such, ANN applications in different fields of agriculture are also growing (Salehi *et al.*, 1988). However, in India the research related to application of ANN in the field of animal science and especially in dairy production is very limited. Accordingly, the current investigation was undertaken for comparative analysis of artificial neural network algorithms for prediction of FL305DMY in Murrah buffalo.

Material and Methods

Data Collection

First lactation records of 301 Murrah buffaloes were collected from the records maintained at Livestock Production Management Section, Indian Veterinary Research Institute I.V.R.I, Izatnagar, Bareilly which falls in India's Upper Gangetic Plain Region. The data were collected from the Murrah buffalo history cum pedigree sheets, calving reports, health records, auction sheets and Daily Milk Yield records maintained at Indian Veterinary Research Institute's Cattle and Buffalo Farm, Izatnagar. A total of 301 buffaloes first lactation records consisting of 4 Test Day Milk Yields, first 4 monthly milk yield, peak yield and age at first calving of each buffalo in the study. The input variable used for prediction of FL305DMY were TD1, TD2, TD3, TD4, M1, M2, M3, M4, age at first calving (AFC) and peak yield (PY), respectively (Table 1). The animals with milk yield of less than 500kg were rejected from study thinking of it as abnormal lactation. Further, complete data was divided into 4 main subsets according to the training: test data division as subset-A (66.67:33.33), subset-B (75:25), subset-C (80:20) and subset-D (90:10). These input variables were further classified into two input sets (Table 2) to predict FL305DMY.

Table 1: Description of variables used in the present study

Input variables		Output variable
TD1	6 th day of lactation	First lactation 305-day milk yield (FL305DMY)
TD2	36 th day of lactation	
TD3	66 th day of lactation	
TD4	96 th day of lactation	
M1	1 st month yield of lactation	
M2	2 nd month yield of lactation	
M3	3 rd month yield of lactation	
M4	4 th month yield of lactation	
AFC	Age at first calving	
PY	Peak yield	

Artificial Neural Network (ANN)

ANN is a smart model which learns from the data that has been given to it while training and further processes it to reach the best result with minimum error. Various models of ANN are available for processing of data but commonly used model is

multilayered feed forward network. The input variables and the subsequent target data are used in back propagation method to train the network till it can estimate a prediction function (Fausett, 1994).

Table 2: Description of input set

Input set	Input variables
Set-1	TD1, TD2, TD3, TD4, AFC and PY
Set-2	M1, M2, M3, M4, AFC and PY

In the present study, a multilayer feed forward neural network with back propagation of error learning mechanism was developed using Neural Network Toolbox (NNT) of MATLAB 7.8.0(MATLAB Users' Guide, R2009a) for prediction of milk yield. Training of network was done using three different algorithms. Back propagation algorithms used are Bayesian regularization (BR), scaled conjugate gradient (SCG) and Levenberg-Marquardt (LM). Maximum 8000 epochs or till the algorithm converged were set. Standardization and Pre processing of input and output data was done using `prestd` function available in NNT to minimize the error. Some of the parameters which were set are momentum (0.05), error goal (0) and learning rate (0.01) else other parameters were kept at the default values as available in NNT under MATLAB.

Bayesian regularized artificial neural systems (BRANNs) are more vigorous than standard back-engendering nets and can lessen or dispose of the requirement for extensive cross-validation. BRANN has training capacity that refreshes the weight and bias values as indicated by Levenberg-Marquardt optimization. BRANN computes and trains on various powerful system parameters or weights, viably stopping those that are not applicable. Scaled conjugate slope (SCG) furnishes a managed learning algorithm with super linear convergence rate. SCG is a variety of a conjugate slope strategy which stays away from the line-search per learning iteration by utilizing a Levenberg-Marquardt approach so as to scale the progression size. By utilizing a stage size scaling component, this technique evades a tedious line-search per learning iteration. SCG network training function that updates weight and bias as per the scaled conjugate slope technique. Levenberg-Marquardt calculation (LM), otherwise called the Damped least squares (DLS) strategy, is utilized to tackle non-linear least squares issues. These minimization issues emerge particularly in least squares bend fitting. The LMA interjects between the Gauss-Newton calculation (GNA) and the technique for gradient descent. Levenberg-Marquardt calculation is an iterative methodology. The LMA is more vigorous than the GNA, which implies that as a rule it finds an answer regardless of whether it begins far away the last least.

Performance Evaluation of Network

For comparing and checking the accuracy of each algorithm was based on coefficient of determination (R^2 -value) and root mean square error (RMSE) values of the test data. The coefficient of determination, predicted error and RMSE values in algorithms were calculated using the following equations:

$$R^2 = \frac{TSS - ESS}{TSS} * 100$$

Where TSS is total sum of squares and ESS is error sum of squares

$$Predicted\ error = \frac{predicted\ yield - actual\ yield}{actual\ yield} \times 100$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (Predicted\ error)^2}{N}}$$

Further the network testing was done using 1 and 2 hidden layers keeping the number of neurons changing till the best result was reached. Initial weights and bias matrix were randomly initialized between -1 and 1. For activation, function tangent sigmoid was used to determine the output. For network response, a pure linear activation function was used on the output layer. The tangent sigmoid and pure linear functions used here are given in equations:

$$f(x) = \frac{\exp(2x) - 1}{\exp(2x) + 1}$$

$$f(x) = x$$

Where x denotes weighted sum of the inputs.

Results and Discussion

For both the input set-1 and 2, all three algorithms BR, LM and SCG showed good result *i.e.*, they showed accuracy more than 70% in Subset-C for the first lactation 305-day milk yield prediction (Table 3 and 4). And the lowest RMSE values were also observed in subset-C in both the input sets. But in all subset-A, B, C and D for input set-1 and 2 it was seen that the accuracy was less for the algorithms LM and SCG where accuracy was more than 53% only while for subset-C it was more than 70%. Best results were seen in subset-C for all three algorithms BR, LM and SCG, the highest coefficient of determination observed were 81.98, 79.89, and 81.56 %, respectively in subset-C of input set-1 (Table 3 and 4). And in input set-2 the highest coefficient of determination observed was 78.33, 75.62 and 74.69 % respectively in the subset-C (Table 3 and 4). And for all three algorithms BR, LM and SCG, the lowest RMSE value observed were 15.79, 17.23 and 16.67 %, respectively in subset-C of input set-1 (Table 3 and 4). And in input set-2 the lowest RMSE value observed was 16.89, 17.98 and 18.70 % respectively in the subset-C (Table 3 and 4). No regular trend was seen when the training -test data was changed from 66.67:33.33 to 90:10 ratio. But it was seen that the R^2 -values increased first when the training data was increased *i.e.*, from 66.77 to 80 % but after that it decreased when training data was increased from 80 to 90% (Table 3 and 4).

Table 3: Comparison of R² and RMSE values of different algorithm of input set-1

Input Set-1								
Algorithm								
			BR		LM		SCG	
SUBSET	Hidden layer	Neurons	R ² (%)	RMSE (%)	R ² (%)	RMSE (%)	R ² (%)	RMSE (%)
Subset-A (66.67:33.33)	1	2	74.82	17.15	56.03	25.8	61.17	24.75
	1	4	74.97	16.99	56.73	26.1	64.25	22.56
	1	5	74.88	16.83	50.51	27.26	65.42	22.25
	1	8	74.98	16.7	50.36	27.56	63.52	23.56
	2	03:03	74.5	17.29	55.42	25.31	62.45	23.86
	2	05:03	74.56	17.08	54.48	25.96	61.89	24.98
	2	05:07	74.65	17.16	53.26	27.21	62.59	23.45
	2	10:03	75.47	17.06	56.63	24.96	62.75	23.86
Subset-B (75:25)	1	4	77.62	18.98	71.67	22.29	67.6	21.89
	1	6	76.89	17.23	68.72	23.62	68.45	21.25
	1	8	76.32	17.56	69.32	23.72	67.85	21.75
	1	10	72.23	18.78	68.23	24.63	67.25	21.56
	2	02:08	77.89	18.56	60.53	23.2	63.25	23.65
	2	03:03	75.55	18.44	64.85	23.03	64.56	22.56
	2	03:06	77.95	19.25	65.62	23.63	62.58	24.25
	2	03:08	77.32	18.56	57.2	24.02	63.58	23.25
Subset-C (80:20)	1	4	81.62	16.29	77.88	18.7	81.44	16.67
	1	6	81.98	16.13	79.89	17.55	81.56	17.64
	1	5	81.56	16.45	78.69	17.86	80.24	17.92
	1	8	81.89	16.96	78.95	17.23	81.32	16.72
	2	03:04	80.23	16.45	71.03	19.43	76.36	18.55
	2	05:06	77.56	16.56	72.5	18.96	75.98	18.56
	2	05:07	81.89	15.79	70.25	19.82	78.65	17.14
	2	10:03	80.56	16.25	71.23	19.26	77.69	17.25
Subset-D (90:10)	1	2	77.56	16.65	69.27	17.47	77.23	16.59
	1	4	76.89	15.83	67.74	18.55	77.69	16.56
	1	6	77.23	15.65	68.58	18.26	75.69	17.58
	1	8	77.56	15.88	68.54	18.23	76.23	17.23
	2	03:06	75.45	16.56	75.22	17.38	70.93	18.91
	2	05:04	71.56	17.23	73.25	18.56	69.63	19.36
	2	05:07	71.89	17.56	71.65	18.45	70.96	18.69
	2	10:03	71.78	15.78	71.56	18.69	71.25	18.12

Table 4: Comparison of R² and RMSE values of different algorithm for input set-2

Input Set-2								
Algorithm								
			BR		LM		SCG	
SUBSET	Hidden layer	Neurons	R ² (%)	RMSE (%)	R ² (%)	RMSE (%)	R ² (%)	RMSE (%)
Subset-A (66.67:33.33)	1	2	73.12	18.23	68.23	21.35	68.03	22.8
	1	4	71.87	19.56	67.54	22.69	69.73	21.1
	1	5	70.3	19.56	68.56	21.56	69.51	21.26
	1	8	74.72	21.23	70.23	19.56	67.36	22.56
	2	03:03	74.66	18.24	71.56	19.21	65.42	23.31
	2	05:03	71.52	18.98	69.23	20.65	62.48	24.96
	2	05:07	67.86	20.56	65.25	23.65	63.26	23.71
	2	10:03	67.39	20.45	66.52	23.56	62.63	24.96
Subset-B (75:25)	1	4	76.63	20.19	71.25	19.56	71.67	19.29
	1	6	76.88	21.28	72.56	19.21	69.72	21.62
	1	8	76.57	21.29	72.98	19.28	70.32	19.72
	1	10	76.76	21.32	69.85	21.14	69.23	20.63
	2	02:08	75.74	19.56	73.21	18.92	68.53	22.2
	2	03:03	73.67	21.26	70.48	19.56	70.85	20.03
	2	03:06	76.32	20.25	72.51	19.21	67.62	22.63

	2	03:08	76.28	19.89	73.56	18.65	68.2	22.02
Subset-C (80:20)	1	4	76.78	16.97	74.56	18.12	73.88	18.7
	1	6	78.33	16.89	75.62	17.98	72.89	19.55
	1	5	77.88	17.78	71.25	19.58	74.69	18.86
	1	8	78.49	17.65	71.56	19.65	72.95	19.23
	2	03:04	76.75	19.45	73.56	18.56	71.03	19.43
	2	05:06	74.85	20.78	71.56	19.85	72.5	18.96
	2	05:07	75.56	20.65	71.52	19.82	70.25	19.82
	2	10:03	74.68	20.89	70.25	21.56	70.23	19.26
	Subset-D (90:10)	1	2	75.12	20.26	72.36	19.56	68.27
1		4	74.35	16.35	71.25	19.12	69.74	21.55
1		6	73.12	17.65	69.56	21.53	69.58	21.26
1		8	72.78	17.45	68.56	21.89	70.54	20.23
2		03:06	71.35	17.65	67.59	22.36	71.22	19.38
2		05:04	70.56	17.45	68.96	21.58	72.25	19.56
2		05:07	72.32	16.15	69.89	21.45	70.65	19.45
2		10:03	70.45	17.39	68.95	21.54	71.56	19.69

It was generally observed that for all the subsets in both the input set the accuracy was better when a single hidden layer was used, when 2 hidden layers was used the accuracy was decreased. Generally speaking, the best outcomes have been revealed in the subset-C in which training–test data has been acquired as 80:20.

In the current investigation it was also seen that coefficient of determination was higher for the input set-1 than input set-2. Which clearly indicates that input set-1 is better for the prediction of first lactation milk yield. Performance of Bayesian regularization algorithm was found better in all the subsets with higher accuracy and lower RMSE values in both input sets. Bayesian regularization clearly outperforms other two algorithms LM and SGG. Similar results were reported by Bhosale and Singh (2015) in Frieswal cattle while findings of Dongre *et al* (2012) in Sahiwal cattle were different, he reported SCG as best algorithm.

Conclusion

On comparing all three algorithms performances it was seen that Bayesian regularization performed best followed by Scaled Conjugate Gradient and *Levenberg-Marquardt*. BR algorithm gives the best accuracy for prediction of first lactation 305-day milk yield *i.e.*, 82%. So, by this current study we can say that Bayesian regularization algorithm can be used for prediction of milk yields. With accuracy more than 80% we can confer that prediction is quite accurate by this method. In future the accuracy of model could be increased with addition of more training and test data in the model.

Conflict of Interests

There is no conflict of interest.

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