

Comparison of artificial neural networks and multiple linear regression for prediction of dairy cow locomotion score

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Article Info	Abstract
Article history: Received: 26 November 2018 Accepted: 29 April 2019 Available online: 15 March 2021	In this study, artificial neural networks (ANNs) were employed to investigate the relationship between locomotion score and production traits. A total number of 123 dairy cows from a free-stall housing farm were used in this study. To compare the effectiveness of the ANNs for the prediction of locomotion score, the multiple linear regression (MLR) model was developed using the eight production traits, body condition score, parity, days in milk, daily milk yield, milk fat percent, milk protein percent, daily milk fat yield, and daily milk protein yield as input variables to predict the locomotion score. The ANN predictions gave a higher coefficient of determination (R ²) values with lower mean squared error (MSE) than MLR. The R ² and MSE of the MLR model were 0.53 and 0.36, respectively. However, the ANN model for the same dataset produced much improved results with R ² = 0.80 and MSE = 0.16, respectively. Globally, the results of this study showed that the connectionist network model was a better tool to predict locomotion scores compared to the multiple linear regression.
Keywords: Dairy cow Locomotion score Neural network Regression models	

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Introduction

Cattle lameness (or mobility) problems are a major health concern and one of the most significant welfare and productivity issues in dairy farming. Lameness is also an economic problem for farmers. Economic losses are caused by reduced milk yield, prolonged calving intervals, culling, and veterinary costs or treatment.¹ Prevention of lameness is the most important step in reducing the negative welfare implications for cows and costs for the farmers.²

Although automated detection methods show potential for identifying lame cows, locomotion scoring likely remains the most practical method for evaluating lameness in dairy cows, and several approaches have been used.³⁻⁵ The common principle is that the cow is assigned a score describing the animal's condition based on posture and stride variables. The scoring scheme can be, for instance, from 1 to 5 (Table 1).⁴

A common problem in all of the visual scoring systems is that they require experience before the scoring becomes consistent, and they are also observer-dependent. Therefore, it is hardly done in practice, and when done for

large herd sizes, it is often done on a subsample of the entire herd. Also, several studies have shown that the results of locomotion scoring are subjective. O'callaghan *et al.* reported that the intra-observer repeatability in gait scoring for the five-point numerical scoring system was only 56.00%, and the inter-observer repeatability was only 37.00%.⁶ Winkler and Willen found 68.00% repeatability of scores among three observers.⁷ Therefore, it is highly relevant to develop automated systems to identify cows experiencing lameness. Several approaches have been introduced to automate locomotion scoring in recent years-force plates, pressure-sensitive walkways, and accelerometers. These automated systems also have several problems. One of the challenges that decrease the accuracy of measurement is skin displacement during locomotion.⁸ Furthermore, Winckler and Willen⁷ suggest that locomotion scoring systems' usefulness is limited to pain reaction indicators.

Artificial neural networks (ANNs) provide a method to characterize synthetic neurons to solve complex problems in the same manner as the human brain does. The comparative advantage of ANNs over more conventional econometric models, such as multiple linear regression

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(MLR), can model complex, possibly non-linear relationships without any prior assumptions on the underlying data-generating process. They can learn and generalize relations between input and output data from examples presented to the network.⁹

Even though the ANNs have applications in diverse areas such as medicine, engineering, and physics, their application in animal sciences is scanty. However, few studies on the application of ANN in predicting feed abrasive value,¹⁰ weekly milk on dairy goats,¹¹ and plasma hormones in broiler¹² have been reported.

There is no literature on neural network modeling for locomotion score prediction using linear body measurements and milk production traits in dairy cows to the best knowledge of the authors. In this study, ANNs were employed to investigate the relationship between locomotion score and body measurements, and milk production traits. Also, in the present study, we compared the performance of the classic approach, MLR and ANNs in estimating dairy cow locomotion score from empirical data that were obtained based on Sprecher *et al.*⁴

Materials and Methods

Animal Data. The current study was conducted at a dairy cow's farm with approximately 160 cows outside the city of Varamin, in the center of Iran's derived wilderness zone. A total number of 123 dairy cows from a free-stall housing farm were used in this study. The cows were gait scored with the locomotion scoring system developed by Sprecher *et al.* (Table 1),⁴ based on a five-point scale (1 = normal locomotion, 2 = mildly lame, 3 = moderately lame, 4 = lame, and 5 = severely lame). Locomotion scoring was performed by the same experienced observer at the parlor's exit after the afternoon milking. At the same time, cows were scored for body condition by the same experienced observer on a scale of 1 to 5, where, 1 = thin and 5 = obese.¹³ Production traits, including parity, days in milk, daily milk yield, milk fat percent, milk protein percent, daily milk fat yield, and daily milk protein, were obtained from farm records nearest to the visit's time.

Table 1. Scoring system for lameness identified during the study and clinical description.

Scores	Description	Assessment criteria
1	Normal	The cow stands and walks with a level-back posture.
2	Mild	The cow stands with a level-back posture but develops an arched-back posture while walking.
3	Moderate	An arched-back posture is evident both while standing and walking.
4	Lame	An arched-back posture is always evident. The cow additionally demonstrates an inability or extreme reluctance to bear weight on one or more of her limbs/feet.
5	Severe	

Development of artificial neural network models.

The data were randomly divided into two subsets. The first subset was the training set (n = 92), used to build the model. The second subset was the testing set (n = 31), which was used to evaluate different models' performance. A 2-layer feed-forward network formed by 1 input neuron, 1 output layer and some hidden units fully connected to both input and output neurons were adopted in this study. The most used learning procedure was based on the backpropagation algorithm. The network read inputs and corresponding outputs from a valid data set (training set) and iteratively adjusted weights and biases to minimize the prediction error. In this study, training gradient descent with Levenberg Marquardt algorithm was applied, and the performance function was the mean square error (MSE), the average squared error between the network outputs and the actual output.

Development of multiple regression models. To compare the effectiveness of the ANNs for the prediction of locomotion score, the MLR model was developed using the eight production traits, body condition scores, parity, days in milk, daily milk yield, milk fat percent, milk protein percent, daily milk fat yield, and daily milk protein yield as input variables to predict the locomotion score. Multiple regression procedure will estimate b_0, b_1, \dots, b_q parameters of the linear equation: $y = b_0 + b_1x_1 + \dots + b_qx_q$, where the regression coefficients b_0, b_1, \dots, b_q represent the independent contributions of each independent variable x_1, \dots, x_q to the prediction of the dependent variable y . The global statistical significance of the relationship between y with the independent variables was analyzed using an analysis of variance to ensure the validity of the model in a quantified manner. The same training data set was used to develop the regression equations, and the effectiveness of prediction from the MLR model a tested using test data set. The Neural Network Toolbox of MATLAB (version 8.3; Math Works Inc., Natick, USA) was employed to construct ANN and developing the MLR models.

Models evaluation. The following parameters were calculated to evaluate the performance and predictive ability of the model: R^2 (coefficient of determination; the correlation coefficient between predicted and observed values) and MSE (mean squared error). The R^2 and MSE values between predicted and observed data were calculated using the following equations:

$$MSE = \frac{\sum_{t=1}^n |y_t - \hat{y}_t|^2}{n}$$

$$R^2 = \frac{SSReg}{SST} = 1 - \frac{SSE}{SST}$$

$$SSReg = \sum_{t=1}^n (\hat{y}_t - \bar{y})^2$$

$$SST = \sum_{t=1}^n (y_t - \bar{y})^2$$

$$SSE = \sum_{t=1}^n (y_t - \hat{y}_t)^2$$

where, y_t = observed value, \hat{y}_t = estimated value, n = number of observations, $SSReg$ = sum of the square of a regression model, SST = sum of the square of the total, and SSE = sum of the square of residuals.

Statistical analysis. To compare the predicted values with the results of laboratory assays, Student t -test was used by SAS Software (version 8.0; SAS Institute Inc., Cary, USA).

Results

Table 2 describes the productive performance of all enrolled cows. The cows were grouped depending on their locomotion score into five groups: Group 1, which represented the locomotion score 1, consisted of 74 cows, and there were 39 cows in group 2, seven cows in group 3, 2 cows in group 4, and 1 cow in group 5. The prevalence of lameness ($LS \geq 3$) was averaged 8.10%. This prevalence of lameness was lower than that of a previous study by Wells *et al.*¹⁴ Those authors estimated that the prevalence of lameness in 17 dairy farms in the USA was 13.70% during summer and 16.70% during spring.

The architecture, specification, and statistic information of the neural networks are listed in Table 3. In the current study, the best number of layers, neurons in the hidden layer and neurons in the output layer were 2, 18, and 1, respectively.

The statistical values of empirical and predicted values by ANN and MLR models and residues, the difference between predicted and observed values, and relative residues are listed in Table 4. Also, scatter plot comparing observed and estimated locomotion scores for the MLR and ANN and scatter plot comparing estimated locomotion scores and residues, observed minus estimated values, are shown in Figures 1, 2 and 3. There was no significant

Table 2. Productive performance of the enrolled cows ($n = 123$).

Items	LS	BCS	Parity	DIM	DMY	MFP	MPP	DMFY	DMPY
Maximum	5.00	4.00	8.00	562.00	55.40	5.07	3.85	2.80	1.40
Minimum	1.00	2.75	1.00	20.00	21.60	1.76	2.21	0.61	0.69
Means	1.46	3.17	2.13	200.20	37.20	3.48	2.88	1.28	1.06
SD	0.64	0.33	1.26	111.30	7.60	0.76	0.26	0.34	0.17

LS: locomotion score; BCS: body condition score; DIM: days in milk; DMY: daily milk yield (kg); MFP: milk fat percent; MPP: milk protein percent; DMFY: daily milk fat yield (kg); DMPY: daily milk protein yield (kg).

difference between actual and predicted locomotion scores using ANN and MLR models (Table 4). Relative error was 12.20 ± 8.00 and 11.70 ± 7.45 for MLR, and ANN approaches, respectively.

Table 3. Architecture, specification, and statistical information of the neural network model.

Measurements	Value
No. of layer	2
No. of neuron in a hidden layer	18
Transfer Function of hidden layer	Tan Sigmoid
No. of neuron in the output layer	1
Transfer Function of the output layer	Pure Line
Train Function	Levenberg-Marquardt
Perform Function	MSE
No. of training elements	86
No. of validation elements	18
No. of testing elements	18
Epoch	1000
Momentum	0.001

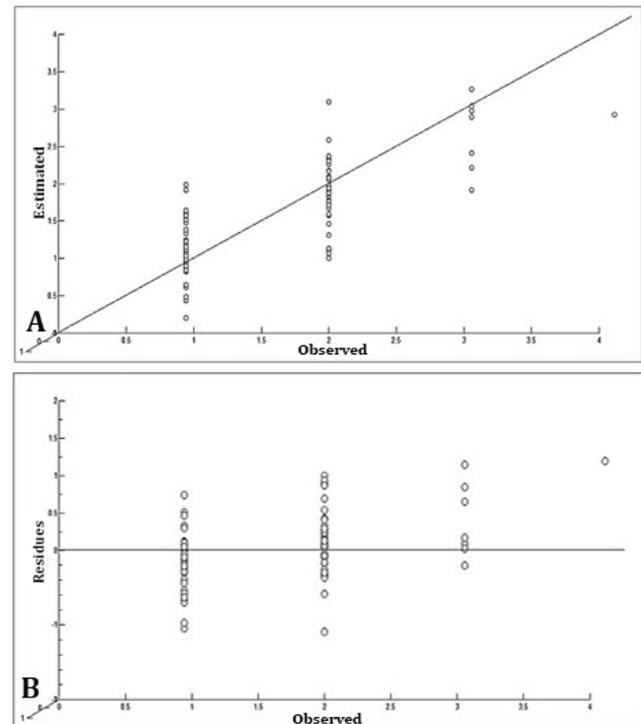


Fig. 1. A) Scatter plot comparing observed and estimated locomotion scores for the artificial neural networks and B) scatter plot comparing estimated locomotion scores and residues, observed minus estimated values.

Table 4. Mean, maximum, minimum, and standard deviation (SD) of empirical and predicted data, as well as residues.

Items	Empirical	Predicted		Residuals		Relative Error	
		MLR	ANNs	MLR	ANNs	MLR	ANNs
Maximum	4	3.14	3.884	1.26	0.86	95.20	120.10
Minimum	1	0.370	0.151	-0.95	-1.21	-63.00	-84.00
Means	1.46	1.47	1.55	0.44	0.38	12.20	11.70
SD	0.64	0.47	0.57	-0.04	-0.08	8.00	7.45

Relative Error = [(predicted - observed)/observed] × 100

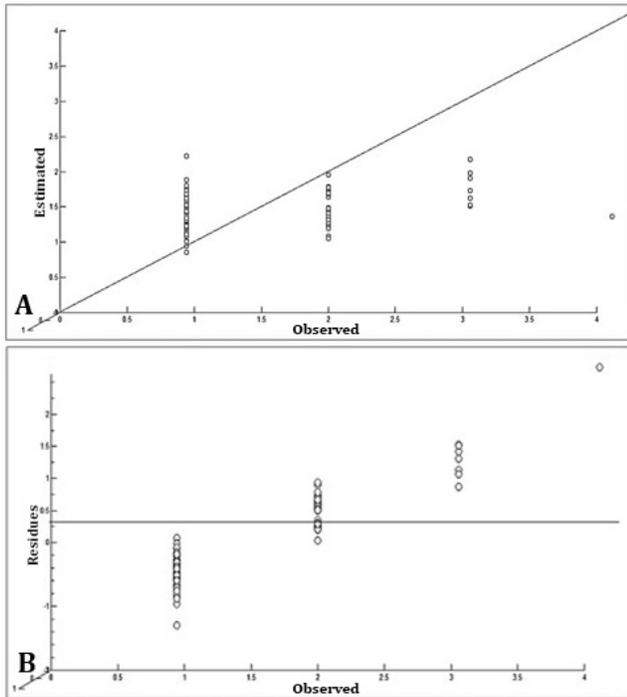


Fig. 2. A) Scatter plot comparing observed and estimated locomotion scores for the multiple regression and B) scatter plot comparing estimated locomotion scores and residues, observed minus estimated values.

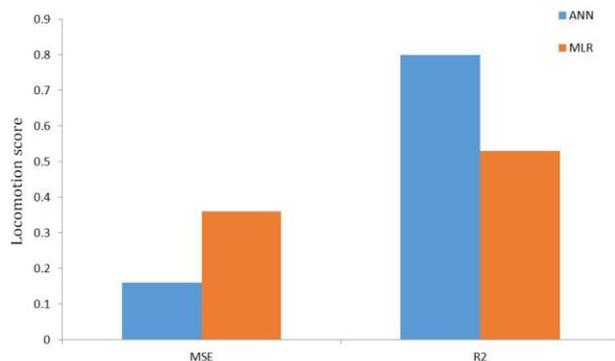


Fig. 3. A bar graph shows R² and MSE of MLR and ANN models for prediction of locomotion score.

Discussion

Selecting architectural characteristics of neural networks such as inputs and outputs, number of layers, number of neurons in each layer, and the number of hidden layer nodes of the ANNs can significantly affect

them. A previous study¹⁵ showed that one hidden layer neural network was enough to approximate any function if enough hidden nodes were presented. This ANNs structure can be effective on the accuracy, correct development of the model, and system behavior. Accordingly, network development's first important aim was to determine the optimal number of hidden layer nodes. There are no theoretical principles for determining this. However, there are many empirical rules.¹⁶ For example, the number of neurons in the hidden layer can be confirmed by the formula: $m = \log_2(n) + \alpha$ where m is the number of neurons in a hidden layer, n is the number of input variables, α is the integer between 0 and 10.⁹ During the network development, series of neural networks with different numbers of hidden layer nodes were trained. According to its generalization ability for the testing set, MSE was calculated on different numbers of the hidden layer nodes. The model which gave the lowest value of MSE was chosen as the final ANN model. In this study, the best number of hidden layer nodes was 18 to predict locomotion score (Table 3). For ANN, the training was stopped after 1000 epochs because the error was increased. In this study, linear transfer for the output layer and the sigmoid transfer function for the input and hidden layer was used in the ANN. This transfer function gave an appropriate response for many applications concerning linear transfer function.

To compare different models in prediction of locomotion score, the ANN approach gave higher R² values with lower MSE than the MLR model (Fig. 3). The R² and MSE of MLR model were 0.53 and 0.36, respectively. However, the ANN model for the same data set produced much-improved results with R² = 0.80 and MSE = 0.16, respectively. The ANN model improved the MSE of the MLR model by 125% and R² by 51%. Compared to some previous MLR studies,¹⁶⁻¹⁷ current MLR models had limited prediction capability with low R² value.

In the ANN model, the regression between observed and estimated locomotion scores showed a slope very close to one and a low dispersion around the regression line (Figs. 2 and 3). On the other hand, estimated locomotion scores versus residues (observed values minus estimated values), showed a slope very close to zero and homogeneous deviations around this value. However, the MLR provides worse results compared to the ANN model. The mean relative error was 8.00 and 7.45 for MLR and ANN prediction, respectively, and was lower for ANN than MLR (Table 3).

For the prediction of locomotion scores of dairy cows, the model that gave maximum R² value with the smallest MSE was considered better, and the results obtained in the present study revealed that the ANN model gave a more accurate prediction of locomotion score than MLR models. However, further studies with larger data sets are required to better determine the feasibility of rapidly predicting locomotion scores using ANN methods.

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Conflict of interest

The authors disclose no conflict of interest.

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