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Machine learning algorithms for predicting peak yield in buffaloes using linear traits

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ABSTRACT

Various studies have proved that linear traits have strong relationship with milk productivity but no such models are available for selection of animals based on linear traits. The present study conducted during 2020-22, is an attempt to develop an intelligent model using machine learning algorithms to predict peak milk yield based on its linear traits for selection of best dairy animals. A dataset on 14 linear traits of 259 buffalos across 5 lactations with peak milk yield was created and used for developing models. Data was collected from the buffalos having 8 to 26 kg peak milk yield maintained at Animal Farm Section, Central Institute for Research on Buffaloes, Hisar and also from private farms maintained by farmers. Predictive models were developed using various machine learning algorithms (artificial neural network, support vector regression and random forest) along with multi-linear regression executed on WEKA machine learning platform. Performance of these models was evaluated using evaluation metrics root mean squared error (RMSE). Results revealed that the Artificial Neural Network (ANN) model performed best with minimum RMSE 2.0308. Rear udder height and Lactation number emerged as the two most important attributes affecting the peak milk yield. Such model will be useful and handy for the stakeholders in selection of best dairy animals based on linear traits in absence of authentic record of peak milk yield.

Keywords: Buffalo, Dairy, Linear traits, Machine learning algorithms, Selection

Linear traits are the measurable physical characters in reference to milk producing abilities of the dairy animals. There is a strong correlation of these traits with production and reproduction parameters in buffaloes (Daliri *et al.* 2008, Dahiya *et al.* 2020). The international committee for animal recording, ICAR (2018) has recommended 18 such traits. On similar lines, the National Dairy Development Board (2017), has selected 20 standard linear traits for classification of cows and buffaloes in India. Among different traits used for evaluating dairy animals, peak yield, i.e. maximum milk yield in a day, has been traditionally used by farmers for selecting probable dairy animals (Kalyankar *et al*. 2003, Dhillod *et al.* 2017). Some studies have considered other udder traits for predicting milk producing ability in dairy animals - rear udder height, udder length, rear udder width, distance of rear udder, and distance of fore-rear teats (Gu *et al*. 2018).

The machine learning algorithms deliver interesting and useful information in form of new knowledge breakthroughs which help in development of decision support systems. These learning algorithms are made to learn from data and improve prediction accuracy of targeted process (Skansi *et al*. 2018). In dairy farms, machine learning has been used effectively in prediction of lameness (Singh *et al.* 2015, Taneja *et al.* 2020), mastitis (Kamphuis *et al.* 2010, Dhoble *et al.* 2019), calving time (Keceli *et al.* 2020), estrus (Devi *et al.* 2019), feed conversion efficiency-blood vitals correlation (Sikka *et al.* 2020), and milk yield (Sharma *et al.* 2007, Gandhi *et al.* 2009, 2010, Dongre *et al.* 2012, Manoj *et al.* 2014). Most widely applied machine learning algorithms in animal production systems are artificial neural network (Kumar *et al.* 2019), random forest (Shahinfar *et al.* 2013), fuzzy logic/ Neuro-fuzzy (Shahinfar *et al.* 2012) and support vector machine (Nguyena *et al.* 2020). There is only limited information available on linear traits measurements and algorithms for modelling milk yield predictions in buffaloes. Therefore, the present study was planned to develop predictive models using different machine learning algorithms to predict peak milk yield based on linear trait measurements collected during the study.

MATERIALS AND METHODS

Data collection: The data on linear traits was collected from 259 lactating healthy Murrah breed buffaloes having calving period between 45 days to 200 days from organised herd (n=138; Animal farm Section, Central Institute for Research on Buffaloes, Hisar) and farmers' elite buffaloes

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from field (n=121; villages from home tract of Murrah buffalo). The selected traits for the study are as per NDDB 2017 guidelines (Supplementary Table 1).

All measurements were recorded by the same person to minimise between-recorder errors. In addition to traits type, data on lactation number (LN) and peak milk yield (PY) was also recorded for these animals. The data collected on different data sheets was stored in a spreadsheet application (MS Excel 2013).

Model formulation: The model formulation consists of mapping input attributes to produce value of output attribute(s). Model development process involved the training and testing of models using machine learning algorithms (MLA). During training, the rules are constructed for prediction, using the given dataset of input and output. The testing process determines the accuracy of rules created during training. If the accuracy is above the acceptable limit then the model is assumed to be trained and can be used to predict output attribute(s) by supplying a new set of input attributes. The selection of suitable machine learning algorithms is critical since the accuracy of prediction is dependent on these algorithms. In the present study, three most popular supervised machine learning algorithms [Artificial Neural Network (ANN), Support Vector Machine Regression (SVMR) and Random Forest (RF)] were selected from three different classes of MLAs to introduce variation among the predictive models so that they do not make identical or correlated errors.

In addition to these three algorithms, conventional statistical method of multiple linear regression (MLR) was also used for developing predictive model. Further, the performance of all these developed models was compared to find out best predictive model for selection of buffalo.

Artificial neural network (ANN): ANN is a computational modelling technique that emulates biological neurons of the nervous system, permitting learning by examples derived from illustrative data that explains a physical phenomenon or a decision-making process. As a key feature, ANN has high learning ability to identify and model complex relationship between independent and dependent variables in a system (Fausett 1994). ANN model consists of artificial neurons arranged in number of layers linked to each other.

In the present study, multi-layer feed forward neural network with back-propagation learning algorithm was used to build a predictive model. Some important parameters to train the model were number of layers, number neurons in each layer, learning rate, momentum, etc. A model was trained by adjusting the values of these parameters during experiments to get best performance.

Support vector machines (SVM): Support vector machines (SVM) for regression is a generalization of support vector machines to estimate real-valued functions (Vapnik 2000). The regularization parameter C and kernel function are two important user-defined parameter for the performance of the fitted model. The SVMR used in this study was SMOreg which uses the sequential minimal optimization algorithm (Platt 1999) to increase the speed of finding the maximum-margin hyperplane.

Random forest (RF): Random forest is ensemble supervised learning algorithm capable of performing both regression and classification tasks using multiple decision trees and a technique called bootstrap aggregation, commonly known as bagging. The model creation process in the random forest is the same as that in the classification and regression tree (CART) method but without pruning (Breiman *et al.* 1984). Number of trees to be grown in the forest, depth of tree and the quantity of features or variables chosen at every node to build a tree are the important parameters required for random forest regression (Breiman 2001).

Multiple linear regression (MLR): Multiple linear regression predicts linear relationship between explanatory (independent) and response (dependent) variables by fitting a linear equation to observed data. As predictive analysis, MLR depends on linear and additive associations of the independent (explanatory) variables and models' relationship between two or more explanatory variables and a response variable by assumption of a linear relationship. A multiple linear regression model with 'n' explanatory (predictor) variables x_1, x_2, ... x_n and a response variable Y, can be written as:

$$y=\beta_0+\beta_1x_1+\beta_2 x_2+\beta_3x_3+...\beta_nx_n+\epsilon \qquad (1)$$

where β_0, constant and β_1, β_2 …. β_n are the coefficients of x_1, x_2, ..., x_n and to be estimated from the data and ϵ, model's random error (residual) term.

Model development platform: All models were developed using open source software Waikato Environment for Knowledge Analysis (WEKA). WEKA is a software product developed by the University of Waikato, New Zealand for data analysis and predictive modelling. It uses the GNU General Public License (GPL). The software is written in the Java™ language and contains a GUI for interacting with data files and producing visual results.

Data pre-processing: The data recorded in spreadsheet on 16 parameters [including Lactation number (LN) and Peak yield (PY)] in addition to 14 parameters (Supplementary Table 1) was made error free by checking data using various methods like manual comparisons, range checks, data visualisation, etc. Following this process, the data was transformed from spreadsheet into WEKA acceptable data format, i.e. attribute file format (.arff) for the purpose of development of predictive models in the WEKA environment. Thus, the final dataset comprised of 15 independent attributes and one dependent attribute (Peak yield) (Lin *et al.* 1987).

Performance evaluation: The performance of models developed for prediction peak milk yield was evaluated using the metrics Root Mean Squared Error (RMSE, Equation 2). It is a standard tool used for performance evaluation in case of numerical predictions.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_{observed,i}-X_{predicted,i})^2}{n}} \qquad (2)$$

where, $X_{observed,i}$, observed value of response variable; $X_{predicted,i}$, is predicted value of response variable and n, number of observations.

RESULTS AND DISCUSSION

Data description: Descriptive analysis on the complete dataset (n=259, 16 attributes including one dependent attribute) was carried out using SPSS (version 20.0) for understanding the distribution and relationship among different traits. Result of this analysis in terms of range, mean, standard error, coefficient of variation and correlation with peak milk yield (PY) of each trait across 5 lactations is given in Table 1.

The linear traits determine the volume of udder. The higher the volume, higher will be the number of milk alveoli available for milk synthesis. It was observed that the variation in udder parameters is directly related to the milk production capacity of the animals. In the present study, there is a large variation in peak milk yield of the animals with minimum of 8 kg and maximum of 26 kg/day. It is known that animals having higher udder width and lower depth will have more udder tissue and thus more capacious udder and presents more possibility for higher milk production. Studies carried out in Holestien cows have proven this (Lin *et al.* 1987, Al-Hered *et al.* 2005, SPSS 2011). Similarly, teats placed further apart is an indication of more voluminous udder and therefore higher milk production. Conformations like body length, body depth, height at wither, heart girth and paunch girth are related with body capacity to support milk production. Therefore, animals which score better on these parameters will have higher peak yield. The described values of height at wither and body length in the present study are comparable to findings reported elsewhere for Murrah buffaloes (Dhillod *et al.* 2017, Dahiya *et al.* 2020).

The phenotypic correlations of linear traits and lactation number with peak yield were found to be significant. Peak milk yield had highly significant correlation with rear udder height, rear udder width, lactation number, fore rear teat distance, naval udder distance and heart girth.

A significant negative correlation between udder depth and peak milk yield for Murrah buffaloes ($r=-0.427$, $P<0.01$) indicated lesser growth of the udder (Gu *et al.* 2018). The highest value of correlation coefficient ($r=-0.680$) of peak yield with rear udder height is significant and negative, indicating that as rear udder height decreases, the peak yield increases. In the present study, the rear udder height was taken from the lower point of vulva to the upper extent of udder. Lower height means the udder has covered more area towards vulva. Higher value of height on the other hand means lesser spread of udder. This again points to lesser voluminous udder and hence lesser yield. Studies across bovine dairy livestock have established that udder as an organ grows till fourth or fifth lactations, leading to a greater number of milk secreting tissue and hence milk production increases with increasing lactation number (Ray *et al.* 1992, Borghese *et al.* 2007). The significantly positive correlation between peak yield and lactation number reaffirms the fact in the present study.

The linear type traits, especially the udder structure and teat conformation traits, are important aspects in determining milk production of dairy buffalo in relation to milk storage capacity (Prasad *et al.* 2010). Udder type traits are also crucial component of breeding and have definitive importance in selection of breeding bulls along with production traits (Tilki *et al.* 2005, Patel *et al.* 2016).

Attribute selection: To reduce number of traits required for model building, a subset of most influential variables was determined through 'feature selection'. The 'Select Attributes' option available in WEKA was used for this

Table 1. Descriptive analysis of the linear traits and production traits of Murrah buffaloes (n=259)

Physical trait / Variable	Range	Mean±S.E.	Coefficient of variation (%)	Correlation with PY
Body length (BL)	127- 163	143.21±0.415	4.7	0.280**
Height at wither (HW)	123-153	137.21±0.438	5.2	0.214**
Heart girth (HG)	185-245	211.14±0.675	5.1	0.528**
Body depth (BD)	185-295	237.45±0.672	4.6	0.220**
Paunch girth (PG)	195-285	224.43±0.736	5.3	0.287**
Udder depth (UD)	5-19	12.08±0.187	24.9	-0.427**
Naval udder distance (NUD)	5-26	16.24±0.246	24.3	-0.542**
Fore teat distance (FTD)	7-22	12.48±0.193	24.9	0.193**
Rear teat distance (RTD)	4-19	9.47±0.171	29.0	0.478**
Fore rear teat distance (FRTD)	5-28	9.79±0.179	29.4	0.539**
Teat length (TL)	3-14	8.26±0.119	23.2	0.414**
Rump width (RW)	10-24	16.34±0.203	20.0	0.521**
Rear udder width (RUW)	8-25	17.10±0.197	18.5	0.572**
Rear udder height (UH)	2-19	9.97±0.243	39.3	-0.680**
Lactation number (LN)	1-5	2.38±0.069	-	0.567**
Peak yield (PY)	8-26	16.06±0.0250	25.0	1.0

**Significant at the 0.01 level (P<0.01) purpose. It is a correlation-based feature subset selection method to select a subset of features that are highly correlated with the class (output attribute) while having low inter-correlation. Finally, the optimum set comprised of 9 independent attributes [udder depth (UD), naval udder distance (NUD), rear teat distance (RTD), fore rear teat distance (FRTD), teat length (TL), rump width (RW), rear udder width (RUW), rear udder height (RUH), lactation number (LN)] and one dependent attribute [Peak yield (PY; kg)].

Artificial neural network: ANN was implemented using the "Multi-layer perceptron" (MLP) algorithm. MLP is a feed forward neural network with back-propagation learning algorithms to optimize the prediction errors. The ANN model was trained to predict Peak yield (dependent variable) using linear traits (independent variables) with different architectures, by varying the number of hidden layers from 1 to 3 and 2 to 10 neurons on each hidden layer. The learning rate and momentum was varied as 0.1, 0.3, 0.4, 0.5, 0.6 and 0.8 respectively. Other parameters were set at their default values. Sigmoid function was used as activation function on all nodes except at output node to add non-linearity in the model. The algorithms were executed for 500, 1000 and 2000 epochs for training the models. The input data was normalised between values -1 to 1 to bring all input attributes on the same scale to get better results. All models were trained and validated with 10-fold cross validation method. The best result with minimum RMSE 2.0308 was obtained with values of parameters as given in Table 2.

Table 2. Optimized parameters for ANN model

ANN parameter	Value
Number of layers	2
Neurons in first layer	5
Neurons in second layer	3
Learning rate	0.1
Momentum	0.4
Training time (epochs)	1000

The scatter plot (Fig. 1) between the original peak values and predicted values through ANN shows high degree of relationship.

Support vector machine: SVM was implemented using "SMOreg" algorithm for regression. Various models were trained by varying the parameter complexity (C) as 1 and 2 and selecting the kernel function as polynomial (Exp=1, 2) and radial basis functions to predict Peak yield based on linear traits. Other parameters were set at their default values. All these models were trained and validated with 10-fold cross validation method and regression results were optimised using the learning algorithm RegSMOImproved. The training data was normalised between -1 to 1 to get the optimum results. Best performance of "SMOreg" was achieved with minimum RMSE as 2.1337 with "polynomial (Exp=1)" as kernel function and complexity (C) at 1. The original values of Peak yield and those predicted through SVM model were plotted (Fig. 2) to measure the degree of relationship between these two variables.

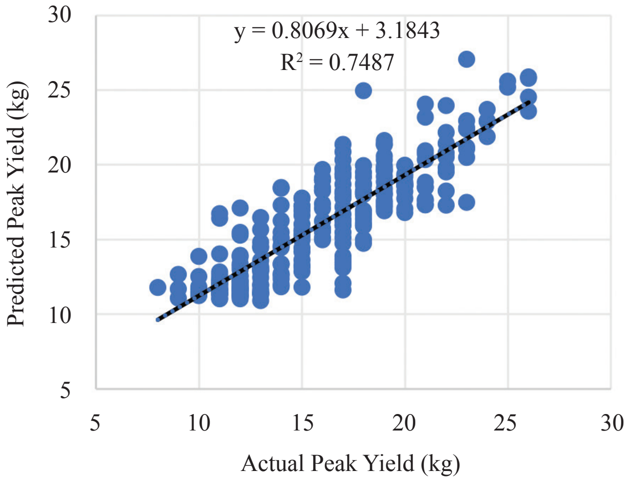

Fig. 1. Scatter plot of comparison of actual and predicted peak yield using ANN model.

Random forest: Random forest algorithm was implemented using the 'RandomForest' feature available under tree classifier in WEKA. Different models were trained by varying the various parameters to check accuracy of the model. Parameters varied were depth of tree, i.e. growth of a tree (*maxDepth* = 0(unlimited) and 10); number of randomly chosen attributes in a subset of data for building a tree (*numFeatures* (k)= 0 (0 means {log2(total number of features) + 1}), 5, 6 and 7); number of trees to build in RF (*numIterations* = 50, 100, 200). Other parameters were set at their default values. All models were trained and validated with 10-fold cross validation method. The optimum results were obtained with minimum RMSE as 2.1215 at parameter values *maxDepth* = 0 (unlimited) growth; *numFeatures* (k)= 0 (0 means {log2(9) + 1=4}); and *numIterations* = 100. In addition, the algorithm also identified the attribute importance (based on average impurity decrease) contributing towards the output attribute (Peak yield) as given in Table 3. The relationship between predicted Peak yield values and the original values is shown in Fig. 3.

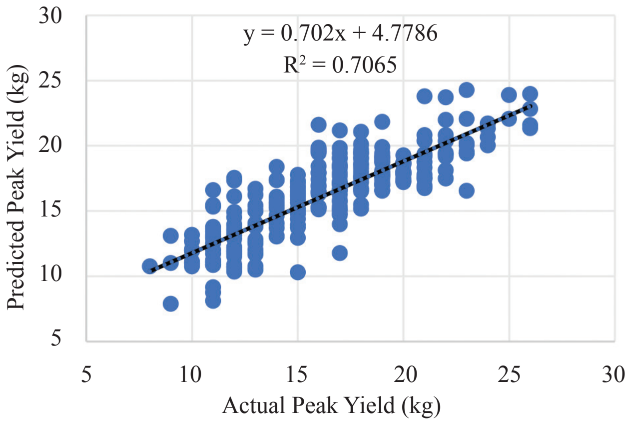

Fig. 2. Scatter plot of comparison of actual and predicted peak yield using SVM model.

Multiple linear regression (MLR): The MLR was

Table 3. Importance of attributes

Attribute	Average impurity decreases
Rear udder height	130.96
Lactation number	97.71
Fore rear teat distance	46.63
Rear udder width	41.32
Rump width	21.76
Udder depth	20.21
Teat length	17.46
Rear teat distance	17.44
Naval udder distance	15.22

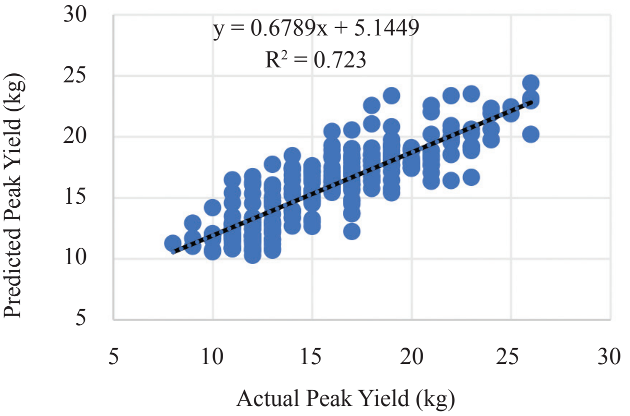

Fig. 3. Scatter plot of comparison of actual and predicted peak yield using RF model.

implemented using the Linear Regression function available under function classifier in WEKA. The optimum results were obtained with minimum RMSE as 2.1553 by setting the value of parameter *attribute selection method* as 'no attribute selection' and other parameters were set at their default values. Models were trained and validated with 10-fold cross validation method. Regression model developed by the model to predict peak yield is given below (equation 3). The relationship between original Peak yield and predicted values is shown in Fig. 4.

$$PY=11.7197+0.1341UD-0.2119NUD+0.2106RTD +0.2068FRTD+0.3469TL+0.668RW+0.1525RUW-0.2564RUH+0.5765LN \quad (3)$$

The results of performance evaluation of all algorithms is presented in Table 4. It was observed that performance of the ANN model is relatively better with minimum RMSE (2.0308) among all other models. The relationship (measured as R^2) between original values of Peak yield and predicted values is maximum in case of ANN (R^2 =0.7415) in comparison to other models. This implies that ANN model has high accuracy of prediction in comparison to other models. It is clearly visible that performance wise (based on RMSE), ANN algorithm is closely followed by RF. SVM algorithm has performed poor with maximum RMSE among all algorithms. Performance of RF, SVM and MLR is very close to each other.

Another significant observation is that there was not much difference in RMSE of all these algorithms. It varied in the range from 2.03 to 2.17. Therefore, further analysis was carried out using paired t-test (in WEKA Experimenter) to determine whether performance of these algorithms differ statistically significant from each other or not (Supplementary Table 2). As per the analysis, it was found that the performance of these algorithms did not differ significantly at 5% level of significance. It means that performance of all algorithms was almost similar and any one of these algorithms can be used for prediction of peak milk yield. Most probably this may be due to the relationship between input attributes (i.e. linear traits) and output attribute (peak yield) which is almost linear. Therefore, the RMSE of linear and non-linear methods is very close to each other.

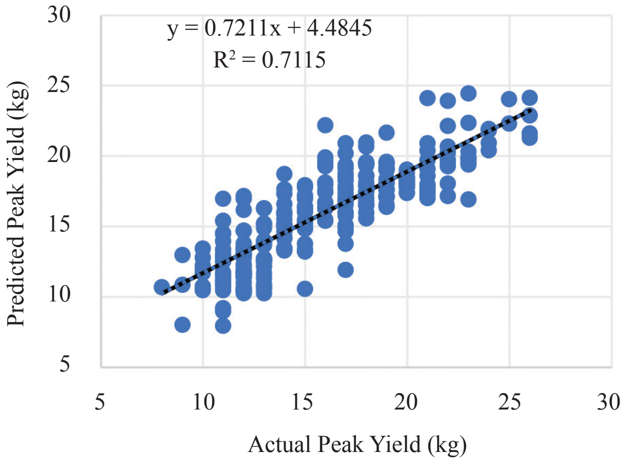

Fig. 4. Scatter plot of comparison of actual and predicted peak yield using MLR model.

Table 4. Performance evaluation of MLAs

Evaluation metric	ANN	SVM	RF	MLR
RMSE	2.0308	2.1733	2.1215	2.1553
R^2	0.748	0.706	0.723	0.711

As per the performance evaluation, ANN algorithm performed best among all algorithms with minimum RMSE, therefore, can be used for prediction of milk yield. However, as per mathematical modelling, MLR is easy to understand and interpret since it gives a simple mathematical equation for prediction of peak yield. RF algorithm which is next to ANN performance-wise provided additional information about important attributes in determining the peak yield. Top three important attributes are 'Rear udder height' (RUH), 'Lactation number' (LN) and 'Fore rear teat distance' (FRTD).

In the present study, an attempt was made to develop a predictive model for selection of high milk producing dairy buffalo based on peak milk yield. The unique feature of the model is peak milk yield predication on the basis of animals' linear traits. Four type of algorithms (artificial neural networks, support vector machine regression, random forest and multi linear regression), were used in developing and comparing the predictive model. The performance of artificial neural network based model outperformed comparatively over others. The linear traits, viz. Rear udder height, Fore rear teat distance along with 'Lactation number' are most important attributes affecting the peak milk yield. Thus, artificial neural network-based model can be used to develop a low cost decision support system for selection of female buffaloes in absence of authentic record of peak milk yield for high productivity and breed improvement programs.

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