Original Research Article

Machine learning-based prediction of cattle body weight using muzzle morphometrics

ABSTRACT

Body weight measurement of cattle is a tedious farm operation but is essential for their health maintenance at farm. This study proposes a novel and easier approach for cattle body weight prediction using muzzle morphometrics. Vrindavani crossbred cattle of different age groups were considered for the study. The muzzle images were collected and analyzed in MATLAB for determination of muzzle dimensions followed by mapping the dimensions to the body weight of the cattle using artificial neural network with varying network parameters. The results of the showed that all muzzle parameters had good correlation with the body weight of the cattle. Further, it was also observed that the combination of Levenberg-Marquardt training algorithm with logsigmoidal transfer function performed the best with model simulation accuracy of 78.07%. The study concludes that muzzle morphometrics may be used for body weight measurements, however, newer or diverse muzzle parameters may be considered in future works to further improve the model accuracy for a more practical application.

Keywords: Artificial neural networks, Image processing, MATLAB, muzzle prints

1. INTRODUCTION

Similar to human fingerprints, cattle muzzle prints exhibit unique patterns of grooves and beaded structures. These irregular features, distributed across the skin surface of the nose area, are characterized by white skin grooves and black convex areas enclosed by the grooves [1]. Muzzle prints serve as precise and unchanging biometric identifiers, comparable in accuracy to human fingerprints, enabling the identification and management of individual animals [2]. Research into animals' muzzle prints, also known as nose prints, dates back to 1921 [3]. According to Sisson and Grossman [4] and Dellamann and Brown [5], distinctive elevations and grooves on the muzzle serve as identifying characteristics. However, the characteristics of muzzles may provide more insight into other cattle features such as milk production and body weight.Indrabayu and colleagues emphasized that the muzzle of cattle represents a distinctive physiological aspect of their anatomy[6]. Cattle muzzle prints exhibit distinguishing characteristics referred to as beads and ridges. Beads are irregularly shaped areas resembling islands, while ridges are elongated features resembling rivers with varying widths. These attributes play a crucial role in identifying individual cattle. According to studies conducted by some researchers muzzle measurement (muzzle width) had significant and positive correlation with milk yield [7, 8]. Pankaj and Nagpaul[9] found positive and significant correlation between body weight and different muzzle measurement. It means that muzzle measurement can be used for prediction of production performance and also for prediction of body weight of animal. However, the relation between the muzzle pattern and body weight may be highly complex. To map such a complicated association of parameters, traditional modelling techniques may not be adequate and a more advanced modelling tool is required. To this effect, the use of machine learning tools has been recommended.

In recent years, machine learning (ML) has demonstrated significant potential in various agricultural applications, including livestock management. Xiong et al. [10] have demonstrated the accuracy of using depth images for predicting body weight (BW) and body condition scores (BCS) of mature beef cows, achieving a strong correlation (r = 0.9166) between image-projected body volume and measured BW. This indicates the viability of non-invasive methods for livestock weight estimation. Bhoj et al. [11] developed a highly accurate machine learning model for predicting the dressed weight of pigs using morphometric measurements, achieving 99.8% accuracy with the LM training algorithm and logsigmoidal transfer function. Similarly, Chu and coworkers developed an automatic detection method for dairy cow mastitis by fusing udder temperature and size features, achieving an accuracy of 88.61% using a deep learning-based approach, thus highlighting the integration of multiple biometric features for health monitoring [12]. Fulbert et al. [13] employed ML techniques for pure-bred taurine recognition, attaining an accuracy of up to 87% with the RBF non-linear SVM model, demonstrating the application of ML in preserving cattle genetic heritage through precise breed identification. Additionally, Chen et al. [14] reviewed deep learning methods for posture detection in pigs, which could be adapted for cattle to monitor health and welfare, showcasing the versatility of ML in animal husbandry. Furthermore, Wang et al. [15] improved pig face recognition using a combination of ResNet and attention mechanisms, achieving 95.28% accuracy, demonstrating the potential of advanced ML techniques in individual animal identification. These studies collectively affirm the efficacy of machine learning in enhancing livestock management through precise and efficient biometric analyses.

Artificial Neural Networks mimic the structure and function of the human brain, comprising interconnected artificial neurons arranged in layers. These layers, including the input, hidden, and output layers, process information by transmitting signals, enabling pattern recognition and learning from data. During training, ANNs adjust the connection weights between neurons to minimize errors between predicted and desired outputs. They excel in tasks such as classification, regression, and feature extraction when abundant training data is available. However, training ANNs can be computationally intensive, and interpreting their decisions may pose challenges. Designing effective ANN architectures involves considerations such as the number of layers, neurons per layer, and choice of activation functions. Despite these complexities, ANNs remain a foundational tool in deep learning, offering substantial capabilities for diverse machine learning applications with appropriate data and computational resources.

In this study ANN was used to map the relationship between the muzzle morphometrics and the body weight of crossbred cattle. The result of this study is expected to spark future work in muzzle-based cattle identification, traceability and management systems.

2. MATERIAL AND METHODS

2.1 Animals considered and their management

The present study was carried out in the Cattle and Buffalo Farm, Livestock Production and Management (LPM) Section, Indian Veterinary Research Institute (IVRI), Izatnagar, Bareilly (U.P.). The data was collected from 100 crossbred cattle (*Vrindavani*-developed by ICAR-IVRI) of different age groups which were kept under uniform managemental conditions. Only healthy animals were selected for the study to avoid error in measurements.

2.2 Image acquisition and processing

Cattle head images were captured in an unconstrained environment using a 64 MP phone camera. Ten images per cattle was collected resulting in a total of 1,000 muzzle images. Images were pre-processed in MATLAB v.2012b (MathWorks Inc., USA) running on an Asus laptop with AMD Ryzen 3, 8GB RAM with Microsoft Window 11 64-bit operating system. For morphometric measurement of the muzzle, images collected from the animals were subjected to processing in MATLAB which involved the selection of the region of interest (ROI) followed by measurement of the specified muzzle morphometry parameters. Various muzzle features were extracted from the images, including upper muzzle length, basal muzzle length, muzzle height, distance between nostrils, muzzle area, and bead count. The most correlated parameters were used as input for the machine learning-based model (ANN).

2.3 Model development

ANN (a form of machine learning) models with feed-forward backpropagation algorithm were developed in MATLAB. Three training functions namely, Levenberg-Marquardt, Gradient Descent with adaptive learning rate backpropagation and Bayesian regularization were used. Two different transfer functions were used in the hidden layer namely, tansigmoid and logsigmoid while purelin was used in the output layer. The number of hidden layer neurons were varied from 5 to 30. Data training to testing ratio was fixed at 70:30.

3. RESULTS AND DISCUSSION

Initial investigations in the form of correlation analysis between the muzzle dimensions and body weight showed that all muzzle measurements had asignificant correlation to body weight and were considered as input to the model with body weight as the output parameter. The models were trained with a termination criteria of 1000 epochs or error goal of 10^{-6}, whichever reached earlier. The prediction efficiency of the different algorithms considered have been detailed in the sections to follow.

3.1 Prediction efficiency using Levenberg–Marquardt (LM) training algorithm

Figure 1 shows the variation in the Overall-R and MSE-validation with LM training algorithm with varying HLNs and transfer function. When logsigmoidal transfer function was used, the Overall-R increased with increase in HLNs till 15 beyond which the R decreased till 25 HLNs. When tansigmoidal transfer is applied highest Overall-R is observed at 15 HLNs 0.873. In general, for LM training algorithm, logsigmoidal transfer function with 30 HLNs was found to be most suitable resulting in Overall-R of 0.884 and MSE of 0.027.

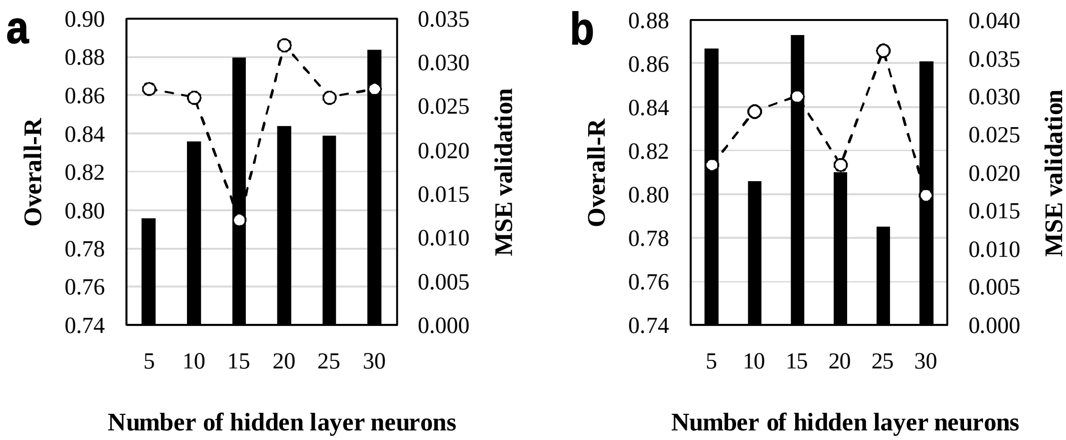

Fig.1. Performance evaluation of MM-BW model with LM training algorithm with (a) logsigmoidal and (b) tansigmoidal transfer function for body weight

3.2 Prediction efficiency usingVariable Learning Rate Backpropagation (GDX) training algorithm

When the tansigmoidal transfer function were used with GDX training algorithm the Overall-R increased as the number of hidden layer neurons increased till 30. Figure 2 illustrates the fluctuation in Overall-R and MSE-validation when employing different hidden layer neurons and transfer functions within the GDX training algorithm. Lowest Overall-R was observed in logsigmoidal transfer function at 5 and 30 HLNs. Overall, for the GDX training algorithm, the logsigmoidal transfer function performed best with 15 hidden layer neurons, yielding Overall-R of 0.839 and MSE of 0.028.

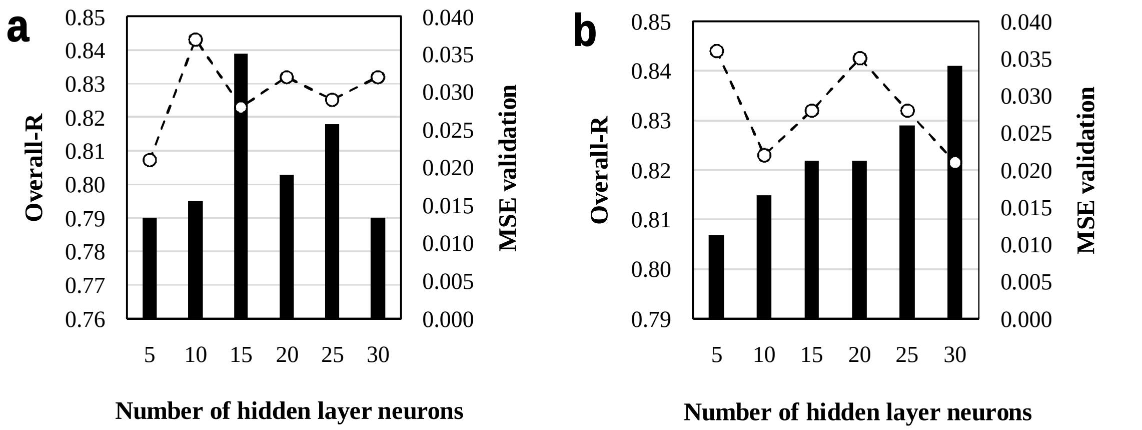

Fig.2. Performance evaluation of MM-BW model with GDX training algorithm with (a) logsigmoidal and (b) tansigmoidal transfer function

3.3 Prediction efficiency usingBayesian regularization backpropagation (BR) training algorithm

When logsigmoidal transfer functions were utilized alongside the BR training algorithm as the number of hidden layer neurons increased from 10 HLNs, the Overall-R demonstrated a downward trend till 30 HLNs. Similarly, in tansigmoidal transfer function Overall-R showed decreasing trend with increase in HLNs. High value of Overall-R was observed at 5 hidden neuron layers in tansigmoidal training function. Lowest MSE validation 0.030 was observed at 25 hidden neuron layers in tansigmoidal transfer function. In general, when employing the BR training algorithm, the tansigmoidal transfer function exhibited optimal performance with 5 hidden layer neurons, resulting in an Overall-R of 0.737 and MSE of 0.045. Figure 3 depicts the variability in Overall-R and MSE-validation while utilizing various combinations of HLNs and transfer functions within the BR training algorithm.

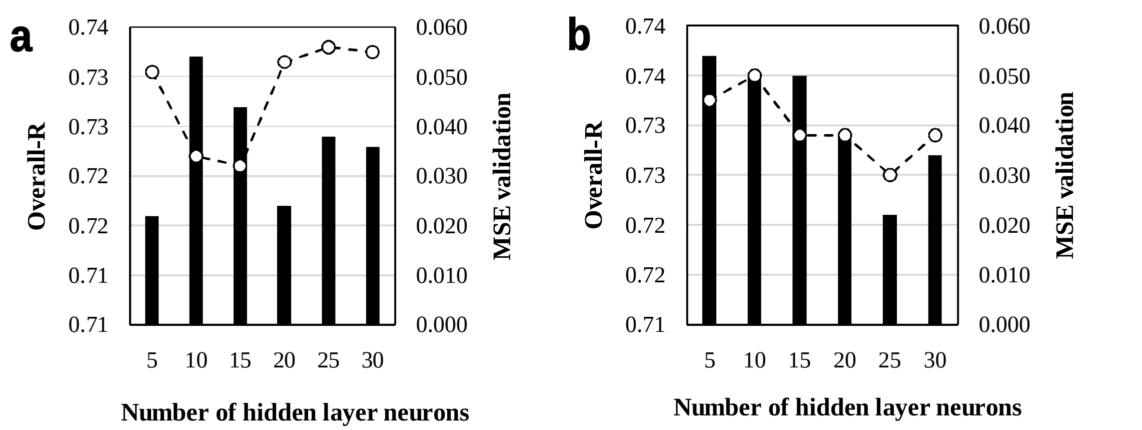

Fig.3. Performance evaluation of MM-BW model with BR training algorithm with (a) logsigmoidal and (b) tansigmoidal transfer function

3.4 Selected ANN model for prediction of body weight

Table 1 shows the comparative performance of the different models generated in this study. Upon applying the LM training algorithm, it was observed that the LM-logsigmoidal transfer function yielded the best performance. This configuration achieved an impressive Overall R value of 0.884 with a relatively low Mean Squared Error (MSE) of 0.027, utilizing 30 HLNs. Subsequently, the GDX training algorithm was utilized with both transfer functions. It was found that the tansigmoidal transfer function performed well under the GDX algorithm, resulting in an Overall R of 0.841 and an MSE of 0.021, also at 30 HLNs. Finally, the BR training algorithm was applied with both the logsigmoidal and tansigmoidal transfer functions. However, this approach resulted in a lower Overall R of 0.737 and a higher MSE of 0.045, utilizing 5 hidden layer neurons.

Table 1. Performance of selected MM-BW model for prediction of body weight with different algorithm

Algorithm	No. of HLNs	TF	Training R	Testing R	Validation R	Overall R	MSE
LM	30	Logsigmoidal	0.867	0.987	0.803	0.884	0.027
GDX	30	Tansigmoidal	0.809	0.928	0.897	0.841	0.021
BR	5	Tansigmoidal	0.729	0.702	0.852	0.737	0.045

3.5 Model simulation

It was noted that the logsigmoidal transfer function, coupled with the LM training algorithm, exhibited the most optimal performance. This configuration, utilizing 30 hidden layer neurons, achieved a remarkable Overall-R value of 0.884, along with a relatively low Mean Squared Error of 0.027. This high Overall-R value indicates a strong correlation between the predicted and actual body weight data, while the low MSE suggests minimal error in the predictions. Following the selection of this model, a simulation was conducted to evaluate its predictive accuracy. During simulation, the model's predictions were compared against the actual body weight data. Through this simulation, the ANN model demonstrated an impressive accuracy of 78.07%. This accuracy metric reflects the degree to which the model's predicted body weights align with the observed values in the dataset.

4. CONCLUSION

The results of this study indicate that muzzle dimensions in terms of the upper muzzle length, basal muzzle length, muzzle height, distance between nostrils, muzzle area, and bead count can be considered for the prediction of body weight of crossbred cattle with relatively good accuracy. However, there is still many parameters in terms of complex muzzle geometries such as perimeter, eccentricity, sectional area etc. that may be considered in the future to improve the accuracy further. The use of convolutional neural networks for direct prediction of body weight based of intrinsic muzzle characteristics may also be looked into to save the time required for feature extraction and training of ANN.

Disclaimer (Artificial intelligence)

Authors hereby declared that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

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