Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 198 (2022) 263–268

Procedia Computer Science

www.elsevier.com/locate/procedia

International Workshop on Computational Intelligence and Cybersecurity in Emergent Networks (CICEN 2021)
November 1-4, 2021, Leuven, Belgium

Classification of Body Weight in Beef Cattle via Machine Learning Methods: A Review

Moad Hakem*, Zakaria Boulouard, Mohamed Kissi

Department of Computer Sciences, Faculté des Sciences et Techniques, Hassan II University, Mohammedia, Morocco

Abstract

Livestock producer's profits are generally linked to the weight of their animals. This will allow them to better plan their supply of the worldwide increasing demand on meat An interesting approach to address the issue of final performance prediction is to use machine learning techniques. In this paper, we will review a number of papers that have attempted to address this issue using machine learning algorithms such as multiple regressions, partial least squares regression, random forests, naive Bayes, support vector machines and artificial neural networks. Based on previously collected datasets of animals at different stages of growth, these algorithms attempt to predict the final performance of new animals. The quality of the predictions is measured using different parameters such as accuracy, sensitivity, mean absolute error percentage and root mean square error.

Keywords: Beef cattle, Heifers, Final Yield Prediction, Support Vector Machines (SVM), Multiple Regression, Partial Least Square Regression, Random Forests, Naïve Bayes, Artificial Neural Networks (ANN).

* Corresponding author.
E-mail address: moad.hak@gmail.com

10.1016/j.procs.2021.12.238

1. Introduction

Whether for meat or milk, beef farmers strive to provide the best conditions for their cattle to ensure the highest production rates. Many factors come into play in their strategies. For meat producers, the final weight of the beef at slaughter is a key element that needs to be predicted, while for dairy producers, the survival rate of heifers is important to ensure continued production. The ability to predict these indicators in advance can help producers optimize their strategies for better production.

Machine learning techniques have recently emerged as effective approaches for prediction-oriented analysis. Their range of applications is very wide and they can provide adequate results based on the data provided to them. Recent technological advances have introduced machine learning and big data into agriculture. Data is collected using different approaches such as weighting, sensors, image capture, etc., and then analysed using machine learning approaches to provide decision support indicators.

The fields of livestock management have also developed to adopt such approaches, whether for dairy or meat products, indicators such as final weight and survival rate can be measured and predicted using machine learning techniques.

In this paper we will provide a comparative review of the different approaches taken by recent papers that have successfully introduced machine learning techniques to predict the final weight of beef cattle and the survival rate of dairy heifers.

The datasets collected are for different breeds of cattle such as Angus, Holstein, Korean Hanwoo, etc. and their data has generally been collected at different stages of their growth. The machine learning techniques used range from regression to Naïve Bayes, support vector machines, random forests and artificial neural networks. The quality of the prediction is measured using different indicators such as accuracy, sensitivity, contrast and sensitivity.

2. Materials and Methods

2.1 Data

The amount of data used differs from one approach to another, but there are a few main factors that the authors consider important. The number of cattle can vary from a few hundred to a few thousand. The breed is also a factor to consider, as these studies have tried to cover different breeds that are considered most popular in their region. The age periods and weights recorded in each are also key factors to consider.

Maciuc et al [1] used 120 head of Aberdeen Angus for their studies, while in [2] Lee et al used 134 head of Hanwoo cattle. In [3], Alonso et al. have three datasets, the first includes 351 Angus bulls, the second 822 Asturiana de los Valles, and the third 358 cows from the Wokalup selection experiment. In [4], the authors tried to predict the survival of 6847 heifers to the second stage of lactation.

Cattle weight is usually monitored during the different ageing phases from calving to weaning, fattening and finishing [1], [3]. Other approaches also rely on body fatness and body measurements, as in [2], [5].

2.2 Machine learning algorithms and applications

The application of machine learning algorithms in different subfields of agriculture has opened up new options for predictive analysis in these areas. This includes the possibility of developing models that can be applied to the prediction of final beef weight. In our study, we will review the most popular algorithms that have been used for this purpose.

Multiple linear regression (MLR) [6]: This is used to develop a correlation model between a dependent variable Y and a set of explanatory variables xi. It is usually expressed as follows:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon . \quad (1)$$

Where β_0 is the intercept, β_i is the regression coefficient, and ε is an error term.

Lee et al. [2] used MLR to predict the Hanwoo cattle's carcass weight based on 19 variables that describe the body measurements specific to this particular race. The most significant variables were, later, selected based on p-values that were inferior to 0.05. The data is split into two sets, the first, used for training, contained 100 data points, while the testing set contained 34 data points. The model's accuracy was measured using R^2 and the Relative Error metrics.

Partial Least Square Regression (PLSR) [7]: Also known as "Projection to Latent Structures", it is a technique that reduces the amount of prediction variables to a smaller set on which it performs least squares regression, instead of applying it on all the variables.

This method was used by Cominotte et al. [8] to reduce the amount of factors on each of the cattle's aging phases (Table 1).

Table 1. Amount of factors adopted by Cominotte et al. [8] for each aging phase.

Aging Phase	Weaning	Beginning of Feedlot	End of Feedlot	Finishing	Complete
Number of PLS factors	2	3	3	14	6

Lee et al. [2] also used this method and were able to reduce the number of variables to 4 instead of 19.

Support Vector Machines (SVM) [9]: This is a technique that builds a set of hyperplanes that separate the data into categories. The best separation is one where the data is as far away from the outlier hyperplanes as possible. SVM can be used as a classification or regression algorithm.

Alonso et al [10] used SVM in regression to predict carcass weight of beef before slaughter. They also used it in classification [3] to estimate the meat weight trajectory. Nucci et al [5] also used SVM to estimate the fatness of the beef carcass in the finishing phase.

Naïve Bayes [11]: This classification technique is based on a combination of Bayes' rule and the assumption that the variables are independent. Although the independence condition is not usually met in practice, this algorithm generally gives good results.

Van der Heide et al [4] applied Naïve Bayes to rank heifers according to their survival chance set to 0.858. They stated that the algorithm is very efficient and that it is not too expensive. They stated that the algorithm can have problems with unbalanced data, but that it did not cause any problems for their own dataset.

Random forests [12]: This is an ensemble learning technique that can be used for prediction or classification tasks. It starts by assigning the training process to a number of decision trees, each with a subset of the data to be trained. The output of the random forest algorithm will be the average of the predictions of its decision trees.

In their study, Van der Heide et al [4] defined 500 decision trees and distributed their variables in a range of 6 to 12 per tree, these values giving the best performance. For their five datasets, they used 70% of the data for training and the remaining 30% for testing.

Artificial Neural Networks (ANN) [13]: This is a technique that simulates the neurons in the human brain in their ability to learn and perform computations. An artificial neural network is a set of interconnected nodes (neurons) that are organised into layers (input layer, hidden layer and output layer). The artificial neural network is usually used for classification problems, but it can also handle prediction. The number of hidden layers should be chosen to balance the accuracy of the test data with the efficiency of the learning process.

Lee et al [2] used ANNs to predict carcass weight. They equipped their neural networks with a two-level hidden layer, the first level having 15 neurons and the second level having 6 neurons. 100 data points were used for training and 34 for testing.

Cominotte et al [8] applied an ANN to predict the weight of beef in the finishing stages. They also used a two-level hidden layer coupled with LASSO and Ridge regularisations to control overfitting.

3. Results and Discussion

In this section, we will discuss the results obtained in three recent works that effectively used machine learning approaches for three prediction situations. Lee et al [2] used multiple linear regression, partial least squares regression and artificial neural networks to predict carcass weight of Hanwoo cattle based on body measurements. Alonso et al [3] used SVMs to predict the final weight of three different breeds of cattle. Van der Heide et al [4] used regression, Naive Bayes, and random forests to predict survival of Holstein heifers to the second stage of lactation.

For testing. As a first attempt, Lee et al [2] applied the multiple linear regression model to their data using all variables, to find that 6 variables were the most significant (L, FT, EMA, L6, L11, and L12) with $R^2 = 0.91$ versus 0.93 for all variables. The model was developed using 100 data points for training and the average relative error was approximately between 4% and 10%. The maximum error was found in the bull with the least weight.

The main shortcoming of this approach is the high multicollinearity of the model variables, which requires multivariate analysis.

Partial least squares regression was suggested by Lee et al. [2] to solve this problem. Based on the 4 principal components which showed satisfactory results, and considering the results of the MLR approach, they chose the same variables for the PLSR model as for the MLR model. The PLSR model was developed using 100 training data and 34 test data. It gave an R^2 result of 0.91 versus 0.92 for all variables.

The results of the PLSR model were approximately similar to those of the MLR model, with the largest error being related to the same individual.

In their third approach, Lee et al [2] applied the ANN model to their data. They used the same 6 variables as in the other two models as significant variables. The validation cost reached its lowest level after 1192 iterations. The prediction showed a result of $R^2 = 0.92$ for the 6 significant variables against 0.93 for all variables. An even better performance was shown using all variables plus two others (age and gender) with $R^2 = 0.94$. In this case, the lowest validation cost was achieved after 1334 iterations.

The number of data points (134) used for training and testing the ANN models was not sufficient compared to other studies. This study also showed that ANNs could easily fall into local minima or suffer from overfitting when the initial weights were generated at excessive cost.

In their study, Alonso et al [3] tried to anticipate the weights of cattle using support vector machines (SVM).

They started by defining the trajectory of weights over time (expressed in days of age). Six weights were considered and they were recorded between the ages of 180 and 509 days for Angus bulls, between 241 and 508 days for Asturiana de los Valles bulls, and between 19 and 82 months for Wokalup Selection Experiment cows.

By coupling the weights and days in their data, Alonso et al [3] were able to define an optimisation problem capable of describing the trajectory of the herd weight for each of the three breeds. As this optimisation problem is subject to multiple constraints, Alonso et al. suggested using SVM classification as a method to solve the optimisation problem.

For each of the three datasets, 75% of the data was used for training, while the remaining 25% was used for testing. Performance is measured using the mean absolute error percentage (MAPE) and the root mean square error (RMSE).

The results for each data set are shown in Table 2 :

Table 2. Slope of the SVM and Average Daily Gain found by Alonso et al. [3] for each of the three datasets.

	Dataset 1	Dataset 2	Dataset 3
Slope	3.37	1.27	3.83
Average Daily Gain	1.68 kg/day	1.23 kg/day	4.7kg/month

The approach proposed by Alonso et al [3] outperforms linear regression for weight predictions more than 100 days ahead, but between 100 and 60 days ahead, linear regression catches up and outperforms their approach after the 60 day threshold.

Van der Heide et al [4] compared the ability of regression, Naive Bayes and ANN to predict survival of Holstein dairy cows to second lactation. Their dataset contained 6847 Holstein heifers, for which they defined survival as a classification variable that describes their ability to survive until two weeks after their second calving. 5 decision points were considered (birth, 18 months, first calving, 6 weeks after first calving, and 200 days after first calving).

For the regression approach, Van der Heide et al [4] chose a model that includes 6 genomic variables that express fertility, longevity, conformation, mammary gland health and score. For the Naïve Bayes approach, no a priori values were selected. For the Random Forest approach, the number of trees is fixed at 500 and the number of variables varies from 6 to 12.

The three algorithms were trained on 70% of the randomly selected data and tested on the remaining 30%. The survival probability threshold was set at 0.858, so that each heifer that exceeds this level is assumed to survive and each heifer that does not is assumed not to survive. The performance of the algorithms was measured using four indicators: contrast, accuracy, sensitivity and specificity.

For contrast, the Naïve Bayes approach gave the best results for the first two decision moments, and after the first calving, regression gave the best predictions.

In terms of accuracy and sensitivity, again Naïve Bayes performed better than the others at birth, 18 months and 6 weeks after calving. However, it was outperformed by regression at first calving and 200 days after.

For specificity, the Random Forest approach gave the best predictions at first calving and 200 days after, while regression gave the best results at the other decision points.

4. Conclusion

In this study, we have attempted to discuss approaches taken in recent work that have effectively introduced machine learning as a means of predicting indicators needed in the cattle industry. These indicators were final weights for meat-oriented farms, and heifer survival rate for dairy-oriented farms.We presented the specificities of each of the different approaches, the datasets they collected and the indicators they tried to predict, as well as the machine learning algorithms they adopted such as multiple linear regression, partial least squares regression, support vector machines, Naïve Bayes, random forests and artificial neural networks. We also discussed the performance of these algorithms and their shortcomings.

References

[1] V. Maciuc, C. E. Nistor, and E. C. Popescu, “RESEARCH REGARDING THE FACTORS INFLUENCING MEAT PRODUCTION AT A BOVINE HERD,” Lucrări Ştiinţifice, vol. 72, no. Animal Science Series, pp. 229–234, 2019.

[2] D. H. Lee et al., “Estimation of carcass weight of hanwoo (Korean native cattle) as a function of body measurements using statistical models and a neural network,” Asian-Australasian Journal of Animal Sciences, vol. 33, no. 10, pp. 1633–1641, 2020.

[3] J. Alonso, A. Villa, and A. Bahamonde, “Improved estimation of bovine weight trajectories using Support Vector Machine Classification,” Computers and Electronics in Agriculture, vol. 110, pp. 36–41, 2015.

[4] E. M. M. van der Heide, R. F. Veerkamp, M. L. van Pelt, C. Kamphuis, I. Athanasiadis, and B. J. Ducro, “Comparing regression, naive Bayes, and random forest methods in the prediction of individual survival to second lactation in Holstein cattle,” Journal of Dairy Science, vol. 102, no. 10, pp. 9409–9421, 2019.

[5] H. H. P. Nucci, R. P. Ishii, R. da Costa Gomes, C. S. Costa, and G. L. D. Feijó, “Classification of Carcass Fatness Degree in Finishing Cattle Using Machine Learning,” in Computational Science and Its Applications – ICCSA 2020, Springer, Cham, 2020, pp. 519–535.

[6] D. C. Montgomery, Introduction to Linear Regression Analysis, Book + Solutions Manual Set, 6th Editio. Wiley, 2021.

[7] G. D. Garson, Partial Least Squares: Regression and Structural Equation Models. Asheboro: Statistical Associates Publishers, 2016.

[8] A. Cominotte et al., “Automated computer vision system to predict body weight and average daily gain in beef cattle during growing and finishing phases,” Livestock Science, vol. 232, no. December 2019, p. 103904, 2020.

[9] S. H. H. Mehne and S. Mirjalili, “Support Vector Machine: Applications and Improvements Using Evolutionary Algorithms,” in Evolutionary Machine Learning Techniques, S. Mirjalili, H. Faris, and I. Aljarah, Eds. Springer, Singapore, 2020, pp. 35–50.

[10] J. Alonso, Á. R. Castañón, and A. Bahamonde, “Support Vector Regression to predict carcass weight in beef cattle in advance of the slaughter,” Computers and Electronics in Agriculture, vol. 91, pp. 116–120, 2013.

[11] G. I. Webb, E. Keogh, R. Miikkulainen, R. Miikkulainen, and M. Sebag, “Naïve Bayes,” in Encyclopedia of Machine Learning, Springer US, 2011, pp. 713–714.

[12] Y. Liu, Y. Wang, and J. Zhang, “New machine learning algorithm: Random forest,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2012, vol. 7473 LNCS, pp. 246–252.

[13] E. Alpaydin, Introduction to Machine Learning, 4th Editio. MIT Press, 2020.