Body Conformation Scoring of Cattle, using Machine Learning

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Abstract: Precision agriculture brings new artificial intelligence techniques closer to everyday farming. Agriculture historical data is easily available, so using this data to teach a machine-learning model, offers various opportunities to enhance farming efficiency. In our study, we develop a machine learning model to estimate some linear traits of Limousin sires (sore for muscularity, length of the rump, muscularity of breast and muscularity of the width of rump), based on a phenotypic score, using artificial intelligence, in Hungary. Phenotypic scores are usually given by the experts in field. Before scoring, many measurements are made on the animals, which takes time and places a high stress on the cattle. A hands-on prediction application can make the whole process faster, and more comparable, regardless of the expert who created the scoring. We found that after collecting sufficient data from previous observations it is possible to train specifically selected artificial intelligence (AI) algorithms to predict linear traits in Limousin breeding bulls. Machine learning (ML) was used to predict the score values for muscularity, length of the rump, muscularity of the breast and muscularity of the width of the rump for this study. We found no similar experiments for the usage of AI algorithms to predict these variables. The coefficient of determination (R^2) of the algorithm, in this study, provided the following range values: (R^2=0.77 to 0.86).

Keywords: artificial intelligence; machine learning; Limousin; bulls; type traits

1 Introduction

AI today is much more than just a scientific discipline in some universities. In previous years, applications of AI algorithms, have been found in many areas of the economy, science and even in everyday life [10]. So, using AI in agriculture is more and more important, as precision agriculture is becoming vital in fulfilling modern economic expectations.

For using AI in any field of science or economy we need a lot of data. IOT technologies and IOT sensors have become cheap and easily accessible for everyone in the past years. So enormous quantity of data is available in agriculture as well. We can measure several different animal data quite easily now to gain valuable data for further analysis. Several software-based solutions have been developed to make use of this enormous number of data [17], but using AI gains more and more importance as this number of data grows.

In 2021, a study [14], was published, where animal farms using complex data for their business plans were examined. This study stated that by using AI techniques to analyse data, we are able to understand the workings of complex biological structures. It can provide useful information from of the huge number of provided data.

AI and machine learning can be used in many aspects of agriculture, not just animal framing. Machine learning has been used to analyse databases, but also for analysing pictures taken of fruits (e.g., apples), individual animals or herds of animals. In an experiment, digital images were used to detect defects in apples using CNN and Transfer Learning [9].

One of the most important measures of the cost-effectiveness of animal husbandry is stocking density, i.e., how many animals can be kept in a given area per unit of time. There are at least two more important factors when observing the costs of animal husbandry: the cost of feeding and the cost of treating diseases. Dealing with both cost factors we will need human intervention. So human resources will thus correlate with stocking density in this way. Using AI algorithms, we can optimize animal feeding, and we can predict diseases as well. Thus, by optimizing intervention, we can significantly optimize costs.

Using IOT sensors and GPS data together with AI, can further enhance our knowledge of managing animal husbandry. [15] showed that by the collected data we can evaluate animal behaviour which can be used for the prevention of disease in advance. Several other studies have confirmed that Big Data and AI can effectively predict various animal diseases [4] [21].

Data has been collected for many years in animal farming to ensure food quality. A huge amount of manually or digitally collected databases are available to teach a machine learning model.

The body conformation scoring (BCS) system is used to categorize cows and serves as a basis for pricing and future usage. There is a close relationship between BCS at calving and the first 90 days after calving to the calf's health and future potential.

Earlier studies have shown that the connection between phenotype and expected progeny difference, is stronger in meat production traits than in other traits [20]. Visually assessed beef traits have a relatively high heritability. We also know from earlier studies, that there is a correlation (0.70<=) between muscularity and slaughter traits and we can safely use different types of classification methods in practice [7] [11]. Proper beef selection is very important in the breeding programs for beef cattle breeds – that is, where type classification can assist better planning.

Body condition scoring is widely used in other aspects of cattle breeding. So new techniques for predicting body condition, are very important for farmers. For example, camera pictures were used to calculate the body condition and production parameters of dairy cows in an experiment with the use of a BCS camera [3].

In Hungary, we have used type classification since 1986, based on four principal quality groups (utility score, score for length, score for width, score for muscularity) and included 22 type traits. Since then, results have proved that type classification can help better selection, in real-life circumstances.

So, our next goal is to introduce AI to help with filed type classification based on earlier expert results. In this research, our goal is to develop an AI model that can estimate some traits of great importance for Limousin bull's classification. Such a model can serve as a basis for developing a more general prediction model for condition scoring of several different types of bulls.

1.1 AI-assisted Body Condition Scoring

The body condition scoring method is used to characterize the fat reserve and energy balance of cattle. Regular body condition scoring is very important for breeding efficiency as it also affects milk production, reproduction and general animal health. In this way, it has an impact on the composition and quantity of animal feed and, on the efficiency of the whole economy. It is important to know when cows can be kept on lower-quality feed, when the quality and content of the feed may need to be improved, or when the existing level should be maintained. This requires a precise definition of the animal production cycle and how to change the feed to improve reproductive biological properties.

Body condition scoring is usually done after various measurements and tests made by an expert. Assisting this expert scoring with an application based on our model is also a promising development opportunity.

[21] presented a method in their study that attempted to estimate body condition scores in cows using images taken with fixed cameras. The captured images were processed using a convolutional neural network and the system was taught to score. The achieved result has an approximate 80% accuracy.

We can see that modern AI methods, properly applied, can give a very accurate estimate, even for qualitative characteristics that could previously only be determined by specialists.

1.2 Regression Results in Cattle Breeding

Regression is one of the most important models which are used in machine learning. In regression models, the predicted output variable should be a continuous variable, such as predicting the weight of an animal on a farm. In our case all possible output variables were continuous.

The regression model also lets us use a supervised learning method, where we'll use past data to predict the output variable.

In earlier studies, mathematical models were used to predict some important factors of cattle beef. This serves us as a good comparison to validate our AI model to traditional mathematical solutions. The results of former normal statistical regressions on live weight and scrotum circumference in cattle breeding are shown in Table 1 as a reference for our AI algorithm.

Table 1
Former results of regression models on live weight and scrotum circumference in cattle breeding

Principal objective	Breeds	Results	Source
Scrotum circumference (SC)	Different beef breeds	Live weight was a strong or medium correlation with scrotum circumference. The prediction equation for SC is based on the age of the bull in the practice.	[2] [8] [13]
Predicting of live weight (LW)	Female dairy cattle, mainly comprising indigenous Zebu and their crosses with Guzerat or Bos Taurus.	The best model to predict LW from heart girth (HG) for the overall data was good with an adjusted R^2 of 0.85.	[19]
	Holstein, Brown Swiss and crossbred cattle.	Chest girth (CG) was the best parameter of all for prediction of body weight in Brown Swiss (R^2=91.1%) and crossbred cattle (R^2=88.8%) in comparison to Holstein (R^2=60.7%).	[15]
	Indigenous, Friesian, Brahman, Red Dane and Crossbred cattle.	LW was highly correlated (r= 0.90) with body length, heart girth and height at withers. Correlation with HG was very strong (r = 0.96).	[5]

	Holstein crossbred cattle (male and female)	Only HG measurement is sufficient (R^2= 0.95) to predict LW reliably in female calves of birth to six months of age.	[1]
	Crossed cows	The effect of HG on live weight was R^2 = 0.53-0.78.	[11]
	Girolando cattle	Step-by-step regression analysis HG and the picture of the surface of the back determine live weight the most (R^2=0.70).	[22]
	Limousin bulls	LW was mainly determined by the width of the shoulders and the wither's height (R= 0.74).	[20]

The best results for predicting live weight were mostly determined by heart girth and chest girth in dairy cattle. In the Limousin breed, live weight was affected by two parameters (width of shoulders and the withers height).

These predictions are important for the breeders for better selection. Another possibility of this prediction for usage in practice is to make a standardization of one parameter using more traits e.g., correction of scrotum circumference by age.

Based on the above assumptions we decided to make a study to estimate some linear traits of Limousin sires (sore for muscularity, length of the rump, muscularity of breast and muscularity of the width of rump) based on phenotypic score using artificial intelligence.

2 Materials and Methods

The objective of this study was to compare the predictive performance of two machine learning methods, linear regression and Poisson regression for the prediction of different phenotype parameters. We wanted to see which model gives a better result and how they compare to the mathematical prediction techniques.

Comparisons in terms of mean absolute error and coefficient of determination were used as metrics.

Regression-based model building in AI, is a machine learning technique that attempts to model the relationship between the independent predictor variables X and a dependent quantitative response variable Y. The predictor and response variables must be numerical values. A general (linear) regression model mathematically looks like this:

$$Y \approx \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (1)$$

Since a regression model approximates the relationship between the variables, by adding an irreducible error term we get:

$$Y \approx \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \in \quad (2)$$

Where ∈ is the mean zero random error.

We also used Poisson regression which is a generalized linear model. Here, the predicted value is linked to a linear combination of the input variables using an inverse link function. Also, the squared loss function is replaced by the unit deviance of a distribution in a reproductive exponential dispersion model (EDM). So, the algorithm will minimize the next function:

$$\min_{w} \frac{1}{2n_{samples}} \sum_i d(y_i, \hat{y}_i) + \frac{a}{2} \|w\|_2^2 \quad (3)$$

Where $\hat{y}_i$ is the predicted value and a is the regularization penalty.

For our training database conformation scores of 325 animals were collected in one Limousin seedstock herd. The animals were the progenies of 18 sires, born between 1990 and 1996. Sire candidates 12 months old were officially qualified at the end of the performance test. Four trait groups were formed, including four traits in each.

For this study, we built a system which can be re-used easily later to be trained with data from other farms. The structure of the workflow of our prediction system can be seen in Figure 1.

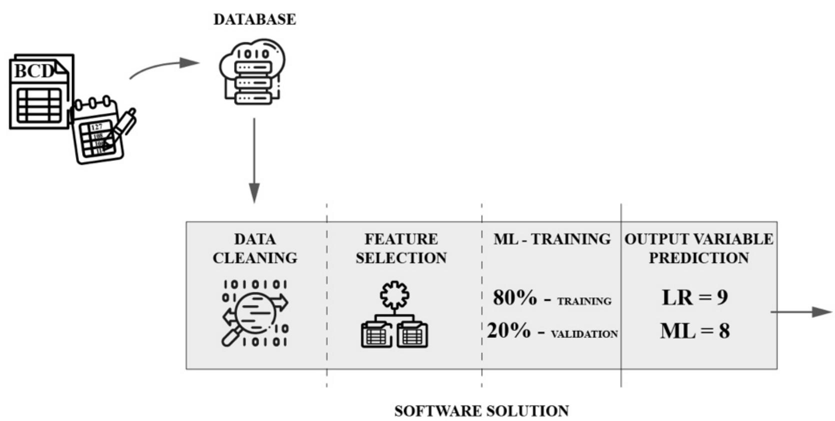

Figure 1
Our software solution for building an application for body conformation scoring of cattle

Recorded data (Table 2) were used to train different regression-based AI algorithms. We built the whole prediction system using Python. The data cleaning and transformation were also written in Python. For teaching the model we used the scikit-learn Python module. For training our machine learning algorithms we have separated our database into two parts. First, we used 80% of our data to train the algorithm. The remaining 20% of the data were used to test and verify the algorithm after training.

Table 2

Description of variables used in our prediction model

Dependent variables	Independent variables
Score for muscularity (0-60 score)	Score for utility value, Score of length, Score for with (0-40 score, or 0-60 score)
Length of the rump (1-9 score)	Length of the body, Length of the back, Length of the loin (1-9 score)
Muscularity of the breast (1-9 score)	Muscularity of shoulder, Muscularity of back, Muscularity of the round of rump, Muscularity of the width of rump (1-9 score)
Muscularity of the width of the rump (1-9 score)	Muscularity of breast, Muscularity of shoulder, Muscularity of back, Muscularity of the round of rump (1-9 score)

We made 10 runs for teaching the model, each time with a different random state – so we ensured that each time the teaching and the validation part of the database was different. In our results we will use the best results from the 10 runs.

3 Results

Although in our experiment we used a little different phenotype parameter to predict the correlation between the parameters, former studies gave us a firm guess of which machine learning model to use for our AI prediction (regression models).

Testing our trained algorithms, the following results were received which are summarized in Table 3 (only the best results are shown in the table).

Table 3

Prediction results and error of the two models (n=325)

Methods of AI	Dependent variables	Mean absolute error, score	Coefficient of determination, R^2
	Score for muscularity (0-60 score)	3.38	0.86

Linear regression-based algorithm	Length of the rump (1-9 score)	0.21	0.93
	Muscularity of breast (1-9 score)	0.35	0.86
	Muscularity of the width of rump (1-9 score)	0.41	0.77
Poisson regression-based algorithm	Score for muscularity (0-60 score)	4.00	0.81
	Length of the rump (1-9 score)	0.23	0.92
	Muscularity of breast (1-9 score)	0.39	0.82
	Muscularity of the width of rump (1-9 score)	0.49	0.73

It can be seen that R^2 values are very similar to each other, especially in the Score for Muscularity score. That means that the model selection was good, and both models could be used to build a useful application. However, the value of R^2 of the Linear regression algorithm was slightly better than the result of the other method for the Length of the rump. The Muscularity of breast results were similar for the first and second models. The Muscularity of the width of the rump data for the Poisson regression-based algorithm was smaller than the R^2 value calculated for the Linear regression model. The mean of the error values during the application of the Linear regression model were small, therefore – based on our data – we would recommend the application of this algorithm in later practice. We calculated larger error values for all four parameters when using the Poisson regression method. In terms of the applicability of the estimate, the value of 86% can be said to be very good and comparable to mathematical modelling.

Our results have a small variability, but well suggest the anatomical correlations. It is not surprising that the score for muscularity can be well estimated from the results of the three other groups of traits ($R^2 = 0.86$). The relatively good, predicted values for the length of the rump ($R^2 = 0.80$) and the muscularity of breast ($R^2 = 0.86$) are very important for the breeders because it makes possible the reduction of the number of the linear traits.

To further evaluate our prediction system, we did additional evaluations for the prediction of the Length of the rump. Since this evaluation was built into the model, we could do exactly the same benchmarks for all the other output variables.

To visualize our result, we created a straight line from the measured values and in the same graph we plotted our predicted values with red dots (Figure 2).

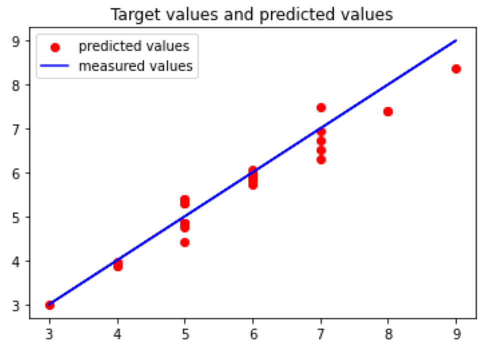

Figure 2
Original target values vs. predicted values

We also created a standard mathematical model for the same prediction as a comparison. We used the statsmodels in Python which is a mathematically verified model to create statistical analysis [6]. The results of the mathematical prediction for the selected output variable can be seen in Table 4.

Table 4
OLS Regression results on the same dataset using Statsmodels

Dep. Variable:	Length of the rump	**R squared:**	0.91
Model:	OLS Adj.	**No. Observations:**	325
Method:	Least Squares		

4 Discussion

Results show us that machine learning prediction using trained models can be used successfully for predicting the scores for our chosen traits: Score for muscularity, Length of the rump, Muscularity of breast, and Muscularity of the width of the rump.

Analysing the measurement results it can be said that by building and using more data from the past even better models can be trained to help real-life trait selection on farms.

Our proposed method for using ML for estimating linear traits on Limousin breeding bulls well fits the line of new technology solutions in helping precision livestock farming. As several ML solutions have been made for diary energy, animal health, animal monitoring and many others [6], our solution can be used for the prediction of several different phenotype parameters using ML.

Considering the modern information technology possibilities, our method can also be easily performed on beef farms using smart tools. So, data can be easily collected and used for training and building new prediction methods for new variables.

Historical scoring data was collected uniformly, thus, the data cleaning software we developed for this study can be used to train the model with new databases.

The machine learning solution proved to be equal to or better than our selected reference mathematical modelling technique. The whole system we developed is fully automatic from the collected data to the predicted value. If data for a different type of beef or different farming environment is available, the model can be easily fine-tuned to give precise results. No expert intervention is needed for teaching and validation can be also done, without any special knowledge.

Conclusions

Based on the main results and the corresponding R^2 values, we can see that trained algorithms can be used with a relatively high confidence level, to predict the important phenotypes of breeding bulls. Of course, we need to collect further data and include that training in the algorithm, to further enhance the effectiveness of the algorithm. We also must analyse the results based on different farm data, to observe the possible differences of the algorithms in different countries.

The initial results, however, prove that sufficiently trained algorithms with can help experts to predict the body condition of many animals. In our study, we found that usually regression-based AI algorithms give good results. We also found that the Linear regression model-based algorithm, gives the best overall result, when predicting the traits of Limousin bulls.

Since this is a general model, which was built using a standard body condition scoring database, this algorithm can be the basis of an application which can be used on-site, to predict some of the body condition scores. Thus, the whole process can be faster and less expensive for farmers.

The model was developed using the results from one farm. Generalization of the model involving data from several other farms could make the model more accurate. Also using the same method for other breeds can alter the results. Further data collection and a more advanced model should be developed in future research projects, to create a generally-usable-application. However, the teaching environment developed for this study can be used to train future models.

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