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A Model to Predict The Live Bodyweight of Livestock Using Back-propagation Algorithm

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Abstract

Cattle is the most popular livestock in Indonesia. Assessments of the live bodyweight of cattle can be conducted through weighing or predicting. Weighing is an accurate method, but it is not efficient due to the prices of scales that most traditional farmers cannot afford. Prediction is a more affordable technique however occurrences of error remains high. To deal with this issue this research has created a model predicting the live bodyweight of cattle through Back-Propagation algorithm. There are four morphometric variables examined in this study: (1) body length; (2) withers height; (3) chest girth; and (4) hip width. Based on comparative results with conventional prediction methods, Schoorl Indonesia and Schoorl Denmark, showed that the method offered has a lower error. Rate of error is 60.54% lower than Schoorl Denmark and 53.95% lower than Schoorl Indonesia.

***Keywords**: Back-propagation, Cattle, Live bodyweight, Morphometric characteristic, Prediction*

1. Introduction

In Indonesia the Bali cattle contributes to the development of livestock industries [1]. Millions of Indonesian families consider Bali cattle the most suitable indigenous cattle breed for the low-input, high stress production system still practiced [2]. Accounting for 25% of cattle population [3], Bali cattle have been used for meat production in small scale units. These cattle are considered being among the most important livestock in the populated regions of Indonesia [4].

The determination of live bodyweight is necessary to: (1) calculate feed requirements; (2) know animal growth; (3) market livestock products; (4) estimate of the animal's cash value; (5) conduct studies such as field experiments; and (6) make an estimation of dressed carcass weight [5]. The live bodyweight of cattle can be determined by weighing them using a scale. However, large capacity scales for cows and bulls are only available in certain locations such as traditional livestock markets or slaughter houses. Possession of this cattle scale among cattle breeders/producers is not common because of its unaffordable price, its impractical size and heavy weight which makes its use in the field inconvenient. The digital version is much smaller in size but its dependence on electricity makes it impractical. Hence it is necessary to create another method for estimating the live bodyweight of livestock [6].

Prediction is another technique which can estimate the live bodyweight of livestock. This technique is cheaper but error is frequent. This is confirmed because the Schoorl formula, employed as one method used, can only be applied on livestock whose live weight is 300 kilograms or over [7]. In addition, traditional farmers estimate the live weight of livestock based on visual cues alone [8].

To deal with the mentioned issues, this study created a model for predicting the live bodyweight of livestock using an Artificial Neural Network of Back-Propagation algorithm. The Back-Propagation algorithm has been chosen because studies have shown that this algorithm is better than the conventional prediction method [9-11]. In addition, this algorithm has also been successful in accomplishing many prediction related cases such as (1) human health issues [12-15]; (2) financial issues [16,17]; and (3) plant disease [18].

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This study used physical morphometries as variables to estimate the live bodyweight of cattle. The variables included four morphometries of cattle known as (1) body length; (2) withers height; (3) chest girth; and (4) hip width. Body length and hip width were chosen since both of them have high correlation coefficient regarding the live bodyweight of cattle [19]. The same characteristic is also showed by withers height and chest girth in that the two variables can estimate live bodyweight of cattle [20].

2. Back-Propagation Algorithm

Back-Propagation algorithm is a multi-layered Artificial Neural Network training method comprising 3 phases [21]: (1) feed forward pattern of input training; (2) calculation and Back-Propagation of respective error; and (3) adjustments of weights. This algorithm can be implemented on the associative pattern, classification of compressed data pattern, robotic control and function of approximation [22]. Algorithm 1 is Back-Propagation which has one hidden layer.

Algorithm 1. Pseudo-code of Back-Propagation algorithm

```
while (iter < MaxIter and err > max_err) do
 for (i = 0 to (sum_of_data-1)) do

  {feedforward phase}
  for (j = 1 to (sum_of_hidden_nds-1)) do
   z_in[j] = 0
   for (k = 0 to (Sum_of_Attrib-1)) do
    z_in[j] ← z_in[j] + x[i,k]*v[k,j]
   endfor
   z[j] ← activation_function(z_in[j])
  endfor
  for (j = 0 to (sum_of_output_nds-1)) do
   y_in[j] ← 0
   for (k = 0 to (sum_of_hidden_nds-1)) do
    y_in[j] ← y_in[j] + z[k]*w[k,j]
   endfor
   y[j] ← activation_func(y_in[j])
  endfor

  {back-propagation phase}
  for (j = 0 to (sum_of_output_nds-1)) do
   s[j] ← (target[j] -
y[j])*activation_function_derivative(y_in[j])
   for (k = 0 to (sum_of_hidden_nds-1)) do
    delta_w[k,j] ← a*s[j]*z[k]
    {weight_adjustment}
    w[k,j] ← w[k,j] + delta_w[k,j]
   endfor
  endfor
  for (j = 1 to (hidden_nd_func-1)) do
   q_in[j] ← 0
   for (k = 0 to (sum_of_outpt_nds-1)) do
    q_in[j] ← s_in[j] + s[k]*w[j,k]
   endfor
   q[j] ← q_in[j] *
activation_function_derivative(z_in[j])
  endfor
  for (j = 1 to (sum_of_hidden_nds-1)) do
   for (k = 0 to (Sum_of_Attrib - 1)) do
    delta_v[k,j] ← a*q[j]*x[k]
    {weight_adjustment}
    v[k,j] ← v[k,j] + delta_v[k,j]
   endfor
  endfor
 endfor
 err ← calculate_err(x,v,w)
 iter ← iter + 1
endwhile
```

3. Research Method

3.1. Data Collection

Data collection was conducted between September 19, 2016 and October 4, 2016 in Pekanbaru City, Riau Province, Indonesia. Variables were observed in the cattle are the live body weight and four morphometric variables (body length, withers height, chest girth, and hip width). Tools were used in the data collection were a digital scale, a measuring tape, and a measuring stick. The digital scale was used to measure the live bodyweight of cattle. The measuring tape was used to find out body length, chest girth and hip width. The measuring stick was used to quantify withers height. The data was collected from 96 livestock comprising 40 cows and 56 bulls.

3.2. Data Normalization

Data normalization was carried out using Min-Max Normalization method before the data were entered the process of Back-Propagation training. This method equalizes range of values among attributes from 0 to 1. Min-Max Normalization formula can be seen in the Formula 1.

$$\mathrm{XNorm_{ij}} = \frac{\mathrm{X_{ij}} - \mathrm{NMin_j}}{\mathrm{NMax_j} - \mathrm{NMin_j}} \quad (1)$$

In Formula 1, $Xnorm_{ij}$ is the value resulting from the normalization at i-th observation at j-th variable, X_{ij} is the original value from i-th observation at j-th variable, $Nmin_j$ is the minimum value of observations at the j-th variable and $Nmax_j$ is the maximum value of observations at j-th variable.

3.3. Architecture of Back-Propagation to Predict The Live Bodyweight

The live bodyweight prediction model was devised by utilizing Artificial Neural Network method of Back-Propagation. The inputs from the Back-propagation are the morphometric characteristics (body length, withers height, chest girth, and hip width) of cattle whereas the target of the Back-Propagation method is live bodyweight of cattle. The output derived from the Back-Propagation model is the prediction of the live bodyweight of the livestock.

The architecture of Back-Propagation that was used can be seen in Figure 1. As can be seen in the figure, in the input layer there are 5 nodes, of which four of these are assigned for morphometric characteristics and one node for bias. The figure also shows one hidden layer with two nodes besides one node for bias. Output layer indicates one node storing estimates of live bodyweight in the form of normalized values. Activation function that is used in the hidden layer and output layer is binary sigmoid. This Back-propagation architecture was made in simple fashion to maintain a low complexity which allows easy implementation on devices that only have low specifications.

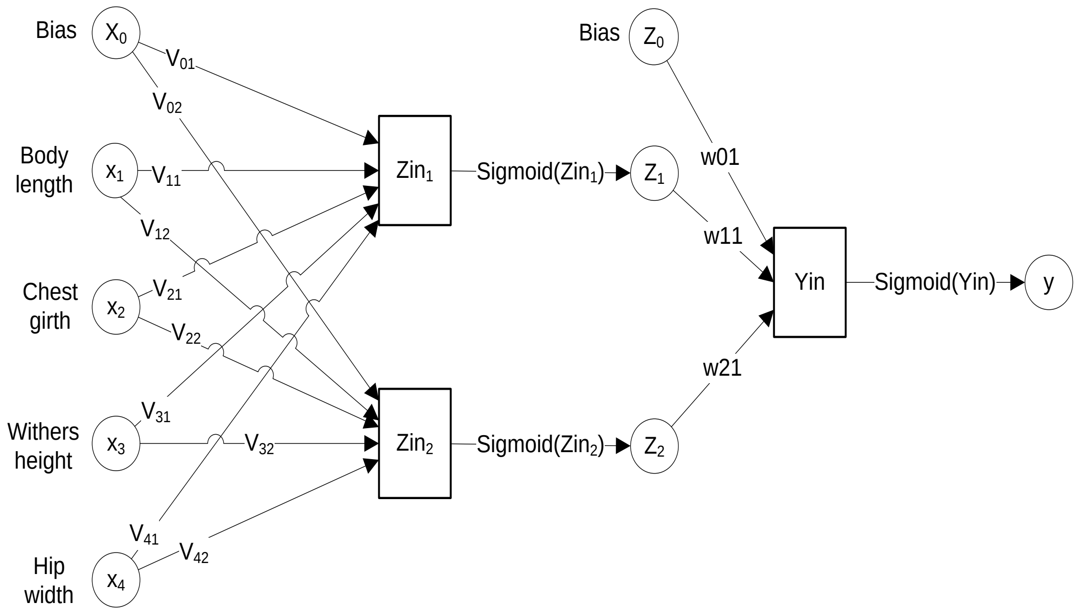

Figure 1. Back-Propagation architecture

In Figure 1, X_i is i-th input value, Y is the output value, Z_j is j-th hidden value, V_{ij} is the weight value of X_i to Z_j and W_{j1} is the weight value of Z_j to Y.

3.4. Denormalization

The output produced by Back-Propagation is the prediction of normalized live bodyweight of livestock. Therefore, to get the actual range of live body weight of cattle denormalization is required. Denormalization can be seen in Formula 2. In Formula 2, X_{ij} is the denormalized value of i-th observation at j-th variable, $Xnorm_{ij}$ is the value got from normalization in i-th observation at j-th variable, $Nmax_j$ is the maximum value of observations at j-th variable and $Nmin_j$ is the minimum value of observations at j-th variable.

$$X_{ij} = XNorm_{ij} \times \left(NMax_j - NMin_j\right) + NMin_j \tag{2}$$

3.5. Experimental Setup for Back-Propagation

The collected data were divided into two parts namely training data (70%) and testing data (30%). The training data comprises 68 cattle consisting of 28 cows and 40 bulls. The testing data comprises 28 cattle consisting of 12 cows and 16 bulls. Training data are used to create a prediction model using Back-Propagation method whereas testing data are used for assessment of model performance. Parameters values were used in the process of making the prediction model using Back-Propagation method can be seen in Table 1. Upon conducting trials, the best performance was selected.

Table 1. Parameters of experiments

No.	Parameter	Value
1	Learning rate (ἀ)	0.025, 0.05, 0.075, ..., 0.975
2	Activation functions	Sigmoid biner
3	Sum of iteration	1000
4	Maximum error	0.001

Performance of the model obtained from the results in backprogpagation training was measured using root means square error (RMSE). The RMSE formula can be seen in Formula 3. In Formula 3, X_i is the actual live bodyweight of a livestock resulting from i-th observation using digital scale, Y_i is the live bodyweight resulting from i-th observation using Back-Propagation prediction model and n is the number of livestock.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{n}} \tag{3}$$

Having got the best model from Back-propagation training, the performance of the model is compared with the conventional methods for the prediction of the live bodyweight of cattle, Danish Schoorl method and the Schoorl Indonesia method. The comparison is performed to determine whether the model offered better than previous methods. The formula of Schoorl Denmark can be seen in Formula 4 whereas the formula of Schoorl Indonesia can be observed in Formula 5.

$$\mathrm{LB} = \frac{(\mathrm{CG} + 22)^2}{100} \tag{4}$$

$$\mathrm{LB} = \frac{(\mathrm{CG} + 18)^2}{100} \tag{5}$$

In Formula 4 and Formula 5, LB is the live bodyweight and CG is chest girth of livestock.

4. Results and Analysis

Algorithm 2 is the best model of Back-Propagation training results. On the algorithm, BL is body length, CG is chest girth, HW is hip width, and WH is withers height. Figure 2 is the comparison of performance between prediction model of Schoorl Denmark, Schoorl Indonesia and Back-propagation. The figure showed that the Back-propagation is the best model because it has the smallest error. In the training data, the Back-propagation model produced RMSE value 58.84% smaller than the Schoorl Denmark method and 52.13% smaller than the Schoorl Indonesia method. Likewise, in the testing data, the Back-propagation model produced RMSE 60.54% smaller than the method of Schoorl Denmark and 53.95% smaller than then method of Schoorl Indonesia.

Figure 3 is the comparison of performance of model produced between cows and bulls. The figure shows that RMSE the bulls are lower than the cows. This means the model offered has better accuracy in bulls than cows. This may occur because the number of bulls data on training data is more 42.85% than female cows. Thus, Back-Propagation is more recognize pattern of the live bodyweight of bulls. In the training data, the values of RMSE of the bulls

31.36% smaller than those found in cows. In the meantime, in the testing data, the values of RMSE of the bulls 57.39% smaller than those found among the cows.

Algorithm 2. The live bodyweight prediction model for cattle

```
{Data Normalization}
BL ← (PB-62)/(154-62}
CG ← (LD-85)/(162-85)
HW ← (LP-7)/(24-7)
WH ← (TP-79)/(115-79}
{prediction using results of back-propagation model}
z_in1 ← 0.2897 + BL*0.3213 + CG*0.6324 + HW*0.9027 + WH*0.2153
z_in2 ← -3.4008 + BL*1.2271 + CG*1.4046 + HW*0.2281 + WH*2.1792
z1 ← sigmoid(z_in1)
z2 ← sigmoid(z_in2)
y_in1 ← -2.3538 + z1*0.5829 + z2*4.3933
y1 ← sigmoid(y_in1)
{denormalization of y1}
y1 ← y1*(286-69)+69 {y1 is the prediction result of live bodyweight of livestock}
```

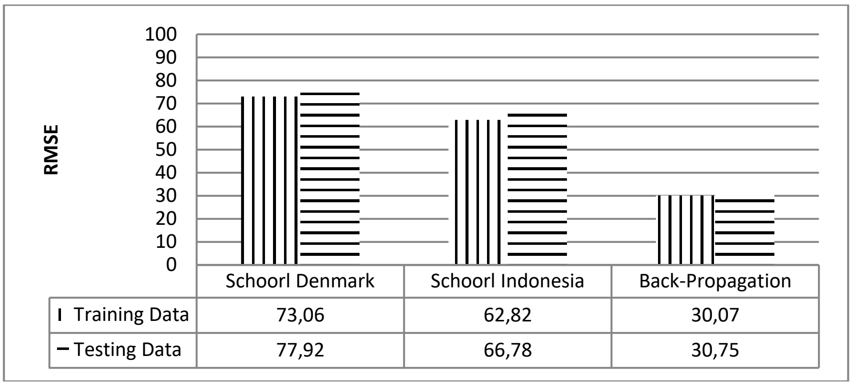

Figure 2. Comparisons of RMSE between Schoorl Denmark, Schoorl Indonesia and Back-Propagation

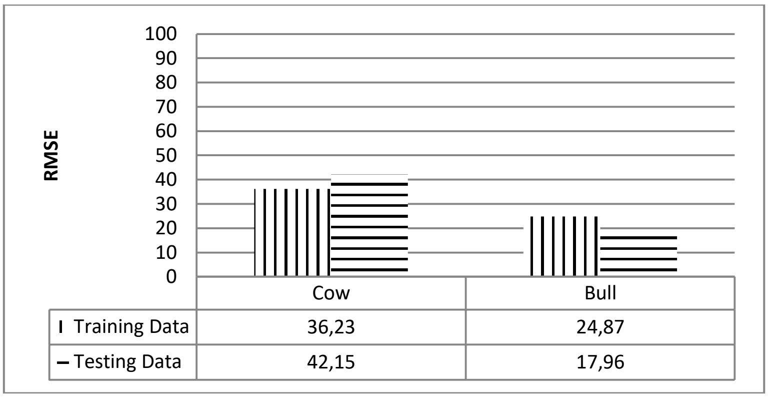

Figure 3. Comparisons of RMSE of proposed model between bulls and cows

5. Conclusion

This study developed new model to predict the live bodyweight of livestock using Back-propagation. The proposed model has a better accuracy than method of Schoorl Denmark and method of Schoorl Indonesia because RMSE of the model lower than the both methods. The results in this study also showed that cows are more difficult to predict than bulls using the proposed model. It can be seen from the comparison of RMSE of the live bodyweight estimation, cows higher than bulls. Therefore, in future studies, the ability of this model should be improved thus it can estimate the live bodyweight of cows with better accuracy.

This research has been successfully made a model to estimate the live bodyweight for cattle. Though Indonesia has several livestock that have been cultivated by the community, such us goat, sheep, and buffalo. Hence, in further studies, researches could be applied for the others livestock.

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