Turkish Journal of Veterinary and Animal Sciences
http://journals.tubitak.gov.tr/veterinary/
Research Article
Turk J Vet Anim Sci
(2021) 45: 716-725
© TÜBİTAK
doi:10.3906/vet-2009-105

An application of least square support vector machine model with parameters optimization for predicting body weight of Harnai sheep breed

Farhat IQBAL[1,*], **Abdul RAZIQ**[1], **Zil E HUMA**[2], **Muhammad ALI**[4]
[1]Department of Statistics, University of Balochistan, Quetta, Pakistan
[2]Department of Zoology, Sardar Bahadur Khan Women's University, Quetta, Pakistan
[3]Center for Advanced Studies in Vaccinology and Biotechnology, University of Balochistan, Quetta, Pakistan

Received: 30.09.2020 • **Accepted/Published Online:** 08.05.2021 • **Final Version:** 25.08.2021

Abstract: This study utilized a model based on the least square support vector machine (LSSVM) for the prediction of body weight (BW) of sheep. Two heuristic algorithms, namely, coupled simulated annealing (CSA) and simplex method (S) were applied to tune the hyperparameters of the LSSVM model. The hybrid CSA-S-LSSVM method is then applied to the male, female and total data of the Harnai sheep breed of Pakistan. Various biometric traits such as withers height, body length, chest girth, face length, paunch circumference, ear length, the length between ears, fat tail width and fat tail length were used as predictors. Goodness of fit measures such as mean absolute error (MAE), root mean square error (RMSE), adjusted coefficient of determination (Adj.R^2), normalized mean square error (NMSE) and mean absolute percentage error (MAPE) were used for evaluation. Comparison of the predictive performance of the proposed model on 10-fold cross-validation against both conventional (ridge regression) and state of the art machine learning (artificial neural networks) methods showed that the CSA-S-LSSVM outperformed both competing models by achieving the least values for MAE, RMSE, NMSE and MAPE and the highest value for Adj.R^2 in both training and testing data sets. The results were promising, accurate and viable for the prediction of BW of sheep.

Key words: Body weight, LSSVM, artificial neural networks, ridge regression, body measurements, deep learning

1. Introduction

Livestock, particularly sheep breeding and production are the mainstays of farmer's livelihood. Body weight (BW) is one of the most accurate and reliable measurements to determine sheep growth. The BW of farm animals can also be measured to improve sheep breeding and to increase meat production. The knowledge and further understanding of body growth and its relationship with other biometric traits allow for novel diet optimization approaches and optimal slaughtering time with consequences on better management and marketing strategies. Among alternative methods, the use of biometric measurements is a valuable and rather simple tool used for the estimation of the BW of production animals. In some cases, these biometric traits can provide a more reliable estimate of the live body weight than modern weighting measurements as the latter can overestimate the BW due to gut fullness [1]. Therefore, it is important to utilize novel and sophisticated methods that can precisely estimate the BW from body measurements of farm animals.

Various statistical methods have been employed by researchers to model and predict the BW (dependent variable) of small ruminants using several body measurements (independent variables). Among these, multiple linear regression (MLR) is one of the simplest and widely used methods (see, for example, [2] and references therein). However, this method fails to produce reliable estimates in the presence of multicollinearity (highly correlated independent variables). Factor scores in MLR were used to predict the BW of the Harnai sheep of Pakistan [3]. Factor and principal component scores in MLR were also employed for predicting the BW of commercial goats of Pakistan in the presence of multicollinearity [4]. Ridge regression [5], a variant of penalized regression, is an alternative method that can be applied to tackle the multicollinearity problem. The BW of Japanese black cattle from various body measurements was predicted using ridge regression (RR) and principal component analyses [6]. Ridge regression among other penalized regression methods was used to predict the BW of Hair goats of Turkey [7]. The live BW of Harnai sheep was predicted using penalized regression models [8]. A different approach was adopted by [9] who showed that a Box-Cox model can be used to precisely estimate the BW of Menz sheep of Ethiopia.

* Correspondence: farhatiqb@gmail.com

One the other hand, data mining and machine learning methods have been gaining popularity among the researcher and practitioners for prediction of live body weight of animals using biometric traits due to their better predictions and ability to handle nonlinearity in data. Artificial neural networks (ANN) is an advanced application of machine learning that can be used for solving nonlinear problems that might not be solved by conventional methods. The ANN along with other among other data mining methods such as applied chi-square automatic interaction detector (CHAID), exhaustive CHAID (ECHAID) and classification and regression tree (CART) were employed to predict the BW of Harnai sheep [10]. The predictive performance of CART, CHAID, ECHAID, multivariate adaptive regression splines (MARS) and ANN was compared in predicting BW of Mengali sheep of Pakistan [11]. Similarly, CART, CHAID, and ANN methods were used to find the best predictive model for BW through various body measurements in the indigenous Beetal goat of Pakistan [12]. The ANN was applied to predict the breeding values of BW of the Kermani sheep breed of Iran [13]. Similarly, [14] compared the predictive performance of ANN and regression models for the prediction of BW of Raini Cashmere goats of Iran.

The support vector machine (SVM), based on statistical learning theory, is a powerful machine learning algorithm that maps input data into high dimensional space by nonlinear mapping [15]. The least square support vector machines (LSSVM) proposed by [16] is an improved version of the SVM. The LSSVM, as a deep learning method, has a theoretical and mathematical foundation that is suitable for small samples and highly nonlinear data. The LSSVM has been widely used in classification, regression and forecasting problems. Nonetheless, besides its diversity in applications, the fitting accuracy and generalization ability of LSSVM mainly depends on the selection of the values of its two hyperparameters, namely, the regularization and kernel parameter. The commonly used parameter optimization methods such as cross validation [17] and grid search [18] methods require a large amount of calculation and can easily fall into the local optimum. Therefore, it is important to employ appropriate search algorithms to determine the optimized values of these hyperparameters of the LSSVM to avoid local minima and overfitting problems and improve prediction accuracy.

Overall, the current literature documents that researchers have been trying to accurately predict the BW of small ruminants through various body measurements by employing traditional models and recently, using a single machine learning method. However, the relationship between BW and body measurements is generally nonlinear and complex. Furthermore, the application of a single method in predicting the BW may be affected by the sensitiveness of the parameters and the overfitting of the data. Since deep learning methods, as an alternative to conventional and machine learning methods, have been found to provide better results for such problems, this study aimed to develop an intelligent deep learning model for accurate prediction for the body weight of sheep from various body measurements. For the sake of this purpose, the LSSVM, a powerful and accurate deep learning method, has been utilized. However, as mentioned earlier, the success of LSSVM mainly depends on the optimal choice of regularization and kernel parameters. Therefore, we combined coupled simulated annealing (CSA) of [19] and the simplex method (S) of [20] to optimize these hyperparameters of LSSVM. Hence, the proposed hybrid model, namely, the CSA-S-LSSVM was employed to estimate and predict the BW of Harnai sheep of Pakistan. [8] applied penalized regression methods on this dataset to predict the body weight of Harnai sheep in the presence of multicollinearity. However, this research applied a novel hybrid deep learning method to accurately predict the body weight of small ruminants using body traits. To the best of our knowledge, this approach has not been used in modeling and predicting the body weight of sheep. Various body measurements such as withers height, body length, chest girth, face length, paunch circumference, ear length, the length between ears, fat tail width and fat tail length were used as predictors of BW. Earlier studies on predictions of BW of sheep and goats have also identified a few of these variables as important predictors (see [3,7,8,21], among others). The data of male, female and total sheep were randomly partitioned into training and testing datasets and 10-fold cross validation was used. The training dataset was further partitioned into training and validation sets for tuning the parameters of the models. The testing dataset was used to evaluate the predictive accuracy of the models. Evaluation measures such as mean absolute error, root mean square error, adjusted coefficient of determination, normalized mean error and mean absolute percentage error were used to evaluate the superiority of the models. The predictive performance of the proposed CSA-S-LSSVM model was then compared with conventional RR and state-of-the-art ANN models.

2. Material and methods

2.1. Data collection

The data used in this study consist of records of 247 male and 510 female Harnai lambs from 0 pairs of permanent incisors to 4 pairs of permanent incisors collected from various districts of Balochistan, Pakistan. The dependent variable was the live body weight (BW) of sheep measured in kg. Various body measurements of Harnai sheep were used as predictors for the BW. These include withers height (WH), body length (BL), chest girth (CG), face length

(FL), paunch circumference (PC), ear length (EL), length between ears (LBE), fat tail width (TW) and fat tail length (TL) measured in cm. The digital weighing scale was used to measure the BW of sheep whereas a measuring tape was used for the measurement of all biometric traits. Animals were held in a standing position when all measurements were taken.

2.2. Statistical analysis

2.2.1. Prediction models

First, we implemented the conventional method of ridge regression (RR) to model and predict the BW of Harani sheep from various biometric traits. Ridge regression is preferred over the multiple linear regression model when the explanatory variables show strong correlations.

Consider the following multiple linear regression model

$$\mathbf{Y} = \mu\mathbf{1}_n + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \qquad (1)$$

where $\mathbf{Y} = (Y_1, Y_2,\ldots,Y_n)'$ is a vector of a dependent variable (observed body weight), $\mathbf{1}_n$ is a column vector of n ones ($i = 1,2,\ldots,n$), μ is called the intercept term, $\mathbf{X}$ is an $n \times p$ matrix of explanatory variables (biometric traits), $\boldsymbol{\beta} = (\beta_1, \beta_2,\ldots, \beta_p)'$ is the vector of regression coefficients and $\boldsymbol{\varepsilon}$ is a vector of residuals with mean $\mathbf{0}$ and variance $\mathbf{I}\sigma_\varepsilon^2$.

The method of ordinary least squares that minimizes the sum of squared residuals is generally used to estimate the unknown parameter vector $\boldsymbol{\beta}$. The ridge regression [5] penalized the least square method to solve the regression problem and keeps all the explanatory variables in the model without doing any variable selection [22].

Next, we apply the widely used artificial neural networks (ANN) model for the prediction of body weights. The artificial neural network [23] is a nonlinear method for solving complex problems. Specifically, in this study, we used a three-layer multilayer perceptron where each layer is connected to another layer by a number of neurons. The input layer had nine nodes – WH, BL, CG, PC, FL, LBE, EL, TW, and TL; the hidden layer contained nine nodes, while the output layer had only one node – body weight (Figure 1). The predictor variables are fed towards the input layer (i.e. a neuron for every independent variable). A tangent sigmoid function was employed as a nonlinear transformation function for computing the output from the summation of weighted inputs of neurons in each hidden layer whereas a pure linear transformation was used as an output layer for getting ANN's response. The number of neurons in the hidden layer was set to 15. The tangent sigmoid function is defined as $f(x) = \{2 / (1+\exp(-2x))\} - 1$.

In the final layer, the outcome value is checked with the actual value of BW using the mean square error (MSE) criterion. The Levenberg–Marquardt algorithm was applied to train the ANN.

The support vector machine (SVM) of [15] is another powerful and widely used machine learning method used for classification, regression and forecasting problems. An improved and modified version of the SVM called the least square support vector machine (LSSVM) was proposed by [16]. This method simplifies the training process of the standard SVM and can considerably reduce the computing time. However, the predictive performance of LSSVM mainly depends on the values of the parameters in the regularization item and kernel function.

The general form of LSSVM function is defined as:

$$y_i(x) = w^T\varphi(x_i) + b, \quad i = 1,2,\ldots,n, \qquad (2)$$

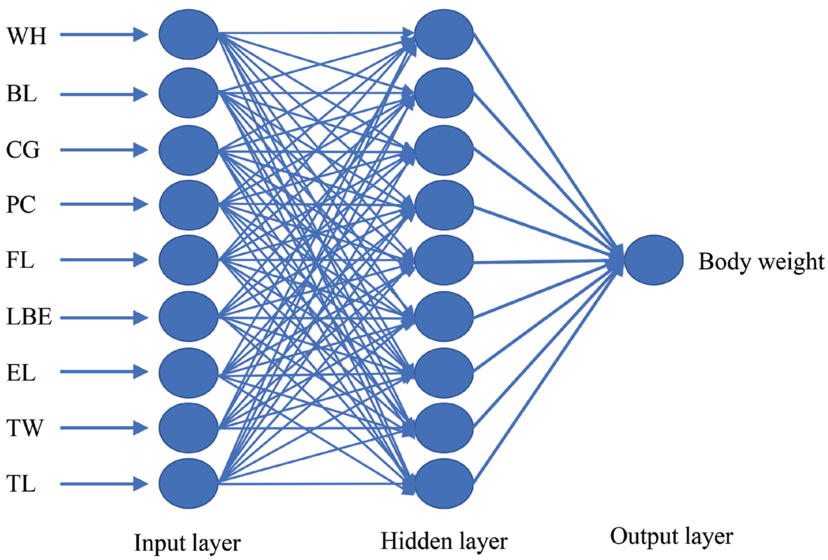

Figure 1. Artificial neural network (ANN) with input, hidden and output layers.

where (x_i, y_i) represents training data pairs, x_i and y_i are the input and output vector, respectively, and d is the dimension of the input vector; $\varphi(x)$ is a nonlinear mapping function used for mapping the input data into higher dimensional feature space; w and b are the weight vector and bias term, respectively. The objective in LSSVM is to optimize the following equation and the superscrip T indicates the transpose of a vector:

$$Minimize\ 0.5\ (w^T w + \gamma \sum e_i^2)$$

$$Subject\ to\ y_i = w^T \varphi(x_i) + b + e_i, \qquad i = 1,2,\ldots,n,$$

where e_i is the error value of input instance i, γ is the regularization parameter used to balance complexity and approximation precision of the model and the superscript T indicates the transpose of a vector and the superscript T indicates the transpose of a vector. The weight coefficient (w) for regression can be written in terms of the Lagrangian multiplier (α) and input vector (x) as

$$w = \sum \alpha_i x_i, \text{ where } \alpha_i = 2\gamma e_i.$$

Introducing the kernel function, the LSSVM equation can be defined as

$$y(x) = \sum \alpha_i K(x, x_i) + b, \tag{3}$$

where $K(x, x_i)$ is the kernel function. The radial basis function (RBF) kernel

$$K(x, x_i) = \exp(-||x - x_j||^2/\sigma^2)$$

was chosen in the present investigation as this kernel achieves the nonlinear relationship well and performs better than other choices, and σ^2 is the kernel (bandwidth) parameter. The regularization parameter γ and kernel function parameter σ^2, also known as hyperparameters of the LSSVM need to be optimized as both play significant roles in the algorithm's performance.

To improve the predictive performance of LSSVM and solve the problem of choosing the parameters of the kernel function, this study used two heuristic algorithms, CSA, and the simplex method. In this hybrid optimization, the CSA was first used to find suitable starting values of the parameters and these values are then passed to the simplex method to finely tune the parameters. The LSSVM coupled with these two heuristic algorithms was selected to construct a nonlinear prediction model to predict the body weight of Harnai sheep. The BW prediction system for sheep through body measurements consists of the data partition, parameter selection, model training and prediction. The implementation process for BW predictions based on the CSA-S–LSSVM is described in Figure 2.

The ridge regression, artificial neural networks and least square support vector machine methods discussed earlier were employed to model and predict the BW of Harnai sheep through other morphological traits. The data (for male, female, and total sheep) were randomly partitioned into training (80%) and testing (20%) data.

2.2.2. Models validation

The predictive performances of methods were evaluated on both training and testing data. A 10-fold cross validation technique was applied, and various goodness of fit measures were used to assess the results of competing models. These include the mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), normalized mean square error (NMSE), and the adjusted coefficient of determination (Adj.R^2).

The MAE is defined as

$$\text{MAE} = 1/n \sum |e_i|,$$

where n is the total number of observations, $e_i = y_i - \hat{y}_i$, is the residual, and y_i and $\hat{y}_i$ are observed and estimated or predicted body weight of i-th sheep.

The RMSE is defined as

$$\text{RMSE} = (\text{SSE}/n)^{1/2},$$

where $\text{SSE} = \sum e_i^2$ is the sum of square errors.

The adjusted coefficient of determination is defined as

$$\text{Adj.}R^2 = 1 - (1 - R^2)(n - 1)/(n - p - 1),$$

where R^2 is the coefficient of determination and p is the number of explanatory variables in the model.

The NMSE is defined as

$$\text{NMSE} = \text{SSE}/(n\sigma^2),$$

where $\sigma^2 = \sum (y_i - \overline{y})^2$.

The MAPE is

$$\text{MAPE} = 1/n \sum |e_i/y_i|$$

The model with the lowest MAE, RMSE, NMSE and MAPE and the highest Adj.R^2values are considered to be the best among competing models. All analysis in the present study has been carried out by using MATLAB (ver. R2019a) software.

3. Results

The data used in this study consisted of various biometric traits of a total of 757 (247 male and 510 female) Harnai sheep. Figure 3 shows the bar chart of average along with standard error of BW and other body measurements such as WH, BL, CG, PC, FL, LBE, EL, FW, and FL for both sexes. The bar chart shows that apart from BW, WH and PC, all other body measurements for female sheep were found larger than the male.

Pearson's coefficient of correlations between all variables under study, for both male and female sheep, were calculated (results not shown for the sake of brevity). High values of the correlation coefficient between the body weight and other body measurements were observed. The strong association indicates that the body measurements used in this study would help in predicting the BW of the Harnai sheep. Besides, all body measurements were found pairwise positively correlated with each other. However, few explanatory variables were found to be strongly correlated with each other in the present study indicating the problem of multicollinearity (see [8] for details on

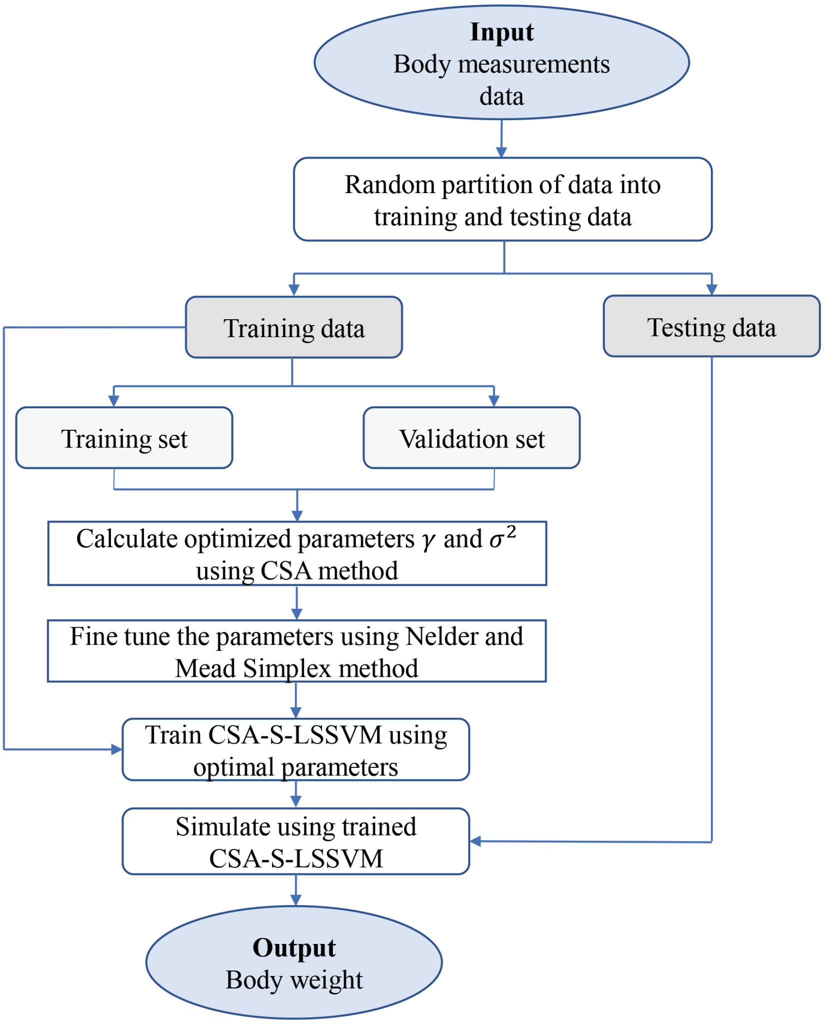

Figure 2. Flow chart for predicting body weight through CSA-S-LSSVM.

correlations among explanatory variables). Hence, instead of using a multiple linear regression model, we applied alternative methods to model and predict the BW of the Harnai sheep.

This study employed RR, ANN and CSA-S-LSSVM models to model and predict the live body weight of the Harnai sheep using various body measurements. These models were fitted to both training and testing datasets of male, female and total sheep data. The optimal values of hyperparameters from CSA-S-LSSVM were found to be $\gamma = 14.940$, $\sigma^2 = 11.152$, for male, $\gamma = 11.200$, $\sigma^2 = 4.6730$, for female and $\gamma = 12.068$, $\sigma^2 = 3.5671$, for total data sets. The performance of the models on training data of male, female and total sheep was compared on 10-fold cross validation using various goodness of fit measures such as MAE, RMSE, and Adj.R^2 and the average results of these measures along with standard errors for the training dataset are reported in Table 1. The average MAE values of 1.2864, 1.5478, and 1.6757 for male, female and total sheep data, respectively, of the CSA-S-LSSVM model, were found the least followed by the ANN model. The RR model had the highest average MAE values for all three data sets (2.3196, 3.3193, and 3.7241). Note that the values of evaluation measures for the RR model were slightly different than those reported by [8] for the same dataset. This slight variation is due to the random partitioning of the data. Similar results were obtained for RMSE where the CSA-S-LSSVM model had the least values, for all three data sets, as compared to the other two models. On the other hand, the average adjusted coefficient of determination (Adj.R^2) values of 0.9843, 0.9740, and 0.9727 for male, female and total sheep data, respectively, were the highest among other competing models. The average Adj.R^2 values (0.9815, 0.9719, and 0.9411) of ANN were found close to those of the CSA-S-LSSVM whereas the RR showed lower values for this evaluation measure.

Next, the predictive performance of the three models considered in this study was evaluated on unseen testing

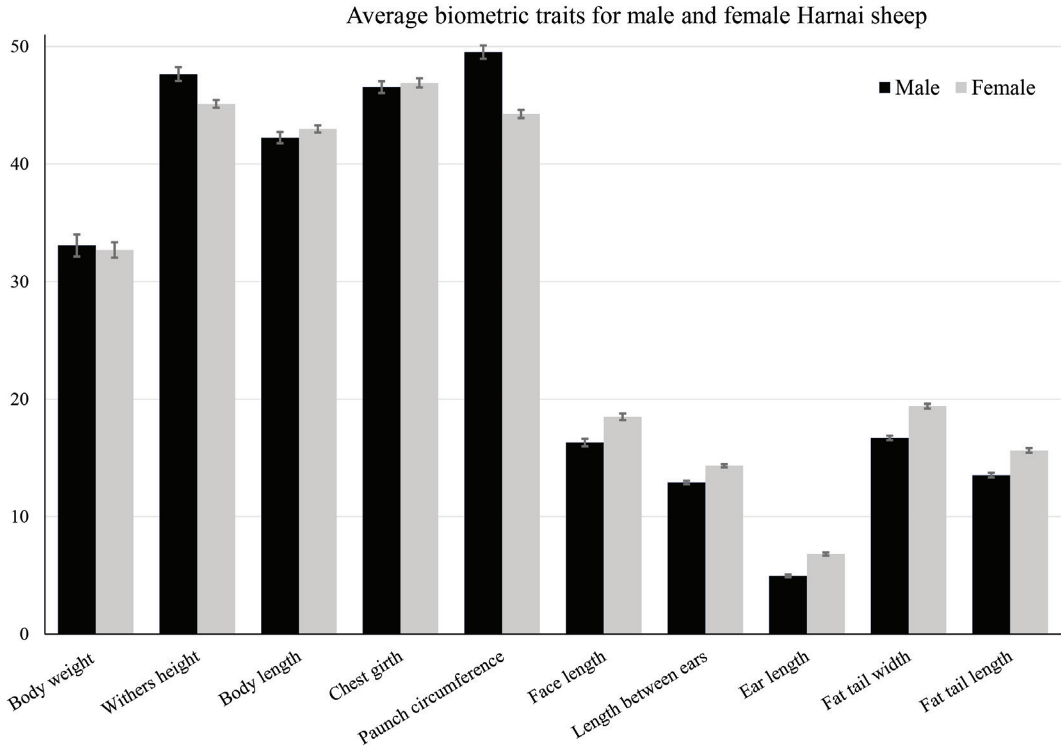

Figure 3. Mean along with standard error of various body measurements for male and female Harnai sheep. Body weights in kg, all other body measurements in cm.

Table 1. Evaluating models on training dataset for male, female and total sheep. Standard errors in parentheses.

Model	Male			Female			Total		
	MAE	RMSE	Adj.R^2	MAE	RMSE	Adj.R^2	MAE	RMSE	Adj.R^2
Ridge	2.3196 (0.074)	3.1133 (0.098)	0.9577 (0.007)	3.3193 (0.194)	4.1419 (0.225)	0.9294 (0.006)	3.7241 (0.250)	4.6362 (0.27)	0.8921 (0.009)
ANN	1.3843 (0.045)	1.8182 (0.116)	0.9815 (0.004)	1.6087 (0.027)	2.4867 (0.119)	0.9719 (0.003)	1.9576 (0.064)	3.5871 (0.196)	0.9411 (0.010)
CSA-S-LSSVM	1.2864 (0.043)	1.7999 (0.093)	0.9843 (0.003)	1.5478 (0.024)	2.2490 (0.106)	0.9740 (0.003)	1.6757 (0.036)	2.7778 (0.117)	0.9727 (0.004)

MAE: mean square error; RMSE: root mean squared error; Adj.R^2: the adjusted coefficient of determination.

data. Table 2 reports the average values of different evaluation measures along with standard errors of models on male, female and total sheep data. For male sheep data, the average MAE and RMSE values (1.2605 and 1.6830, respectively) of the CSA-S-LSSVM model were found the smallest followed by the ANN model (1.3405 and 1.8212, respectively). The average Adj.R^2 values of the CSA-S-LSSVM and ANN models were 0.9860 and 0.9753, respectively. The average Adj.R^2 value of the CSA-S-LSSVM was also the highest (0.9860) as compared to ANN (0.9753) and RR (0.9298). Based on the values of these evaluation measures, we could say that the predictive performance of the RR model is way below the other models. For female and total sheep data, the CSA-S-LSSVM model outperformed both ANN and RR in terms of producing the least values of MAE and RMSE and the highest Adj.R^2 value. Hence, we concluded that the CSA-S-LSSVM model is an accurate and reliable model for predicting the BW using various body measurements of Harnai sheep. The ANN model also showed promising results than the RR model. The normalized importance (%) and relative importance of body measurements from the ANN model were shown in Figure 4.

We further examined the performance of these models based on other evaluation metrics such as NMSE and MAPE. Bar charts in Figure 5 show the values of these evaluation measures for both training and testing data. It can be seen from both charts that the CSA-S-LSSVM model performed better than both ANN and RR models in terms of NMSE and MAPE. The RR produced very high values of these evaluation measures and hence failed to provide accurate predictions of BW. Both the CSA-S-LSSVM and ANN models showed promising results which indicate that the predicted values of BW from these models are close to the observed values.

Since, both CSA-S-LSSVM and ANN models showed excellent predictive performances, we closely examined the predictive performance of these two models by plotting the values of the observed body weight against the values of predictive body weight for both testing and training data in Figure 6. From both charts, we observed that the values of the CSA-S-LSSVM were closer to the 45^{o} line as compared to the values of the ANN model. This was true for both training and testing data and hence further strengthened our findings that the CSA-S-LSSVM model provides accurate predictions on body weight than the commonly used conventional (RR) and state-of-the-art machine learning (ANN) models.

4. Discussion

Several authors [2,3,8,10] have shown that variables concerning body measurements (withers height, body length, chest girth, face length, paunch circumference, ear length, length between ears, fat tail width and fat tail

Table 2. Evaluating models on the testing dataset for male, female and total sheep. Standard errors in parentheses.

Model	Male			Female			Total		
	MAE	RMSE	Adj.R^2	MAE	RMSE	Adj.R^2	MAE	RMSE	Adj.R^2
Ridge	2.6507 (0.110)	3.3426 (0.155)	0.9298 (0.005)	3.4128 (0.114)	4.4301 (0.161)	0.8917 (0.011)	3.4108 (0.123)	4.2110 (0.121)	0.9105 (0.009)
ANN	1.3405 (0.022)	1.8212 (0.128)	0.9753 (0.005)	2.1174 (0.120)	3.1254 (0.143)	0.9420 (0.008)	2.1035 (0.123)	3.1012 (0.165)	0.9497 (0.006)
CSA-S-LSSVM	1.2605 (0.047)	1.6830 (0.128)	0.9860 (0.003)	2.0537 (0.121)	3.0049 (0.150)	0.9498 (0.009)	2.0948 (0.126)	3.0051 (0.184)	0.9563 (0.006)

MAE: mean square error; RMSE: root mean squared error; Adj.R^2: the adjusted coefficient of determination.

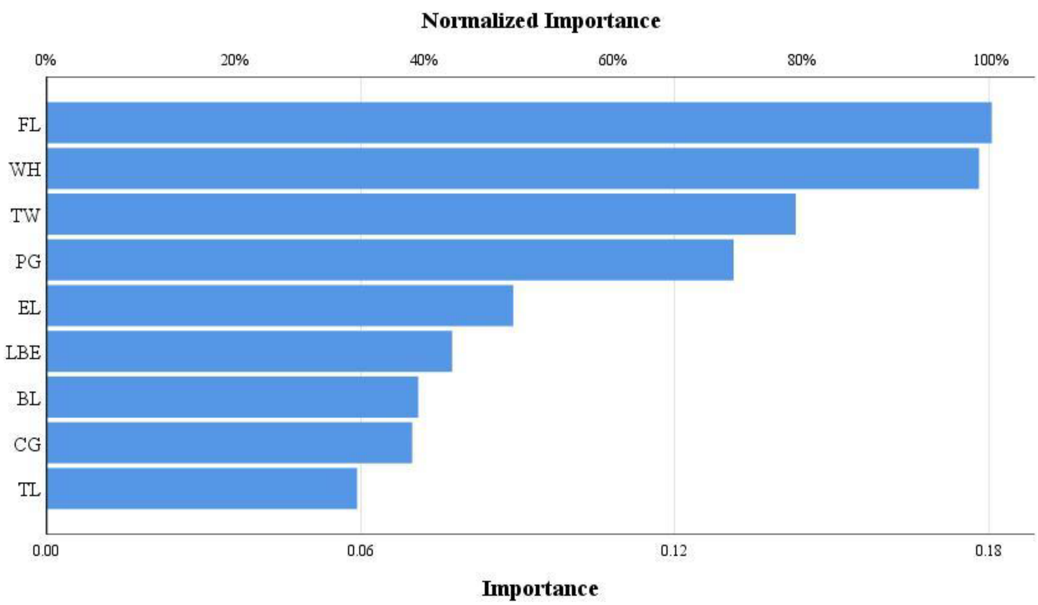

Figure 4. Normalized importance (%) and importance of explanatory variables from the ANN model.

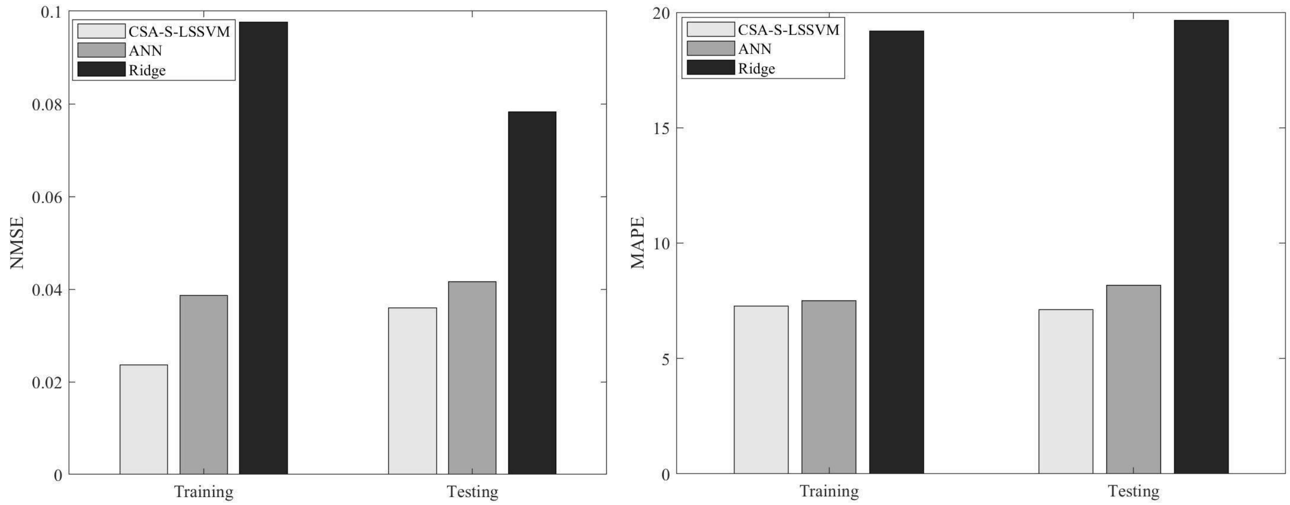

Figure 5. Normalized mean squared error values (left) and mean absolute percentage error (right) for all methods in training and testing stages.

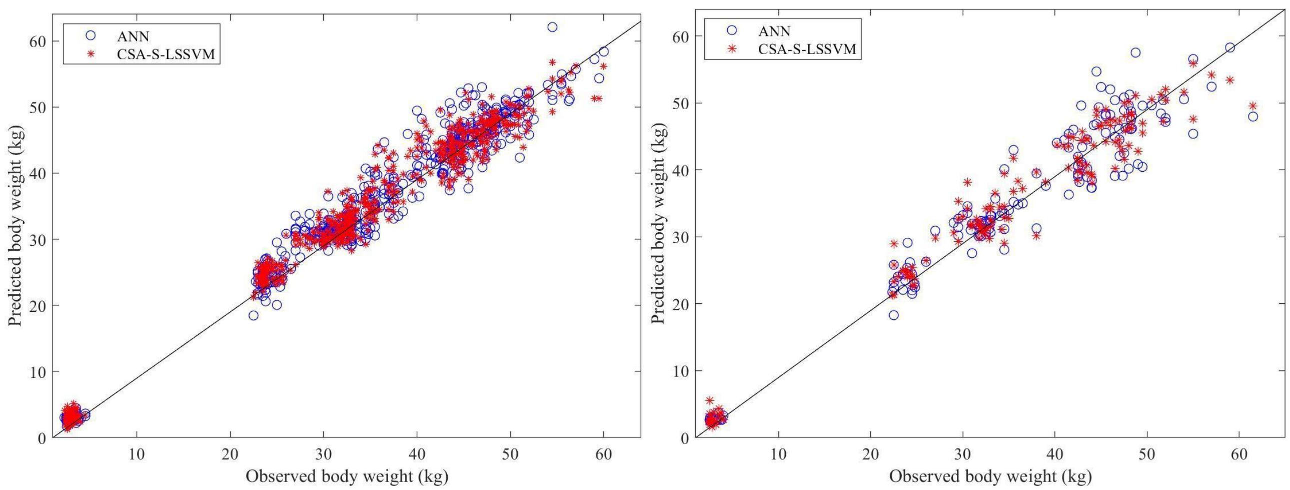

Figure 6. Observed and predicted body weights for CSA-S-LSSVM and ANN models on training (left) and testing (right) datasets.

length) are the measures with the greatest ability to predict the body weight of sheep and goats. These nine variables used in this study may be sufficient to properly predict the BW of sheep. Therefore, the results obtained in this paper cannot be affected by the variables employed, and all are valid for our regression problem. A Student's t-test was applied to check the significant difference between biometric traits of male and female sheep and the results (not reported here) showed significant differences ($p < 0.05$) between the sexes for all biometric measurements except BW, CG and BL.

Phenotypic correlation coefficients between various body measurements and body weight of sheep have been calculated separately for both sexes to provide a more accurate approach to body weight estimation from body measurements. Few other studies have also reported correlations between various body measurements of small ruminants. Withers height and chest girth were found correlated with BW in commercial goats of Pakistan [4]. A positive correlation between BW with body measurements such as HG, BL and EL was reported in Hararghe goats of Ethiopia [24]. Body weight was found strongly correlated with HG and BL in Jamunapari goats of India [21]. Similarly, BL and WH were reported to be strongly correlated with BW in Western African Dwarf goats of Nigeria [25] and CG, BL and WH were observed to be correlated with BW in Hair goats of Turkey [7]. The high positive phenotypic correlation (results not reported here) between BW and all other body measurements used in this study for both male and female sheep show that these predictors can be used as important predictors for body weight estimation of sheep.

The average adjusted coefficient of determination value of 0.9843 of CSA-S-LSSVM for male Harnai sheep found in this study is higher than 0.8760 of MLR with factor scores [3] and 0.9177 of the elastic net method [8] for the same male sheep data. The average Adj.R^2 value (0.9740) for female Harnai sheep found in this study is also higher than those previous studies on Harnai sheep (0.9190 and 0.9158). The highest R^2 value of 80.30 % reported by Sam et al. (2016) for African Dwarf goats and the adjusted R^2 values of 90.48 % and 76.68 % reported by [7] for male and female Hair goats, respectively, were also found lower than the average Adj. R^2values of this study.

From the results we obtained, it can be deduced that for accurate prediction of the BW of small ruminants, it is not only necessary to choose correctly the variables, but also the proper establishment of the methodology and the appropriate model that can model the complex relationship and handle nonlinearity in the data. The CSA-S-LSSVM model employed in this research has been shown to model the relationship between BW and body measurements of Harnai sheep quite well. The predictive performance of the proposed model was also found better than the other competing models (Figures 5 and 6).

In this study, we proposed a hybrid CSA-S-LSSVM model for the prediction of the body weight of Harnai sheep. Based on the achieved results of this study, it can be concluded that the proposed hybrid model is an accurate and reliable model for predicting body weight using body measurements in small ruminants. The predictive performance of the proposed model was shown to be quite promising than other competing models. Overall, this study emphasized the merits of using the LSSVM model with parameter optimization algorithms to get better results in predicting the BW using body measurements. Further, the results of this study suggest that the proposed deep learning method could be a useful tool for researchers and practitioners aiming to accurately predict the BW of small ruminants using various body measurements. Finally, this study contributes to the development of more reliable prediction models and anticipates that the findings may encourage researchers to further investigate the potential of other machine learning methods in modeling the nonlinear and complex relationship between the target and explanatory variables. The results of this research are expected to help practitioners, researchers, and livestock stakeholders to accurately predict the live body weights of animals from various body measurements using better alternative approaches in case of multicollinearity and to make swift decisions on livestock management.

References

1. Obike OM, Ibe SN, Oke UK. Estimation of pre- and post-weaning body weight of rabbits in a humid tropical environment using linear body measurements. American-Eurasian Journal of Agricultural & Environmental Sciences 2010; 9 (4): 440-444.
2. Waheed HM, Moaeen-ud-Din M, Khan MS, Saif-ur-Rehman M, Nawaz-ul-Rehman MS. Prediction of monthly body weight from body measurements in Beetal goats reared under field and farm conditions. Journal of Animal and Plant Sciences 2020; 30 (1): 25-31.
3. Khan MA, Tariq MM, Eyduran E, Tatliyer A, Rafeeq M et al. Estimating body weight from several body measurements in Harnai sheep without multicollinearity problem. Journal of Animal and Plant Sciences 2014; 24 (1): 120-126.
4. Eyduran E, Waheed A, Tariq MM, Iqbal F, Ahmed S. Prediction of live weight from morphological characteristics of commercial goat in Pakistan using factor and principal component scores on multiple linear regression. Journal of Animal and Plant Sciences 2013; 23 (6): 1532-1540.
5. Hoerl AE, Kennard RW. Ridge regression: biased estimation for nonorthogonal problems. Technometrics 1970; 12 (1): 55-67. doi: 10.1080/00401706.1970.10488634
6. Malau-Aduli AEO, Aziz MA, Kojina T, Niibayashi T, Oshima K et al. Fixing collinearity instability using principal component and ridge regression analyses in the relationship between body measurements and body weight in Japanese black cattle. Journal of Animal and Veterinary Advances 2004; 3 (12): 856-863.
7. Akkol S. The prediction of live weight of hair goats through penalized regression methods: LASSO and adaptive LASSO. Archives of Animal Breeding 2018; 61 (4): 451-458. doi: 10.5194/aab-61-451-2018
8. Iqbal F, Ali M, Huma ZE, Raziq A. Predicting live body weight of Harnai sheep through penalized regression models. Journalof Animal and Plant Sciences 2019; 29 (6): 1541-1548.
9. Wamatu J, Alkhtib A, Rischkowsky B. Simple and robust model to estimate liveweight of Ethiopian Menz sheep. Animal Production Science 2019; 59 (12): 2265-2272. doi: 10.1071/AN18006
10. Ali M, Eyduran E, Tariq MM, Tirink C, Abbas F et al. Comparison of artificial neural network and decision tree algorithms used for predicting live weight at post weaning period from some biometrical characteristics in Harnai sheep. Pakistan Journal of Zoology 2015; 47 (6): 1579-1585.

11. Celik S, Eyduran E, Karadas K, Tariq MM. Comparison of predictive performance of data mining algorithms in predicting body weight in Mengali rams of Pakistan. Revista Brasileira de Zootecnia 2017; 46 (11): 863-872. doi: 10.1590/s1806-92902017001100000512

12. Eyduran E, Zaborski D, Waheed A, Celik S, Karadas K et al. Comparison of the predictive capabilities of several data mining algorithms and multiple linear regression in the prediction of body weight by means of body measurements in the indigenous Beetal goat of Pakistan. Pakistan Journal of Zoology 2017; 49 (1): 257-265. doi: 10.17582/journal.pjz/2017.49.1.257.265

13. Ghotbaldini H, Mohammadabadi M, Nezamabadi-pour H, Babenko OI, Bushtruk MV et al. Predicting breeding value of body weight at 6-month age using Artificial Neural Networks in Kermani sheep breed. Acta Scientiarum, Animal Sciences 2019; 41: e45282. doi: 10.4025/actascianimsci.v41i1.45282

14. Khorshidi-Jalali M, Mohammadabadi MR, Esmailizadeh A, Barazandeh A, Babenko OI. Comparison of artificial neural network and regression models for prediction of body weight in Raini Cashmere goat. Iranian Journal of Applied Animal Science 2019; 9 (3): 453-461.

15. Cortes C, Vapnik V. Support-vector networks. Machine Learning 1995; 20 (3): 273-297. doi: 10.1007/BF00994018

16. Suykens JAK, Vandewalle J. Least squares support vector machine classifiers. Neural Processing Letters 1999; 9 (3): 293-300. doi: 10.1023/A:1018628609742

17. Zhang Y, Yang Y. Cross-validation for selecting a model selection procedure. Journal of Economics 2015;187 (1): 95-112. doi: 10.1016/j.jeconom.2015.02.006

18. Liu X, Jia D, Li H. Research on kernel parameter optimization of support machine in speaker recognition. Science Technology and Engineering 2010; 10: 1669-1673.

19. Xavier-de-Souza S, Suykens JAK, Vandewalle J, Bolle D. Coupled simulated annealing. IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics 2010; 40 (2): 320-335. doi: 10.1109/TSMCB.2009.2020435

20. Nelder JA, Mead R. A simplex method for function minimization. The Computer Journal 1965;7 (4): 308-313. doi: 10.1093/comjnl/7.4.308

21. Das SK, Yadav BPS. Productive performance of Jamunapari goat under semi intensive system of management. Indian Journal of Animal Research 2015; 49 (2): 254-257.

22. Zou H, Hastie T. Regularization and variable selection via the elastic net. Journal of Royal Statistical Society Series B Statistical Methodology 2005; 67 (2): 301-320.

23. McCulloch WS, Pitts W. A logical calculus of the ideas immanent in nervous activity. The Bulletin of Mathematical Biophysics 1943; 5 (4): 115-133. doi: 10.1007/BF02478259

24. Tsegaye D, Belay B, Haile A. Linear body measurements as predictor of body weight in Hararghe Highland goats under farmers environment Ethiopia. Global Veterinaria 2013; 11 (5): 649-656. doi: 10.5829/idosi.gv.2013.11.5.76135

25. Sam I, Ekpo J, Ukpanah U, Eyoh G, Warrie M. Relationship between linear body measurement and live body weight in West African Dwarf Goats in Obio Akpa. Journal of Biology, Agriculture and Healthcare 2016; 6 (16): 118-124.