RESEARCH ARTICLE Indian Journal of Animal Research, Volume 59 Issue 12: 2143-2152 (December 2025)

Prediction of Norduz Sheep Live Weight using Multilayer Perceptron Neural Networks and Least Square Support Vector Machines

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10.18805/IJAR.BF-2023

ABSTRACT

Background: Statistical analyses have played a fundamental role in the scientific determination of production traits and environmental factors influencing meat productivity. In recent years, machine learning methods have been increasingly explored due to their potential to enhance the accuracy and efficiency of live weight prediction in sheep.

Methods: In this study, the predictive performance of various machine learning algorithms for estimating body weight in Norduz sheep was comparatively evaluated. multilayer perceptron neural networks (MLPNN) and least squares support vector machines (LS-SVM) were employed, with various network configurations and hyperparameter combinations tested. Biometric measurements-namely age, height at withers (HW), body length (BL), chest width behind paddles (CW), chest depth (CD), chest girth (CG) and thigh circumference (TC)-were utilized as input variables, while body weight (BW) served as the target variable.

Result: The MLPNN model configured using the Bayesian Regularization algorithm and the TanSig activation function yielded the lowest error rates and the highest generalization capability. Within the LS-SVM model, the most accurate predictions were obtained using the radial basis function (RBF) kernel, with optimal hyperparameters set at $\sigma = 5$ and $\gamma = 10$. Among the biometric traits, Chest Girth was identified as the most influential variable for predicting live weight across both models. Furthermore, Age and Height at Withers were found to be critical determinants in the neural network model, whereas Chest Depth and Chest Width were more prominent in the LS-SVM model.

Key words: Biometrical measurement, Least square support vector machines, Neural networks, Norduz sheep.

INTRODUCION

Sheep farming significantly contributes to the food and textile sectors, with the sustainability of products like meat, milk and wool depending on healthy animal populations (Sönmez and Kaymakçı, 1987). Accurate live weight prediction is closely linked to productivity and profitability, playing a vital role in agricultural sustainability. Biometric measurements are essential in animal breeding and research, aiding in breed standard evaluation and growth assessment influenced by environmental and nutritional factors (Sowande and Sobola, 2008; Riva *et al.,* 2004; Shirzeyli *et al.,* 2013). Live weight is a key indicator of health, nutrition and development and biometric traits support selection and genetic improvement programs (Riva *et al.,* 2004). While direct weight measurement is feasible in well-equipped farms, extensive systems often lack such infrastructure, making body measurement-based estimation a practical solution (Olatunji-Akioye and Adeyemo, 2009; Shirzeyli *et al.,* 2013).

In recent years, various statistical techniques have been developed to evaluate economically significant biometric traits in sheep, such as live weight, milk yield and wool production (Basak *et al.,* 2024. Recently, machine learning methods have been increasingly investigated due to their potential to improve the accuracy and efficiency of live weight prediction in sheep (Khanikar *et al.,* 2024; Karakus, 2025). Extensive research in the literature has demonstrated that body measurements serve as practical, accurate and reliable parameters for estimating the live weight of various sheep breeds. Research has been conducted on Thalli sheep by Abbas *et al.* (2021) and Tırınk (2022); on Harnai sheep by Iqbal *et al.* (2021); on Norduz sheep by Çakmakçı (2022); on Mengali rams by Çelik *et al.* (2017); on Kajli sheep by Faraz *et al.* (2023); on Balochi sheep by Norouzian and Vakili Alavijeh (2016) and Huma and Iqbal (2019); on Romane sheep by Tırınk *et al.* (2023b); and on Suffolk-polish merino sheep by Tırınk *et al.* (2023a). These studies collectively highlight the applicability of machine learning techniques across a broad range of breeds for live weight estimation.

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How to cite this article: Akıllı, A. and Akkol, S. (2025). Prediction of Norduz Sheep Live Weight using Multilayer Perceptron Neural Networks and Least Square Support Vector Machines. *Indian Journal of Animal Research*. **59(12):** 2143-2152. doi: 10.18805/IJAR.BF-2023.

Submitted: 15-05-2025 **Accepted:** 03-08-2025 **Online:**12-09-2025

Although machine learning has been applied to predict body weight in several sheep breeds (Abbas *et al.,* 2021; Huma and Iqbal, 2019; Tirink *et al.,* 2023a), studies on Türkiye's native breeds remain limited. While algorithms have been used for Thalli, Balochi, Corriedale, Akkaraman and Morkaraman breeds (Tirink, 2022; Tirink *et al.,* 2023b), research involving Norduz sheep is scarce (Çakmakçı, 2022). Endemic to the Norduz region in Van's Gürpınar district, this breed has adapted to harsh Eastern Anatolian conditions for over 250 years (Yılmaz *et al.,* 2012a; Aydın *et al.,* 2024; Karakuş, 2024). Conservation of this breed is considered essential, as Türkiye is located at the intersection of three global biodiversity hotspots (Gür, 2016) and hosts the richest temperate flora (Şekercioğlu *et al.,* 2011). Although native breeds make up most of the country's 45 million sheep (Aydın *et al.,* 2024), many are endangered and require protection (Yılmaz *et al.,* 2012b). In Norduz sheep, limited datasets, measurement standardization issues and restricted access to weighing tools hinder the accuracy of machine learning models (Yıldırır *et al.,* 2023; Mia *et al.,* 2025).

This study aims to predict the live weight of Norduz sheep using machine learning methods, specifically MLPNN and LS-SVM, based on age and various biometric measurements.

MATERIALS AND METHODS

Data source

The data set comprises the results of study involved 312 Norduz sheep biometric trait record aged 1 to 4 years, reared at the Van Yüzüncü Yıl University Research and Application Management Directorate (Van Yüzüncü Yıl University Rectorate Animal Experiments Local Ethics Committee, decision number: 2018/10). The input variables were defined as Age, HW, BL, CW, CD, CG and TC with BW serving as the output variable.

Data preprocessing and model evaluation

The dataset was normalized using the D-Min-Max method, as defined in Equation 1 (Akıllı and Atıl, 2020). To prevent overfitting and underfitting, the data were randomly partitioned and k - fold cross -validation was applied to ensure robust performance evaluation. Error metrics were assessed at each training, testing and validation stage. Model performance was evaluated using mean squared error (MSE), mean absolute percentage error (MAPE) and R^2_{Adj}. The model yielding the lowest MSE and MAPE, along with the highest R^2_{Adj} on the test set, was identified as optimal. Formulations of these metrics are provided in Equations 2-4, where y_i denotes the actual value, $\hat{y}_1$ the predicted value and n the number of observations. All implementations and evaluations were conducted using Matlab (R2024b) and Python (v3.12) on the Google Colab platform. The development and evaluation process are summarized in Fig 1.

$$\chi'_i = 0.1 + (0.9 - 0.1)\frac{\chi_i - \chi_{min}}{\chi_{max} - \chi_{min}} \quad ....(1)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_1)^2 \quad ....(2)$$

$$MAPE = \left(\frac{100}{n}\right)\sum_{i=1}^{n}\left|\frac{(y_i - \hat{y}_1)}{y^i}\right| \quad ....(3)$$

$$R^2_{Adj} = 1 - (1 - R^2)\frac{(n-1)}{(n-p-1)} \quad ....(4)$$

Neural networks

This study employed the MLP model, trained by adjusting weights to align outputs with target values using the backpropagation algorithm (Rana *et al.,* 2021; Haldar *et al.,* 2023). The mathematical representation of the output is given in Equation 5. Where x_j is the input vector, (i = 1, 2..., n), w_j represents the weight vector, b is the bias term, f is the activation function and y is the output. An activation function limits a neuron's output to a finite range, enhancing computational stability and nonlinearity (Haykin, 1999). This study employs two sigmoidal activation functions commonly used in multilayer perceptrons, presented in Equation 6 (Ostovar *et al.,* 2025) and Equation 7 (Dubey *et al.,* 2022). The Logistic Sigmoid maps real numbers to [0,1], supporting probability-based interpretations, while the Tanh function compresses inputs to [-1,1], both regulating output amplitude (Haykin, 1999; Dubey *et al.,* 2022).

$$y = f\left(\sum_{i=1}^{n} w_j x_j + b\right) \quad ....(5)$$

$$LogisticSigmoid = \frac{1}{1 + e^{-(x)}} \quad ....(6)$$

$$Tanh = \frac{e(\chi) - e(-\chi)}{e(\chi) + e(-\chi)} \quad ....(7)$$

The normalized importance of the predictor variables was assessed using connection weights and the Garson algorithm (Ma *et al.,* 2024).

Least square support vector machine

A specialized variant of SVM (Ahmad, 2023), known as LS-SVM, was developed by Suykens *et al.* (2002) to reduce the complexity associated with optimization procedures in quadratic programming problems.

In this study, the training set comprises pairs $\{x_i, y_i\}$ with model parameters designated as $w \in R$ and $b \in R$ Equation 8 defines w; as the weight vector and b represents the bias term. The nonlinear mapping function φ is defined as $\varphi: R \rightarrow R$. The initial step in creating a kernel-based model involves configuring the Lagrange function, presented in Equation 9, to address the optimization problem. Here, α_i represents the Lagrange multipliers.

$$L(w, b, e; \alpha) = \frac{1}{2}w^T w + \frac{1}{2}\gamma\sum_{i=R}^{N} e_i^2 - \sum_{i=R}^{N}\alpha_i(w^T\varphi(x_i) + b + e_i - y_i \quad ....(8)$$

$$y(x) = \sum_{i=R}^{N} \alpha_i K(x, x_i) + b \quad ....(9)$$

In the subsequent step, derivatives with respect to the primal and dual variables are computed using the Lagrange formulation and the formulation is then aligned with the Karush-Kuhn-Tucker (KKT) conditions to ensure optimality. The results are derived from the partial derivatives with respect to the parameters w, b, e and a. The kernel matrix is defined as $\Omega_{ij} = \varphi(x_i)^T \varphi(x_j) = K(xi, xj)$, for (i, j = 1, ..., N). In high-dimensional feature spaces, the mapping function φ is not explicitly defined within kernel-based methods. Kernel functions are required to meet Mercer's conditions (Mercer, 1909). The application of Mercer's conditions to the matrix facilitates the derivation of the LS-SVM for regression, as expressed in Equation 8 (Suykens *et al.,* 2002).

In this study, radial basis function (RBF) and Polynomial Kernel Function were used. Their mathematical expressions are given in Table 1. The Grid Search method was employed to optimize the RBF model, with σ ranging from 1-100 and γ from 0.46-1. Variable importance was assessed using the permutation importance technique (Dai *et al.,* 2024).

RESULTS AND DISCUSSION

Descriptive statistics for biometric measurements of Norduz sheep were given in Table 2. The mean Age of the sheep was determined as 2.21 years, with a standard deviation of 1.07 years. Overall results indicated that variables' distributions closely approximating normality. Heatmap of pearson correlation coefficients among biometric parameters with body weight was included in Fig 2. The results of the correlation analysis indicated statistically significant associations between most of the examined biometric variables and BW.

Fig 3 and 4 present training and testing error metrics for MLP networks. As seen in Fig 3 and Fig 4, the TanSig function yielded lower MSE and MAPE values with algorithms such as BR, LM and CGB. The BR algorithm maintained low error levels across neuron counts, demonstrating high stability and generalization performance.

MLP models with varying neuron numbers and TanSig/LogSig activation functions were evaluated in detail, with optimal numerical outcomes reported in Table 3. Most algorithms showed no significant overfitting or underfitting; however, some failed to balance training and test errors, indicating generalization issues. The BR algorithm, configured with 30 hidden neurons and TanSig function, yielded the lowest test errors and the highest , while also achieving the best AIC and BIC scores. In contrast, GD, GDM and GDX algorithms resulted in relatively high errors, with many configurations displaying underfitting. Graphical summaries of Table 3 are provided in Fig 5.

Fig 5 provides graphical representations of performance metrics for configurations that fit the dataset effectively and exhibit strong generalization capabilities within MLP networks. In Fig 5, graphical representations of performance

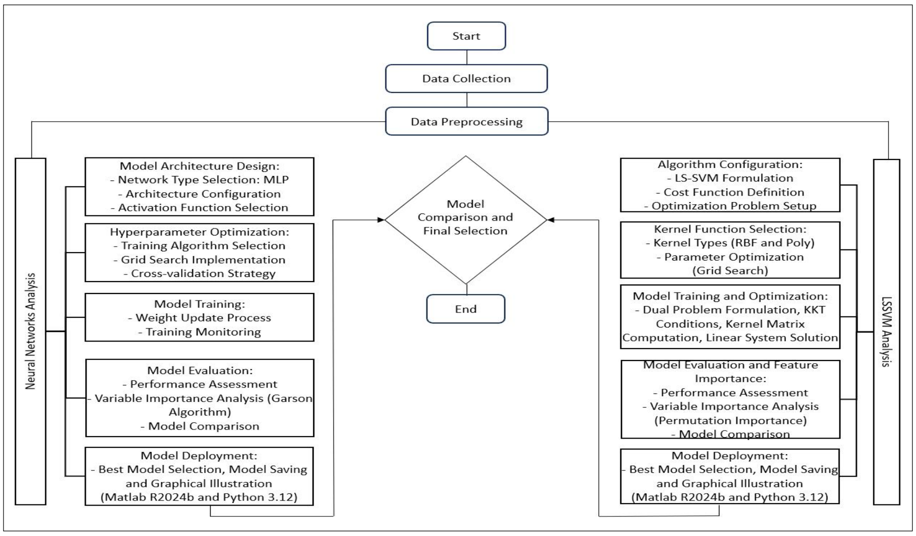


Fig 1: Flowchart of model development and evaluation processes for NN and LSSVM algorithms.

Table 1: Kernel functions.

Kernel functions	Equations	Description
Radial basis function (RBF)	$K(x_i, x_j) = e \frac{\|x_i - x_j\|^2}{\sigma^2}$	σ^2 is the variance of the Gaussian kernel.
Polynomial kernel function	$K(x_i, x_j) = (x^T_i x_j + t)^d$, $t \geq 0$	t is the intercept and d the degree of the polynomial.

metrics for MLP configurations with strong generalization capability are presented. The BR algorithm with TanSig and LogSig activation functions yielded the lowest MSE and MAPE values and the highest R^2_{Adj}. Additionally, the LM, SCG and CGB algorithms also demonstrated low error rates and high R^2_{Adj} values.

Table 4 presents the statistical performance metrics of the LS-SVM model using the RBF Kernel across various σ and γ combinations. A notable overfitting instance was observed at σ=1 and γ=10, with a large gap between training and test errors. The best performance was achieved at σ=5 and γ=10, yielding low and balanced errors, indicating effective generalization. Conversely, high σ (≥30) and low γ (≤1) led to increased errors in both sets, suggesting underfitting and insufficient learning capacity.

In Fig 6, graphical representations of performance metrics are included for various σ and γ hyperparameter combinations configured with the RBF Kernel function in the LS-SVM technique. As supported by the data presented in Table 4, at low σ (σ = 1) values, as the γ parameter increases, the error rates in the training set decrease rapidly, while the error rates in the test set tend to increase

Table 2: Descriptive statistics of Norduz Sheeps' data.

Variables*	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Age	2.2083	1.0660	1	4	0.7298	-0.7180
HW	69.836	3.7916	59	78	-0.2489	-0.4407
BL	65.019	3.5693	53.7	73.8	-0.839	0.5544
CW	18.168	2.3965	12.6	32.6	0.8753	3.5229
CD	29.173	2.2846	19.2	34.5	-0.195	0.3991
CG	93.738	7.8496	68	115	0.0268	-0.0033
TC	50.221	5.1121	37	68	0.2732	0.1325
BW	50.630	9.1053	31.4	77.2	0.2757	-0.1800

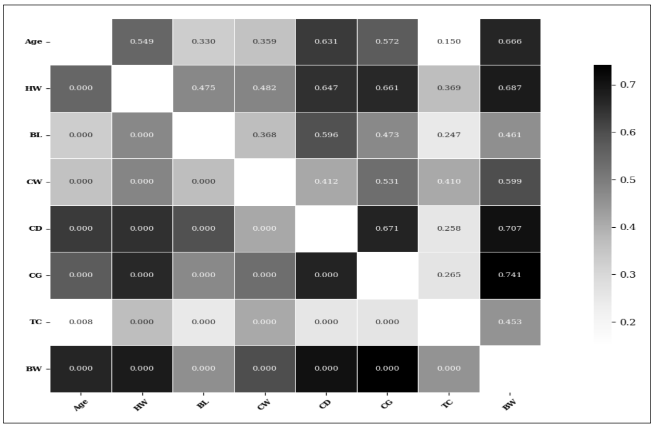


Fig 2: Heatmap of pearson correlation coefficients among biometric traits.

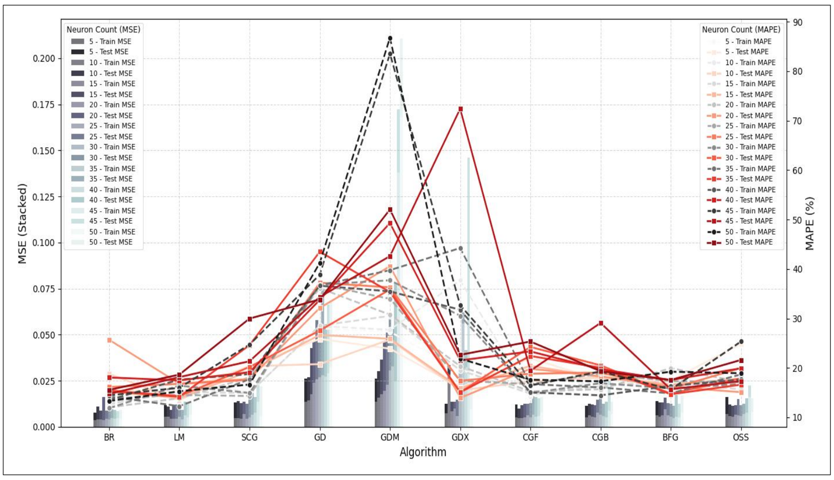


Fig 3: Error metrics for MLP network with 'TanSig' activation function.

after a certain point. On the other hand, at medium σ values (especially for σ=5 and σ=10), as γ increases, both training and test error values decrease significantly and follow a balanced course. As can be seen in Fig 6, at moderate values (notably σ=5 and σ=10), an increment in γ is linked with a pronounced reduction in error rates for both training and testing. Conversely, in conditions with high σ ($\sigma \geq 50$) and low γ ($\gamma \leq 2.15$), a significant rise in error rates for both training and testing is detected, suggesting the emergence of underfitting and a lack of adequate generalization capacity.

In Table 5, the statistical performance metrics for different polynomial degrees of the LS-SVM model with a Polynomial Kernel Function are presented. It was observed that lower degrees (1 and 2) yielded low training errors, while test errors remained relatively higher but acceptable.

According to Tables 3 and 4, the highest prediction performance was achieved by the MLP model configured with the BR algorithm and TanSig activation function. In Fig 7(a), a close alignment between observed and predicted values is illustrated, indicating that the BR-TanSig model captured dataset fluctuations effectively. The Pearson correlation coefficient was calculated as 0.898. Fig 7(b) presents the normalized importance of independent variables. CG, HW and age were identified as the most influential predictors, while BL contributed the least to model performance.

Table 3: Statistical performance criteria for MLP Networks.

Train.	Act.	Number of	Train		Test				
Alg.	Func.	Neuron	MSE	MAPE	MSE	MAPE	R^2_{Adj}	AIC	BIC
BR	TanSig	30	0.0041	11.8499	0.0040	15.4366	0.7773	-324.901	-307.884
	LogSig	20	0.0038	12.8865	0.0051	13.8387	0.7048	-310.569	-293.552
LM	TanSig	15	0.0044	15.1133	0.0047	13.8971	0.7398	-315.914	-298.897
	LogSig	40	0.0045	13.8824	0.0055	18.5382	0.7432	-305.503	-288.486
SCG	TanSig	20	0.0067	18.0886	0.0068	17.7541	0.6576	-293.196	-276.179
	LogSig	20	0.0053	16.3732	0.0064	16.1914	0.7010	-296.642	-279.624
GD	TanSig	5	0.0137	27.9799	0.0125	25.8557	0.3027	-255.518	-238.501
	LogSig	10	0.0219	34.6478	0.0145	31.6464	0.2182	-246.446	-229.429
GDM	TanSig	20	0.0194	30.7539	0.0265	40.5467	.	-209.083	-192.066
	LogSig	30	0.0358	41.7508	0.0137	27.9637	0.2033	-249.822	-232.805
GDX	TanSig	25	0.0059	17.3965	0.0087	17.3848	0.4366	-278.115	-261.098
	LogSig	5	0.0131	23.2027	0.0183	42.9689	0.0137	-232.002	-214.985
CGF	TanSig	10	0.0047	14.3215	0.0051	17.2675	0.6966	-310.528	-293.511
	LogSig	25	0.0058	16.9315	0.0055	17.8335	0.5564	-305.714	-288.697
CGB	TanSig	15	0.0055	16.2882	0.0063	18.1696	0.7074	-297.252	-280.235
	LogSig	15	0.0045	15.0646	0.0065	17.4771	0.6976	-295.966	-278.949
BFG	TanSig	25	0.0061	17.3414	0.0066	15.7819	0.6738	-294.984	-277.967
	LogSig	15	0.0060	17.4987	0.0063	17.7177	0.6909	-297.823	-280.806
OSS	TanSig	10	0.0058	17.1835	0.0060	17.8300	0.7084	-300.559	-283.542
	LogSig	5	0.0067	18.9869	0.0076	18.3517	0.5532	-286.262	-269.245

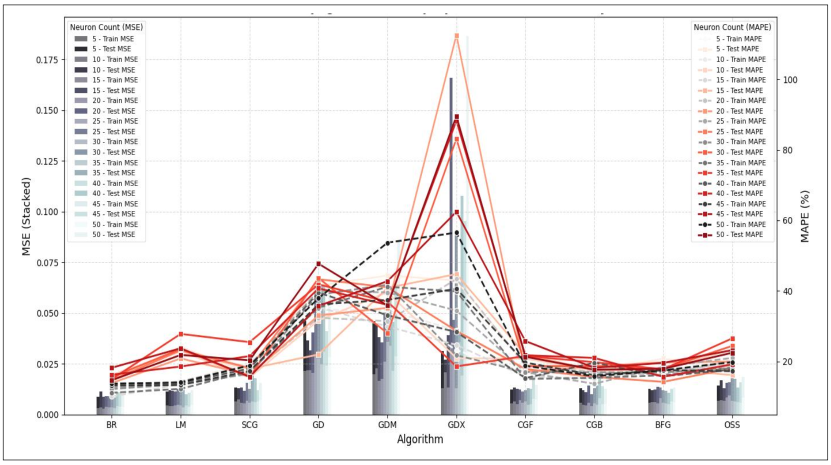


Fig 4: Error metrics for MLP network with ‘Logsig’ activation function.

In the domain of sheep farming, it has been reported that machine learning algorithms employing k-fold repeated cross-validation have yielded successful outcomes for body weight prediction, as demonstrated in several studies (Shahinfar and Kahn, 2018; Huma and Iqbal, 2019; Çakmakçı, 2022; Chay-Canul *et al.,* 2024; Hamadani and Ganai, 2023; Tırınk *et al.,* 2023a; Tırınk *et al.,* 2023b). Unlike in conducted study by Tırınk (2022), our research has explored neural network methods in a more detailed manner, assessing various configurations comprehensively. Similarly, in the study by Akkol *et al.* (2017), BR algorithm outperformed other network

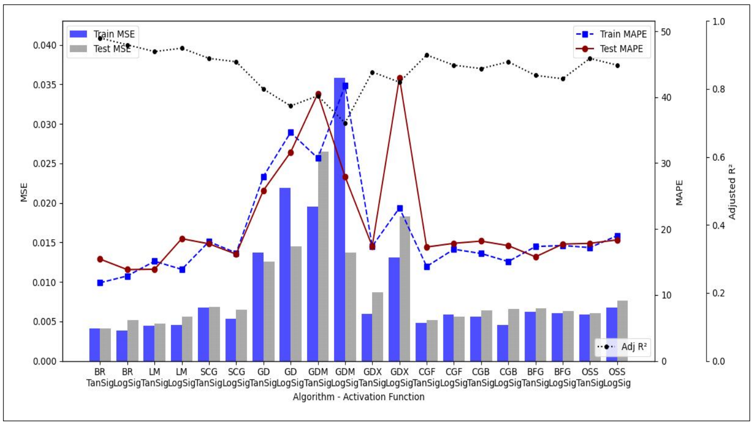


Fig 5: Performance metrics by algorithm and activation function for MLP networks.

Table 4: Statistical criteria for LS-SVM with radial basis function.

Hyperparameters		Train		Test				
σ	γ	MSE	MAPE	MSE	MAPE	R^2_{Adj}	AIC	BIC
1	0.46	0.0038	14.6365	0.0083	22.1682	0.5973	-431.380	-413.652
1	1	0.0023	11.1339	0.0076	20.9853	0.6309	-439.469	-421.741
1	2.15	0.0013	8.24426	0.0073	20.3503	0.6438	-442.796	-425.068
1	4.64	0.0007	5.91862	0.0073	20.1277	0.6431	-442.604	-424.876
1	10	0.0003	4.03606	0.0075	20.1773	0.6329	-439.981	-422.253
5	0.46	0.0049	15.3838	0.0067	19.0847	0.6747	-451.230	-433.502
5	1	0.0044	14.4219	0.0063	18.3540	0.6932	-456.667	-438.938
5	2.15	0.0040	13.6673	0.0061	17.9858	0.7034	-459.830	-442.102
5	4.64	0.0036	12.9584	0.0060	17.8141	0.7067	-460.863	-443.135
5	10	0.0033	12.3680	0.0060	17.7728	0.7052	-460.397	-442.668
10	0.46	0.0063	17.8813	0.0081	21.9421	0.6055	-433.280	-415.552
10	1	0.0055	15.9310	0.0072	20.1333	0.6495	-444.294	-426.565
10	2.15	0.0050	14.9269	0.0067	19.1737	0.6719	-450.424	-432.695
10	4.64	0.0047	14.3761	0.0064	18.6899	0.6860	-454.521	-436.792
10	10	0.0043	13.8914	0.0062	18.3194	0.6962	-457.600	-439.872
20	1	0.0075	20.1536	0.0094	24.2499	0.5449	-419.998	-402.269
20	2.15	0.0061	17.1898	0.0079	21.4793	0.6171	-436.066	-418.337
20	4.64	0.0054	15.6579	0.0071	19.9889	0.6518	-444.887	-427.159
20	10	0.0051	15.0649	0.0068	19.2955	0.6697	-449.804	-432.075
30	1	0.0102	24.6375	0.0121	28.4159	0.4112	-396.047	-378.319
30	2.15	0.0076	20.3065	0.0094	24.4112	0.5404	-419.080	-401.351
30	4.64	0.0062	17.2718	0.0079	21.5942	0.6142	-435.369	-417.641
30	10	0.0055	15.7303	0.0072	20.0772	0.6496	-444.322	-426.594
50	1	0.0144	30.0927	0.0165	33.5553	0.2012	-367.670	-349.942
50	2.15	0.0112	26.0948	0.0132	29.8000	0.3604	-388.339	-370.611
50	4.64	0.0083	21.6246	0.0102	25.6204	0.5045	-412.089	-394.361
50	10	0.0065	18.0708	0.0083	22.3665	0.5954	-430.944	-413.216
100	4.64	0.0138	29.3908	0.0158	32.9033	0.2311	-371.225	-353.496
100	10	0.0106	25.2042	0.0125	28.9527	0.3918	-393.024	-375.296

structures significantly. In Norouzian and Alavijeh (2016)'s study, similar to our results, LM algorithm was employed with a sigmoid activation function, demonstrating substantial effectiveness, according to our results. Unlike our study, a measurement system employing Kinect as a sensor for BW prediction was developed by Chay-Canul *et al.* (2024). Similar to our study, Iqbal *et al.* (2021) also employed the RBF Kernel function; however, it introduced two heuristic algorithms, simulated annealing and the simplex method, for adjusting the hyperparameters of the LS-SVM model. Additionally, research by Huma and Iqbal (2019) also included support vector machines, it is seen that the generalization abilities of the models are quite successful. In the study executed by Çakmakçı (2022), contrary to our study, the Boruta algorithm was employed for feature selection. However, align with our results, the most significant variables were found as Chest width, CD and HW. Since the animals in the study had completed their developmental period, it is considered that the significance level of BL differed from the findings of the present study. Another point of divergence is that age was included as an independent variable in our model to assess the effects of different developmental stages. Additionally, the inclusion of the age variable resulted in differences in the correlations among the variables. Contrary to our study results, it was reported that the CART model exhibited lower RMSE and MAPE values compared to the NN mode with different biometric measurements in Çelik *et al.* (2017)'s study. Similar to our study; thoracic perimeter was among the important variables in estimating body weight of sheep. Ali *et al.* (2015) conducted research with different biometric measurements from our

Table 5: Statistical criteria for LS-SVM with polynomial kernel function.

Degree	Train		Test				
	MSE	MAPE	MSE	MAPE	R^2_{Adj}	AIC	BIC
1	0.0046	14.7933	0.0065	19.2498	0.6831	-451.652	-431.391
2	0.0028	11.3246	0.0067	18.5905	0.6737	-448.952	-428.692
3	0.0009	6.4162	0.0370	25.6397	.	-290.557	-270.296
4	2.1348	0.5941	0.2502	88.9621	.	-112.835	-92.5751
5	1.0896	0.0113	0.2419	87.9896	.	-115.969	-95.7086

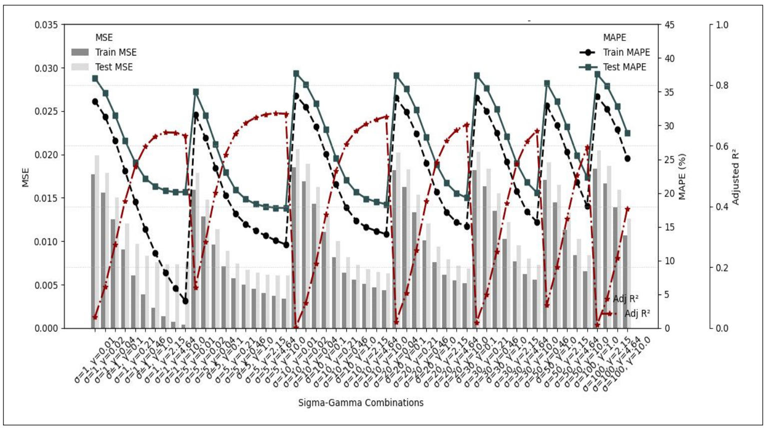
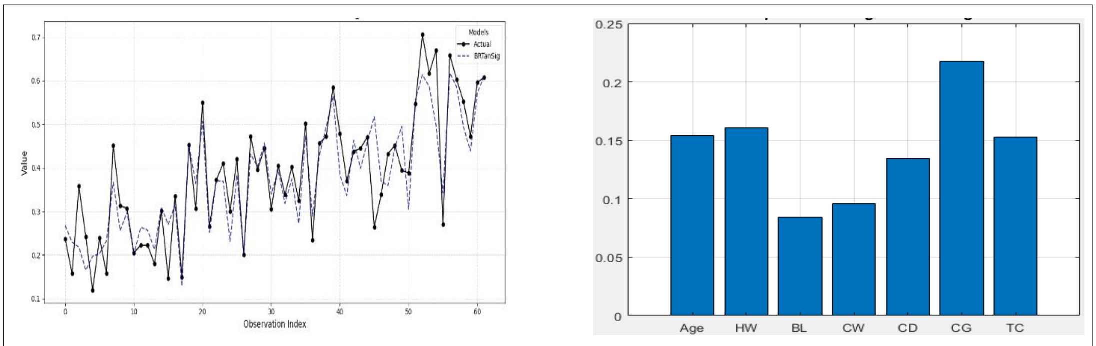


Fig 6: Comparative performance metrics of LS-SVM for sigma-gamma combinations.



(a) (b)

Fig 7: Actual and predicted values of BR algorithm- normalized importance score of MLP (b).

study. Our results are aligned with existing studies in the literature, indicating that chest girth (CG) measurement can be regarded as one of the essential biometric parameters for predicting BW (Sabbioni *et al.,* 2020; Gurgel *et al.,* 2021; Djaout *et al.,* 2022).

The potential of machine learning algorithms to support livestock management has been demonstrated. Body weight estimation based on traits such as chest girth and height at withers has been shown to facilitate the assessment of growth, the optimization of feeding strategies and the selection of superior animals without requiring direct weighing, particularly in resource-limited systems. Certain limitations should be acknowledged. The sample size (n = 312) and the use of data from a single location may limit generalizability. Additionally, variations in biometric traits caused by environmental factors such as nutrition and seasonal conditions may reduce prediction accuracy. To enhance reliability, broader validation across diverse datasets is recommended.

CONCLUSION

In this study, the predictive performances of neural networks and LS-SVM models for estimating the live weight of Norduz sheep were compared. Both models demonstrated strong predictive capabilities when optimized, with parameter tuning shown to be critical for success. In the LS-SVM model, biometric variables such as CD and CG had the greatest influence, while age and HW were more prominent in the MLP model. Consistent with the literature, CG emerged as the most influential variable across both models. The study emphasizes the necessity of systematic parameter optimization and adaptive model selection based on dataset characteristics. Findings are intended to support the integration of machine learning into small livestock systems and the development of data-driven prediction and decision support tools. The application of biometric analysis, particularly live weight estimation, is considered to enhance breeder productivity, support genetic selection processes and contribute to sustainable livestock practices. It is anticipated that the results will guide future research involving different breeds and age groups and inform the development of real-time prediction systems. Integrating the proposed model into mobile-based tools may offer practical benefits in livestock management. A user-friendly application enabling rapid weight estimation *via* basic biometric inputs could improve herd management, especially in rural areas with limited access to veterinary services. Further studies are recommended to assess the feasibility, scalability and practical applicability of such systems in diverse field conditions.

ACKNOWLEDGEMENT

Authors' contributions

Aslı Akıllı conceptualisation, methodology, analysis, writing, review, editing; Suna Akkol conceptualisation, methodology, writing, data collection, review, editing. Both authors have read and approved the finalised manuscript.

Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Informed consent

No animal experiments were conducted in this study. As such, approval from an animal ethics committee was not applicable.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish or preparation of the manuscript.

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