Proceedings of the 15th International Symposium
Modern Trends in Livestock Production
October 29 –31, 2025, Belgrade, Serbia

PREDICTION OF BW FOR GRAZING CATTLE FROM BODY MEASUREMENTS BY USING ARTIFICIAL NEURAL NETWORK LINEAR AND RANDOM FOREST REGRESSION APPROACHES

Yalçın Bozkurt, Serkan Özkaya, Cevdet G. Tüzün

Isparta University of Applied Sciences, Faculty of Agriculture, Department of Animal Science, 32260, Isparta, Turkey
Corresponding author: Yalçın Bozkurt, yalcinbozkurt@isparta.edu.tr

https://doi.org/10.5937/AnimTrend25046B

Abstract: Prediction ability of Linear and Random Forest Regressions and Artificial Neural Network analysis was evaluated for relationships between body weight and body measurements such as Body Length (BL), Wither Height (WH), Heart Girth (HG), Body Depth (BD), Heap Height (HH), and Heap Width (HW), were studied using 232 data in total from 29 head Simmental beef cattle observed during a 4-month grazing performance in Kars in the east of Turkey. Body weight was regressed on the body measurements. Linear, quadratic and cubic effects of heart girth indicated that heart girth measurements would be useful in predicting body weight (R^2= 88.0, 89.8 and 90.8%, respectively). However, quadratic effect was found statistically significant ($P<0.05$). Similarly, regression of body length including linear, quadratic and cubic effects, R^2 values were obtained 82.2, 83.9 and 84.0%, respectively and linear effect was found statistically significant ($P<0.05$). The regression equation which is including all body measurements, R^2 value was found 95.1%. The regression of body weight on heart girth had high R^2 (88.0%), followed by body length (82.2%). The regression equations which is including both heart girth and body length was found high R^2 (93.8%). The correlation coefficient between body weight and body measurements were found the highest in HG and BL (r= 0.94 and 0.91, respectively). Similarly, R^2 values for HG were found the highest among the other individual variables by RF, ANN and LR analysis while the determination coefficients of BL were lower for RF, ANN and LR (50, 63 and 62% respectively) while the same values for HG were higher and similar by RF, ANN and LR (87, 87 and 86% respectively). The results showed that heart girth and body length measurements were the best prediction parameters in predicting body weight in all methods. In terms of predictive ability of the methods used in this study, there was no superiority among them. However, it would be ideal to use the Random Forests algorithm with advantages in dealing with data complexity and non-linear patterns for prediction of body weight based on measurements from digital images of the animals on grazing conditions.

Key words: prediction body weight, Simmental, beef cattle, body measurements, Random Forest Regression

Introduction

There are challenges in determining the body weights of animals, especially those raised in small commercial enterprises and pastures. Therefore, estimating body weight using body measurements has been practiced for many years. The estimation of body weights of animals using body measurements was first researched in the United Kingdom (Şekerden et al., 1991). Body weight plays a significant role in determining the economic characteristics of cattle and the condition of animals (Polgar at al., 1997; Ulutaş et al., 2001). The relationship between body measurements and body weight depends on the animals' level of nutrition, age, and breed (Çağlar and Şekerden, 1993). Body weight is used in ration preparation, determining body condition scores, and establishing the first mating time for heifers (Bozkurt, 2006; Willeke and Dürsch, 2002).

Researchers frequently use the multiple linear regression model (MLR) to examine the causal relationship between an animal's body weight and other body measurements. However, MLR only examines the linear relationship between the set of independent and the dependent variables. This may occasionally be complicated or nonlinear, which might lead to bias in the MLR predictions. Additionally, multicollinearity, a significant correlation between independent variables, can be a big problem for MLR.

The use of artificial intelligence for farming practices is rapidly becoming popular. However, the studies comparing the most popular supervised learning algorithms and ranking them are still scanty. Research for the comparison of various machine learning techniques in animal sciences for the prediction of disease, performance, hatchability lactation, genetic merits, body weights, disease diagnosis and predictions. For all the studies stated, algorithms like artificial neural networks, Support Vector Machines, K-nearest neighbours etc. have been found to be very useful and, in most cases, better than the conventional approaches due to the large amount of data (Pérez-Rodríguez et al., 2013; Kayri, 2016).

Random Forest model is a machine learning method that can be utilized for both classification and regression problems (Ersin and Yaz, 2023). The working principle of the Random Forest Regression model is similar to the decision tree structure. The dataset is randomly divided into small subsets, and decision trees are constructed based on these subsets. During the prediction phase, the average of the predictions from the decision trees created from the dataset is taken (Arslankaya and Toprak, 2021). This algorithm is an ensemble learning method created by combining multiple decision trees.

Numerous studies have been conducted and continue to be conducted on predicting body weight using body measurements. However, there is limited research on predicting body weight using body measurements in Simmental breed animals, especially those raised in pastures (Heinrichs et al., 1992) and (Gilbert et al., 1993) indicated that body measurements can be used in body weight predictions and that there is a close relationship between body weight and body measurements. In many studies, it has been reported that the heart circumference parameter within the body measurements of animals can be used alone to predict body weight (Bozkurt, 2006; Willeke and Dürsch, 2002; Msangi et al., 1999; Poivey et al., 1980). Özkaya and Bozkurt (2007), in their study involving three different breeds (Holstein, Brown Swiss, and their hybrids), reported that body weight could be predicted using metric measurements. However, they noted a decrease in the predictive power of body weight using metric measurements in large-sized animals like Holstein when compared to Brown Swiss and hybrids.

The aim of this study is to predict the body weights of Simmental breed male calves raised under pasture conditions using body measurements and to determine the best prediction parameter. Numerous algorithms have been described by scientists as promising for resolving a range of animal science issues. Predicting future performance is an essential topic that, if done correctly, might assist in making critical decisions for raising income and productivity. Therefore, this study compared the most widely used machine learning algorithms and ranked them according to how well they could predict liveweights on a 12-month beef production system.

Materials and Methods

Material

In this study, 29 male calves raised in the pastures of Kars province locates in the eastern part of Turkiye were used as the material. The study animals were Simmental breed male calves, commonly found in the region, with varying body weights (178.5–343.0 kg). The animals were exclusively grazed in the pasture approximately 4 months and were not fed with any commercial feed.

Body weight measurements

The performance of the animals (BW) was monitored fortnightly by using mobile weighing scale (TruTest) and a total of 232 data were collected. Additionally, certain body measurements (Body Length (BL), Wither Height

(WH), Heart Girth (HG), Body Depth (BD), Heap Height (HH), and Heap Width (HW)) were taken using a measuring stick and measuring tape. Since the animals were under pasture conditions, they were weighed and measured only once.
The parts of the body where measurements were taken are as follows:

Body Length: The portion measured from the shoulder point to the outside angle of the ischium, determined with a measuring stick.
Wither Height: The vertical distance from the highest point of the withers to the ground (vertical distance from the animal's shoulder to the ground), measured with a measuring stick.
Heart Girth: The circumference measurement taken just behind the shoulder blades with a measuring tape.
Body Depth: The vertical distance measured just behind the shoulder blades and immediately behind the front legs with a measuring stick.
Heap Height: The vertical distance between the front heap and the ground, measured with a measuring stick.
Heap Width: The distance measured between the prominences of the hip bones with a measuring stick.

Statistical analysis

A Ryan-Joiner normality test was applied to all data using the Minitab statistical software package. Descriptive statistics and regression analysis of body measurements with body weight were performed using the Minitab, statistical software package. Correlation coefficients between parameters were obtained. Polynomial regression analysis of body weight on body measurements was conducted. Body weight was obtained in kilograms, and body measurements were taken in centimeters.

The effect of the linear, quadratic, and cubic coefficients of the independent variables on body weight is shown in the following model:

$$y = b_0 + b_1 x_i + b_2 x_i^2 + b_3 x_i^3 + e_i$$

y = the observed body weight of the ith animal, b_0 = constant, b_1, b_2, b_3= linear, quadratic, and cubic coefficients, X_i = Body measurements (BL, HG, WH, BD, HH, and HW), e_i = Error.

A Random Forest model is a powerful machine learning algorithm that can be effectively used for predicting liveweight in animals based on various input features such as age, height, girth, breed, and other physiological or environmental factors.

Python was used for developing RF and MLR models, including linear models and used for comparisons with the results obtained from Minitab Statistical software program. In this study prediction ability of the models was evaluated within the scope of R^2 (determination of coefficient) instead of RMSE (Root Mean Square Error) or CV (coefficient of variation) to avoid cumbersome presentation of the results.

Below is an outline of the steps implemented a Random Forest model for bodyweight prediction:

1. Data Preparation

- Collection of Data: The data gathered on bodyweight and relevant features (body measurements).
- Cleaning of Data: The missing values, outliers handled, and data consistency ensured.
- Traits Engineering: Creating meaningful features (body measurements) and traits (e.g., ratios like Heart girth-to-wither height).
- Splitting of Data: The dataset divided into training and testing sets (e.g., 80% training, 20% testing).

2. Model Implementation in Python

the scikit-learn library:

Copy the code# Import necessary libraries

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Load your dataset
data = pd.read_csv('liveweight_data.csv')  # Replace with your dataset
X = data.drop(columns=['Bodyweight'])  # Features
y = data['Liveweight']  # Target variable

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize and train the Random Forest model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

```
# Make predictions
y_pred = rf_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
```

3. Model Optimization

- Hyperparameter Tuning: The techniques like Grid Search or Random Search used to optimize parameters such as n_estimators, max_depth, and min_samples_split.
- Feature (traits) Importance: Analyze body measuremets importance to understand which variables contribute most to the prediction.

4. Interpretation and Deployment

- Interpret Results: Tools like SHAP (SHapley Additive exPlanations) and determination coefficients (R^2) used to interpret the model's predictions.
- Deploy Model: The trained model saved using libraries like scikit-learn or pickle for deployment in real-world applications.

Results

The averages of body weight and body measurements are shown in Table 1. Table 2 presents the regression equations that provide the best predictions using the body measurements taken from the animals. The regression results for the linear, quadratic, and cubic effects of each body measurement on body weight are shown in Table 3.

Table 1. Descriptive statistics of body measurements and body weight

Variables	Mean±SE
BW (kg)	236.76±6.23
BL (cm)	113.95±1.20
WH (cm)	108.43±0.70
BD (cm)	50.21±0.60
HH (cm)	113.98±0.68
HW (cm)	34.64±0.45
HG (cm)	141.07±1.20

BW: Body weight, BL: Body length, WH: Wither height, BD: Body depth, HH: Heap height, HW: Heap width, HG: Heart girth, SE: Standard error

As seen in Table 2, the regression equation including all body measurements yielded the highest R^2 value for predicting body weight (95.1%). It was observed that in regression equations where the heart girth measurement was absent, the R^2 value decreased (Table 2). The second-highest R^2 value was obtained in the regression equation that did not include HW (95.0%). The R^2 values for regression equations containing only BL and only HG were 82.2% and 88.0%, respectively (Table 2). The R^2 value was 93.8% in the regression equation containing both BL and HG. As shown in Table 2, the predictive power of body weight with WH, BD, HH, and HW measurements was found to be very low. A 1 cm change in HG measurement results in a 4.89 kg change in body weight (Table 2).

The polynomial regression analysis of body weight on body measurements (Table 3) revealed the highest values for BL and HG measurements (84.0% and 90.8%, respectively). The cubic coefficients for all body measurements showed a slight increase, and the R^2 value for the HH measurement remained constant. However, while the linear coefficient was statistically significant for all measurements, the quadratic coefficient was also significant for HG and BD measurements ($P < 0.05$).

Table 2. Regression equations to predict body weight using body measurements

Equations	R^2 (%)
Y= -411+2.00 BL*+0.86 WH–0.83 BD–1.38 HH–0.18 HW+3.67 HG*	95.1
Y= -476+4.37 BL*+1.49 WH+1.14 BD+0.91 HH–3.12 HW	86.9
Y= -414+2.04 BL*+0.87 WH–0.78 BD–1.31 HH+3.63 HG*	95.0
Y= -469+2.31 BL*+0.53 WH–0.69 BD–0.88 HW+3.19 HG*	94.4
Y= -406+2.14 BL*+0.68 WH–1.29 HH–0.35 HW+3.43 HG*	94.8
Y= -385+2.02 BL*-0.58 BD-1.10 HH+0.30 HW+3.79 HG*	94.7
Y= -363+0.96 WH-1.74 BD-2.51 HH*+2.64 HW+5.51 HG*	91.6
Y= -465+2.14 BL*+0.37 WH-1.01 BD+3.32 HG*	94.2
Y= -418+4.09 BL*+1.52 WH+0.46 BD	84.9
Y= -449+2.19 BL*-0.002 WH+3.10 HG*	93.8
Y= -446+2.15 BL*-0.83 BD+3.40 HG*	94.2
Y= -475+0.53 WH-1.33 BD+5.11 HG*	88.7
Y= -424+4.13 BL*+1.75 WH*	84.8
Y= -331+4.36 BL*+1.42 BD	83.6
Y= -449+2.19 BL*+3.09 HG*	93.8
Y= -301+4.72 BL*	82.2
Y= -390+5.75 WH*	42.5
Y= -58.3+5.88 BD*	31.7
Y= -352+5.17 HH*	31.7
Y= -14.6+7.26 HW*	27.9
Y= -453+4.89 HG*	88.0

BW: Body weight, BL: Body length, WH: Wither height, BD: Body depth, HH: Heap height, HW: Heap width, HG: Heart girth, * It is statistically significant ($P<0.05$).

While the linear coefficient for the HW measurement was statistically insignificant (P > 0.05), the quadratic coefficient was found to be statistically significant (P < 0.05).

Table 3. Regressions of body weight on the linear, quadratic and cubic effects of each body measurements

Variables	Constant	Linear	Quadratic	Cubic	R^2 (%)
BL	-301.02	4.72*			82.2
	566.01	-10.15*	0.06		83.9
	3285.86	-80.00*	0.66	-0.00	84.0
WH	-390.21	5.78*			42.5
	3033.55	-57.60*	0.29		45.5
	-97956.90	2754.79*	-25.78	0.80	49.1
HH	-351.97	5.17*			31.7
	-36.50	6.67*	-0.01		31.7
	521.36	-18.96*	0.22	-0.00	31.7
HW	-14.64	7.26*			27.9
	934.66	-47.34*	0.78		31.1
	-26181.80	2309.38*	-67.20	0.65*	43.1
BD	-58.26	5.88*			31.7
	1519.85	-57.59*	0.64*		43.0
	-4501.04	308.23*	-6.73*	0.05	44.1
HG	-453.11	4.89*			88.0
	844.39	-13.25*	0.06*		89.8
	17719.20	-364.97*	2.50*	-0.01	90.8

BW: Body weight, BL: Body length, WH: Wither height, BD: Body depth, HH: Heap height, HW: Heap width, HG: Heart girth, * It is statistically significant (P<0.05).

Table 4. Correlation coefficients between the body measurements and the body weight

Variables	BL	WH	BD	HH	HW	HG
BW	0.91	0.65	0.56	0.56	0.53	0.94

BW: Body weight, BL: Body length, WH: Wither height, BD: Body depth, HH: Hip height, HW: Hip width, HG: Heart girth,

All correlations were found to be statistically significant (P < 0.05). The highest correlation between body weight and body measurements was obtained in BL and HG measurements (0.91 and 0.94, respectively). All obtained correlations were statistically significant (P < 0.05).

The first stage of artificial intelligence-based data analysis is to adapt the data to the designed artificial intelligence model. In this context, the obtained data has been standardized initially. The StandardScaler function from the sklearn library was used for this process. StandardScaler is the process of rescaling each feature value of the dataset so that the mean is zero and the standard deviation is one. This process allows machine learning algorithms to work accurately when the features in the dataset are of different scales. After standardizing the data, it was divided into a training set and a test set. This separation involves using a certain portion of the dataset for training and the remaining portion for testing. In the literature, this ratio is generally observed to be 70% for training and 30% for testing. Due to the small size of our dataset, 80% of the data was used for training and 20% for testing in our study.

The analyses were conducted using the Python programming language in the Spyder editor. For Random Forest, the max-depth parameter was set to 10. For classical artificial neural networks, only input and output layers were used without hidden layers, as the data size is small. The 'HWd' function was used as the optimizer for training the neural network, and 'mean squared error' was used as the loss function. The model was trained for 60 epochs, with data being sent one by one in each epoch. All hyperparameters were optimized and determined.
Six variables used in predicting the output in the dataset were employed in combinations from one to six, and the combinations that achieved the highest results were determined. These combinations and the success rates of the models (R^2 values) are presented in Table 5.

It was observed that Logistic and random forest Regression and classical neural network models produced similar results. The combination of HW BL WH HG HH parameters for the Random Forest model yielded the highest result with an R2 value of 0.89. For Logistic Regression, the combination of HW BL WH HG BD produced the highest result with an R2 value of 0.93. Similarly, for the classical Artificial Neural Network, the combination of BL WH HG resulted in the highest R2 value of 0.93. Furthermore, when considering individual variables such as BL and HG their R2 values were found the highest among the other individual variables. However, as seen Table 5 the determination coefficients of BL were lower for RF, ANN and LR (0.50, 0.63 and 0.62 respectively) while the same values for HG were similar in RF, ANN and LR (0.87, 0.87 and 0.86 respectively).

Table 5. The results of RF, ANN, and LR Analysis

Variables	RF	ANN	LR
HW BL WH HG HH BD	0.8645	0.8586	0.8467
HW BL WH HH BD	0.6608	0.6623	0.6888
HW BL WH HG BD	0.8808	0.9259	**0.9353**
BL WH HG HH BD	0.8752	0.8676	0.8831
HW BL WH HG HH	**0.8977**	0.8828	0.8876
HW BL HG HH BD	0.8894	0.8618	0.8792
HW WH HG HH BD	0.8762	0.8632	0.8718
HW BL HG BD	0.8696	0.9028	0.8990
HW WH BD	0.5505	0.6196	0.6398
BL WH HG	0.8835	**0.9318**	0.9328
BL HG BD	0.8599	0.9020	0.8998
WH HG BD	0.8328	0.9006	0.8935
BL WH	0.7738	0.7697	0.7371
BL HG BD	0.8640	0.8929	0.8995
WH HG BD	0.8381	0.8991	0.8935
BL	0.5027	0.6270	0.6262
HG	0.8686	0.8710	0.8563

BW: Body weight, BL: Body length, WH: Wither height, BD: Body depth, HH: Heap height, HW: Heap width, HG: Heart girth,

Discussion and Conclusion

Since there is limited research on predicting body weight using body measurements in Simmental cattle on grazing conditions, the obtained values were evaluated in comparison with results from studies on other breeds. The regression equation including BL, WH, BD, and HG measurements (Table 2) yielded an R^2 value of 94.2%. This value was higher than those reported by (Tüzemen et al., 1995; Tüzemen et al., 1993) and (Özkaya and Bozkurt, 2007) (90.7%, 90.7%, and 66.1%, respectively, and 91.8%). The R2 value obtained for the regression equation including BL, WH, and HG measurements (93.8%) was higher than values reported by (Özkaya and Bozkurt, 2007), (Ulutaş et al., 2001), and (Çağlar and Şekerden, 1993) (66.1%, 91.3%, 82.5%, and 75.8%, respectively), but lower than the value reported by Şekerden et al. (1991) (97.7%) and similar to the value reported by (Bozkurt, 2006) (93.6%).

As seen in Table 2, the R^2 value obtained for the regression equation including only BL measurement (82.2%) was higher than those reported by (Ulutaş et al., 2001), (Çağlar and Şekerden, 1993), (Tüzemen et al., 1993), (Bozkurt, 2006), (Özkaya and Bozkurt, 2007) (68.3%, 55.4%, 67.0%, 70.4%, and 47.7%, respectively) but lower than values reported by (Heinrichs et al., 1992), (Şekerden et al., 1991) (93.0% and 96.1%). It was similar to the value reported by (Özkaya and Bozkurt, 2007) (79.2%). The R^2 value obtained for the regression equation including only HG measurement (88.0%) was higher than values reported by (Goe et al., 2001), (NesamBLni et al., 2000), (Ulutaş et al., 2001), (Çağlar and Şekerden, 1993), (Özkaya and Bozkurt, 2007) (75%, 74%, 73.1%, 64%, and 60.7%, respectively) but lower than values reported by (Willeke and Dürsch, 2002), (Gilbert et al., 1993), (Şekerden et al., 1991), (Özkaya and Bozkurt, 2007)(94%, 95%, 97.3%, and 91.1%, respectively). However, the value obtained for the equation including only HG measurement (88.0%) was close to values reported by (Tüzemen et al., 1993), (Bozkurt, 2006), (Özkaya and Bozkurt, 2007) (87%, 89.9%, and 88.8%, respectively). The R^2 value obtained for the regression equation including both BL and HG measurements (93.8%, Table 2) was higher than values reported by (Ulutaş et al., 2001), (Çağlar and Şekerden, 1993), (Tüzemen et al., 1993) (80.6%, 74.8%, and 90%, respectively) but lower than the value reported by (Şekerden et al., 1991) (97.7%) and similar to the value reported by (Bozkurt, 2006) (93.2%).

In their study, (Nesamblni et al., 2000), (Bozkurt, 2006) suggested that the cubic coefficient (78% and 90.2%, respectively) could be a better predictor for HG measurement, while (Ulutaş et al., 2001), (Heinrichs et al., 1992), (Özkaya and Bozkurt, 2007) reported that the quadratic coefficient was a better predictor (95.1%, 98%, 94.4%, and 89.8%, respectively). The results of the study on Simmental male cattle (Table 3) concluded that the quadratic coefficient is a better predictor for estimating body weight compared to other body measurements. The obtained R^2 value (90.8%) was higher than that reported by (Nesamblni et al., 2000), similar to (Bozkurt, 2006), and lower than values reported by (Heinrichs et al., 1992), (Ulutaş et al., 2001), (Özkaya and Bozkurt, 2007) (98%, 94.4%, and 89.8%, respectively).

As shown in Table 4, a high correlation was obtained between body weight and BL and HG measurements (r=0.91 and 0.94, respectively). The correlation coefficient obtained between BL and BW was higher than values reported by (Yanar et al., 1995), (Tüzemen et al., 1995), (Özkaya and Bozkurt, 2007) (0.40, 0.70, and 0.69, respectively, and 0.89), and similar to the value reported by (Özkaya and Bozkurt, 2007*)* (0.91). The correlation coefficient obtained between HG and BW was higher than values reported by (Yanar et al., 1995), (Tüzemen et al., 1995), (Özkaya and Bozkurt, 2007) (0.85, 0.86, and 0.78, respectively) and similar to the values reported by (Özkaya and Bozkurt, 2007) (0.95 and 0.94).

Numerous research has evaluated artificial neural network models with linear and random forest regression to forecast domestic animal performance for various reproductive and productive variables (Saberioon et al. 2018; Van der Heide et al. 2019). The linear model in this investigation had a coefficient of determination (R^2=0.93) that was similar to Tsegaye et al. (2013) and our results were also in line with those of Huma and Iqbal (2019) (R^2=0.92). In a study done with other domestic farm animals, the weight of Baluchi sheep was estimated using RF by Huma and Iqbal (2019), and the coefficient of determination (R^2) was similar to the current study (R2=0.98). But the R^2 values of the nonlinear models in this investigation were greater than those in the study by Ali et al. (2015), which employed decision tree algorithms and artificial neural networks to predict the live weight of Harnai sheep with an accuracy of 0.81 to 0.84. Simmental cattle are intensively raised, especially in the Eastern Anatolia region of Turkey. Regression equations are recommended for predicting body weights of Simmental cattle on grazing conditions. The equations obtained have a high predictive power for estimating body weight. Predicting body weight is important for determining the needs of animals and monitoring their performance. Although using a scale to determine body weight is a more accurate method, especially during the summer months when animals are grazed and housed in pastures, it is recommended to use body measurements, especially heart girth measurement, due to the difficulty of using a scale to track body weights. Moreover, weighing animals under grazing conditions is a stressful activity and reduces their welfare.

In conclusion, the results showed that heart girth and body length measurements were the best prediction parameters in predicting body weight in all methods. In terms of predictive ability of the methods used in this study, there was no superiority among them. However, it would be ideal to use the Random Forests algorithm with advantages in dealing with data complexity and non-linear patterns for prediction of body weight based on measurements from digital images of the animals on grazing conditions.

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