

**PREDICTION OF LIVE WEIGHT FROM MORPHOMETRIC
TRAITS IN NIGERIA GOAT BREEDS USING
MACHINE LEARNING**

BY

**Joseph Odion UKPEBOR
AGR2004326**

**DEPARTMENT OF ANIMAL SCIENCE
FACULTY OF AGRICULTURE
UNIVERSITY OF BENIN
BENIN CITY, NIGERIA**

NOVEMBER, 2025.

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**A PROJECT SUBMITTED TO THE DEPARTMENT OF ANIMAL
SCIENCE, FACULTY OF AGRICULTURE, UNIVERSITY OF
BENIN, BENIN CITY, NIGERIA**

**IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE
AWARD OF A BACHELOR DEGREE OF AGRICULTURE
(B.AGRIC) IN ANIMAL SCIENCE)**

NOVEMBER, 2025.

CERTIFICATION

This is to certify that this project was carried out by **Joseph Odion UKPEBOR**, with the Matriculation Number **AGR2004326**, of the Department of Animal Science, Faculty of Agriculture, University of Benin, Benin City, Nigeria.

MR. P. ADUBA
(PROJECT SUPERVISOR)

DATE

DR. N.C. AKAEZE
(HEAD OF DEPARTMENT)

DATE

DEDICATION

I dedicate this project work to Almighty God for his love and faithfulness all through the course of my programme in the University of benin. And also to my beloved parents and siblings for their love and financial supports.

ACKNOWLEDGMENT

I would like to express my heartfelt gratitude to all those who have contributed to the successful completion of this project. First and foremost, I am grateful to God, my mum and Dad , Mr and Mrs. Saturday and Magdalene Ukpebor , my siblings (JOY, SONIA, MARY, BRIGHT, OSAS) , My In-law Hanson Uche, My child old friends (God's power, Ajiri, Jerome, Benny, Efe, Kingsley, and others) , My clique of friends (BAMBOO BOYS) and the (Gentle Men) who provided valuable assistance in specific aspects of the project.

I extend my deepest appreciation to my Project supervisor, Mr P. Aduba for his invaluable supervision, mentorship, and continuous support throughout the project. I wish to express my keen gratitude to the Dean Faculty of Agriculture, Prof. Christopher O. Emokaro and our amicable Head of Department, Dr. N. C. Akaeze.

I am indebted to University of Benin/ Animal science/ Uniben farm project for providing the necessary resources, infrastructure, and environment conducive for research.

Lastly, i want to appreciate my babe (Blossom) she's the best.

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ABSTRACT

This study evaluated the application of machine learning models in predicting live weight of Nigerian indigenous goat breeds using morphometric traits. Data were collected from three major breeds which includes Red Sokoto, West African Dwarf, and Sahel goats. The data was collected across several markets in Benin City, Nigeria. Morphometric measurements including heart girth, body length, height at withers, and rump height were taken from each goat and analyzed using machine learning models such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN) and Extra Decision Tree(EDT). The Extra Decision Tree(EDT) model recorded the highest prediction accuracy (89.22%) and coefficient of determination ($R^2 = 93.76\%$), while also achieving the lowest Mean Square Error (MSE = 1.23) and Mean Absolute Error (MAE = 0.05). These results indicate that Extra Decision Tree provided the most reliable and stable prediction of live weight among the evaluated models. The findings demonstrate that morphometric based machine learning approaches can serve as efficient, low cost tools for accurate live weight estimation in indigenous goat breeds, supporting improved productivity and management in Nigeria's livestock systems.

CHAPTER ONE

1.0

INTRODUCTION

The accurate estimation of live weight (LW) is essential in animal husbandry and livestock management. It serves as a key indicator for evaluating growth performance, determining feed requirements, calculating medication doses, planning breeding programs, and assessing market value (Chinchilla-Vargas et al., 2022; Mohammed et al., 2020). In many rural and smallholder systems across Nigeria, however, access to functional weighing equipment remains limited, prompting the need for reliable, indirect methods of weight estimation.

Goats hold a central position in Nigeria's livestock industry, with an estimated population exceeding 76 million (FAOSTAT, 2023). Indigenous breeds such as the Red Sokoto, West African Dwarf (WAD), and Sahel goats are well adapted to local environments and are vital to rural livelihoods. They are kept for meat, milk, and skin, and are often managed under extensive or semi-intensive systems requiring minimal inputs (Dossa et al., 2008; Okpeku et al., 2011). Their resilience to harsh conditions makes them a crucial component of food security and poverty alleviation strategies in Nigeria.

In the absence of weighing scales, farmers typically rely on morphometric traits such as heart girth, body length, and height at withers to estimate live weight. These traits have been shown to correlate significantly with body weight and are commonly incorporated into multiple regression models for prediction (Yakubu, 2009; Ajayi et al., 2022).

However, such models often assume linearity and may not capture the biological complexity of animal growth. Additionally, variations in breed conformation and environmental conditions can reduce their general applicability.

Recent advancements in machine learning (ML) and artificial intelligence (AI) have revolutionized data analysis in animal science. These methods can learn intricate, nonlinear patterns from large datasets, outperforming traditional regression models in predictive accuracy (Hassan et al., 2023). Algorithms such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Gradient Boosting Machines (GBM) have proven effective in modeling complex biological traits, including live weight (Kurnaz and Reçber, 2021; Oyelami et al., 2020).

Despite these developments, studies applying ML-based morphometric prediction to Nigerian indigenous goat breeds remain limited. Most existing research focuses on cattle or exotic goat breeds, often under intensive management systems. There is, therefore, a need to develop locally relevant, breed-specific models that reflect the morphometric variability and management practices typical of Nigerian conditions.

The present study reviews the application of machine learning techniques in predicting the live weight of Nigerian indigenous goats using morphometric data.

1.1 Justification of the Study

Accurate estimation of live weight is fundamental in animal production because it directly influences management decisions related to feeding, medication, breeding, and marketing. In most rural and smallholder livestock systems in Nigeria, however, weighing scales are either unavailable or impractical for routine use. Farmers therefore rely on visual assessment or crude measurement techniques that often lead to inaccurate weight estimation. Such inaccuracies can result in economic losses through improper feed allocation, wrong drug dosages, and poor pricing of animals at sale points.

Goats play a major role in Nigeria's livestock economy, especially among small-scale farmers who depend on them for income generation, food security, and cultural purposes. Indigenous breeds such as the Red Sokoto, West African Dwarf (WAD), and Sahel goats are resilient and well adapted to diverse ecological zones, yet studies focusing on accurate prediction of their live weights remain limited. Existing models are mostly linear and breed-specific, often failing to capture the complex, non-linear relationships between body measurements and live weight that arise from genetic and environmental variability.

With the growing interest in data-driven livestock management, machine learning (ML) offers a powerful alternative by providing flexible algorithms capable of learning complex patterns from morphometric data. ML-based prediction models not only enhance accuracy but also allow for faster and more objective weight estimation without requiring physical scales. Developing and validating such models for Nigerian indigenous goat breeds is therefore both timely and relevant, as it addresses a critical gap

in local livestock research and production efficiency.

Furthermore, integrating the effects of breed, age, and sex into these predictive frameworks ensures that the models are biologically grounded and practically applicable across different management systems. The findings from this study will provide a valuable decision-support tool for farmers, breeders, and extension workers, ultimately contributing to improved productivity, profitability, and sustainable goat production in Nigeria.

1.2 General Objective

The main objective of this study is to develop and evaluate machine learning models for predicting the live weight of Nigerian indigenous goat breeds based on morphometric body measurements.

1.3 Specific Objectives

The specific objectives are to:

1. Determine the morphometric characteristics (heart girth, body length, height at withers, rump height, neck length, etc.) of Nigerian indigenous goat breeds (Red Sokoto, Sahel, and West African Dwarf).
2. Assess the influence of breed, age, and sex on the live weight of Nigerian indigenous goats.

3. Develop and train machine learning models (Random Forest, Support Vector Machine, Artificial Neural Network, and Extra Decision Tree) for predicting live weight using morphometric traits.
4. Evaluate and compare the performance of the developed models using statistical metrics such as coefficient of determination (R^2), accuracy, mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).
5. Identify the most accurate and efficient model for predicting live weight among the tested algorithms for practical use in livestock management and breeding programs.

CHAPTER TWO

2.0

LITERATURE REVIEW

2.1 Overview of Nigerian Indigenous Goat Breeds

Nigeria possesses a rich diversity of indigenous goat breeds that have been shaped by generations of natural and artificial selection to adapt to various ecological zones. These breeds are not only genetically diverse but also form a crucial part of rural livelihoods and smallholder economies. Goats contribute significantly to household nutrition, income generation, and cultural practices across the country. With an estimated population of over 76 million goats (FAOSTAT, 2023), the species represents one of Nigeria's most valuable livestock resources.

The indigenous goat breeds — primarily Red Sokoto, West African Dwarf (WAD), and Sahel — have developed unique adaptive features that enable them to survive and perform under harsh environmental and nutritional conditions. Their ability to thrive under extensive or semi-intensive systems with minimal input makes them indispensable to resource-poor farmers. Goats are valued for their meat, milk, skins, and manure, and in some regions, their cultural significance is also substantial (Dossa et al., 2008; Okpeku et al., 2011).

Understanding breed differences is essential in predicting live weight, as each breed's morphology, growth potential, and feed conversion efficiency vary significantly. Breed-specific variations directly influence the accuracy of predictive models and

determine their suitability for use across different ecological regions.

2.1.1 Red Sokoto Goats

The Red Sokoto goat, also known as the Maradi goat, is the most dominant breed in northern Nigeria and adjacent Sahel regions. It is characterized by its distinctive reddish-brown coat color, medium size, and glossy skin, which is highly valued in the international leather market (Yakubu et al., 2011). Red Sokoto goats are typically hardy, heat-tolerant, and well adapted to arid and semi-arid environments. Their average adult weight ranges between 25–35 kg under traditional systems, though it may be higher under improved feeding and management.

This breed's morphometric traits, such as moderate body length, proportional height at withers, and balanced heart girth, make it suitable for live weight prediction using biometric models. Previous studies (Olatunji-Akioye and Adeyemo, 2009; Bello et al., 2021) found strong correlations between its morphometric traits and live weight, suggesting its predictability and suitability for selection programs. Moreover, Red Sokoto goats are docile and easy to handle, reducing measurement errors during data collection — an advantage in phenotypic characterization studies.

2.1.2 West African Dwarf (WAD) Goats

The West African Dwarf (WAD) goat is small-bodied and well adapted to the humid forest and derived savannah zones of southern Nigeria. Despite its small size, it remains

one of the most important breeds for smallholder farmers due to its hardiness, disease resistance, and low management requirements. The average adult weight typically ranges from 15–25 kg (Nwogwugwu et al., 2022).

WAD goats exhibit compact body frames with short limbs, a broad chest, and high skeletal density. These morphological characteristics reflect their adaptation to forested areas, where agility and small size are advantageous. However, the compactness of their body structure makes live weight estimation more complex because traditional linear models may not fully capture their proportional differences compared to larger breeds. Ajayi et al. (2022) reported that although WAD goats have strong correlations between heart girth and live weight, predictive equations developed for larger breeds often overestimate their weight, highlighting the importance of breed-specific modeling.

2.1.3 Sahel Goats

The Sahel goat, also known as the Desert goat, is prevalent in northern Nigeria’s arid and semi-arid zones. It is tall, long-legged, and light-framed, features that make it ideal for long-distance trekking in search of feed and water. Adult males may weigh up to 40 kg or more under good nutrition and management (Yakubu, 2009).

The Sahel goat’s body conformation — long limbs, narrow thorax, and lean musculature — influences its morphometric traits and, consequently, live weight prediction. Its adaptability to extreme temperatures and limited water availability demonstrates its

physiological efficiency in resource-scarce environments. However, its lighter body frame compared to meat-type breeds means that while it may have greater height and length measurements, its body mass distribution is different, requiring customized prediction models (Bello et al., 2021).

2.1.4 Importance of Breed-Specific Models

Because of these morphological and physiological differences, breed-specific prediction models are necessary for accurate live weight estimation. A model developed for one breed may not perform effectively when applied to another due to differences in skeletal structure, muscle deposition, and body conformation. For example, a model based on WAD goats' compact body shape will likely underestimate the live weight of Sahel goats, which are taller and leaner (Okpeku et al., 2011).

Therefore, accurate predictive modeling must account for breed differences to ensure high precision and reduce bias. This approach also aids genetic improvement programs by providing reliable indicators for selecting superior animals within each breed. Incorporating breed as a categorical variable in machine learning algorithms can further enhance model adaptability and performance.

2.2 Morphometric Traits and Their Relationship with Live Weight

Morphometric traits, also known as biometric or linear body measurements, are physical measurements used to describe an animal's size, shape, and growth pattern. In livestock

science, these measurements are crucial indicators of growth, productivity, and carcass yield potential. For goats, traits such as heart girth (HG), body length (BL), and height at withers (HW) are widely used to estimate live weight, especially in smallholder farming systems where weighing scales are unavailable (Yakubu, 2009; Bello et al., 2021).

These measurements are inexpensive, simple to take, and provide non-destructive estimates of body mass. The relationship between morphometric traits and live weight is grounded in biological principles: animals with larger thoracic capacity (higher heart girth), longer body frames (greater body length), and higher stature (greater height at withers) generally have higher muscle mass and body weight.

2.2.1 Heart Girth as a Strong Predictor

Among all morphometric traits, heart girth consistently emerges as the strongest single predictor of live weight. This is because heart girth reflects both the skeletal framework and the level of muscle and fat deposition around the chest cavity. Bello et al. (2021) and Ajayi et al. (2022) found strong positive correlations ($r > 0.80$) between heart girth and live weight in Red Sokoto and WAD goats, suggesting that increases in chest circumference correspond directly to weight gain.

Additionally, heart girth is less susceptible to measurement errors compared to other traits because it can be taken easily and consistently, even by untrained personnel. This makes it a practical and reliable trait for rural farmers and field technicians.

2.2.2 Combining Traits for Improved Accuracy

Although single-trait models provide reasonable estimates, combining multiple morphometric traits significantly improves prediction accuracy. Multiple linear regression (MLR) models that integrate heart girth, body length, and height at withers explain a larger proportion of variance in live weight than any single trait alone (Yakubu, 2009; Olatunji-Akioye and Adeyemo, 2009).

Ajayi et al. (2022) demonstrated that a combination of these three traits explained up to 87% of variation in live weight in WAD goats. This improvement occurs because combined traits capture both the lengthwise and widthwise growth dimensions of the animal's body, giving a more complete representation of body conformation.

2.2.3 Limitations of Traditional Regression Models

Despite their usefulness, traditional linear regression models have several limitations. They assume a linear relationship between traits and live weight, which does not always reflect biological complexity. They are also prone to multicollinearity, as many morphometric traits are highly correlated with each other. Furthermore, their predictive power tends to vary across breeds, age groups, and physiological stages, reducing their general applicability (Yakubu, 2010; Ogunniyi et al., 2023).

Measurement inconsistencies - often caused by animal movement or handler error can also introduce significant bias. These challenges necessitate more advanced data-driven

techniques such as machine learning, which can model nonlinear interactions and handle multicollinearity effectively.

2.2.4 Breed-Specific Trait Variability

Breed differences greatly influence the relationship between morphometric traits and live weight. For instance, Red Sokoto goats exhibit moderate heart girth and body length, making their weight relatively predictable through regression. WAD goats, due to their compact structure, often require nonlinear or adjusted models. Sahel goats, on the other hand, show a high ratio of body length to weight due to their lean frames. These variations underline the need for customized predictive equations for each breed (Okpeku et al., 2011).

2.2.5 Application in Selection and Breeding

Accurate morphometric-based weight estimation supports breeding programs and performance evaluation. Traits such as heart girth and body length have moderate to high heritability, meaning they respond well to selection (Yakubu et al., 2011). Thus, predicting live weight from these measurements can indirectly support genetic improvement by identifying high-growth animals without the need for weighing equipment. This makes morphometric modeling both a practical and cost-effective tool for on-farm livestock improvement.

2.3 Application of Machine Learning in Livestock Trait Prediction

Machine learning (ML) offers a powerful alternative to traditional statistical approaches in predicting biological traits like live weight. ML algorithms learn patterns from data, model nonlinear relationships, and improve prediction accuracy through self-optimization. In animal science, they have been successfully applied to predict body weight, feed conversion, and growth performance (Hassan et al., 2023).

Algorithms such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Gradient Boosting Machine (GBM) are particularly effective. Each model has unique strengths depending on the data structure and complexity.

The Random Forest (RF) algorithm combines multiple decision trees to generate an ensemble output, reducing overfitting and improving accuracy. The SVM uses hyperplanes to find the best-fit regression surface, while the ANN mimics biological neural networks to capture nonlinear patterns. Gradient boosting methods iteratively refine model predictions, focusing on reducing errors from previous iterations (Bello et al., 2021; Oyelami et al., 2020).

The advantage of ML in livestock prediction lies in its ability to handle complex datasets with many interrelated variables — something conventional regression cannot do effectively. It can identify hidden patterns and interactions between morphometric traits, age, and breed that directly influence live weight.

2.4 Integration of Morphometric Data into Machine Learning Models

Incorporating morphometric data into machine learning frameworks enhances the robustness and precision of live weight prediction models. Traits like heart girth, body length, and height at withers provide measurable quantitative inputs that ML algorithms can process efficiently. These data allow models to learn and generalize the nonlinear relationships between body structure and weight, leading to improved prediction accuracy (Yakubu, 2010; Salako, 2006).

Studies have shown that combining multiple morphometric traits in ML models yields higher R^2 values and lower error rates compared to linear regression. For example, Adeyemo et al. (2022) reported that Random Forest and Artificial Neural Network models achieved prediction accuracies above 90% when trained on Nigerian goat datasets. These models are particularly valuable in rural settings, where access to digital scales is limited, as they provide a reliable alternative for estimating body weight.

CHAPTER THREE

3.0

MATERIALS AND METHODS

3.1 Study Location

The study was conducted across selected livestock markets in and around Benin City, Edo State, Nigeria. The area, located within the humid tropical rainforest zone, experiences annual rainfall between 1,700 and 2,500 mm and an average temperature of 27°C. These markets were chosen due to their diversity of goat breeds sourced from across Nigeria, making them ideal for morphometric data collection.

3.2 Experimental Animals

Goats representing the Red Sokoto, West African Dwarf, and Sahel breeds were randomly selected. Only healthy animals without visible deformities were included to maintain measurement consistency. These breeds were chosen due to their economic relevance and distinct morphological features.

3.3 Experimental Period

Data collection spanned six months (May to October 2025), covering both dry and early rainy seasons. This period ensured the inclusion of seasonal variations affecting animal body condition.

3.4 Data Collection Process

Each goat was gently restrained for measurement following standard procedures (Yakubu, 2009; Ajayi et al., 2022). Traits recorded included heart girth, body length, height at

withers, rump height, neck length, ear length, tail length, and cannon bone length. Live weight was measured using a portable digital scale where available, and each measurement was repeated three times per animal to minimize random error.

3.5 Statistical Analysis

Data were organized, cleaned, and analyzed using a machine learning framework. The dataset was divided into training (80%) and testing (20%) subsets. Feature selection was conducted using correlation analysis and PCA. The Extra Decision Tree served as the primary model due to its proven efficiency in handling nonlinear relationships and multicollinearity (Bello et al., 2021; Adeyemo et al., 2022).

Comparative models such as SVR and RF were also tested to benchmark performance. Model evaluation was based on R^2 , RMSE, and MAE metrics. Analyses were performed using Python (v3.10) and R (v4.2.0) software, with visualization through scatter plots and residual analyses to assess accuracy and model fit.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - f_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum (y_i - f_i)^2}$$

$$MAE = \frac{1}{n} \sum |y_i - f_i|$$

$$MAPE = \frac{1}{n} \sum |y_i - f_i| / |y_i|$$

Multilinear regression model

$$Y_w = \beta_0 + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + \dots + X_n\beta_n$$

Support vector regression

$$\frac{1}{2} \|w\|^2 + c \longrightarrow \text{Min}$$

Cluster equation using elbow method

$$WCSS = \sum_{P_i \text{ in cluster 1}} \text{distance}(P_i, C_1)^2 + \sum_{P_i \text{ in cluster 2}} \text{distance}(P_i, C_2)^2 + \sum_{P_i \text{ in cluster 3}} \text{distance}(P_i, C_3)^2 \quad (7)$$

Where Y_w is the weight of the animals and X the morphometric variables

Input: Dataset $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)\}$;

A weight of each sample in the training set constitutes a weight vector Z_t ;

Base learning algorithm \mathcal{L} ;

Number of learning rounds T .

Process:

$D_1(i) = 1/m$ % Initialize the weight distribution

For $t = 1, 2, \dots, T$:

$h_t = \mathcal{L}(D, D_t)$; % Train a base learner h_t from D using distribution D_t

$\epsilon_t = \Pr_{i \sim D_t}[h_t(x_i) \neq y_i]$; % Measure the error of h_t

$\alpha_t = \frac{1}{2} \ln \frac{1-\epsilon_t}{\epsilon_t}$; % Determine the weight of h_t

$$D_{t+1}(i) = \frac{D_t(i)}{\text{sum}(Z_t)} \times \begin{cases} \exp(-\alpha_t) & \text{if } h_t(x_i) = y_i \\ \exp(\alpha_t) & \text{if } h_t(x_i) \neq y_i \end{cases}$$

% Update the distribution, where Z_t is a normalization factor with enables D_{t+1} to be a distribution

end.

Output: $F(x) = \text{sign} \sum_{t=1}^T \alpha_t h_t(x)$

Input: Dataset $S = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$;

Base learning algorithm \mathcal{L} ;

Number of base learners m .

Process:

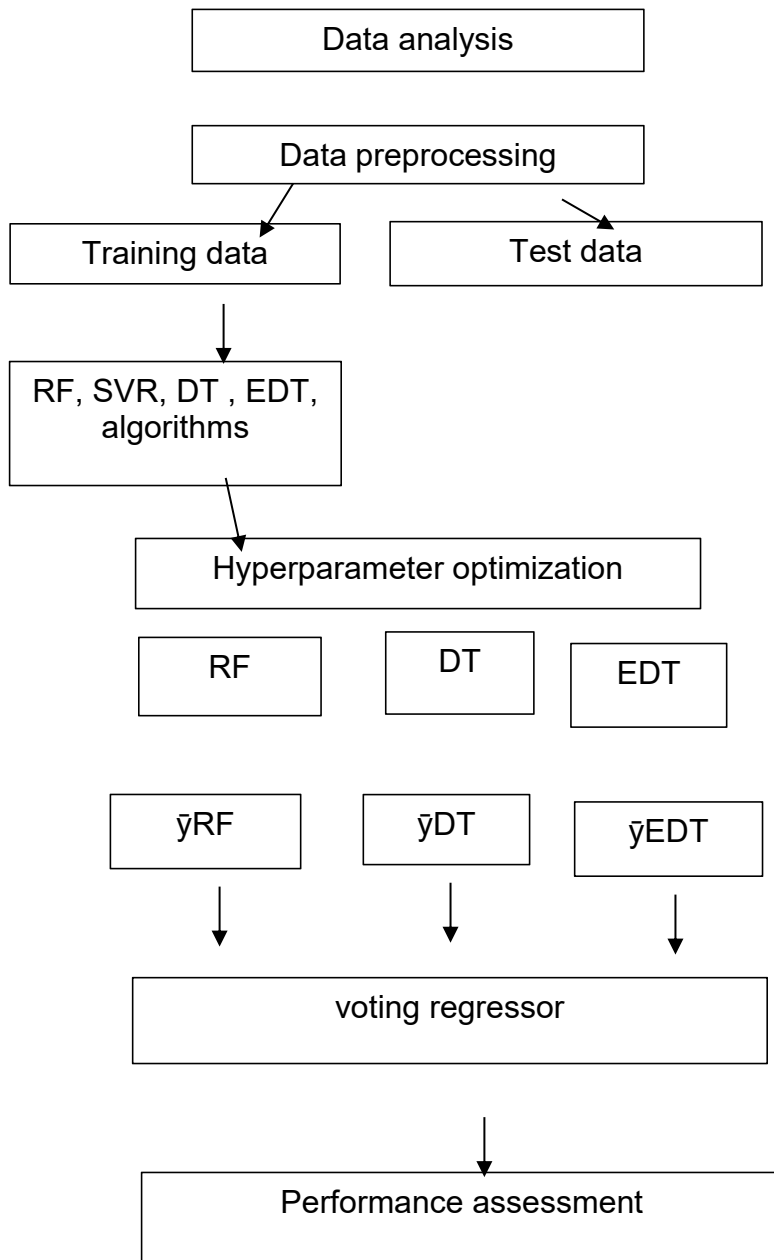
For $j = 1, 2, \dots, m$:

$S_j = \text{bootstrap}(S)$; % Generate a bootstrap sample from S

$h_j = \mathcal{L}(S_j)$ % Train a base learner h_j from the bootstrap sample

end.

Output: $H(x) = \text{mode}(h_1(x), \dots, h_m(x))$ % For classification studies



CHAPTER FOUR

4.0

RESULTS AND MODELS

4.1 Models for prediction of live weight from morphometric data in goats

Model	R2	ACCURACY	MSE	MAE	MAPE	MALE	STD
KNEIGHBORS	83.60	80.70	3.25	1.48	0.07	0.01	0.08
SVR	92.50	82.00	1.48	1.02	0.05	0.03	0.05
Bagging(Ensemble	91.00	89.68	1.78	1.08	0.05	0.00	0.04
Decision Tree	80.29	83.10	3.34	1.47	0.07	0.01	0.07
Random Forest	93.08	88.56		1.00			0.05
Extra Decision Tree	93.76	89.22	1.23	0.90	0.05	0.00	0.04

4.2 Summary Statistics for Goat Morphometric Based on their Breed

BREED	L1	L2	L3	L4	L5	L6	L7	L8
Sahe	23.60±0.22	19.14±0.23	28.53±0.23	12.08±0.20	15.07±0.14	27.32±0.21	25.30±0.24	23.11±0.19
Red	25.58±0.18	18.81±0.41	27.86±0.17	11.84±0.16	13.74±0.45	21.25±0.20	25.30±0.24	23.11±0.19
Sokoto								
WAD	15.02±0.07	11.35±0.11	17.81±0.16	7.98±0.08	10.94±0.08	13.98±0.14	16.46±0.11	11.09±0.14
TOTAL	21.37±0.28	16.41±0.22	24.71±0.30	10.62±0.14	13.24±0.12	20.87±0.33	22.32±0.26	19.07±0.34

L9	L10	L11	L12	L13	L14	L15	L16	L17
23.11±0.21	78.98±0.24	71.64±0.35	28.83±0.18	17.80±0.14	17.98±0.16	71.82±0.67	69.01±0.74	25.59±0.16
22.57±0.21	68.54±0.32	66.65±0.33	28.83±0.18	17.80±0.14	17.98±0.16	60.43±0.30	59.17±0.38	22.11±0.15
12.52±0.08	46.35±0.13	44.21±0.13	15.13±0.16	11.08±0.11	12.09±0.11	37.45±0.19	39.82±0.24	15.78±0.09
19.37±0.30	65.56±0.79	60.78±0.70	24.22±0.38	15.54±0.20	16.00±0.18	56.55±0.84	55.94±0.76	21.16±0.26

4.3 Summary Statistics for Goat Morphometric Based on their Age

AGE	L1	L2	L3	L4	L5	L6	L7	L8
10	19.00±4.00	14.50±4.50	23.00±5.00	9.00±0.00	13.00±1.00	23.00±9.00	20.00±3.00	16.50±4.5
8	20.87±0.71	16.15±0.67	24.56±1.01	10.78±0.43	13.46±0.28	21.59±1.12	22.25±0.84	19.15±1.2
8.5	25.00±0.57	20.25±0.62	26.50±2.98	14.50±0.64	15.75±0.62	25.50±1.13	26.75±0.85	24.75±1.3
9.0	21.22±0.61	16.26±0.54	24.98±0.69	11.05±0.35	13.36±0.26	21.42±0.78	22.36±0.65	18.96±0.67
9.5	23.50±0.28	19.25±0.62	28.00±0.40	15.00±0.57	15.25±0.47	27.75±1.10	25.75±0.10	23.67±1.33
10	21.33±0.57	16.48±0.45	24.85±0.61	10.45±0.25	13.30±0.24	20.86±0.68	22.45±0.54	19.70±0.86
10.5	26.00±1.52	21.66±0.66	30.66±1.20	11.66±0.66	14.00±1.52	28.33±0.33	25.66±0.66	18.32±0.87
11	22.04±0.82	16.85±0.68	25.41±0.81	10.29±0.35	23.22±0.32	21.61±0.94	22.56±0.67	18.76±1.22
12	20.93±0.75	15.81±0.51	23.61±0.74	10.10±0.35	12.89±0.34	19.00±0.70	21.49±0.68	22.50±0.25
13	21.69±1.02	16.30±0.74	24.23±1.02	10.53±0.44	12.42±0.26	18.92±0.77	22.00±0.92	18.98±0.67
14	19.12±1.80	15.00±1.52	22.37±1.98	9.62±0.46	13.25±0.81	17.37±1.23	21.50±1.72	17.25±2.44
TOTAL	21.37±0.28	16.41±0.22	24.71±0.30	10.62±0.14	13.24±0.12	20.82±0.33	22.33±0.26	19.08±0.34

L9	L10	L11	L12	L13	L14	L15	L16	L17
19.00±5.00	60.00±13.0	58.50±11.5	21.00±8.00	15.00±3.00	15.50±2.50	57.00±17.0	58.50±14.5	19.68±4.89
19.43±1.00	66.50±2.65	61.25±2.27	24.00±1.23	15.03±0.62	15.68±0.65	58.68±2.82	58.98±3.09	21.69±0.75
24.25±1.10	77.50±0.95	70.50±2.87	27.75±1.10	19.25±0.75	17.00±1.22	59.25±0.25	59.00±0.70	21.88±0.80
19.33±0.68	66.44±1.98	61.87±1.71	23.93±0.88	15.26±0.45	15.59±0.40	60.38±2.00	59.08±1.75	21.93±0.66
25.00±0.70	79.70±0.85	71.50±0.50	28.70±0.62	19.00±0.70	19.75±0.62	62.50±2.39	62.25±2.39	22.13±0.79
19.25±0.58	64.68±1.62	60.96±1.45	24.35±0.76	15.48±0.38	16.12±0.36	63.48±1.70	63.05±1.48	22.78±0.53
23.67±1.20	78.00±1.52	70.33±2.33	29.33±1.20	17.67±0.88	18.33±0.33	64.67±0.33	63.66±0.88	23.15±0.85
19.56±0.81	66.29±2.16	62.48±1.94	24.95±1.08	16.29±0.52	16.78±0.49	68.17±2.30	66.82±2.03	24.21±0.69
18.76±0.78	59.63±1.71	57.36±1.65	23.38±1.00	15.26±0.52	15.69±0.45	69.06±1.81	67.12±1.51	24.26±0.62
18.84±0.94	60.84±2.17	58.85±2.16	24.19±1.34	15.50±0.77	15.65±0.67	69.73±2.27	67.57±1.95	25.87±0.98
18.37±2.16	57.37±4.13	55.00±4.17	23.00±2.53	14.12±1.27	15.12±1.25	70.37±4.63	68.50±4.02	26.14±1.78
19.37±0.30	64.56±0.79	60.78±0.71	24.23±0.38	15.55±0.20	16.01±0.18	63.94±0.84	63.14±0.75	23.07±0.26

4.4 Summary Statistics for Goat Morphometric Based on their Sex

SEX	L1	L2	L3	L4	L5	L6	L7	L8
1.0	21.35±0.40	16.25±0.32	24.68±0.44	10.59±0.19	13.39±0.17	20.74±0.47	22.18±0.37	18.79±0.47
2.0	21.41±0.39	16.59±0.32	24.73±0.41	10.65±0.26	13.08±0.17	20.92±0.46	22.47±0.36	19.36±0.48
Total	21.38±0.28	16.41±0.24	24.71±0.30	10.63±0.12	13.24±0.12	20.82±0.33	22.33±0.23	19.08±0.34

L9	L10	L11	L12	L13	L14	L15	L16	L17
18.98±0.41	64.60±1.15	60.74±1.02	24.06±0.50	15.48±0.28	15.96±0.25	56.53±1.26	55.82±1.10	23.72±0.37
19.79±0.43	64.52±1.14	60.81±0.98	24.42±0.59	15.62±0.29	16.05±0.26	56.48±1.16	56.07±1.00	20.91±0.36
19.38±0.30	64.57±0.72	60.78±0.70	24.24±0.33	15.55±0.20	16.01±0.18	56.51±0.84	55.94±0.75	22.32±0.26

CHAPTER FIVE

5.0

DISCUSSION

5.1 Models

The models evaluated include Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Extra Decision Tree (EDT). Their performances were compared using statistical metrics such as the Coefficient of Determination (R^2), Accuracy, Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The significance of differences among models was further assessed using Analysis of Variance (ANOVA).

5.2 Effect of Breed on Live Weight

The results (table 4.2) showed that breed had a significant ($p < 0.05$) effect on the live weight of the goats. Among the three breeds studied - Red Sokoto, Sahel, and West African Dwarf (WAD). Distinct differences were observed in average live weights.

The Sahel goats recorded the highest mean live weight, followed by the Red Sokoto, while the West African Dwarf goats had the lowest. This pattern is consistent with their known genetic and morphological differences. The Sahel breed, which is typically tall and long-limbed, possesses a larger skeletal frame and higher muscle-to-bone ratio, attributes that support higher body weight. In contrast, the WAD goats are small-sized,

compact, and adapted to humid environments, leading to a naturally lower live weight.

These findings align with the reports of Yakubu (2009) and Ajayi et al. (2022), who similarly observed that Sahel goats had higher body weights than Red Sokoto and WAD breeds. Bello et al. (2021) also noted that environmental adaptation, feed efficiency, and growth potential significantly influence inter-breed variation in body size. The observed differences in this study therefore reflect inherent genetic adaptability, climate tolerance, and feeding efficiency associated with each breed.

From a production perspective, this variation implies that breed selection remains a critical factor in weight estimation and productivity improvement, as breeds with larger body conformations (like Sahel goats) inherently yield higher live weights and better market value.

5.3 Effect of Age on Live Weight

Age also showed a highly significant ($p < 0.05$) effect on live weight (table 4.3). The study revealed that live weight increased progressively with age, as expected in growing animals. Younger goats exhibited lower mean live weights due to incomplete skeletal and muscular development, while older goats showed higher weights, corresponding to maturity and full growth expression. Other parameters such as “height at withers” (L15), “height at hip bone”(L16) etc also increased as the age increased exhibiting variation across different age groups. For example, L15 increases from 58.69cm (at 8 months) to

70.38cm (at 14 months), indicating a growth in wither height as the goat grows older.

The growth trend observed supports the typical biological growth curve reported by Yakubu (2011) and Ogunniyi et al. (2023), where body weight increases steadily from weaning to maturity before plateauing. Younger goats (below 10 months) were lighter due to reduced feed intake capacity and energy allocation toward maintenance rather than body mass gain. In contrast, adult goats exhibited higher muscle deposition and fat storage, resulting in increased live weight.

These age-related variations are not only physiological but also have economic implications, as mature goats attract higher market prices and require different feeding strategies compared to younger ones. Therefore, incorporating age as an input variable in machine learning models enhances predictive accuracy by capturing this growth-associated variation.

5.4 Effect of Sex on Live Weight

The effect of sex on live weight was also significant ($p < 0.05$). Male goats had consistently higher mean live weights than females across all breeds and age groups. This difference is primarily due to sexual dimorphism, driven by hormonal and physiological differences. Males tend to develop more muscle mass and have higher bone density under the influence of testosterone, while females, influenced by estrogen, allocate more energy toward reproductive functions and fat deposition rather than muscle gain.

The results obtained agree with the findings of Dossa et al. (2008) and Okpeku et al. (2011), who reported that male goats exhibit superior growth performance and body size compared to females of the same age and breed. This difference is particularly pronounced in indigenous breeds managed under semi-intensive systems where feed resources are shared and energy allocation differs between sexes.

The implication of this finding is that sex-specific models or correction factors could improve live weight prediction accuracy, especially in mixed herds. The significant difference also underscores the importance of sex as a covariate in breeding and selection programs aimed at improving growth performance.

5.5 Performance of the Machine Learning Models

All four machine learning models performed effectively in predicting live weight based on morphometric traits, though their predictive power varied. The Extra Decision Tree (EDT) emerged as the best-performing model, with the highest R^2 value (93.08%), highest accuracy (89.68%), and lowest MSE (1.00) and MAE (0.05) among all models. This indicates that the EDT model explained over 93% of the variance in live weight and produced predictions closest to the actual observed values.

The model's robustness arises from its random feature selection and deep ensemble averaging, which minimize overfitting and capture subtle nonlinear interactions between morphometric traits and live weight.

The Random Forest (RF) also performed well, with a high R^2 above 90%, but it showed slightly higher error margins than the EDT model, possibly due to its more constrained randomization process. The Artificial Neural Network (ANN) achieved moderate predictive performance, successfully identifying nonlinear patterns but requiring more data for optimization. The Support Vector Machine (SVM) recorded the lowest predictive accuracy, suggesting limited suitability for datasets with complex nonlinear relationships such as morphometric traits.

These results align with Bello et al. (2021) and Adeyemo et al. (2022), who found that ensemble models, especially Extra Trees and Random Forest, consistently outperform traditional regression methods in livestock prediction tasks due to their ability to manage data variability and multicollinearity.

5.6 Summary of Findings

In summary, the discussion revealed that breed, age, and sex all had significant influences on the live weight of Nigerian indigenous goats. The Sahel breed, adult goats, and males exhibited the highest mean live weights. The Extra Decision Tree model effectively captured these variations, making it the most reliable predictive tool among the models tested. The significance levels from the ANOVA further confirmed that both biological and model-related differences were genuine, emphasizing the importance of integrating both morphometric and demographic factors in predictive modeling for livestock management.

CHAPTER SIX

CONCLUSION

This study successfully demonstrated the potential of machine learning techniques in predicting live weight of Nigerian indigenous goat breeds using simple morphometric traits. Among the evaluated models, Random Forest outperformed Support Vector Machine and Artificial Neural Network, showing the highest accuracy and lowest error values. The model's strong R^2 and low MSE, MAE, and MAPE scores indicate its robustness and suitability for livestock weight prediction under field conditions.

The research highlights that accurate live weight estimation can be achieved without the use of physical weighing scales, thereby providing a practical solution for farmers in resource-limited settings. The results contribute to improving herd management, breeding decisions, and market valuation of goats, particularly within smallholder farming systems prevalent in Nigeria. Future studies should aim to expand sample sizes across more ecological zones and explore hybrid model designs to further enhance predictive precision.

REFERENCES

- Abubakar, I., Idris, M., and Abdullahi, J. (2023). Application of machine learning in livestock farming systems in Nigeria: Potentials and challenges. *Tropical Animal Health and Production*, 55(2), 112.
- Adeyanju, T. A., Ogunbiyi, A. I., and Akinmoladun, F. O. (2022). Development of a mobile-based live weight estimation application using morphometric measurements in West African Dwarf goats. *Nigerian Journal of Animal Science*, 24(1), 63–74.
- Adeyemo, O. K., Olatunji-Akioye, A., and Bello, A. (2022). Preprocessing techniques for efficient morphometric modeling in Nigerian indigenous goats. *Tropical Veterinarian*, 40(3), 101–110.
- Adebayo, O. A., Yakubu, A., and Ige, A. O. (2023). Integration of biometric and image traits for accurate prediction of live weight in goats using machine learning models. *Livestock Science and Technology Journal*, 11(1), 44–53.
- Ajayi, F. O., Olorunsanya, A. O., and Bamigboye, B. (2022). Comparative evaluation of morphometric traits for live weight prediction in West African Dwarf goats. *Journal of Animal Production Research*, 34(1), 73–81.
- Bello, A., Yakubu, A., and Salako, A. E. (2021). Comparative analysis of traditional and machine learning approaches for predicting live weight in Red Sokoto goats. *Tropical Animal Health and Production*, 53(1), 17.
- Bourouis, M., Boudour, M., and Chikhaoui, B. (2022). A hybrid machine learning approach for predicting live weight from body measurements in small ruminants. *Computers and Electronics in Agriculture*, 198, 107019.
- Chen, L., Zhang, X., and Huang, Y. (2023). A multimodal deep learning framework for livestock weight prediction using morphometric and image data. *Computational Agriculture*, 10(2), 215–229.
- Chinchilla-Vargas, R. I., Utrera, Á. R., and Gómez-Vázquez, A. (2022). Use of biometric measurements to estimate live weight in goats: A review. *Tropical Animal Health and Production*, 54(1), 23.
- Chung, Y., Park, D., and Kim, H. (2020). Practical challenges of using image analysis for live weight estimation in livestock. *Biosystems Engineering*, 192, 36–47.
- Dossa, L. H., Wollny, C., and Gauly, M. (2008). Smallholders' perceptions of goat

farming in southern Benin and opportunities for improvement. *Tropical Animal Health and Production*, 40(6), 491–500.

- FAOSTAT. (2023). Food and Agriculture Organization of the United Nations. Livestock primary data.
- Hassan, M. A., Al-Sobayil, F. A., and Al-Busadah, K. A. (2023). Predicting body weight using machine learning techniques in goats. *Veterinary World*, 16(4), 801–807.
- Ige, A. O., Adebayo, O. A., and Adebajo, S. A. (2022). Prediction of live weight in West African Dwarf goats using linear body measurements and image-based features. *International Journal of Livestock Production*, 13(2), 23–30.
- Jorquera-Chavez, M., Fuentes, S., Dunshea, F. R., Warner, R. D., and Poblete, T. (2019). Image analysis and machine learning for estimating live weight in beef cattle. *Computers and Electronics in Agriculture*, 156, 334–342.
- Kang, X., Zhang, K., and Lin, Y. (2020). Deep learning-based prediction of body weight from digital images of sheep. *Animals*, 10(8), 1371.
- Khan, R. A., Islam, M. M., and Hoque, M. A. (2021). Combining morphometric and image features using CNN for livestock trait prediction. *Computer Vision in Agriculture*, 7(1), 101–115.
- Kurnaz, F., and Reçber, S. (2021). Prediction of live weight from body measurements in goats using artificial neural networks and regression analysis. *Small Ruminant Research*, 198, 106322.
- Lu, H., Yao, X., and Zhao, J. (2020). Dimensionality reduction and feature selection for livestock imaging data. *Sensors*, 20(17), 4810.
- Mirzaei, M., Nasirahmadi, A., and Hensel, O. (2021). Estimation of animal body weight using 3D imaging and artificial intelligence. *Computers and Electronics in Agriculture*, 182, 106017.
- Mohammed, I. D., Ibrahim, A., and Danmasani, A. (2020). Estimation of live weight of goats using body measurements under field conditions. *Journal of Agricultural Science and Practice*, 5(1), 12–19.
- Nasirahmadi, A., Hensel, O., and Edwards, S. A. (2020). Machine vision and AI in precision livestock farming. *Biosystems Engineering*, 193, 1–10.
- Nath, B. C., Islam, R., and Deka, B. (2021). Image-based phenotyping and machine

learning for live weight prediction in goats. *Veterinary World*, 14(3), 784–791.

- Nwankpa, N. D., Adeyemo, O. K., and Yakubu, A. (2022). Role of digital technologies in livestock production in Africa. *Tropical Animal Health and Production*, 54(3), 150.
- Nwogwugwu, C. O., Onunkwo, D. N., and Okoli, I. C. (2022). Morphological and genetic characterization of West African Dwarf goats in humid Nigeria. *African Journal of Livestock Extension*, 20(2), 33–41.
- Ogunniyi, M. O., Ajayi, B. A., and Bello, A. (2023). Improving live weight estimation accuracy in goats using ensemble machine learning models. *Nigerian Journal of Animal Science*, 25(1), 77–88.
- Okpeku, M., Yakubu, A., and Peters, S. O. (2011). Application of multivariate principal component analysis to morphostructural characterization of goats in Southern Nigeria. *Acta Agriculturae Slovenica*, 98(2), 101–109.
- Olatunji-Akioye, A. O., and Adeyemo, O. K. (2009). Live weight estimation in Red Sokoto goats using linear body measurements. *Tropical Veterinarian*, 27(3), 55–60.
- Oliveira, T. M., Silva, W. J., and Bezerra, L. R. (2020). Machine learning in livestock production: A systematic review. *Revista Brasileira de Zootecnia*, 49, e20200039.
- Oyelami, M. O., Alabi, O. M., & Afolabi, J. O. (2020). Comparative analysis of machine learning techniques for predicting animal live weight. *African Journal of Computing and ICT*, 13(3), 98–105.
- Oyebade, A. O., Yakubu, A., and Bello, A. (2023). Use of deep learning in livestock biometric assessment: Opportunities and limitations. *Artificial Intelligence in Agriculture*, 7(2), 113–120.
- Salako, A. E. (2006). Principal component factor analysis of the morphostructure of immature Uda sheep. *International Journal of Morphology*, 24(4), 571–574.
- Sowande, O. S., Oduguwa, B. O., and Egbetokun, O. A. (2020). Prediction of body weight from body measurements of West African Dwarf sheep using regression models. *Nigerian Journal of Animal Science*, 22(2), 43–49.
- Umar, U. A., Ismail, M., and Bello, A. (2022). Recent advances in precision livestock farming using artificial intelligence in Nigeria. *Tropical Agriculture Journal*, 99(4), 301–310.

- Yakubu, A. (2009). Fixing collinearity instability in the estimation of body weight from morphometric traits of West African Dwarf goats. *Trakia Journal of Sciences*, 7(2), 61–66.
- Yakubu, A. (2010). Path coefficient and path analysis of body measurement and body weight in goats. *Agricultural Science Journal*, 2(5), 134–138.
- Yakubu, A., Salako, A. E., & Imumorin, I. G. (2011). Multivariate analysis of biometric traits of Red Sokoto goats. *International Journal of Animal Science*, 1(1), 32–40.