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Predicting some Milk Constituents from Linear Body Measurements and Udder Characteristics of Bunaji Cows Utilizing Machine Learning Techniques

[*1,3]Adetunji O. Iyiola-Tunji, [2]Idris O. Muniru, [3]Yahya M. Muktar, [4,5]Paul A. John, [5]Hauwa K. Yahaya, [3]Kenedy Kevin and [3]Jamila Yusuf

[1]*National Agricultural Extension and Research Liaison Services, Ahmadu Bello University, Zaria, Kaduna State*
[2]*Department of Biomedical Engineering, Faculty of Engineering, University of Ilorin, Ilorin, Kwara State*
[3]*Department of Animal Science and Range Management, Modibbo Adama University, Yola, Adamawa State*
[4]*Biotechnology Advance Research Centre, Sheda, FCT, Abuja*
[5]*Department of Animal Science, Ahmadu Bello University, Zaria, Kaduna State*

Corresponding author email: tunjiyiola@yahoo.com; Tel:+2347034234136

Abstract

Machine Learning techniques are capable of being used in agriculture since they are powerful, fast and flexible tools for classification and predictions of traits of economic importance, particularly those involving nonlinear systems. This study aimed to show how well machine learning methods could predict milk's crude protein and fat content based on the Bunaji cows' linear body measurements and udder characteristics. Forty (40) lactating Bunaji cows from two dairy farms in Yola South Local Government Area, Adamawa State, were purposefully selected for the study. Milk samples were collected from the cows (one-off measurement). The crude protein and fat content of the milk were determined in percentage. An ensemble model consisting of the random forest (RF), support vector machine (SVM) and neural network (NN) algorithms were created using the Orange Software. The models were cross-validated using five folds to assess their robustness. Mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2) are the metrics utilized for the evaluation. Using the udder features, the approach was used to construct demonstrative models for the prediction of milk protein content. The SVM and RF learners had MSE that was lower than that of NN, showing that the two were superior to NN. The lower performance of NN in this study can be explained on the basis of extremely low data that was available for this study. RF learners exhibited a low likelihood of mistakes in predicting crude protein from udder traits despite the study's small data set. Large data sets were needed for machine learning techniques. As a result, these models must be improved with lots of data.

Keywords: Artificial Intelligence, Machine Learning, Milk composition, Cattle

1.0 Introduction

Milk production from indigenous breeds of cattle in Nigeria represents an important component of the agribusiness sector of the smallholder economy with great economic, nutritional and social implications (Oladapo and Ogunekunn, 2015). According to Nayak *et al.* (2018), tropical regions are home to more than 50% of the world's cattle, and Nigeria is one of the top producers of cattle in Sub-Saharan Africa (Kubkomawa, 2017;Sam and Usoro, 2022). Traditional pastoralists are in charge of more than 80% of this (Kubkomawa, 2017). Water, carbohydrates, fats, proteins, minerals, and vitamins are all components of milk (Heinrich *et al*., 2005; Matei *et al*., 2010). According to diverse breeds and individual cows, milk composition varies (Dandare *et al*., 2014; Oladapo and Ogunekunn, 2015).

Machine learning techniques are one of the components of artificial intelligence. It is the technique that gives computers the potential to learn without being programmed (Tyagi, 2021). The techniques are capable of being used in agriculture since they are powerful, fast and flexible tools for classification and predictions of traits of economic importance particularly those involving nonlinear systems (Liakos *et al*., 2018; Shahinfar *et al*., 2021). These techniques have been used for the detection of mastitis (Hyde *et al*., 2020), detection of estrus (Wang *et al*., 2020), discovery of reasons for culling (Shahinfar *et al*., 2021), interpretation of somatic cell count data, assessment of the efficiency of reproductive management (Caraviello *et al*., 2006). Applications have also included the definition of modern groups for the purpose of genetic evaluation and the construction of decision-support systems for analyzing test-day milk yield data from the Dairy Herd Improvement (DHI) programme from automated milking systems (Cabrera *et al*., 2020). Therefore, this study aimed to show how well machine learning methods could predict milk's crude protein and fat content based on Bunaji cows' linear body measurements and udder characteristics.

2.0 Materials and Methods

2.1 Experimental Site

In Yola South Local Government Area (YSLGA), Adamawa State, forty (40) lactating Bunaji (White Fulani) cows were purposefully chosen from two dairy farms. Yola South L.G.A. is located on Latitude $9^0 20'$ and $9^0 33'$N; longitude $12^0 30'$ and $12^0 50'$ E. The region experiences moderate temperatures all year long, with December having the lowest average low of 16.9°C and August and September having the lowest average high of 31.3°C. The highest average high is 42.80°C in March, and the highest average low is 27.00°C in April. Yola South L.G.A. is in the Northern Guinea Savannah zone (Idi and Abubakar, 2022).

2.2 Animals and their Management

The Bunaji cows were reared through a semi-intensive system. They were fed on sown pastures of indigenous grasses and legumes. Concentrate feeds and some roughages were fed to the stocks in the morning before being led to graze on the pastures.

2.3 Data collection

Data collection was done from the two farms were 20 cows were sampled from each of the farms.

2.3.1 **Milk samples**

Milk samples were collected from Bunaji cows (one-off measurement). The milk's crude protein and fat content were determined in percentage using the method described by Bradley *et al*. (1992) and Kala *et al*. (2019).

2.3.2 Udder trait measurements

Udder traits were measured using measuring tapes in cm as described by (Papachristoforou and Mavrogenis, 1981) and (Alphonsus, 2009). The udder traits measured were as follows: (i.) udder length: from attachment to middle of udder, (ii.) udder circumference: above teats to be measured with a flexible tape, (iii.) right and left teat lengths: measured from attachment of teat with udder to the end of teats by using a caliper, (iv.) teat number: visibly counted on the cow, (v.) teat length: from the base of the udder to the tip of the teat, measured using caliper, (vi.) teat diameter: taken in the middle of teats, using caliper, (vii.) udder width: above teats at rear of udder, (viii.) distance between teats: between the two teats attachment with udder, (ix.) cistern height: taken as the distance from the base of the teat to a point midway before the attachment of the udder to the abdominal wall, (x.) teat angle: measured with a protractor by placing it on the udder with the midline of the protractor in line with the linea alba which divides the mammary gland into two, (xi.) teat floor distance: taken using a ruler as the distance between the tip of the teat and the ground.

2.3. 3 The linear body measurements

The following descriptions for reference marks on body measurement according to the method of FAO, 2012) were adapted: BWT: Body weight using a flexible weigh-band calibrated in centimeters and kilograms. The weigh-band was sourced from the Animal Care Service Konsult in Nigeria. It was put around the chest of the cow and the weight was read directly from the tape. The horn length (HLT) is the measurement of the horn's length from tip to base (cm). Face length (FLT) is the measurement from the horny part of the forehead to the upper lip (cm). Ear length (ELT) is the distance between the zygomatic arch's base and the ear's tip (cm). The distance between the outside edges of both eyes is used to calculate head width (HWD) (cm). Neck circumference (NCR): The measurement of the neck's circumference at its middle (cm). Foreleg length (FLL) is the measurement from the olecranon process's extremities to the coronet's mid-lateral point (cm). The term "height at withers" (HTW) refers to an animal's height as measured from the ground to the point of its withers, which is the highest point of the *Processus spinalis* of the thoracic vertebra (cm). Chest girth (CGT): This is the measurement of the circumference of the torso just behind the front legs (cm). Body length (BLT) is the measurement from the pin bone to the tip of the shoulder (lateral tuberosity of the humerus) (cm). The length around the cannon is used to calculate the loin girth (LGT). RHT: Rump height is the height from the rump to the ground (cm). This was measured as the length of the hind limb, and the rear leg length (RLL) (cm). The tail length (TLT) (cm) was measured as the distance between the tip of the tail and the base end of the tail touching the body. Teat length; measured from the udder base to the end of the teat tip. Body weight (BWT) of cows was grouped into three weight classes: (i.) 300 to 350 kg, (ii.) 351 to 400 kg, and (iii.) 401 to 450 kg.

2.4 Statistical analysis

The effect of weight class on linear body measurements was analysed using the General Linear Model Procedure of SAS (SAS, 2004) as shown in the model below:

$Yij = \mu + Bi + Eij$ .... Equation 1

Where:

μ= population mean,

Bi = body weight class and

E_{ij} = random error particular to the ij^{th} observation.

The Duncan Multiple Range Test (DMRT) of Duncan (1955) was used to compare statistically significant means. The Phenotypic correlation was determined as follows:

$r_p = \frac{\sigma A_1 A_2}{\sqrt{\sigma^2 A_1 . \sigma^2 A_2}}$ .... Equation 2

Where:

σ_{A1A2} = the covariate between traits A_1 and A_2 and

${\sigma_{A1}}^2$ and ${\sigma_{A2}}^2$ = variance for traits A_1 and A_2, respectively.

Stepwise regression analysis with forward selection was generated using the Proc reg analysis of SAS (2004). Dimension reduction analysis of SPSS Version 26 (SPSS, 2019) was used to generate principal components through Varimax rotation and eigenvalues greater than 1. The factor scores were subjected to stepwise regression analysis. An ensemble model consisting of the random forest, support vector machine, and neural network algorithms were created using the Orange Software. Figure 2.1 depicts the model training arrangement. The models were cross-validated using five folds to assess their robustness. Mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) are the metrics employed for the evaluation. Using the udder features, the approach was used to construct demonstrative models for the prediction of milk protein amounts.

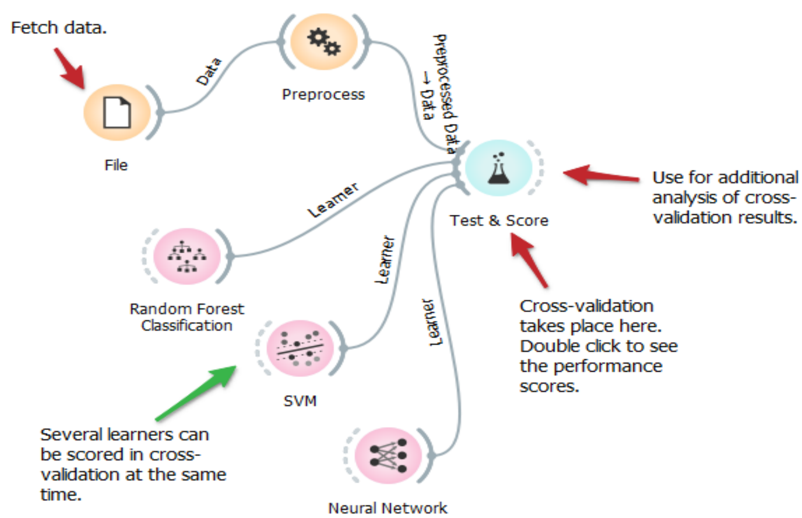

Figure 2.1: Pictorial representation of the model configuration

2.0 Results and Discussion

3.1 Effect of Weight Class on Linear Body Measurement of Bunaji Cows

The impact of weight class on the linear body measurements of Bunaji cows are presented in Table 3.1. Face length, head width, horn length, ear length, neck length, neck circumference, fore leg length, height at wither, chest girth, body length, loin girth, rump height, rear length, tail length, and teat length were all significantly ($p<0,05$; 0.01) impacted by weight class. The Bunaji cows within the weight class 401 to 450 kg were superior to those within the weight class of 300 to 350kg and 351 to 400kg in terms of FLT (51.44±0.29 cm), HWD (20.33±0.41cm), HLT (63.11±5.17 cm), ELT (23.00±0.33 cm), NLT (38.89±1.48 cm), NCR (88.78±1.71 cm, FLL (80.67±1.91 cm), HTW (132.00±0.62 cm), CGT (175.00±1.58 cm), RHT (135.89±0.86 cm). While TTL (8.56±0.29 cm). BLT (130.93±1.11 cm), LGT (175.47±2.30 cm) and RLL (92.13±1.23 cm) in weight class 351 to 400 were similar to BLT (131.00±1.67 cm), LGT (174.33±4.94 cm) and RLL (91.44±1.65 cm) in weight class 401 to 450kg. Longer TLT (109.60±2.68 cm) was observed in Bunaji cows within the weight class 351 to 400kg whereas the shortest TLT (105.69±2.85cm) was recorded in weight class 300 to 350kg. The superiority of some of the biometric traits recorded in Bunaji cows within the weight class 401 to 450kg and 351 to 400kg compared to those within the weight class 300 to 350kg might be attributed to age differences. The younger cows weighed less than the older ones in the farms where the study was conducted. The average value of 330 to 350 kg for female Bunaji cows given by (Dairo *et al*., 2011) is comparable to the weight class value for Bunaji cows in the present investigation, which ranges from 300 to 350 kg. The findings of this study were in agreement with those of Adejoro and Salako (2012), who noted that the typically favorable influence of animal age on body weight and size is not surprising, given that it is normal for animal size and shape to rise with age. The authors also claimed that as animal age, their physical characteristics also grow, a process known as growth.

3.2 Effect of Weight Class on Udder Traits, Crude Protein and Lipids of Milk from Bunaji Cows

The effect of weight class on udder traits, crude protein and lipids of milk from Bunaji cows are presented in Table 3.2. The weight class of Bunaji cows significantly ($p<0.0.5$) affected teat diameter, teat floor distance, udder length, udder circumference, udder width and cistern height whereas teat number, crude protein and lipid were however not significantly affected ($p>0.05$). Wider teat diameter (6.22±0.36cm), longer teat floor distance (61.67±2.19cm), longer udder length (19.33±0.88cm), wider udder circumference (60.00±2.19cm), wider udder width (16.67±0.97cm) were recorded in Bunaji cows within the weight class 401 to 450kg compared to the other weight class. The cistern height (23.19±0.68cm) in weight class 300 to 350kg was statistically similar to (24.89±0.98cm) in weight class 401 to 450kg. The shortest TDM (5.36±0.30cm), TFD (55.81±1.85cm), UDL (17.50±0.65cm), UCR (57.19±1.17cm) and UDW (14.88±0.55cm) weight class 300 to 350kg were also similar to TDM (5.20±0.20cm), TFD (57.13±1.79cm), UDL (16.80±0.74cm), UCR (57.27±1.74cm) and UDW (15.07±0.60cm) in weight class 351 to 400kg. The difference in age of the cows might be attributed to the weight class's considerable effect on the udder features of Bunaji cows. Animals with healthy udders live longer and are more productive (Buenger *et al*., 2001).

Table 3.1: Effect of weight class on linear body measurements of Bunaji cows

Trait	Weight class (kg)				
	300 to 350	351 to 400	401 to 450	SEM	LOS
FLT(cm)	47.50±0.35^{c}	49.53±0.32^{b}	51.44±0.29^{a}	0.31	*
HWD(cm)	19.50±0.20^{b}	19.53±0.32^{b}	20.33±0.41^{a}	0.18	*
HLT(cm)	57.38±2.45^{b}	53.00±3.37^{c}	63.11±5.17^{a}	2.01	*
ELT(cm)	22.69±0.22^{b}	23.27±0.27^{a}	23.00±0.33^{a}	0.15	*
NLT(cm)	34.44±0.75^{c}	35.20±1.13^{b}	38.89±1.48^{a}	0.66	*
NCR(cm)	76.69±1.48^{b}	78.47±1.99^{b}	88.78±1.71^{a}	1.26	*
FLL(cm)	78.75±1.10^{b}	81.47±0.92^{b}	80.67±1.91^{a}	0.71	*
HTW(cm)	127.81±0.84^{c}	130.07±0.80^{b}	132.00±0.62^{a}	0.53	*
CGT(cm)	157.81±0.87^{c}	164.73±0.94^{b}	175.00±1.58^{a}	1.20	*
BLT(cm)	128.69±0.77^{b}	130.93±1.11^{a}	131.00±1.67^{a}	0.65	*
LGT(cm)	164.88±1.96^{b}	175.47±2.30^{a}	174.33±4.94^{a}	1.75	*
RHT(cm)	131.69±0.76^{c}	133.73±0.96^{b}	135.89±0.86^{a}	0.56	*
RLL(cm)	87.75±0.96^{b}	92.13±1.23^{a}	91.44±1.65^{a}	0.76	*
TLT(cm)	105.69±2.85^{b}	109.60±2.68^{a}	106.67±3.12^{ab}	1.66	*
TTL(cm)	6.69±0.33^{b}	7.07±0.27^{b}	8.56±0.29^{a}	0.21	*

BWT: Body weight; FLT: Face length; HWD: Head width; HLT: Horn length; ELT: Ear length; NLT: Neck length; NCR: Neck circumference; FLL: Fore leg length; HTW: Height at withers CGT: Chest girth; BLT: Body length; LGT: Loin girth; RHT: Rump height; RLL: Rear leg length TLT: Tail length; TTL: Teat length. LOS = level of significance; *p<0.05; **p<0.01. ^{abc}Means with different superscripts along the same row show significant differences

Table 3.2: Effect of weight class on udder traits, crude protein and lipid of Bunaji cows

	Weight class (kg)				
Trait	300 to 350	351 to 400	401 to 450	SEM	LOS
TDM(cm)	5.36±0.30^{b}	5.20±0.20^{b}	6.22±0.36^{a}	0.17	*
TFD(cm)	55.81±1.85^{b}	57.13±1.79^{b}	61.67±2.19^{a}	1.14	*
TNR(cm)	4.00±0.00	4.00±0.00	4.00±0.00	0.00	NS
UDL(cm)	17.50±0.65^{b}	16.80±0.74^{b}	19.33±0.88^{a}	0.45	*
UCR(cm)	57.19±1.17^{b}	57.27±1.74^{b}	60.00±2.19^{a}	0.93	*
UDW(cm)	14.88±0.55^{b}	15.07±0.60^{b}	16.67±0.97^{a}	0.39	*
CTH(cm)	23.19±0.68^{a}	21.20±0.70^{c}	24.89±0.98^{a}	0.48	*
CP %	3.47±0.13	3.50±0.13	3.40±0.20	0.08	NS
Lipid %	3.07±0.11	3.12±0.12	3.08±0.07	0.06	NS

TDM: Teat diameter; TFD: Teat floor distance; TNR: Teat number; UDL: Under length; UCR: Udder circumference; UDW: Udder width; CTH: Cistern height; CP: Crude protein; SEM: Standard error of mean; LOS: Level of significant; *****p<0.05: Significant at 5% level of probability; NS: Not significant. ^{abc}Means with different superscripts along same row shows significant differences

3.3 Correlations among Linear Body Measurements, Crude Protein and Lipid Contents of Milk from Bunaji Cows

The correlation among linear body measurements, crude protein and lipid contents of milk from Bunaji cows are revealed in Table 3.3. With the exception of non-significant and negative relationships, which occur among other traits, some of the traits were significantly ($p<0.05$; 0.01) and positively correlated ($r=0.296$-0.929) among themselves. Body weight and FLT ($r=0.649$), NCR (r=0.518), CGT (r=0.929), and RHT (r=0.466) all showed significant correlations ($p<0.01$). Other body dimensions also showed high coefficient of relationships among themselves; FLT with NCR (r=0.443), HTW (r=0.636), CGT (r=0.611), RHT (r=0.560), RLL (r=0.425); ELT with RLL(r=0.435); NLT with NCR (r=0.482), CP (r=0.435); NCR with HTW (r=0.500), CGT (r=0.536) and RHT (r=0.416); FLL with RHT (r=0.540), RLL (=0.635); HTW with RHT (r=0.844), RLL (r=0.618); RHT with RLL (r=0.671); and between CP and lipid (r=-0.643), which showed negative correlation. Low coefficient of relationships ($p<0.05$) were also observed among other body dimensions of Bunaji cows. The existence of a positive relationship between body weight and biometric features indicates that the traits are pleiotropic, or regulated by the same gene. Additionally, other traits might improve as a result of this. The findings of this study concur with those of John and Iyiola-Tunji (2018), who found that body weight and morphometric traits of donkeys in northwestern Nigeria exhibit positive and highly correlated associations. According to Mavule *et al*. (2013), who found that body parts developed at a varied rate within distinct age groups, patterns of growth of body parts dependent on age have been highlighted. Dim *et al*. (2012) reported a high coefficient of determination for BLT, HWT and CGT. They, however, reiterated that CGT is more reliable which thus confirms the results of this study. According to Maiwasha *et al*. (2002), moderate to high correlation coefficients between growth traits indicate that the two sets of growth characteristics are likely impacted by the same genes, and the selection of one is likely to increase the other, producing a significant genetic benefit. According to Anupam *et al*. (2020), there was a negative phenotypic correlation between udder depth and milk production, fat, and protein. According to Nemcova *et al*. (2007), the fore udder attachment, udder cleft, and udder depth all had a negative association with milk supply.

3.4 Correlated Relationships among Udder Traits, Crude Protein and Lipid Content of Milk of Bunaji Cows

Correlation among udder traits, crude protein and lipid content of milk of Bunaji cows are presented in Table 3.4. Significant ($p<0.05$; 0.01) and positive relationships (r=0.219-0.718) exist among udder dimensions of the Bunaji cows. High and positive correlation exists between teat length and teat diameter (r=0.718) and udder width (r=0.631); teat diameter and udder circumference (r=0.460), udder width (r=0.510); udder length and udder width (r=0.604) and cistern height (r=0.527); udder circumference and udder width (r=0.463); udder width and cistern height (r=0.463); and crude protein and lipid (r=0.463). Other traits showed low to negative relationships among themselves. The direct udder measurements were negatively correlated with crude protein and lipid. In contrast to udder depth, which was adversely correlated with milk supply, Berry *et al*. (2004) found that type features such fore udder attachment and rear udder height favorably correlated with milk yield. The back leg set rear view was found to be favorably correlated with milk yields, according to the same investigators. Correlations between measurements of udder and rates of crude protein and lipids were negatively correlated with the exception of high and positive correlation, which exist between CP and lipid (r=0.63, $p<0.01$). This indicates that usefulness of udder measurements in predicting milk flow would be limited except for CP and lipid, which were high. The findings of this study are consistent with those of Alphonsus *et al*. (2017) and DeGroot *et al*. (2002), who found that traits related to udder attachment had a negative genetic relationship with milk yield while traits related to udder capacity had a positive relationship with milk yield.

Table 3.3: Phenotypic correlation among linear body measurements, crude protein and lipid contents of milk of Bunaji cows

	BWT(kg)	FLT	HWD	HLT	ELT	NLT	NCR	FLL	HTW	CGT	BLT	LGT	RHT	RLL	TLT	CP
FLT(cm)	0.649**															
HWD(cm)	0.191	0.372*														
HLT(cm)	0.080	0.296*	0.351*													
ELT(cm)	0.182	0.377*	0.135	0.099												
NLT(cm)	0.337*	0.251	0.136	0.107	0.124											
NCR(cm)	0.518**	0.443**	0.433*	0.054	0.116	0.482**										
FLL(cm)	0.303*	0.202	0.125	-0.037	0.241	0.067	0.202									
HTW(cm)	0.431*	0.636**	0.331*	0.063	0.398*	0.160	0.500**	0.382*								
CGT(cm)	0.929**	0.611**	0.219	0.052	0.074	0.367*	0.536**	0.229	0.339*							
BLT(cm)	0.194	0.184	0.122	-0.342	-0.103	0.112	0.225	0.355*	0.393*	0.109						
LGT(cm)	0.339*	0.148	-0.123	-0.150	-0.290	-0.043	0.178	-0.072	0.021	0.299	0.121					
RHT(cm)	0.466**	0.560**	0.342*	0.052	0.389*	0.175	0.416**	0.540**	0.844**	0.385*	0.317*	0.093				
RLL(cm)	0.362*	0.425**	0.118	0.044	0.435**	0.012	0.053	0.636**	0.618**	0.303*	0.180	-0.185	0.671**			
TLT(cm)	0.056	0.170	-0.063	-0.046	0.172	-0.040	-0.130	-0.302	-0.059	0.068	-0.216	0.057	-0.072	0.024		
CP %	-0.131	-0.087	0.139	0.261	-0.236	0.435**	0.036	-0.186	-0.135	-0.088	-0.025	-0.061	-0.231	-0.245	-0.077	
Lipid %	0.026	-0.068	0.217	0.114	-0.029	0.331*	0.173	-0.057	-0.061	0.033	0.028	-0.010	-0.124	-0.176	-0.129	-0.643**

BWT: Body weight; FLT: Face length; HWD: Head width; HLT: Horn length; ELT: Ear length NLT: Neck length; NCR: Neck circumference; FLL: Fore leg length; HTW: Height at withers; CGT: Chest girth; BLT: Body length; LGT: Loin girth; RHT: Rump height; RLL: Rear leg length TLT: Tail length; CP: Crude protein. ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

Table 3.4: Correlation among udder traits, crude protein and lipid contents of milk of Bunaji cows

	TTL	TDM	TFD	TNR	UDL	UCR	UDW	CTH	CP
TDM(cm)	0.718^{**}								
TFD(cm)	0.398^{*}	0.178							
TNR(cm)	C	C	C						
UDL(cm)	0.350^{*}	0.344^{*}	0.452	C					
UCR(cm)	0.398^{*}	0.460^{**}	0.292	C	0.334				
UDW(cm)	0.631^{**}	0.510^{**}	0.307	C	0.604^{**}	0.463^{**}			
CTH(cm)	0.337^{*}	0.367^{*}	0.319^{*}	C	0.527^{**}	0.178	0.463^{**}		
CP	-0.155	0.200	-0.362	C	-0.481^{*}	-0.280	-0.455^{**}	-0.345^{*}	
Lipid	-0.119	-0.355^{*}	-0.264	c	-0.368^{*}	-0.368	-0.416^{**}	-0.283	0.643^{**}

TDM: Teat diameter; TFD: Teat floor distance; TNR: Teat number; UDL: Under length; UCR: Udder circumference; UDW: Udder width; CTH: Cistern height; CP: Crude protein; Kg: Kilogram; SEM: Standard error of mean; LOS: Level of significant; *****$p<0.05$: Significant at 5% (2-tailed); **$p<0.01$: Significant at 1% level of probability (2-tailed); NS: Non-significant at ($p>0.05$); ** Correlation is significant at the 0.01 level (2-tailed); C: Cannot be computed because at least one of the variables is constant.

3.5 Rotated Component Matrix for Body Weight and Linear Body Measurements, Udder Traits, Crude Protein and Lipid Contents of Milk of Bunaji Cows

The rotated component matrix for body weight and linear body measurements, udder traits, crude protein and lipid contents of milk of Bunaji cows are presented in Table 3.5. The first principal component (PC) accounted for 17.001% of the total variance with loadings of face length (0.567), ear length (0.620), fore leg length (0.716), height at wither (0.788), rump height (0.791) and rear leg length (0.875), which were the major contributors of PC I. PC II also contributed positively to the factor loadings, which were mainly udder traits; teat floor distance (0.515), udder length (0.798), udder width (0.654), cistern height (0.799) with the exception of crude protein (0.709), which contributed negatively. The head width (0.564), neck length (0.709), neck circumference (0.678) and lipid (0.651) were the factor loadings in PC III, which accounted for 11.829% of the total variance. PC IV accounted for 10.515% of the total variance with loadings of teat length (0.657), teat diameter (0.783) and udder circumference (0.699). PC V had a total variance of 9.851%, which constitute body weight (0.783), chest girth (0.788) and loin girth (0.679). In PC VI, horn length (0.794) contributed positively whereas body length (-0.758) contributed negatively to the factor loadings with 6.445% as the total variance. Tail length was the only trait that contributed positively to the factor loadings, which accounted for 1.475% of the total variance. According to Putra *et al.* (2020), seven body measurements, including body size (PCI) and body shape (PC II), were used to describe the body conformation of Pasundan cows. Principal component analysis can be used to determine an animal's body conformation (Mishra *et al.*, 2017). According to Heryani *et al.* (2018), white Taro cows' WH, BL, CG, CW, RH, and RW body dimensions were included in PC I. This is identical to the results of this study's six linear biometric measurements, where PC I was primarily influenced by face length, ear length, foreleg length, height at wither, rump height, and rear leg length.

Table 3.5: Rotated component matrix for body weight and linear body measurements (udder traits, crude protein and lipid contents of milk) of Bunaji cows

Variable	Component							
	I	II	III	IV	V	VI	VII	Communalities
BWT(kg)	0.395	0.191	0.247	0.094	**0.783**	0.050	0.038	0.881
FLT(cm)	**0.567**	0.143	0.285	0.305	0.390	0.122	0.259	0.751
HWD(cm)	0.305	0.009	**0.564**	0.422	-0.208	0.102	-0.053	0.646
HLT(cm)	0.097	-0.041	0.248	0.339	-0.089	**0.794**	-0.127	0.842
ELT(cm)	**0.620**	0.115	0.063	-0.212	-0.160	0.192	0.483	0.742
NLT(cm)	0.046	0.020	**0.709**	-0.092	0.260	0.020	0.063	0.586
NCR(cm)	0.236	0.373	**0.678**	-0.005	0.287	-0.156	-0.105	0.772
FLL(cm)	**0.716**	-0.038	-0.077	-0.021	0.096	-0.1.06	-0.373	0.679
HTW(cm)	**0.788**	0.174	0.250	0.100	0.066	-0.195	-0.008	0.766
CGT(cm)	0.297	0.208	0.282	0.115	**0.788**	0.070	0.044	0.853
BLT(cm)	0.286	-0.028	0.181	0.206	0.012	**-0.758**	-0.222	0.782
LGT(cm)	-0.197	-0.073	0.099	0.236	**0.679**	-0.287	-0.048	0.656
RHT(cm)	**0.791**	0.221	0.143	0.264	0.135	-0.133	-0.048	0.803
RLL(cm)	**0.875**	0.008	-0.164	-0.059	0.102	0.074	0.026	0.814
TLT(cm)	-0.092	-0.013	-0.088	0.141	0.071	0.012	**0.870**	0.799
TTL(cm)	0.028	0.348	0.252	**0.657**	0.321	0.037	0.273	0.796
TDM(cm)	-0.041	0.260	-0.066	**0.783**	0.226	0.114	0.116	0.765
TFD(cm)	0.320	**0.515**	-0.045	0.080	0.252	-0.061	0.138	0.462
UDL(cm)	0.239	**0.798**	0.089	0.249	-0.009	-0.109	-0.032	0.778
UCR(cm)	0.106	0.180	-0.262	**0.699**	0.073	-0.089	-0.088	0.623
UDW(cm)	0.120	**0.654**	0.003	0.436	0.022	0.072	0.167	0.665
CTH(cm)	-0.233	**0.799**	-0.024	0.104	0.129	0.162	-0.168	0.776
CP	-0.240	**-0.612**	0.579	-0.032	-0.034	0.142	-0.102	0.800
Lipid	-0.122	-0.417	**0.651**	-0.237	0.010	0.043	-0.067	0.675
Variance %	17.001	12.829	11.002	10.515	9.851	6.445	6.114	73.789
Eigen value	4.080	3.079	2.641	2.524	2.364	1.547	1.475	

BWT: Body weight; FLT: Face length; HWD: Head width; HLT: Horn length; ELT: Ear length NLT: Neck length; NCR: Neck circumference; FLL: Fore leg length; HTW: Height at withers; CGT: Chest girth; BLT: Body length; LGT: Loin girth; RHT: Rump height; RLL: Rear leg length TLT: Tail length; TDM: Teat diameter; TFD: Teat floor distance; TNR: Teat number; UDL: Under length; UCR: Udder circumference; UDW: Udder width; CTH: Cistern height; CP: Crude protein; %: Percent.

3.6 Prediction of Crude Protein and Lipid Content of Milk of Bunaji Cow from Linear Body Measurements, Udder Traits and Principal Components

Regression equations for prediction of crude protein and lipid content of milk of Bunaji cow from linear body measurements, udder traits and principal components are shown in Table 3.6. The prediction equation predicted crude protein and lipid using principal component analysis as a total for prediction with good coefficients of determination, R^2=0.787 and 0.655, respectively. However, moderate crude protein (R^2=0.463) from udder traits and body linear measurements (R^2=0.446) were predicted whereas the lipid contents of Bunaji cows showed low levels of predictability. The evaluation of the regression equation criteria showed that the combination of PC1, PC2, PC3, PC4 and PC5 showed better prediction ability (R^2). Also, the combination of two udder traits; UDL and UDW in a single multivariate equation improved the prediction (R^2) of the model. The combination of three milk composition in a regression model gave the highest coefficient of determination (R^2=58.99) as reported by Alphonsus (2015), which is in agreement with the result of this study.

Table 3.6: Regression equations for prediction of crude protein and lipid content of milk of Bunaji cow from linear body measurements, udder traits and principal components

Source of variables	Prediction equation	R^2
Linear body measurements	CP = 5.204 + 0.01221HLT – 0.16853ELT + 0.06949NLT – 0.143388TTL	0.446
	Lipid = 0.53526 + 0.09832HWD + 0.03804NLT – 0.10185TTL	0.231
Udder traits	CP = 5.39998 – 0.06105UDL – 0.05567UDW	0.463
	Lipid = 5.3663 – 0.03661UDL – 0.02243UCR	0.233
Principal Components	CP = 3.468 – 0.12682PCI +0.32315PCII + 0.3042PCIII + 0.07425PCIV	0.787
	Lipid = 3.09275 – 0.16696PCII + 0.26082PCIII – 0.09516PCIV	0.655

CP: Crude protein; HLT: Horn length; ELT: Ear length; NLT: Neck length; TTL: Teat length; HWD: Head width; UDL: Udder length; UDW: Udder width; UCL: Udder circumference; PC: Principal component.

3.7 Ensemble Algorithm Evaluation for Crude Protein and Fat Content of Bunaji Cows

The Ensemble algorithm evaluation for crude protein and fat are shown on Table 3.7 and 3.8. Machine learning algorithms feed on past data to generalize a pattern. Several algorithms have merits and demerits. The objective of ensemble methods is to increase generalizability/robustness over a single estimator by combining the predictions of numerous base estimators constructed with a specific learning procedure. (https://scikit-learn.org/stable/modules/ensemble.html). SVM learner and random forest learner outperformed the artificial neural network (ANN, or just NN) in terms of mean squared error (MSE), which indicates that the two were superior to NN. The lower performance of NN in this study can be explained on the basis of extremely low data that was available for this study. Hence the use of the word 'demonstration' for the models generated. This is connoting the fact that this study was proposed only to demonstrate the useability of machine learning tools at predicting crude protein content of milk. This method can be used to train several other farm animal biological models.

The other measures (RMSE, MAE, and R2) likewise demonstrated that NN performance was subpar when attempting to forecast crude protein from Bunaji cows' udder features. In general, neural networks are data-hungry models. They need a lot of data points to generalize well. SVM was also depicted to be poor in performance in modeling in this study on the basis of RMSE. SVM has been reputed to be more suitable for cases where the features are more relative to the sample data (Ray, 2017).

Table 3.7: Ensemble algorithm evaluation of crude protein

Model	MSE	RMSE	MAE	R^2
SVM Learner	0.202	0.449	0.370	0.255
Random Forest Learner	0.258	0.258	0.413	0.049
Neural Network	0.563	0.563	0.595	-1.077

SVM = support vector machine; MSE = Mean square error; RMSE = Root mean square error; MAE = mean absolute error ;R^2 = Coefficient of determination

Table 3.8: Ensemble algorithm evaluation of fat

Model	MSE	RMSE	MAE	R^2
SVM Learner	0.154	0.393	0.305	0.009
Random Forest Learner	0.183	0.428	0.341	-0.175
Neural Network	0.295	0.543	0.408	-0.890

SVM = support vector machine; MSE = Mean square error; RMSE = Root mean square error; MAE = mean absolute error; R^2 = Coefficient of determination

3.8 Comparison of the Models

The comparison of the models is shown in Tables 3.9 and 3.10. Each cell displays the likelihood that the model in the row will have a higher score than the model in the column. Low numbers suggest that the change is insignificant. Thus, the likelihood that SVM will estimate with more mistakes than RF is, for example, 0.936 (please note that the maximum probability is 1). The likelihood that NN will estimate with greater errors than RF is also 0.858. On the other hand, the least trustworthy chance of error is 0.064 in favour of the RF learner.

Table 3.9: Model comparison by MSE for crude protein

Model	SVM Learner	RF Learner	NN
SVM Learner		0.064	0.117
RF Learner	0.936		0.142
NN	0.883	0.858	

SVM = support vector machine; RF = Random Forest; NN = Neural Network

Table 3.10: Model comparison by MSE for fat

Model	SVM Learner	RF Learner	NN
SVM Learner		0.229	0.211
RF Learner	0.771		0.278
NN	0.789	0.722	

SVM = support vector machine; RF = Random Forest; NN = Neural Network

3.9 Model plotting

The charts in Figures 3.1, 3.2 and 3.3 showed the actual values of crude protein recorded on Bunaji cows in blue, green and red, while the predicted values were depicted as wavy lines in orange, yellow and maroon colours. The figures demonstratively showed that all the models presented very poor predictions of crude protein from udder traits. This is understandable because the data set was extremely low. It is noteworthy that adding more data to the algorithms will cause tremendous improvement in the models. Similar trends were also obtained in the estimations of lipids in Figures 3.4, 3.5 and 3.6.

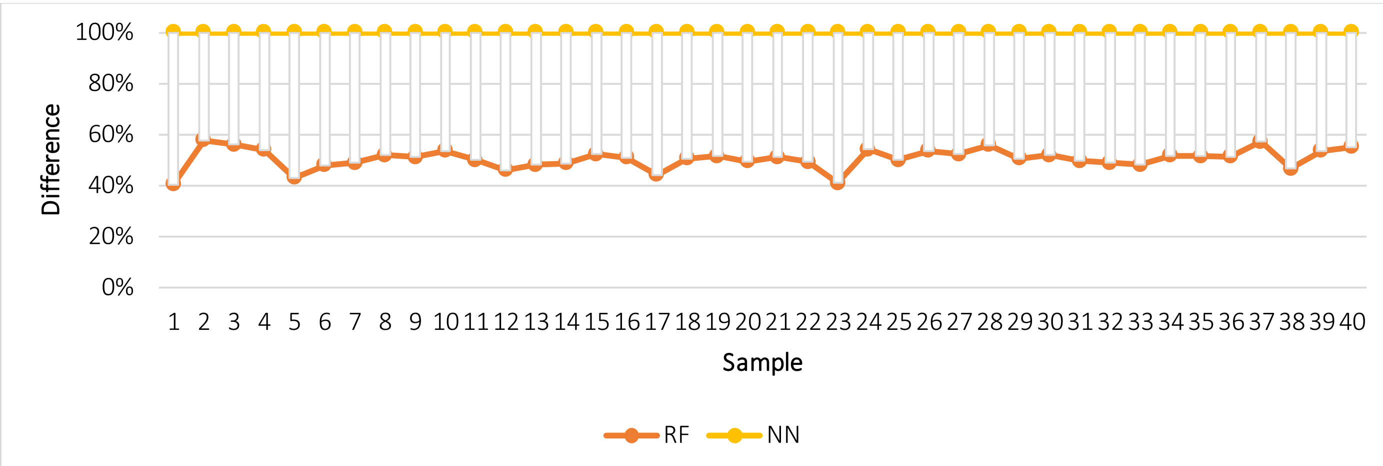

Figure 3.1: Prediction difference versus sample (RF - cp)

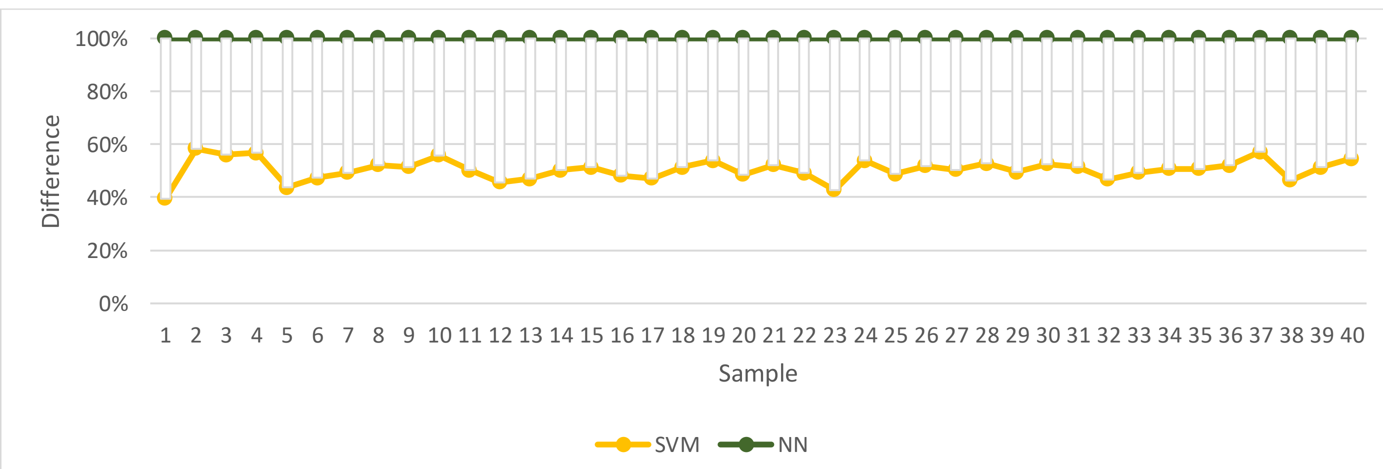

Figure 3.2: Prediction difference versus sample (SVM - cp)

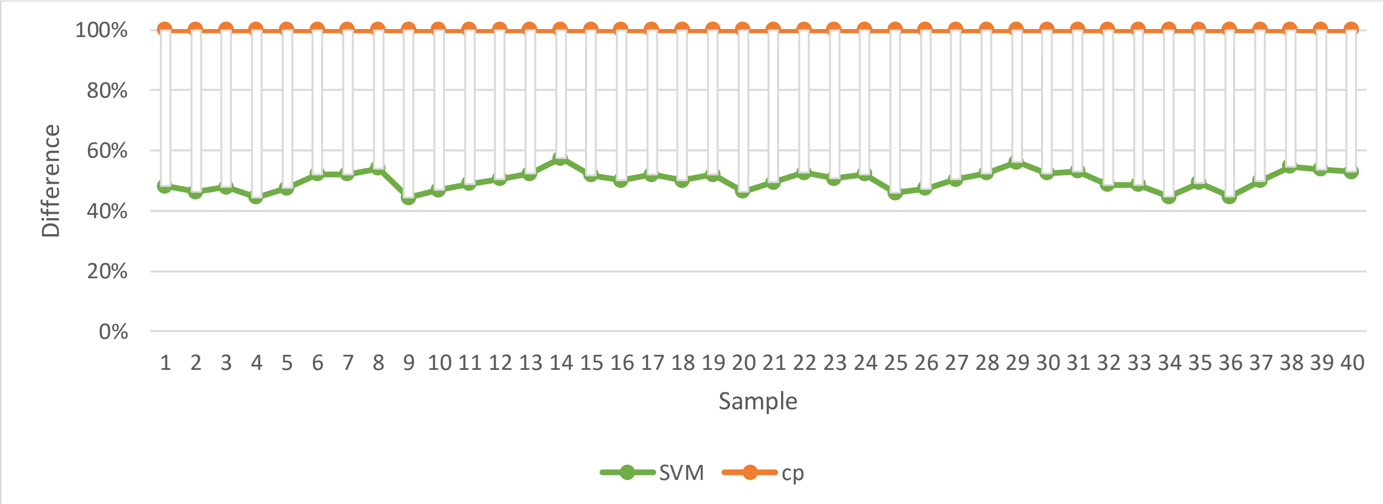

Figure 3.3: Prediction difference versus sample (NN - cp)

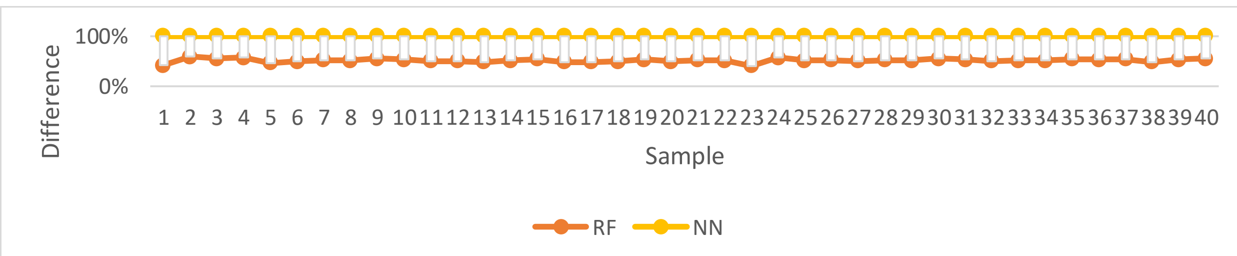

Figure 3.4: Prediction difference versus sample (RF - fat)

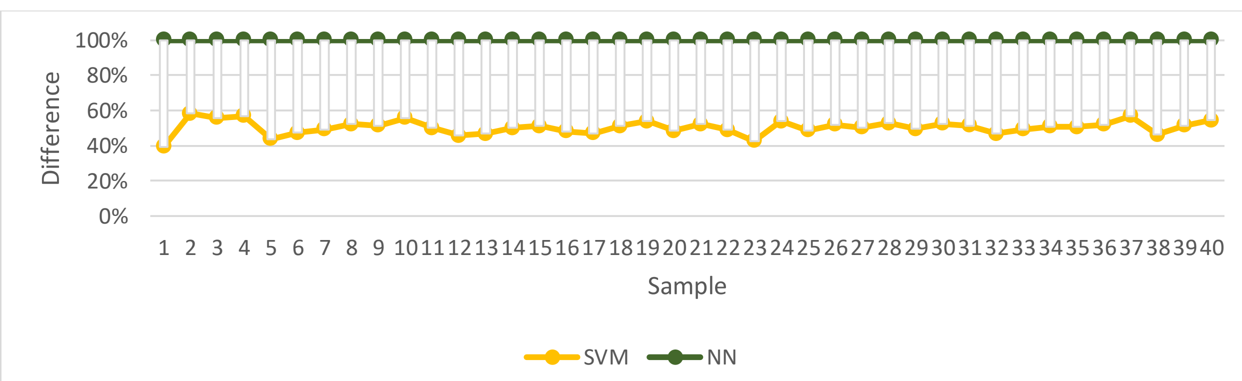

Figure 3.5: Prediction difference versus sample (SVM - fat)

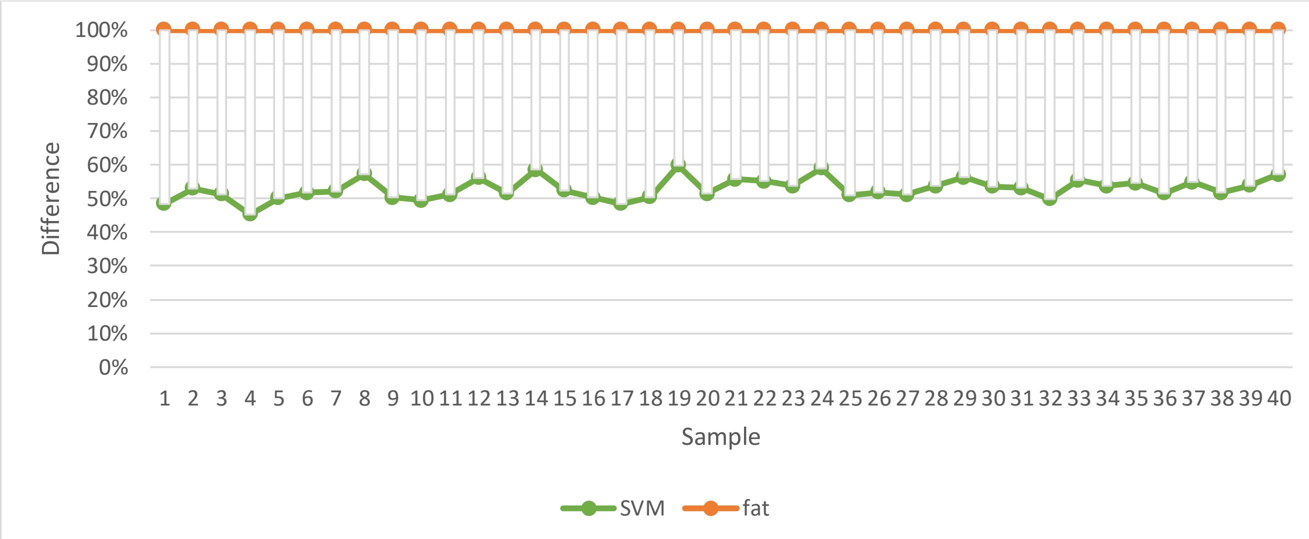

Figure 3.6: Prediction difference versus sample (NN - fat)

4.0 Conclusion and Recommendation

Random Forest (RF) Learner exhibited a low likelihood for mistake in predicting crude protein from udder traits despite the study's small data set. Large data sets were needed for machine learning techniques. As a result, these models must be improved with lots of data.

References

Adejoro, F.A and Salako, A.E. (2012). Morphometric Characterization of the Balami Sheep of Nigeria. *African Journal of General Agriculture*, 8(4): 169-73.

Alphonsus, C. (2015). Prediction of total milk yield in early lactation of dairy cows using milk composition measures. *Livestock Research for Rural Development*, 27(8). Retrieved April 3, 2023, from http://www.lrrd.org/lrrd.27/8/alph27154.htl.

Alphonsus, C., Akpa, G.N., Barje, P. P., Nwagu, B. I., Yashim, S. M., Achi, N. P. and Sam, I. M. (2017). Genetic and Phenotypic Correlations between Fertility and milk Composition traits of Friesian X Bunaji cows. *Journal of Animal Production Research*, *29*(1), 16-23.

Alphonsus, C., Akpa, G.N. and Oni, O.O. (2009). Repeatability of objective measurements of linear udder and body conformation traits in Friesian X Bunaji cows. *Animal Production Research Advances*, 5(4), 224-231.

Anupam, S., Sharad, M., Santra, A.K., Nishma, S., Ruptal, P., Bobade, M.D., Ashutosh, D., Neetu, S. and Sudheer B. (2020). Correlation between the Linear Type Traits and Milk Yields and its Composition in Dairy Cattle. *International Journal of current Biology and Applied Sciences*, ISSN: 2319-7706 Volume 9 Number 4.

Berry, P.D., Buckley, F. and Dilon, P. (2004). Genetic Relationships among Linear Type Traits, Milk Yields, Body Weight, Fertility and Somatic Cell Count in Primiparous Dairy Cows. *Irish Journal of Agricultural and Food Research*, 43: 161-176.

Bradley, R.L.J., Arnold, E., Barbano, D.M., Semerad, R.G., Smith, D.E. and Viries, B.K. (1992). Chemical and physical methods. In Marshall R.T. (Eds) Standard Methods for the Examination of Dairy Products, Washington: *National Academy Press*, Pp. 433-533.

Buenger, A., Ducrocq, V. and Swalve, H.H. (2001). Analysis of survival in dairy cows with supplementary data on type score and housing system from a region of North-West Germany. J*ournal of Dairy Science*, 84: 1531-1541.

Cabrera, V.E., Barrientos-Blanco, J.A., Delgado, H. and Fadul-Pacheco, L. (2020). Symposium review: Real-time continuous decision making using big data on dairy farms. *Journal of Dairy Science*, *103(4)*, 3856-3866.

Caraviello, D.Z., Weigel, K.A., Craven, M., Gianola, D., Cook, N.B., Nordlund, K., Fricke, P.M. and Wiltbank, M.C. (2006). Analysis of Reproductive Performance of Lactating Cows on Large Dairy Farms Using Machine Learning Algorithms. *Journal of Dairy Science*, 89: 4703-4722.

Dairo, F.A.S., Afolabi, A. and Sanusi, J. (2011). Ruminant Animal Production: National Open University of Nigeria. Retrieved on 22nd March, 2018 from http://www.nou.edu.ng.

Dandare, S.U., Ezeonwumeh, I.J. and Abubakar, M.G. (2014). Comparative analysis of nutrient composition of milk from different breeds of cows. *European Journal of Applied Engineering and Scientific Research*, 3(2): 33-36.

DeGroot, B.J., Keown, J.F., van Vleck, L.D. and Marotz, E.L. (2002). Genetic parameters and responses of linear type, yield traits and somatic cell scores to divergent selection for predicted transmitting ability for type in Holsteins. J*ournal of Dairy Science*, 85: 1578-1585.

Dim, N.I., Egahi J.O. and Tanko, M.U. (2012). Zoometrical Measurements of Body Parts and their Relationship with Lives weight in Bunaji Cows in Zaria. *International Journal of* Advance *Biological Research*, 2 (2): 339-341.

Duncan, D. B. (1955). New Multiple F-test. *Biometrics*, 11: 1-42.

Food and Agricultural Organization of the United Nation. (2012). Phenotypic Characterization of Animal Genetic Resources. Food and Agricultural Organization of the United Nation Animal Health and Production Guideline No.11. Rome. Retrieved on 15th October, 2017; From: http://www.google.com.

Heinrichs, A.J., Jones, C. and Bailey, K. (2005). Milk components: Understanding the causes and importance of milk fat and protein variation in your dairy herd. Retrieved February 12, 2023 from http://extension.psu.edu/animals/dairy/health/nutrition/and feeding/diet formulation-and–evaluation/milk-components-understanding-the-causes-and-importance-of-milk-fat-and protein-variationin-your-dairyherd-1.

Heryani, L.G.S.S., Susari, N.N.W. and Gunawan, I.W.N.F. (2018). Principal component variables of Taro white cattle morphometric based on body measurements. *Bulletin of Veterinary Udayana*, 10: 93-99. https://www.analyticssteps.com/blogs/6-major-branches-artificial-intelligence-ai

Hyde, R.M., Down, P.M., Bradley, A.J., Breen, J.E., Hudson, C., Leach, K.A. and Green, M.J. (2020). Automated prediction of mastitis infection patterns in dairy herds using machine learning. *Scientific Reports*, *10*, 4289. https://doi.org/10.1038/s41598-020-61126-8

Idi, B.Y. and Abubakar, I.M. (2022). Vegetation and land surface temperature relationship using MODIS data; a case study of central vegetation zone of Adamawa state, Nigeria. *Journal of Earth Science and Climate Change*, *13*, 630. DOI: 10.4172/2157-7617.1000630

John, P.A. and Iyiola-Tunji, A.O. (2018). Characterization of Adult donkeys in North West Nigeria using Morphometric Traits. *Nigerian Journal of Genetics*, 32: 40-49.

Kala, R., Samková, E., Hanuš, O., Pecová, L., Sekmokas, K. and Riaukienė, D. (2019). Milk Protein Analysis: An Overview of the Methods – Development and Application. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *67(1)*, 361-375.

Kubkomawa, H.I. (2017). Indigenous breeds of cattle, their Productivity, Economic and Cultural Values in Sub-Saharan Africa: A Review: *International Journal of Research Studies in Agricultural Sciences*, 3(1): 27-43.

Liakos, K.G., Busato, P., Moshou, D., Pearson, S. and Bochtis, D. (2018). Machine learning in Agriculture: A review. *Sensors*, 18(8): 2674. DOI: 10.3390/s18082674

Maiwasha, A.N., Bradfield, M.J., Theron, H.E. and Van Wyk, J.B. (2002). Genetic parameter estimates for body measurements and growth traits in South African Bonsmara cattle. *Livestock Production Science*, 75: 293-300.

Matei, S.T., Groza, I., Andrei, S., Bogdan, L., Ciupe, S. and Petrean, A. (2010). Serum metabolic parameters in Healthy milk from different species. Asian-Australas. *Journal of Animal Science*, 29(7): 1022-1028.

Mavule, B.S., Muchenji, V., Bezuidenhout, C.C. and Kunene, N.W. (2013). Morphological structure of Zulu sheep based on principal component analysis of body measurements. *Small Ruminant Resarch*,111: 23-30.

Mishra, S.P., Uttam, S., Subhash, T., Sanjay, D., Devi, P.S., Reshma, S., Sasmita, P. and Menals, L. (2017). Multivariate statistical data analysis principal component analysis (PCA). *International Journal of Livestock Research*, 7: 60-78.

National Bureau of Statistics, (2010). Animal abstract of statistics. Retrieved on 2nd April, 2018; from: http://www.Nigerianstatisticsgov.ng/pages/download/7/.

Nayak, V., Pathak, P. and Adhikary, S. (2018). Rearing Climate Resilient Livestock for Better Productivity. A Review: *International Journal of Livestock Research*, 8(3): 623.

Nemcova, E., Stipkova, M. and Zavadilova, L. (2007). The Relationship Between Somatic Cell Count, Milk Production and Six Linearly Scored Type Traits in Holstein Cows. *Czech Journal of Animal Science*, 52: 437-446.

Oladapo, A.F. and Ogunekunn, T.O. (2015). Quality Assessment of fresh milk from traditionally managed Nigerian Bunaji and Bokolooji Breeds of Cattle. *The Pacific Journal of Science NNLRS and Technology*, 16(1): 280-285.

Papachristoforou, C. and Mavrogenis, A. (1981). Udder characteristics of Chios sheep and their relation to milk production and machine milking. *Agricultural Research Institute*, Cyprus, Technical Paper, 20, ISSN, 03790932.

Putra, W.P.B, Said, S. and Arifin, J. (2020). Principal component analysis of body measurements and body indices in Pasundan cows. *Black Sea Journal of Agriculture*, 3(1): 49-55.

Ray, S. (2017). https://www.analyticsvidhya.com/blog/2017/09/understaing-support-vector-machine-example code/?__cf_chl_captcha_tk__=pmd_0e9213802b158cc3d7271f494bfbeba6a2fccb6e-1628128890-0-gqNtZGzNAw2jcnBszQhO

Sam, I. M. and Usoro, O. O. (2022). Influence of Slaughter age on Carcass Composition and Beef yield of White Fulani Cattle. *Animal Research International*, *19*(2), 4452-4459.

SAS (Statistical Analysis System). (2004). *SAS/STAT user's guide version 9.1*, Cary, NC: SAS Institute Inc.

Shahinfar, S., Mehrabani-Yaganeh, H., Lucas, C., Kalhor, A., Kazemian, M. and Weigel, K.A. (2021). Prediction of breeding values for dairy cattle using artificial neural network and neuro fuzzy systems. Computational and Mathematical methods in Medicine vol. 2012, Article ID 127130, 9 pages, 2012. https://doi.org/10.1155/2012/127130

Tyagi, N. (2021). Six (6) major branches of Artificial Intelligence https://www.analyticssteps.com/blogs/6-major-branches-artificial-intelligence-ai

Wang, J., Bell, M., Liu, X and Liu, G. (2020). Machine learning techniques can enhance dairy cows estrus detection using location and accelerated data. *Animals*, *10*, 1160. DOI: 10.3390/ani/0071160