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Comparison of linear discriminant analysis, support vector machine and artificial neural network in classifying Nigerian local turkeys based on plumage colours using biometric traits

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Abstract

The ability of linear discriminant analysis (LDA), support vector machine (SVM), and artificial neural network (ANN) models to differentiate biometric traits of Nigerian local turkeys was investigated in this study. The biometric traits (bodyweight, body length, breast girth, thigh length, shank length, keel length, wing length, and wingspan) in 200 (20-week-old) turkeys were measured. Seventy percent of the datasets were used to train the three models, with the remaining 30 % being used to test their performance. All biometric traits were positively associated, with strong correlation values for several pairs of traits. In the testing dataset (Lavender = 30.0 %, Black = 51.9 % and White = 65.5 %), the LDA had lower classification efficiency than in the training dataset (Lavender = 55.2 %, Black = 43.4 %, and White = 65.5 %), indicating that the training model was not efficient in classification at the testing stage. In comparison to the training dataset (Lavender = 100.0 %, Black = 87.3 % and White = 98.2 %), the SVM showed low classification efficiency for the testing dataset (Lavender = 70.0 %, Black = 76.0 % and White = 64.0 %). However, in ANN, there was no variation in classification efficiency between the testing and training datasets (Lavender = 100.0 %, Black = 100.0 % and White =100.0 %). In categorizing turkey plumage colours, the ANN model is the most powerful, followed by SVM. When the dataset's normality or multi-colinearity is broken, we propose using an ANN model rather than a standard model like the LDA for classification of biometric traits of Nigerian local turkeys.

Keywords: classification, testing, mixed methods, training

1 Introduction

Turkey (*Meleagris gallopavo*) is gaining popularity in Nigeria as a result of its ability to increase the poultry industry and contributes to the supply of meat and eggs. Nigeria's fast-growing turkey industry necessitates an active research method in order to claim its production, especially given the potentials linked with it (Adeoye *et al*., 2017). Nigerian domestic turkeys have a multi-coloured plumage that can range from black to lavender to white. They are one of Nigeria's least studied poultry species, with minimal effort put into describing them using biometric traits based on plumage colours (Adenaike *et al*., 2020). Many authors (Yakubu *et al*., 2009, Adeoye *et al*., 2017, Adenaike *et al*., 2018) have established that biometric data can be used as a proxy or complementary role in the description of livestock breeds. This is due to the influence of environmental, geographical, physiological, nutritional, and morphological characteristics on a breed's identification.

In this regard, analyses of easily measured biometric traits allow researchers to investigate areas such as breed or strain structure, degree of variability between populations (based on colours), morphological models harmony, and the definition of morphological models for specific breeds or populations (Herrera, 2007). As a result, it's critical to thoroughly examine the morphological traits that allow us to identify differences between breeds, as well as to investigate the use of various discrimination methods to evaluate the potential of each of the traits under consideration. Classic statisti-

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cal prediction and classification methods (such as logistic regression, principal component analysis, discriminant analysis, and so on) have been used in the study of biometric traits for classification in livestock, but they have a number of limitations: the assumptions on which they are based and the results from them are often not the best possible. Heuristic approaches, on the other hand, such as artificial neural networks (ANNs) and support vector machines (SVM), adapt to changes in a non-restricted manner and require far fewer or no assumptions. ANNs and SVMs give a single tool for solving a variety of problems that traditional statistical methods cannot or will not solve. They have been employed in different fields including ecology (Goethals *et al.*, 2007; Gutiérrez-Estrada *et al.*, 2008; Gutiérrez-Estrada & Bilton, 2010), fisheries (Robotham *et al.*, 2011) and chickens (Yakubu *et al.*, 2018; Siddique *et al.* 2021). However, in animal science, the usage of ANNs and SVM is still uncommon. This low use of ANN and SVM in animal research is confounding, given that data analyses are frequently performed in this discipline, despite the fact that a few studies have proven that ANNs and SVM are more potent than traditional methods. ANNs and SVM, unlike traditional statistical methods, try to solve problems by explicit learning. The major goal of this study was to see how accurate LDA, SVMs and ANN were at classifying three different plumage colours of Nigerian local turkeys using biometric data. The accuracies of the LDA, SVM, and ANN algorithms are compared, and the reasons for the differences in classification accuracies are explained. Therefore, the turkey plumage colours can be used by researchers as a genetic marker, useful for identifying breeds, populations and breeding groups with their specific traits thereby generating information essential for the implementation of breeding schemes suitable for village turkey producers in Nigeria.

2 Materials and methods

2.1 Location of study

The experiment was conducted at the Poultry Breeding Unit of the Directorate of University Farms of the Federal University of Agriculture, Abeokuta, Ogun State, Nigeria. The site is on latitude 7°10′ N and 3°2′ E.

2.2 Data collection and biometric traits

A total of 200 male Nigerian local turkeys, aged 20 weeks, were used in the study. The turkeys consisted of 39 white plumage, 80 lavender plumage and 81 ,black plumage colour. The following biometric traits were evaluated for each individual turkey: i) bodyweight (BW, g); ii) body length (BL, cm); iii) breast girth (BG, cm); iv) thigh length (TL, cm); v) shank length (SL, cm); vi) keel length (KL, cm); vii) wing length (WL, cm); viii) wing span (WS, cm).

2.3 Linear discriminant analysis

Linear discriminant analysis is a statistical approach for assigning new individuals to previously identified or established categories. The study is based on a set of data from n individuals, each of whom has p quantitative variables (independent variables) measured as a profile. A qualitative variable (dependent variable) with two or more categories defined by other techniques on the other hand, groups each individual into a category. This results in a n*(p+1) table with a profile for each case and a group for each case. A discriminant model is derived from this table and compared to the profile of new individuals. Khattree & Dayanand (2000), and Daniel (2020) among others provide detailed descriptions of the procedures. The model is given below:
$Z_{jk} = a + W_1X_1 + W_2X_2 + ... + W_nX_n$ Where
Z_{jk}=discriminant Z score of discriminant function j,
a = intercept
W_i= discriminant weight for independent variable,
X_{jk}= independent variable.

2.4 Artificial neural network model

Artificial neural networks (ANNs) are mathematical models based on the human brain's neural architecture. The multilayer perceptron (MLP) is the most commonly studied and used type of ANNs (Rumelhart *et al.*, 1986). These models learn in an iterative manner, with the dataset being presented to the neural network as many times as is necessary to achieve a specific level of error. These supervised ANNs enable for the analysis of complicated datasets and their nonlinear grouping into two or more groups. Tsoukalas & Uhrig (1997), Czerwinski *et al.* (2007), and Pulido-Calvo & Portela (2007) provide thorough descriptions of MLP performance. One input layer, one or two hidden layers, and one output layer makes up the conventional three or four layers MLP. Nodes or neurons are the processing elements in each layer. In our situation, the MLP's input data is biometric traits, and the output is the classification results. Weights, which are equivalent to synapse strength in biological neural nets, are used to connect the neurons. There are numerous approaches forcalibrating or learning MLPs. The usual backpropagation procedure was used in this study, and it was solved with R software. The model is given below:
$W_j = 1/\left(1 + exp - \sum input + \theta_j\right)$
where W_j is the output of the j^{th} node and $theta_j$ is the threshold value of the j^{th} node for output. The output of

Table 1: *Comparison of biometric traits among three plumage colour variants of Nigerian local turkeys.*

	Plumage colour		
Traits	*lavender*	*black*	*white*
bodyweight (g)	2441.03±86.36^{b}	2743.50±67.07^{a}	2550.37±57.41^{ab}
body length (cm)	36.62±0.43	36.39±0.32	36.10±0.38
breast girths (cm)	62.24±1.90	52.22±0.54	50.90±0.44
shank length (cm)	11.63±0.12^{b}	12.28±0.14^{a}	11.98±0.09^{ab}
keel length (cm)	12.13±0.18	12.50±0.128	12.23±0.12
wing length (cm)	29.79±0.35^{b}	31.89±0.36^{a}	30.99±0.23^{a}
wingspan (cm)	64.31±0.74^{b}	67.77±0.769^{a}	65.84±0.51^{ab}
thigh length (cm)	17.45±0.23^{b}	18.14±0.18^{a}	17.73±0.14^{ab}

^{ab} Means within the same row having different superscript are significantly different ($p < 0.05$)

the hidden nodes may also be conditioned by a non-linear function to provide limits on output values.

2.5 *Support vector machine*

The support vector machine (SVM) is a supervised machine learning technique that can be used for regression and classification (Cortes & Vapnik, 1995). The basic principle behind SVM is that it creates hyperplanes in a multi-dimensional space to split objects into different classes. The boundaries between different classes are then defined using a decision plane. SVM uses an iterative training procedure to build an ideal hyperplane, which is used to minimize an error function. When the goal is to classify categorical variables, the error function's form is typically divided into two categories: Classification SVM Type 1 (also known as C-SVM classification) and Classification SVM Type 2 (also known as -SVM classification). In this research, the classification SVM type used was C-SVM. For this type of SVM, training involves the minimization of the error function. The model is given below:
$\gamma i\,(w.xi + b) \geq 1 - \zeta i, i = 1...m$
where w is a vector normal to hyperplane ζi is slack variables and b is an offset. If the value of $w.xi + b > 0$ then it is a positive point otherwise it is a negative point.

2.6 *Statistical analysis*

All the biometric traits were analysed using one way analysis of variance (ANOVA) with Tukey's honestly significant difference ($p < 0.05$) (SAS, 2010) to determine significant differences among the levels of plumage colour variants. The coefficients of correlation between biometric traits were calculated. Three classification approaches, linear discriminant analysis (LDA), support vector machines (SVM), and backpropagation neural networking for ANN, were used to further analyze the data. R software (version 4.0.2) was used to perform correlation, LDA, SVM, and ANN analyses on biometric data. The data was divided into two sets: a 70:30 training set and testing set. The mass package was used for LDA. The caret package algothrim estimated the best-suited tuning parameter or cost (C) value, and a seed value was set for 2,000 for the SVM analysis. The ANN classification algothrim was employed with a low learning rate (0.01), a threshold value (0.01), a number of maximum steps (10,000), and one hidden layer using neural-net package to classify the plumage colours. The confusion matrix and ROC curves were used to compare the classification results provided by the models using the ROCR package. A function was built for multiple ROC curves to compute multi-class AUC for the plumage colours. The models' classification accuracies were compared by Paired Sample t-test using One Sample Kolmogorov Smirnov test.

3 Results

The differences in various biometric traits among the three colour variants of turkeys are shown in Table 1. Body weight, shank length, wing length, wing span, and tail length all differed significantly ($p < 0.001$). However, there were no significant differences in body length, breast girth, or keel length between the colour variants ($p > 0.05$). When compared to Lavender, turkeys with black plumage had higher body weight, shank length, wing length, wing span, and tail length. The white plumage colour variants have longer wings than the lavender plumage variants.

Table 2 shows Pearson correlations between biometric traits in three plumage colour variants of Nigerian local turkeys. The correlation coefficients between biometric traits were generally positive. They were also very high and significant except for the correlation between breast girths and other traits. The shank length and wing span had the highest positive correlation coefficient (0.9460), followed by

Table 2: *Pearson correlations among biometric traits in three plumage colour variants of Nigerian local turkeys.*

Biometric traits	*BW*	*BL*	*BG*	*SL*	*KL*	*WL*	*WS*
BL	0.8844***						
BG	0.1178^{ns}	0.1361^{ns}					
SL	0.8608^{***}	0.7891^{***}	0.0664^{ns}				
KL	0.9317^{***}	0.8673^{***}	0.0841^{ns}	0.8380^{***}			
WL	0.8863^{***}	0.7731^{***}	0.0672^{ns}	0.9137^{***}	0.8382^{***}		
WS	0.9160^{***}	0.8153^{***}	0.0869^{ns}	0.9460^{***}	0.8723^{***}	0.9363^{***}	
TL	0.9301^{***}	0.8533^{***}	0.1258^{ns}	0.8808^{***}	0.9275^{***}	0.8879^{***}	0.9172^{***}

BW: bodyweight; BL: body length; BG: breast girth; SL: shank length; KL: keel length; WL: wing length; WS: wing span; TL: tigh length. $^{***}p < 0.001$; ns: not significant

body weight and keel length (0.9317). Body length and wing length (0.7731) had the lowest, positive, and significant correlation coefficient, followed by body length and shank length (0.7891).

According to the LDA, two linear discriminant functions accounted for 93.02 and 6.98 % of the total variation in the biometric variables. The first linear discriminant function (LD1) was a linear combination of traits that distinguished between the three plumage colours the best. The second linear discriminant function (LD2), which was orthogonal to the first, was the next best linear combination (Table 3).

Table 3: *Linear discriminant structure of the three turkey plumage colour variants.*

Traits	*LD1*	*LD2*
Body weight	0.00	0.00
Body length	−0.57	0.19
Breast girths	−0.01	−0.01
Shank length	0.33	0.85
Keel length	−0.36	−0.23
Wing length	0.57	0.13
Wing span	−0.11	0.00
Thigh length	0.16	−1.31
Variance accounted for (%)	93.02	6.98

LD1: First linear discriminant function;
LD2: Second linear discriminant function.

Figure 1 shows a bi-dimensional plot created with the two linear discriminant functions that depicts the relationship between the three plumage colour variants. There was no clear distinction among individuals of the three plumage colours on the plot.

Support vector machine analysis was first performed to find the best model for gamma ranging from 0.25 to 4, and cost ranging from 4 to 16. According to the SVM results, the best gamma model had a cost of 1 to 16 and a gamma of 0.25 to 2. A better fit is indicated by a larger cost parameter, and a gamma of 0.25 or less is also indicative of a better fitting model. The SVM model was refitted using the best gamma and cost values (8 and 0.25, respectively) including 10-fold cross validation. The model estimates 103 support vectors, with 41 in the lavender, 23 in the black, and 39 in the white. Figure 2 shows the ANN, which shows the input nodes (biometric traits), hidden node, and output node (plumage colour). Each input was synaptically coupled to the output node, and the buried layer node largely influences the neural network's classification efficiency. With 3532 steps, the overall error was 40.873. The node weights ranged from -27.5125 (BL) to 23.294 (BW).

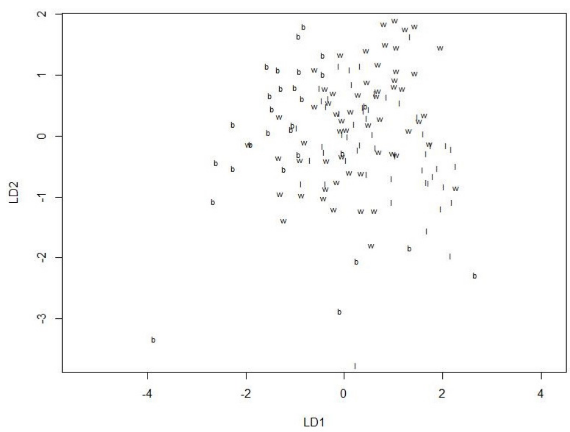

Fig. 1: *Linear discriminant representation of the three plumage colour variants in Nigerian local turkeys. w = white plumage, l = lavender plumage, b = black plumage.*

The large coefficients (27.513, 23.294, and 23.321) of BL, BW, and BG respectively appeared to be the most important predictors for the classification process using ANN, while BL, WL, and SL (0.570, 0.570, and 0.850) appeared to be the most important predictors for LDA. SVM, on the other hand, does not generate values to assess each variable's contribution to the prediction. The errors were estimated using the data from the matrices used in the

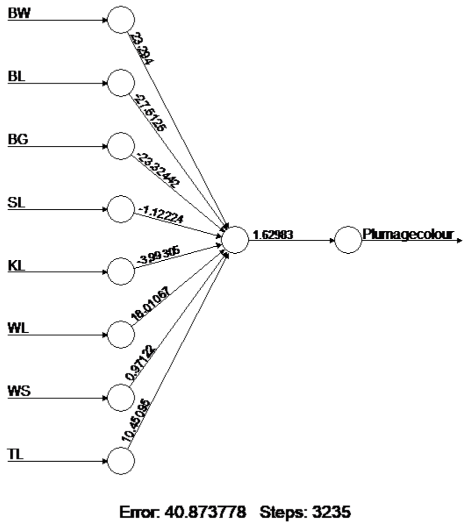

Fig. 2: *The structure of the artificial neural network with one hidden layer and 9 input variables.*

LDA, SVM, and ANN models. For biometric traits of Nigerian local turkeys, Table 4 illustrates the percentage classification performance of LDA, SVM, and ANN. The testing dataset (Lavender = 30.0 percent, Black = 51.9 percent, and White = 65.5 percent) had lower classification efficiency than the training dataset (Lavender = 55.2 percent, Black = 43.42 percent, and White = 65.5 percent). Similarly, compared to the training dataset (Lavender = 100.0 percent, Black = 87.3 percent, and White = 98.2 percent), the SVM analysis revealed low classification efficiency for the testing set (Lavender = 70.0 percent, Black = 76.0 percent, and White = 64.0 percent). However, there was no difference in classification efficiency for the testing set (Lavender = 100.0 %, Black = 00.0 %, and White = 100.0 %) compared with the training dataset (Lavender = 100.0 %, Black = 100.0 %, and White = 100.0 %) in ANN.

The results were also corroborated by the areas obtained by LDA, SVM, and ANN under Receiver Operating Characteristic Curves (ROC). For a variety of cut-offs, ROC curves are shown against (1- specificity) on the X-axis and sensitivity on the Y-axis. The ANN model has the largest area under the ROC curve when compared to the LDA and SVM models as shown in Table 5. Using the Paired Sample t-test, the differences between the areas were determined to be significant ($p < 0.05$).

4 Discussion

The use of morphological traits to characterize Nigerian local turkeys has substantial consequences for their well-being and improvement. One of the ways to achieve this characterisation is to classify turkeys based on plumage colours using machine learning models. The mean values of all biometric traits measured in this study were within the range reported for Nigerian local turkeys by Ilori *et al.* (2016) and Durosaro *et al.* (2016). The results of BW, SL, WL, WS, and TL in black plumage turkeys against lavender plumage turkeys showed that black plumage was superior to lavender. This contradicts the findings of Adeyemi & Oseni (2018), who found that, with the exception of abdomen circumference, tail feather length, and number of caruncles, white colour variant means was considerably greater than black and lavender variants. The literature on Zagorje turkey biometric traits based on plumage colours revealed that black and lavender colours had higher averages for BW, BL, TL, and SL (Janjecic & Muic, 2007). The observed differences in

Table 4: *Percentage classification efficiency for different machine learning algorithms (linear discriminant analysis, support vector machine and artificial neural network) for biometric traits of Nigerian local turkeys.*

	Accuracy	
Classification method	*Training sample (%)*	*Test sample (%)*
linear discriminant analysis		
Lavender*	55.2	30.0
Black	43.4	51.9
White	65.5	34.8
Overall accuracy	55.0	43.3
support vector machine		
Lavender	100.0	70.0
Black	87.3	76.0
White	98.2	64.0
Overall accuracy	94.3	70.0
artificial neural network		
Lavender	100.0	100.0
Black	100.0	100.0
White	100.0	100.0
Overall accuracy	100.0	100.0

* Plumage colour.

Table 5: *Area under receiver operating characteristic (ROC) for artificial neural network (ANN), support vector machine (SVM) and linear discriminant analysis (LDA) models.*

Plumage colour	*ANN*	*SVM*	*LDA*
Black	1.000^a	0.847^b	0.645^c
Lavender	1.000^a	0.232^b	0.345^b
White	1.000^a	0.781^b	0.537^c

[abc] Means within the same row having different superscript are significantly different ($p < 0.05$).

biometric traits across the three colour variants could be related to underlying intra-population features or attributes, as reported by few authors (Latshaw & Bishop, 2001; Ajayi *et al*., 2008; Adeyemi & Oseni, 2018) that morphometric measurements are useful in differentiating sizes as well as shapes of animals.

Selection for one characteristic may lead to a correlated response in the other trait in a turkey breeding program based on genetic correlations between two traits (Falconer & Mackay, 1996). Correlations reveal the interrelationships between traits, which is an essential knowledge for turkey breeding, conservation, and management. All biometric traits were shown to be positively associated in this study, with certain pairs of traits having significant correlation coefficients. This implies that when the turkeys' BW grows, the linear body measurements will increase in response to the high positive correlations that exist between them with the exception of body length. This means that selecting for higher BW will result in higher levels of other traits. The positive and high correlations found in this study are consistent with the findings of Djebbi *et al.* (2014), Ogah (2011), and Adeoye & Oladepo (2018). Positive and high correlations among biometric traits meant that these traits were highly predictable. This suggests that the correlation value of one trait can be used to predict the other. Highly linked traits are more likely to be influenced by the same gene activity, indicating that one gene influences the other and thus forming the basis for local turkey genetic selection and upgrading (Yakubu, 2013).

Each discriminant function indicating the contribution of each of the main traits to influence the classification choice of the plumage colour variants was utilized to build linear combinations of the original traits using biometric data from the LDA. However, none of the discriminant functions clearly differentiate the three plumage colours based on the biplot. This is comparable to the findings of Adeyemi & Oseni (2018), who found that lavender and black plumage colours overlapped in Nigerian local turkeys. Singularity, also known as small sample size or under-sampling, is one of the major flaws in the LDA methodology. This difficulty emerges as a result of high-dimensional trend classification issues or an insufficient number of training samples available for each class in comparison to the sample space's dimensionality (Lu *et al*., 2005; Su *et al*., 2017; Tharwat *et al*., 2017).

The more serious the violation of LDA assumptions, the worse the classification performance will be. The accuracy of the testing dataset was lower than that of the training dataset, probably due to the testing dataset's small sample size and non-linearity. If the classes are not linearly separable, LDA will not be able to find a lower-dimensional space. In other words, LDA fails to locate the LDA space when discriminatory information is not in the means of classes. In both LDA and SVM, the lower classification efficiency in the testing dataset compared to the training dataset suggests that the training model was inefficient in classification at the testing stage. To avoid over-fitting, SVM employs a regularization term, and it is free of local optimum and multicollinearity unlike LDA.

The results of this study revealed that the ANN model was more effective than the LDA and SVM models in predicting and classifying the plumage colours of Nigerian local turkeys. This could be related to the assumptions behind LDA. In discriminant analysis, we assumed that both the dependent and independent distributions are normal. However, some of the biometric traits employed in this investigation were not normally distributed. As a result, these characteristics had a significant impact on the LDA results. Furthermore, the implementation of LDA is linked to specific predictor assumptions, particularly multi-collinearity, which limits its applicability. Correlation between predictors should be avoided because it generates computational issues. These assumptions, on the other hand, are not as critical for ANN. The benefit of employing neural networks is that they can be fitted to any dataset and do not require the model assumptions that nonlinear approaches do (Seber and Wild, 2003). When estimating a noisy nonlinear model, the advantages of the ANN includes their flexibility and lack of a priori assumptions. One downside of neural network models is that they lack parameters that could be beneficial for comparison and development.

When accuracy in the training dataset is higher than the testing dataset in studies where SVM and ANN algorithms were employed to categorize small sample datasets, it implies that the model's training is not working well. For supervised learning methods of classification, a larger dataset increases the odds of lower error rates and higher learning ability for machine learning algorithms.

Previous studies that compared the models found that the ANN model is more efficient than the LDA model in expressing total classification accuracy. According to Abo Elfadl & Abdallah (2017), the ANN model exhibited greater classification accuracy (93.6 %) in the fertility status of Friesian cattle than the LDA model (79.9 %). The regions under Receiver Operating Characteristic Curves (ROC) obtained by ANN, SVM, and LDA further validated these findings. The basic purpose of ROC curves was to compare different discriminating rates. In comparison to the LDA model, the ANN model has the most areas under ROC curves, followed by SVM.

5 Conclusion

The results of the linear discriminant analysis (LDA), support vector machine (SVM) were similar, implying that a linear discrimination of the input is insufficient for classification and prediction of group membership for biometric traits data in Nigerian local turkeys. In terms of expressing total classification accuracy, accuracies of successfully classified cases for plumage colour variants, the ANN model outperforms the other two models. If the independent variables used for prediction and classification is not regularly distributed and there is multicollinearity among the variables, Neural Networks analysis may be effective.

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Conflict of interest

We declare that there is no conflict of interest with any financial, personal, or other relationships with other people or organisation related to the material discussed in this manuscript.

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