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Comparison of Artificial Neural Network and Binary Logistic Regression for Classification of Chiropteran Dietary Specializations

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Abstract Discrimination between dietary specializations of bats has been largely analyzed using multivariate techniques such as discriminant and principal component analysis. In this study, models based on an artificial neural network (Multi-layer feed forward neural network) and Binary Logistic Regression (BLR) were compared in their ability to differentiate between insectivorous and frugivorous bats using habitat and morphometric measurements on captured bats. Although both models had similar diagnostic performance based on the area under the ROC (99% vrs 99.09%), sensitivity (97.6% vrs 96.8%) and specificity (95.3% vrs 93.8%) values, the logistic model was superior to the neural network model. We therefore recommend that if prediction is the sole objective, then ANNs provide acceptable results whiles BLR could be used to identify factor effects on classification. Further studies on these models may consider incorporating other dietary habits as well as factor effects (predictors) which could improve the accuracy of predictions.

Keywords Artificial Neural Network, Binary Logistic Regression, Chiroptera, Frugivore, Insectivore

1. Introduction

Over millennia, organisms have evolved different trophic specializations in relation to morphological adaptations to changing ecological patterns. Chiropterans are armed with varied dietary apparatus which enable them to efficiently partition their resources hence, accounting for the success and abundance of this mammalian order. These trophic specializations include insectivory (feeding on insects), piscivory (feeding on fishes), carnivory (feeding on amphibians and small mammals), sanguivory (feeding on blood of mammals), frugivory (feeding on fruits), nectarivory (feeding on nectar, pollen and petals), folivory (feeding on leaves, buds and other green plant parts) and omnivory (reflects dietary overlap between phytophagy and animalivory) (Hill and Smith, 1984; Ferrarezzi and Gimenez, 1996; Simmons, 1998; Patterson *et al*., 2003; Giannini and Kalko, 2004, 2005).

As such, morphometry is an important aspect in animal/wildlife studies. Coupled with appropriate statistical methods (parametric and non-parametric) it has been widely used in wildlife research. Multivariate statistics such as Principal Component and Discriminant Analyses have largely been used to analyze ecological data (McGarigal *et al*., 2000) especially in bats, to efficiently discriminate between species as well as dietary specializations. For instance, Palmeirim *et al.* (1989) used Reciprocal Averaging (also known as Correspondence Analysis), a non-parametric analog to Principal Component Analysis (PCA) to study the trophic structure of frugivorous birds and bats. Van Cakenberghe *et al.* (2002) quantitatively examined the relationship between cranial shape and diet using PCA. Santana *et al.* (2010) also used discriminant analysis to separate groups of bats with different diets using the mechanics of bite force production.

However, such techniques to discriminate between dietary specializations using morphometry, require a lot of effort and in some instances dead bat specimens. Hence, there is the need for more efficient and animal friendly techniques to be adopted by researchers.

The use of Artificial Neural Network (ANN) as an alternative to other standard statistical methods is gaining more prominence. For instance, its application has been reported in ecological and environmental science (Colasanti, 1991; Lek *et al*., 1996; Bastarache *et al*., 1997; Mastrorillo *et al*., 1998; Gozlan *et al.,* 1999; Olden and Jackson, 2001; Scardi, 2001), as well as medicine and molecular biology ((Lerner *et al*., 1994; Albiol *et al*., 1995; Faraggi and Simon, 1995). This technique seeks to simulate the structure and functionalities of the biological central nervous system in information processing. There is evidence to suggest that

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ANNs outperform other statistical methods such as Logistic Regression (LR) (Lapuerta *et al.,* 1997; Li *et al.,* 2000; Nilson *et al.,* 2006). In contrast, others have reported that the differences in the results obtained by both ANN and LR models are negligible (Lang *et al.* 1997; Tafeit *et al.,* 1999; Ergun *et al.,* 2004). This study is therefore aimed at using simple yet commonly measured bat body parameters as well as habitat variables to compare the discriminatory ability of both Binary Logistic Regression (BLR) and Artificial Neural Networks in classifying bat dietary specializations.

2. Methodology

2.1. Study Area

The study was conducted at Kosane in the Dormaa West district of the Brong Ahafo Region, Ghana. The district was carved out of Dormaa which lies within longitude 3°–3°30' W and latitude 7°–7°30' N. The types of vegetation that characterize the area are unused forest, broken forest, grassland and extensively cultivable forestland and forest reserves. It has a bimodal rainfall pattern with a dry spell that spans from November to February. Mean annual rainfall values in the area are between 1,250mm and 1,750mm with an average temperature high of 30°C and a low of 26.1°C (Dormaa Municipal Assembly, 2006).

2.2. Capture of Bats

Bats were captured with the aid of 12 x 2.5m mist nets set at ground level at identified fly ways in three of each randomly selected agro-ecosystem type (Citrus farms, Mixed farms, Fallow lands, Teak plantations, Oil palm plantations, Maize farms) following a reconnaissance survey. The elevation and distance of each agro-ecosystem to roosts of bats was measured and recorded. Mist nets were monitored periodically from 18:30 hours each day until they were closed at 02:00 hours the following day. Each captured bat was marked to avoid double sampling and then released at the same site of capture. During this period, species identification and morphometric (body mass and forearm length) measurements of the chiropterans was carried out. Species were later classified into two foraging guilds based on diet (Hill and Smith, 1984; Giannini and Kalko, 2004). Fruit-eating bats were classified as frugivores whiles insect-eating bats were classified as insectivores. Out of the total of 253 captured bats, 128 had a frugivorous diet whiles the remaining 125 were insectivorous. Sexing of individuals was based on the presence of male external genitalia (Racey, 1988). Captured bats were also classified into three age groups namely; juveniles, sub-adults and Adults (Nelson, 1965; Vardon and Tidemann, 1998; Holmes, 2002).

2.3. Artificial Neural Network

ANNs are modelling techniques that are widely used to solve problems of prediction or to uncover patterns in data. Though there are many different types of ANNs in use today, the multi-layer Feed Forward Neural Network (FFNN) was employed in this research. This ANNs architecture consists of an input layer, a hidden layer and an output layer. After passing the sample through the network, the output value is calculated using the equation;

$$y_k = f\left[\sum_j w_i f\left(\sum_j \left(w_i x_i\right) + b_j\right) + b_k\right] \quad (1)$$

where;

$f(.)$ is the activation function

y_k is the kth output value

x_i is the ith input variable or feature

w is the weighting value used in the hidden and output layers and

b's are the network biases

The logistic (sigmoid) function, which is the most common and widely used activation function, was employed in this study. The equation for this function is given by;

$$f\left(x\right) = \frac{1}{\left[1 + \exp^{(-x)}\right]} \quad (2)$$

A single (one) hidden layer architecture was used because past studies have found it to be sufficient in most situations (Wong *et al.,* 1995; Fowler and Clarke, 1996). This is because it permits the approximation of any continuous function, provided an adequate number of nodes are found (Haykin, 1999). Determining the number of nodes to be placed in a single hidden layer is a difficult process. Though there are several 'rules of thumb', systematically experimenting with the number of hidden nodes in a network, as done in this study, provides the best fit without a priori assumptions (Marzban and Stumpf, 1996).

2.3.1. Back Propagation Algorithm

When using the sigmoid (logistic) function, the slope approaches zero as the input gets larger causing changes in the weights and biases. Hence, the network was trained using the resilient back propagation algorithm on the training data set to eliminate the effects of the magnitudes of the partial derivatives. Weights were first adjusted to meet the minimum of the MSE criterion function after feed forwarding the training set. The equation used for the weights adjustment is given by;

$$J\left(w\right) = \frac{1}{2}\left\|\hat{y} - y\right\|^2 \quad (3)$$

where $\hat{y}$ and y are the vectors of target (predicted) and output (observed) values respectively. To minimize the criterion, the weight adjustment value was calculated by;

$$\Delta w = -\eta \frac{\partial J}{\partial w} \quad (4)$$

where η is the user-input learning rate which regulates the magnitude of changes in weights and biases during optimization. The error from the output layer is then back-propagated to the other layers starting from the end and working backwards to the input layer. The training ends when the network error (MSE) is below a set level or when the maximum number of epochs is reached iteratively.

2.3.2. Generalized Weights

The effect of each covariate x_i for the neural network model can be expressed as generalized weights (Intrator and Intrator, 2001). These generalized weights however depend on all other covariates in the model. The interpretation of generalized weights for neural network models is analogous to logistic regression and can be defined as the individual covariate's contribution to the log-odds. The generalized weights for each covariate were computed using the relationship;

$$\tilde{w}_i = \frac{\partial}{\partial x_i} \log\left[\frac{\pi(x)}{1-\pi(x)}\right] \tag{5}$$

The distribution of these generalized weights for a given data set will suggest if an input variable has a strong effect on the output of the neural network model or not. A linear effect is implied when the variance is small and vice versa for a non-linear effect.

2.3.3. Independent Variable Contribution

A number of methods have been proposed to determine the impact of input variables (Garson, 1991; Dimopoulos *et al.,* 1995; Goh, 1995; Lek *et al.,* 1996). This study employed Garson's (1991) algorithm modified by Goh (1995) to determine the relative importance of explanatory variables on chiropteran dietary habits. Since this algorithm uses absolute weight values in its computation, it is difficult to interpret the direction of the relationship between input and output variables. The relative importance of each input variable is therefore defined as

$$c_{ij} = w_{ij} \times w_{jk} \tag{6}$$

$$r_{ij} = \frac{|c_{ij}|}{\sum_{i=1}^{n} |c_{ij}|} \tag{7}$$

$$S_i = \sum_{j=1}^{v} r_{ij} \tag{8}$$

$$RI_i = \left[\frac{S_i}{\sum_{i=1}^{n} S_i}\right] \times 100 \tag{9}$$

where;

c_{ij} is the contribution of each input neuron to the output through each hidden neuron

r_{ij} is the relative contribution of each input neuron

S_i is the sum of input neuron contributions

RI_i is the relative importance of each input variable

i, j, k respectively represent the input, hidden and output layer of the network

v is the total number of nodes in the hidden layer of the network

n is the total number of input variables in the neural network

2.4. Binary Logistic Regression (BLR)

This research employed BLR to model the dichotomous dependent variable of dietary specialization (insectivore or frugivore) with independent variables (Sex, Age, Agro-ecosystem, Moon phase, roost Distance, Elevation, Forearm length, and Body mass).The logistic regression model for a dichotomous response is given by;

$$P(Y = 1/X = x) = \pi(x) = \frac{e^{(\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\cdots+\beta_k X_{ik})}}{1+e^{(\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\cdots+\beta_k X_{ik})}} \tag{10}$$

Equation (10) has a linear relationship for the log odds (logit) as;

$$\operatorname{logit}[\pi(x)] = \log\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_0 + \sum \beta_i X_i \tag{11}$$

where β_0 is the intercept and β_i are the regression coefficients of the variable X_i. The computed value $\pi(x)$ is a probability in the range 0 to 1. Thus, a cut-off point (usually 0.5) is set to predict group membership for subjects whose $\pi(x)$ values fall below or above it.

2.4.1. Hosmer Lemeshow Test

An overall goodness-of-fit test is required once a logistic regression model has been fit to a given set of data. Although several goodness-of-fit tests have been proposed (example: Cox, 1958; Tsiatis, 1980; Brown, 1982; Azzalini *et al*., 1989; le Cessie and van Houwelingen, 1991; Su and Wei, 1991), the Hosmer-Lemshow (1980) test was used in this study. This goodness-of-fit test groups subjects into deciles based on the values of the estimated probabilities such that y_{ij} is the binary outcome for observation $j(j=1,\cdots,n_i)$ in group $i(i=1, \cdots,g)$. It then compares the number actually in each group (observed) to the number predicted by the logistic regression model (expected). If $\hat{\pi}_{ij}$ is the probability for the fitted model, then the statistic is given by;

$$G_{HL} = \sum_{i=1}^{g} \frac{\left(\sum_j y_{ij} - \sum_j \hat{\pi}_{ij}\right)^2}{\left(\sum_j \hat{\pi}_{ij}\right)\left[1 - \frac{\left(\sum_j \hat{\pi}_{ij}\right)}{n_i}\right]} \tag{12}$$

This test statistic has an approximate chi-square distribution. If the associated p-value of the test is greater than the 0.05 significance level, then the fitted model is adequate at the 5% significance level.

3. Results

3.1. Classification of Dietary Habits Using FFNN

Figure 1 is a diagram of the trained neural network on the dietary habits of chiropterans evaluated using 75% of the dataset. The remaining 25% was used to validate the model.

Based on the selection criteria, a neural network of five hidden neurons with a single layer was suitable for modeling the dietary habits of chiropterans (Accuracy=0.967, AIC=202.5957, BIC=387.6761). However, an examination of the generalized weight plots for each covariate in the model showed that Sex and Agro-ecosystem type had no influence on the dietary habits of chiropterans (Figure 2). Thus, all their generalized weight values were close to zero.

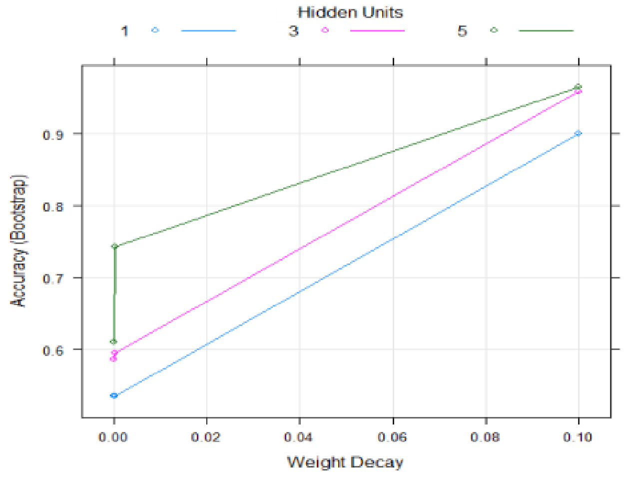

Figure 1. Trained neural network of chiropteran dietary habits

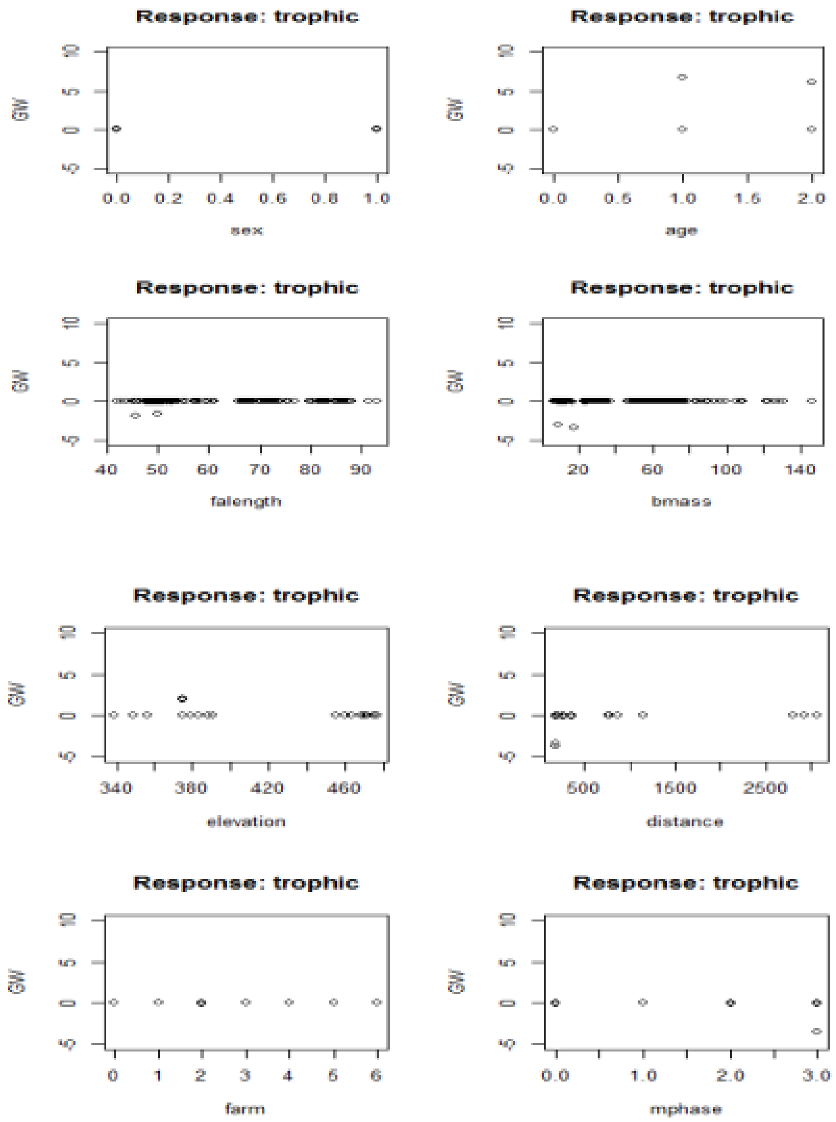

Figure 2. Generalized weight plots for dietary covariates

The remaining predictor variables (Age, Forearm length, Body mass, Elevation, roost Distance from foraging sites and to an extent Moon phase) had a non-linear effect on the response variable since some of their generalized weights were greater than one. Exploring the 'significant' predictor variables, two reduced neural network models were fitted and compared. The first model contained all the 'significant' predictor variables whiles the second model excluded additional moon phase. The results revealed that the second model (AIC=99.9388, BIC=236.3138) outperformed the former (AIC=165.8037, BIC=318.4139) which had all six predictor variables incorporated in the model. The network topology of the selected model is presented in Figure 3. The range for the estimated weights of the neural network model is –9.382 to 27.199.

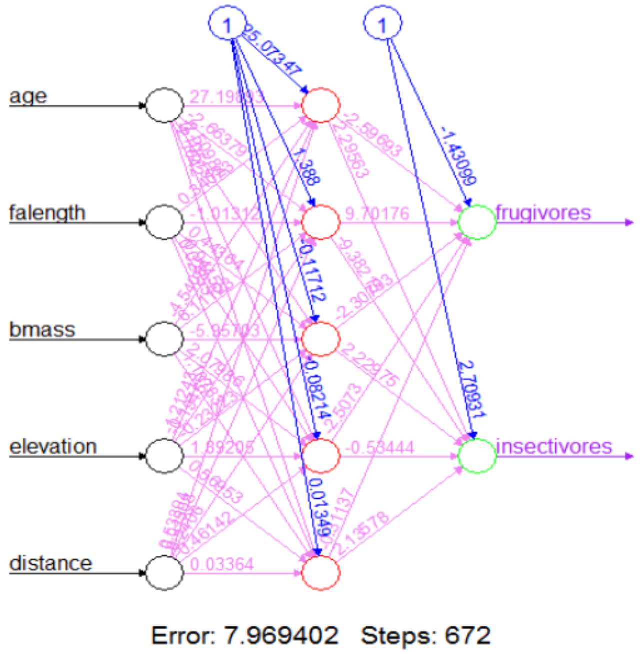

Figure 3. Network topology of final neural network model

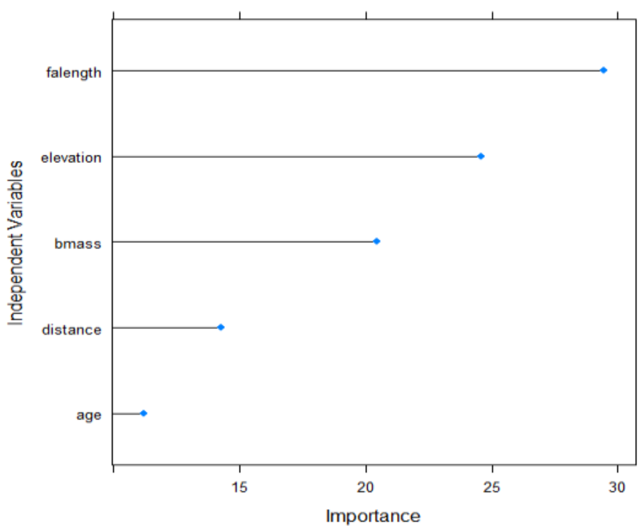

Figure 4. Contribution of each of the five independent variables to the classification of bat dietary habits – obtained by Garson's algorithm

The relative importance of the input variables for the final neural network model is illustrated in Figure 4. The results indicate that forearm length and elevation of foraging sites have the greatest influence on how the neural network classifies the dietary habits of chiropterans. Thus, forearm length contributed the highest importance of 29.4% to the classification of dietary habits followed by elevation with a contribution of 24.6%. Also, the contribution of body mass was 20.5% while distances of foraging sites from roosts had a contribution of 14.3% on the predictive nature of the model. The variable with the least contribution was age which measured an importance contribution value of 11.2%.

3.2. Classification of Dietary Habits Using BLR

A binary logistic regression was used to model the probability of a chiropteran being insectivorous or frugivorous. An a priori model for the analysis included the following independent variables; type of Agro-ecosystem, Sex, Age, Moon phase, Forearm length, Body mass, Elevation and roost Distance from foraging sites. The final model with the variables Body mass, Forearm length, Age, Elevation and roost Distance were jointly found to be statistically significant in determining the dietary habits of chiropterans (Table 1).

Table 1. Parameter Estimates of Reduced BLR Model

Parameter	Estimate	Std. Error	Wald Chi-square	*P*–value	Odds ratio
Intercept	27.02040	6.03050	20.07610	<0.0001	NA
Juvenile	-1.54370	0.70660	4.77260	0.0289	0.048
Sub-adult	0.05090	0.87410	0.00340	0.9536	0.236
Forearm L.	-0.25590	0.09420	7.38470	0.0066	0.774
Body mass	-0.31000	0.05600	30.69900	<0.0001	0.733
Elevation	-0.02250	0.00855	6.19700	0.0085	0.978
Distance	0.00327	0.00076	18.54230	<0.0001	1.003

Apart from sub-adults and roost distance from foraging sites, all other parameters exhibited a negative relationship with the dietary habits of chiropterans. Thus, with decreasing forearm length and body mass, a chiropteran is more likely to be insectivorous. Also, with decreasing elevation and increasing distance of forage sites from roosts, a chiropteran is more likely to be classified as insectivorous.

There was no evidence of lack of fit for the selected model following a diagnostic test using the Hosmer and Lemeshow test, which gave a test statistic of 25.6907 with a *P*-value of 0.07. Thus, the binary logistic regression model was adequate.

3.2. Comparative Analysis of Statistical Methods

In order to select the most adequate model for the classification of chiropteran dietary habits, the diagnostic performance of BLR and FFNN were compared. The results indicate that both the BLR and FFNN have nearly similar diagnostic performance though most of the tests favored BLR (Table 2).

Table 2. Diagnostic Performance of Predictive Models

Method	AIC	Sensitivity	Specificity	AUC
BLR	78.476	97.600	95.300	0.9900
FFNN	99.938	96.800	93.800	0.9909

For instance, the sensitivity test which is a measure of accuracy indicated that 97.6% of the events of interest were correctly classified by the BLR model. On the other hand, the FFNN correctly classified 96.8% of the events of interest (insectivores) which was a bit lower than the BLR model. Also, the specificity test revealed that 95.3% and 93.8% of frugivores were correctly classified by the BLR and FFNN models respectively. The ability of the two models to discriminate between the two dietary habits was 99% for BLR and 99.09% for FFNN. Considering their AICs however, BLR was much preferred to FFNN since this selection criterion ensured, as well as favored, simplicity and parsimony among these competing models.

4. Discussion

The negligible difference in discriminatory power (based on area under ROC curve, sensitivity and specificity) between the two developed models were similar and consistent with other findings (Lang *et al.,* 1997; Ergun *et al.,* 2004). Both the BLR and ANN models indicated that Forearm length, Elevation, Body mass, roost Distance from foraging sites, and Age significantly influenced dietary classification of bats. These factors which were confirmed in studies elsewhere (Fleming, 1991, 1993; Hughes *et al.,* 1995; Adams, 1996, 1997) have been arranged in order of magnitude based on each independent variable's contribution for the ANN. One important advantage of BLR over ANN is its ability to identify factor effects and their directions on the response variable (interpretability of model parameters). This has often led to the ANNs description as a "black box" in ecological modeling due to its lack of explanatory power (Paruelo and Tomasel, 1997; Özesmi and Özesmi, 1999). Another disadvantage of ANNs is their inability to handle missing data. They however compensate for this by being able to simultaneously handle numerous variables (Bishop, 1995; Zou *et al.,* 2008). As such, other predictive variables could be examined and used to improve the predictive accuracy of the model. Again, the problem of dimensionality is managed well in ANNs than other statistical methods, even with small sample sizes. The dynamic approach employed to analyze dietary specializations enables ANNs to modify their internal structure in relation to a functional objective by using the data to generate the model via learning without supervision. Therefore in complex biological or ecological systems, the predictive range of BLR is extended in ANN by replacing identity functions (linear combinations) with nonlinear activation functions. Hence, ANNs become powerful techniques when underlying relationships are unknown. Thus, they are able to explore hidden layers to find nonlinearities, interactions, and nonlinear interactions among independent variables.

5. Conclusions

The study revealed that both models (FFNN and BLR) had similar diagnostic performances. Also, the two models clearly indicated that Forearm length, Elevation, Body mass, roost Distance from foraging sites, and Age had significant effect on the dietary classification of chiropterans. We therefore conclude that if prediction is the sole objective, then ANNs provide acceptable results whiles BLR could be used to identify factor effects on classification. Also, ANNs could be used to achieve globally more accurate predictions when further studies incorporating other dietary habits (dependent variables) as well as predictors (independent variables), are to be conducted.

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