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ANIMAL PRODUCTION

Use of artificial neural network to model reproductive performance and mortality of non-descript rabbits

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ABSTRACT. This study was carried out to predict average number of kits per birth and mortality number of non-descript rabbits in Plateau State, Nigeria using artificial neural network (ANN). Data were obtained from a total of 100 rabbit farmers. The predicted mean value for number of kits per birth using ANN (6.60) was similar to the observed value (6.52). As regards mortality, the predicted mean value using ANN (17.75) was also similar to the observed value (17.80). Primary occupation, experience in rabbit keeping, flock size and credit type were the parameters of utmost importance in predicting number of kits per birth. The fairly high coefficient of determination (R^2) (55.7%) and low root mean square error (RMSE) value of 1.22 conferred reliability on the ANN model. The R^2 value obtained in the prediction of mortality using ANN implies that 61.1% of the variation in the number of mortality can be largely explained by the explanatory variables such as flock size, age of farmers, experience in rabbit keeping and average number of kits per birth. The low RMSE value of 3.82 also gave credence to the regression model. The present information may be exploited in taking appropriate management decisions to boost production.

Keywords: connectionist; reproduction; lagomorphs; tropics.

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Introduction

The need for rabbits (*Oryctolagus cuniculus*) and attention given to rabbit production in the agricultural sector in Nigeria is growing high with respect to the increase in demand for animal protein (Amaefule, Iheukwumere, & Nwaokoro, 2005; Yakubu & Adua, 2010; Oseni, & Lukefahr, 2014) and as experimental animals (Ansa, Akpere, & Imasuen, 2017; Oloruntoba, Ayodele, Adeyeye, & Agbede, 2018).). Rabbit production is one of the livestock enterprises with the greatest potential and room for expansion (Lukefahr & Cheeke, 1990; Silva et al., 2009; Földešiová, Baláži, Chrastinová, & Chrenek; Rioja-Lang et al., 2019). In Nigeria, however, the sub-sector is beset with a myriad of problems including poor reproductive function and high mortality rates. According to Fadare and Fatoba (2018), there existed high negative (-0.722) correlation between mortality rate and litter size, indicating that the higher the mortality rate the fewer the litter size of rabbits. There is need therefore, to identify associated factors so as to devise appropriate means to improve on rabbit productivity and profitability. In this context, the use of appropriate modelling techniques will facilitate understanding of such underlying factors.

Artificial neural network (ANN) is a modelling tool which mimics the human brain; and improves the accuracy of prediction by capturing higher-order interactions between covariates (Hamache, Benkortbi, Hanini, & Amrane, 2017). It has been used to predict body weight (Salawu et al., 2014) and develop a pharmacokinetic model (Lin et al., 2015) in rabbits; and in other mammals to estimate growth (Yakubu & Madaki, 2017) and reproduction (Zaborski et al., 2019), predict disease occurrence (Zanella-Calzada et al., 2018), analyse behavior and forecast heat stress (Yakubu, Oluremi, & Ekpo, 2018).

There is dearth of information on the use of robust algorithms to forecast reproductive performance and mortality rate in rabbits in Nigeria. This study, therefore, aimed at comparing the performance of non-descript rabbits reared in two agro-ecological zones of Plateau State, north central Nigeria. It equally predicted mortality and average number of kits per birth in non-descript rabbits using artificial neural network.

Material and methods

The study was conducted in Plateau State, north central Nigeria. Plateau State is located between latitude 80° 24'North and longitude 80° 32' and 100° 38 east. The altitude ranges from 1,200 meters (400 feet) to a peak of 1,829 meters above sea level in the Shere hills range near Jos (http://www.plateaustate.gov.ng/page/at-a-glance). The two distinct agro-ecological zones; a humid sub-temperate region in the North and a sub-humid hotter region that is part of the Northern Guinea Savanna ecological zone of Nigeria in the South of Plateau State were covered.

Pre-survey information was sought from the local government livestock officers on the possible areas of rabbit production. A total of 100 rabbit keepers (50 per zone) were sampled randomly in selected villages.

Information was sought from the respondents using questionnaires and one-on-one interview. Information obtained included the socio-economic characteristics of the respondents, livestock ownership, system of production, flock sizes and structure, productive and reproductive performance indices, mortality rate, health and other routine management practices. The International Ethical Guidelines for Biomedical Research (CIOMS, 2002) involving Human Subjects and the Global code of conduct for research in resource-poor settings were strictly adhered to.

T-test was used to examine the effect of zone on average number of kits per birth and mortality number and significant means tested at 95% confidence interval. The relationship between the dependent variables (average number of kits per birth and mortality number; each handled singly) and the independent variables was also established using Artificial Neural Network (ANN). Age of farmers, marital status, educational background, primary occupation, experience in rabbit keeping, source of foundation stock, management system, health management practices, breeding control, land ownership, land size, personal savings, access to credit and credit access type, nest box provision, flock size, birth interval, use of herbs and season were the input explanatory variables fitted into the ANN model to predict average number of kits per birth and mortality number. Here, Multilayer Perception (MLP) with Back-Propagation network was used (Ahmad, 2009). The network was trained with 80% of the data set while the testing for model validation was executed with 20% of the data set after training. The MLP-Predicted value for the response variable was saved. The hyperbolic tangent function and the linear activation function were employed for the hidden and output layers in ANN as described by Celik, Eyduran, Karadas, and Tariq (2017) as follows:

Hyperbolic tangent:

$$f\ (x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

Linear:

$$f(x) = x,$$

in which *x* represents the weighted sum of inputs to the neuron and *f*(*x*) denotes the outputs obtained from the neuron.

The efficiency of the models was determined using coefficient of determination (R^2), adjusted R^2 and root mean square error (RMSE) as earlier described in Yakubu, and Madaki (2017). SPSS (2015) was employed in all analyses.

Results

Flock size was significantly ($p < 0.05$) higher in the Northern compared to the Southern part of Plateau State. Other variables such as doe age at first birth, birth interval, average number of kits per birth and total mortality were statistically not significant ($p > 0.05$) (Table 1).

The independent variables importance and their ranking in the estimation of average number of kits per birth using artificial neural network are shown in Table 2 and Figure 1. Primary occupation, experience in rabbit keeping, flock size and credit type were the variables of utmost importance in predicting litter size.

The R^2 value obtained in the prediction of average number of kits using ANN implies that 55.7% of the variation in average number of kits can be explained by the explanatory variables especially primary occupation, experience in rabbit keeping, flock size and credit type (Figure 2). The adjusted R^2 (55.2%) and low RMSE value of 1.22 conferred reliability on the regression model.

Table 1. Descriptive statistics of the performance of rabbits.

Parameters	Zone	Mean	Standard Error
Flock size	Southern	19.78^{b}	1.74
	Northern	44.78^{a}	4.35
Doe age at first birth	Southern	6.82^{ns}	0.18
	Northern	6.42	0.17
Birth interval	Southern	52.80^{ns}	1.49
	Northern	48.78	1.69
Average number of kits per birth	Southern	6.52^{ns}	0.31
	Northern	6.52	0.20
Total mortality	Southern	16.98^{ns}	0.69
	Northern	18.62	1.00

^{ab}Means along column with different superscripts are significantly different ($p < 0.05$). ^{ns} = not significant

Table 2. Independent variables importance in the prediction of average number of kits per birth using artificial neural network.

Parameters	Importance	Normalized Importance (%)
Sex	0.013	6.9
Marital status	0.007	4.0
Education status	0.009	4.8
Primary occupation	0.187	100.0
Access to credit	0.033	17.7
Type of credit	0.184	98.2
Personal savings	0.002	0.9
Foundation stock source	0.023	12.3
Management system	0.007	3.5
Breeding control	0.010	5.5
Nest boxes provision	0.015	7.9
Access to veterinary	0.000076	0.0
Veterinary category	0.064	33.9
Season of highest number of kits' birth	0.001	0.7
Use of Herbs	0.019	10.3
Age	0.012	6.4
Land size	0.039	20.8
Flock size	0.186	99.4
Experience in rabbits	0.186	99.5
Birth interval	0.002	0.9

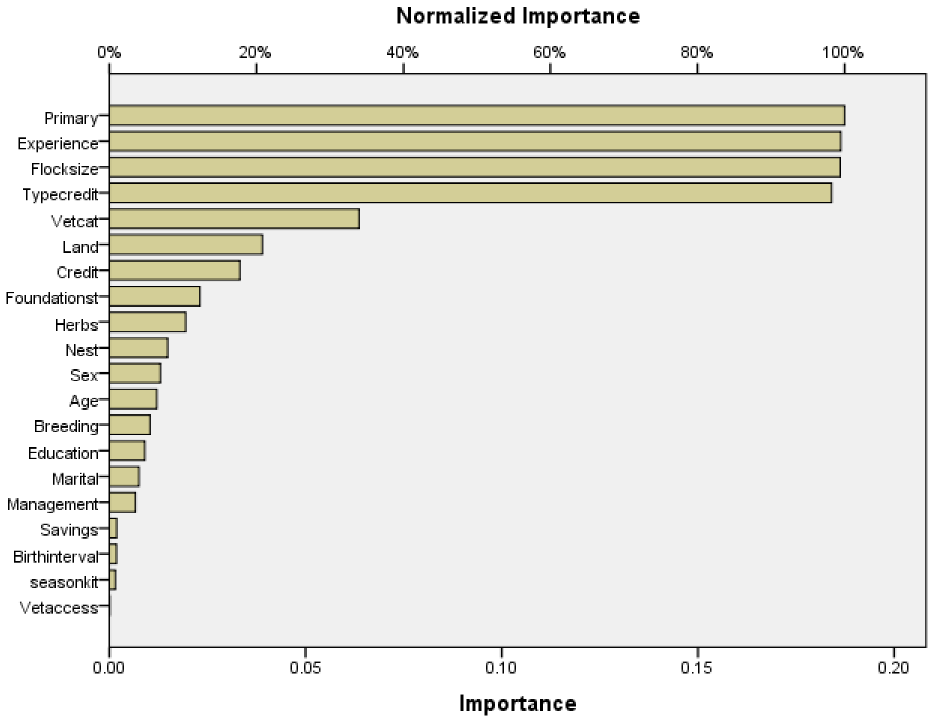

Figure 1. A graphical representation of variables importance in the prediction of average number of kits per birth using artificial neural network.

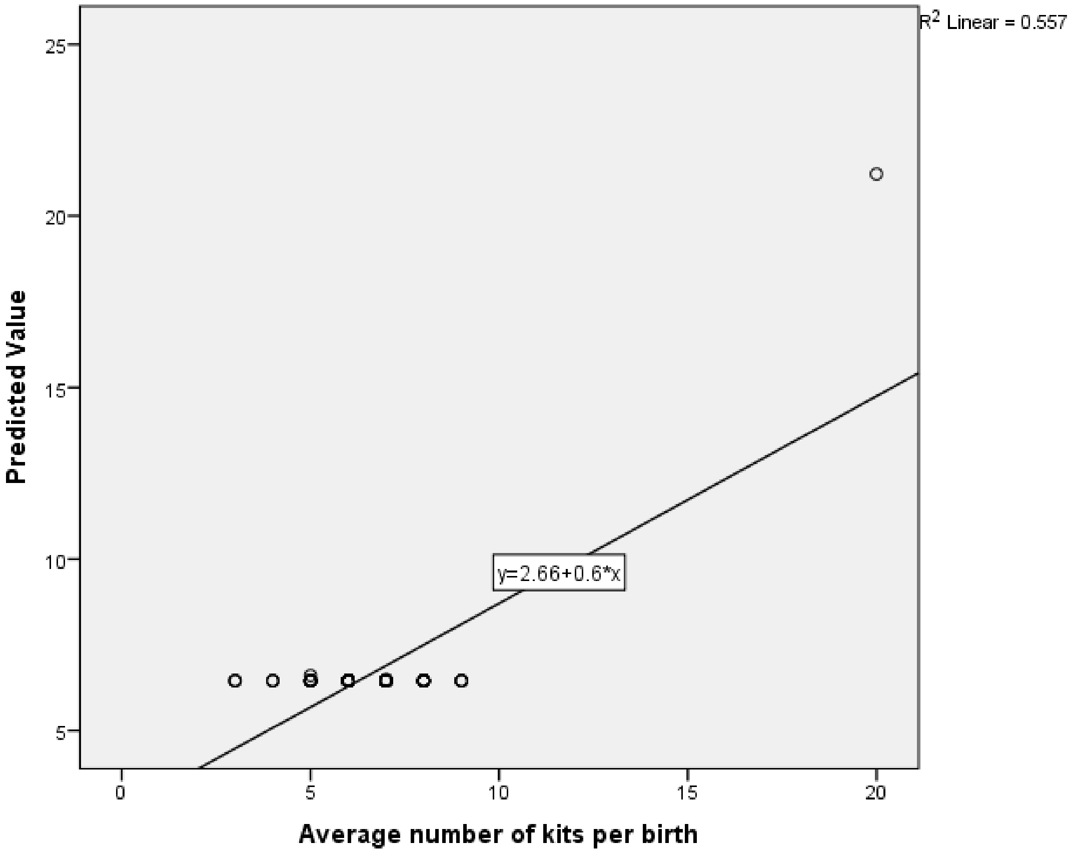

Figure 2. Scatter plot of the prediction of average number of kits per birth using artificial neural network. y = 2.66 + 0.6*x, where y = predicted average number of kits per birth, *x* = observed average number of kits per birth.

The independent variables importance and their ranking in the estimation of average number of mortality using artificial neural network are shown in Table 3 and Figure 3. Flock size, age of farmers, experience in rabbit keeping and average number of kits per birth were more important in predicting the number of mortality.

Table 3. Independent variables importance in the prediction of mortality using artificial neural network.

Parameters	Importance	Normalized Importance (%)
Sex	0.046	21.3
Marital status	0.025	11.6
Education status	0.030	13.9
Primary occupation	0.053	24.9
Access to Credit	0.031	14.2
Type of credit	0.043	19.9
Personal Savings	0.020	9.3
Foundation stock source	0.070	32.5
Management system	0.021	9.6
Breeding Control	0.020	9.2
Nest boxes provision	0.011	5.0
Access to Veterinary	0.013	6.1
Veterinary category	0.047	21.7
Season of highest number of kits' birth	0.015	6.9
Use of Herbs	0.007	3.1
Average number of kits per birth	0.083	38.9
Season of highest number of mortality	0.013	6.1
Age	0.108	50.5
Land size	0.022	10.1
Flock size	0.215	100.0
Experience in rabbits	0.096	44.9
Birth interval	0.014	6.5

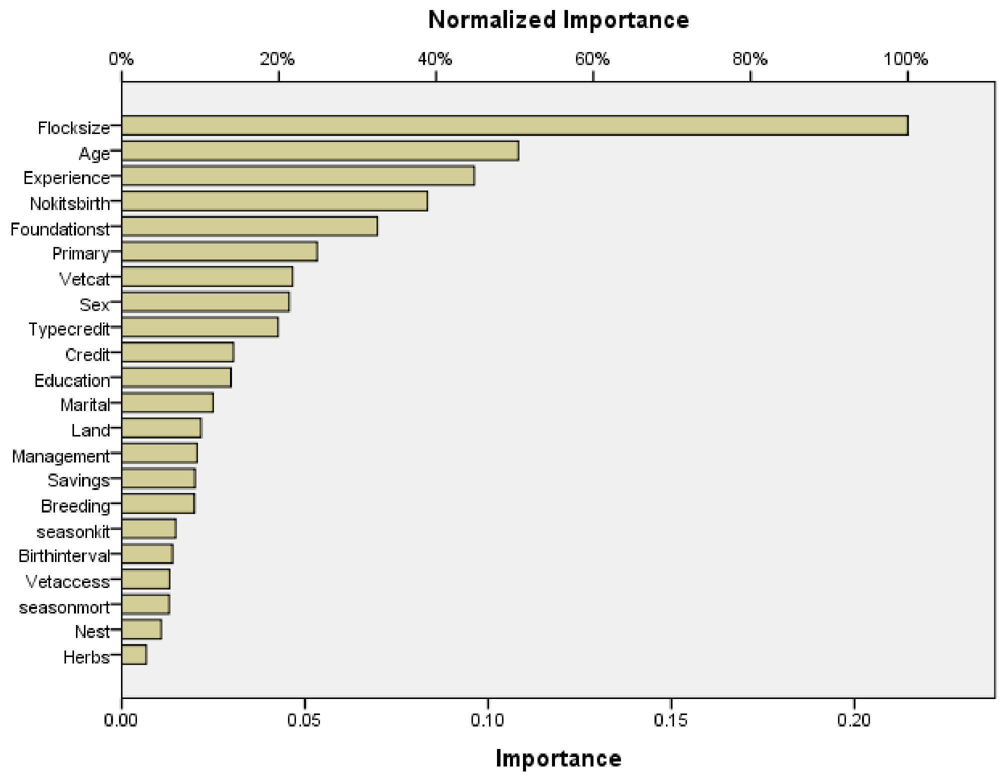

Figure 3. A graphical representation of variables importance in the prediction of mortality using artificial neural network.

The R^2 value obtained in the prediction of mortality using ANN implies that 61.1% of the variation in the number of mortality can be largely explained by the explanatory variables such as flock size, age of farmers, experience in rabbit keeping and average number of kits per birth. The adjusted R^2 (60.7%) and low RMSE value of 3.82 conferred reliability on the regression model (Figure 4).

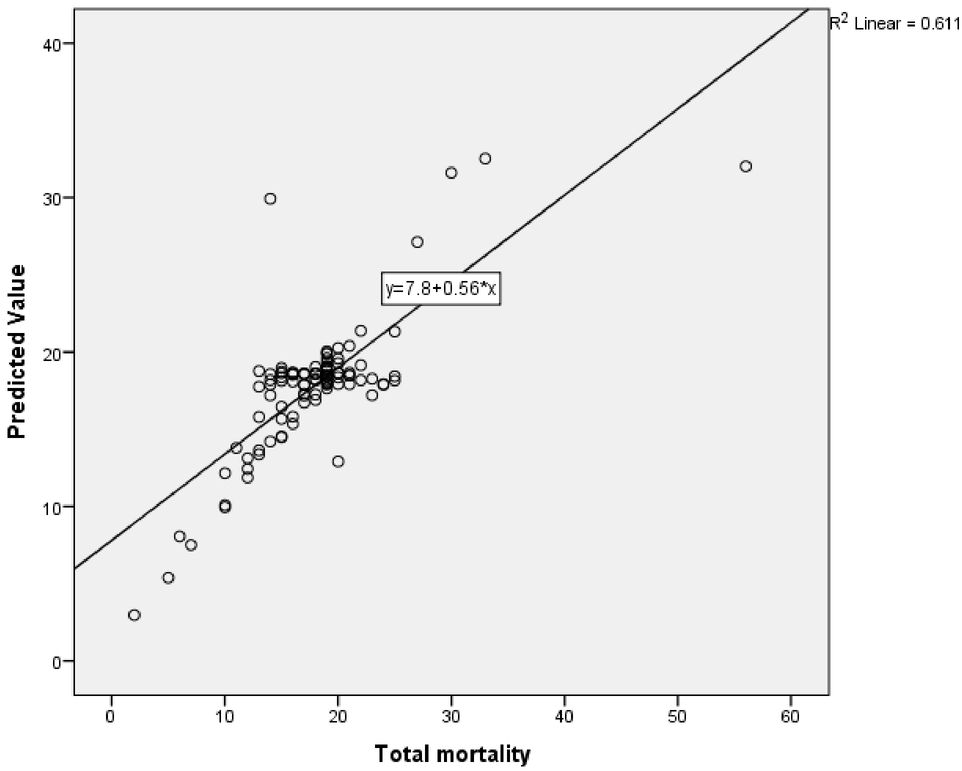

Figure 4. Scatter plot of the prediction of mortality using artificial neural network. $y = 7.8 + 0.56^{*}x$, where y = predicted mortality, x = observed mortality.

The summary statistics of observed and predicted average number of kits per birth and mortality rate of rabbits are shown in Table 4. The predicted mean value for number of kits per birth using ANN (6.60) was similar to the observed value (6.52). The Standard deviations were 1.48 (ANN) and 1.82 (observed), respectively. With regard to mortality, the predicted mean value using ANN (17.75) was also similar to the observed value of 17.80. Their respective standard deviations were 4.36 and 6.10.

Table 4. Descriptive statistics of the observed and predicted average number of kits per birth and mortality rate.

Parameter	Mean	Standard deviation	Minimum	Maximum
Average number of kits per birth				
Observed	6.52	1.82	3.00	20.00
ANN Predicted	6.60	1.48	6.45	21.22
Mortality				
Observed	17.80	6.10	2.00	56.00
ANN Predicted	17.75	4.36	2.96	32.53

Discussion

Rabbit production in recent years has played a very important role in the supplementation of the inadequate supply of protein for human development. The rabbits used in the present study could not be assigned into any particular breed or breeds because they originated from different crosses. The higher flock size observed among farmers in the northern part of Plateau State could be attributed to better environmental conditions. The relatively cool nature of Plateau north could have created conducive atmosphere for rabbit rearing compared to the hotter southern part of the State. However, it is possible that other factors (management inclusive) could have influenced the flock size. Agea, García, Blasco, and Argente (2019) reported that rabbits required protective environment to survive; which is a determinant factor in spatio-temporal variability in survival (Tablado, Revilla, & Palomares, 2012). In a related study, Savietto, Martínez-Paredes, and Pascual (2019), reported that the reproductive performance of rabbits was affected by the environmental conditions the animals were subjected to. The mean flock size obtained in this study for rabbits in Plateau north is higher than the 28 rabbits per flock reported by Adedeji, Osowe, and Folayan (2015). The average number of kits per litter recorded in the current study (6.52) is comparable to that reported for New Zealand White (6.50), but higher to values recorded for Fauve de Bourgogne (5.17), Chinchilla (5.43) and British Spot (5.89) breeds of rabbits (Jimoh & Ewuola, 2017). However, Ajayi, Ologbose, and Esenowo (2018) reported a range of 4-9 kits litter^{-1}.

In the livestock sector, machine learning algorithms have the potential for early detection and warning of problems, which represents a significant milestone in the livestock industry. Production problems such as poor reproduction and high mortality (Hungu et al., 2013; Rosell & Fuente, 2016; Espinosa et al., 2020) generate economic loss that could be avoided by acting in a timely manner. In the current study, training and testing of support vector machines are addressed, for an early detection factors related to reproductive capacity and mortality. The ANN algorithm, however, predicted mortality better than the average kits per birth. Such information could enable farmers to take into consideration the determinant factors that greatly influence both dependent variables. Creating an enabling environment on the basis of such independent variables therefore may increase average kits per birth and reduce mortality to the lowest ebb. Experience in rabbit keeping as an important indicator of mortality in rabbits has been stressed. It is believed that increased knowledge by rabbit owners may assist in early identification and management of diseases to avoid mortality (Welch, Coe, Niel, & McCobb, 2017; O'Neill, Craven, Brodbelt, Church, & Hedley, 2019). For the modelling of biological parameters, neural networks have been recommended as alternative to traditional regression analysis as they produce little or no overestimation of the observed dependent variables (in this wise, average kits per birth and mortality) (Ahmad, 2009; Archontoulis & Miguez, 2015; Yakubu & Madaki, 2017). In a related study, Lin et al. (2015) reported the use of ANN in pharmacokinetic experiment in rabbits for convenience and improved predictions. ANN has been used to define kinetic subpopulations spermatozoa in the domestic cat (Contri et al., 2012).

Conclusion

Flock size was higher among rabbit farmers in the northern than the southern part of Plateau State, Nigeria. Primary occupation, experience in rabbit keeping, flock size and credit type were the four important parameters in the prediction of number of kits per birth using ANN. Flock size, age of farmers, experience in rabbit keeping and average number of kits per birth were the predominant variables for mortality prediction. Considering the moderate to high variation explained by ANN model in the prediction of number of kits per birth and mortality rate, it could be used in the prediction of reproductive and mortality rate in non-descript rabbits.

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