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Feasibility of Wildlife Conservation Based on Artificial Neural Network

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Abstract: Biological species resources are the basis of human survival and the inexhaustible power of social and economic development, and are strategic resources for the sustainable development of the national economy. In order to solve the shortcomings of the existing research on wildlife nature conservation, based on the discussion of wildlife species resources, wildlife species resource values and artificial neural network models, this paper investigates and discusses the location, geological conditions, biomass data collection and artificial neural network parameter design of the study area. The wild biomass estimation model and threat prediction model based on artificial neural network are established. The experimental data show that the mean square error (MES) and nonlinear fitting rate (RNL) of the algorithm in biomass assessment and threat prediction of 20 sample sizes are 0.857 and 0.985 respectively. The algorithm has good performance.

1. Introduction

Under the background of industrialization and rapid urbanization, the intensity of land development and the interference of human beings to the ecosystem are increasing, the pressure on the living environment of organisms is increasing, coupled with indiscriminate hunting and deforestation, the biodiversity of the earth is facing the most serious challenge ever, and the risk of biodiversity loss is increasing year by year across the globe.

Nowadays, more and more scholars have done a lot of research in wildlife nature conservation through various technologies and system tools, and have also made certain research achievements through practical research. Garriga identified 535 independent wildlife images, including 10 families, 4 orders, 17 species of mammals and 4 families, 2 orders, 10 species of birds. Among them, 5 species are classified as Category I of national protected wild animals and 8 species are classified as Category II. The Hodgson otter and the wooden turtle are new species in the nature reserve, while the black spotted mouse is the first species discovered after the Wenchuan earthquake. Among mammals, the number of independent images of young lemurs, yellow tailed horses and grey bellied small foxes accounted for 50.2%, and among birds, the number of independent images of sand tailed small foxes and yellow tailed small Tragopan temminckii accounted for 91.6%. It provides important baseline information for the management and protection of wildlife in Baishuihe National Nature Reserve [1]. Eid considers a predator-prey system provided by an additional food under the inhibition of the predator. In the control parameter space, the model uses the control parameters, the quality and quantity of additional food to analyze. The results show that the biological system can be controlled and guided to an ideal state by appropriately selecting additional food for predators. It is also possible to eliminate any of the interacting species. The quality and quantity of extra food play a crucial role in system dynamics, which reminds ecological administrators to be cautious when selecting extra food to achieve the goals in the biological protection plan [2]. The Dziadzio study evaluated the local residents' awareness of wildlife conservation and conservation performance. The respondents (association members) were selected by purposive sampling. The data were analyzed by SPSS and Microsoft Excel. The majority of respondents prefer personal land use rights and obtain land plots in other places. In a single land, crop planting is the preferred land use mode. The decrease in the number of pasture and livestock is considered to be the result of the increase in the number of wild animals. However, most people think that wildlife is a kind of benefit, but this situation decreases with the approaching of the reserve. Although livestock is the main livelihood, most members do not want to use livestock grazing to replace protection. Most respondents prefer to kill any destructive wild species, rather than through legal means [3]. Although the existing research on wildlife nature conservation is very rich, there are still some limitations in its practical application.

This paper is based on the concept and value of wildlife species resources, the data collection of the research area location, geological conditions and biomass, and the design of artificial neural network parameters. Combined with the artificial neural network model, the biomass evaluation of the study area was studied, and the model of wild biomass evaluation was proposed. The threat of wildlife living environment is predicted by artificial neural network, which provides a basis for scientific protection of wildlife.

2. Design Discussion on the Feasibility of Wildlife Nature Conservation Based on Artificial Neural Network

2.1. Wildlife Species Resources

(1) Wild plants, animals and microbial species in nature.

(2) Wild relatives of crops and artificially cultivated varieties [4].

(3) The two species contain materials of genetic functional units (gene and DNA levels), namely genetic material [5]. It has the same connotation and value with "biodiversity". Both of them contain the internal requirements for the protection of species and genetic material diversity. The difference is that "biodiversity" also includes the diversity of the entire ecosystem. The protection of biological species resources is an important component, or even the core, of the protection of biological system diversity and even biodiversity [6].

2.2. Wildlife Species Resource Value

The value of wildlife species resources also has the following specific values:

(1) Direct value refers to the price of energy industrial resources that can be directly used as resources by biological species, which can be generally reflected in monetary terms. Including the meaning of life, labor value, etc. [7].

(2) Indirect value refers to the economic benefits that cannot be directly reflected in monetary form, such as the non consumption use value of maintaining the earth's ecological balance and stabilizing ecology and the possible consumption choice value of turning the future environment into reality [8].

2.3. Artificial Neural Network Model

The basic principle of the artificial neural network The basic principle of the artificial neural network is to constantly acquire knowledge through the external environment and optimize its own parameters (such as weight) according to certain learning rules, so that the actual output gradually tends to the ideal output over time [9]. There are three kinds of artificial neural network learning methods according to the amount of information in the external environment: supervised learning; Unsupervised learning; Strengthen learning [10].

(1) Error back propagation

The training and parameter updating of the error back propagation model mainly rely on the error back propagation algorithm, which inputs the input and target output values into the network in the form of vector pairs [11]. The general steps of the back propagation algorithm are as follows:

$$G(Q,a) = \frac{1}{2m}\sum_{x=1}^{m}(w^{(x)} - r^{(x)})^2 + \frac{\gamma}{2}Q^N Q \tag{1}$$

1) The chain derivative is used to calculate the derivative value of the cost function on the neuron weight of each network layer layer by layer, and update the parameter value of each layer [12].

2) When the neural network outputs the result through forward propagation, it compares it with the predetermined output, calculates the error of the two, and propagates back to each layer of the network. Generally, the weight value is updated by the BP algorithm [13].

(2) BP neural network model evaluation index

The evaluation indexes of BP neural network prediction effect are mse and RNL [14].

1) Mean square error mse:

$$MES = \frac{1}{m}\sum_{x=1}^{m}(r_x - \hat{r}_1)^2 \tag{2}$$

2) The nonlinear fitting rate in the R-squared is used to evaluate the model effect, and the calculation formula is as follows:

$$RNL = 1 - \sqrt{\frac{\sum(r_x - \hat{r}_1)^2}{\sum r_x^2}} \tag{3}$$

m represents the length of the predicted data, r_x represents the measured value, and $\hat{r}_1$ represents the predicted value. The smaller the mse, the better the prediction effect of the network [15]. The value of RNL is close to 1, which means that the closer the predicted value is to the measured value, the better the model effect is, and the higher the accuracy of simulation and prediction is.

3. Investigation and Discussion on the Feasibility of Wildlife Nature Conservation Based on Artificial Neural Network

3.1. Biomass Data Collection

According to the differences in DBH and age of masson pine, Chinese fir and Phyllostachys pubescens in the study area, samples of masson pine, Chinese fir and Phyllostachys pubescens were collected, including masson pine, Chinese fir and Phyllostachys pubescens. The age force, DBH, ground diameter, tree height, crown width, crown length and other factors of all samples were measured. The sampling sites are distributed in nine provinces in the south. This data is used to model and estimate the biomass of masson pine in Jiangle County, Fujian Province. Table 1 shows the statistical information of main survey factors of sample trees [16].

Table 1. Main investigation factors of sample trees

Tree species	Number of Tree	Statistic	Diameter at breast height/cm	Tree height/m	Aboveground biomass /kg	Root biomass /kg
Pinus massoniana	206	Min	2.5	2.90	1.60	0.30
		Max	32.20	24.00	79.03	77.01
		Average	15.10	13.70	24.15	24.51
Chinese fir	29	Min	6.10	4.20	4.55	0.80
		Max	27.14	26.30	225.82	51.20
		Average	16.25	17.50	78.95	15.82
Bamboo	30	Min	5.10	8.30	2.53	0.90
		Max	14.20	19.60	36.25	9.15
		Average	9.66	13.52	13.62	4.28

3.2. Parameter Design of Artificial Neural Network

This paper first conducts batch normalization preprocessing of the data, distributes the threat sample data obtained in the form of training and testing set 8:2, trains the training set samples, and conducts experimental test analysis on the test set samples [17]. Finally, in the parameter adjustment stage, the size, number, optimization algorithm and iteration number of convolution kernels are controlled in turn to adjust appropriately, find the optimal parameters, and establish a threat prediction model for threat prediction [18].

Table 2. Specific parameters of each layer of neural network

The network layer	The specific parameters
IN the input layer	15*15*1
C1Convolution layer	Convolution kernel 3*3*25, step size 1, activation function Relu
P1Pooling layer	3*3 pooling, step size 2,max pooling
C2Convolution layer	Convolution kernel 3*3*25, step size 1, activation function Relu
P2Pooling layer	3*3 pooling, step size 1,max pooling
FC connection layer	1024 neurons
OUTOutput layer	5 output nodes,softmax classification

4. Application Discussion on the Feasibility of Wildlife Nature Conservation Based on Artificial Neural Network

4.1. Wild Biomass Estimation Model Based on Artificial Neural Network

(1) Construct the artificial neural network model.

(2) Remote sensing factor parameters, terrain factor parameters and biomass samples of 30 sample areas were used as training data sets. In order to avoid the inundation of small data information, the simulation results were reduced through reverse normalization. The data of the sample area is preprocessed as the output variable of the model.

(3) According to the characteristics of the biomass data set, the input layer of function tansing is the transfer function, so as to ensure that the input value of the hidden layer is between (-1,-1); The linear function purelin is the transfer function of the output layer, and its expression is. The calculation process of the model can be intuitively seen from Figure 1.

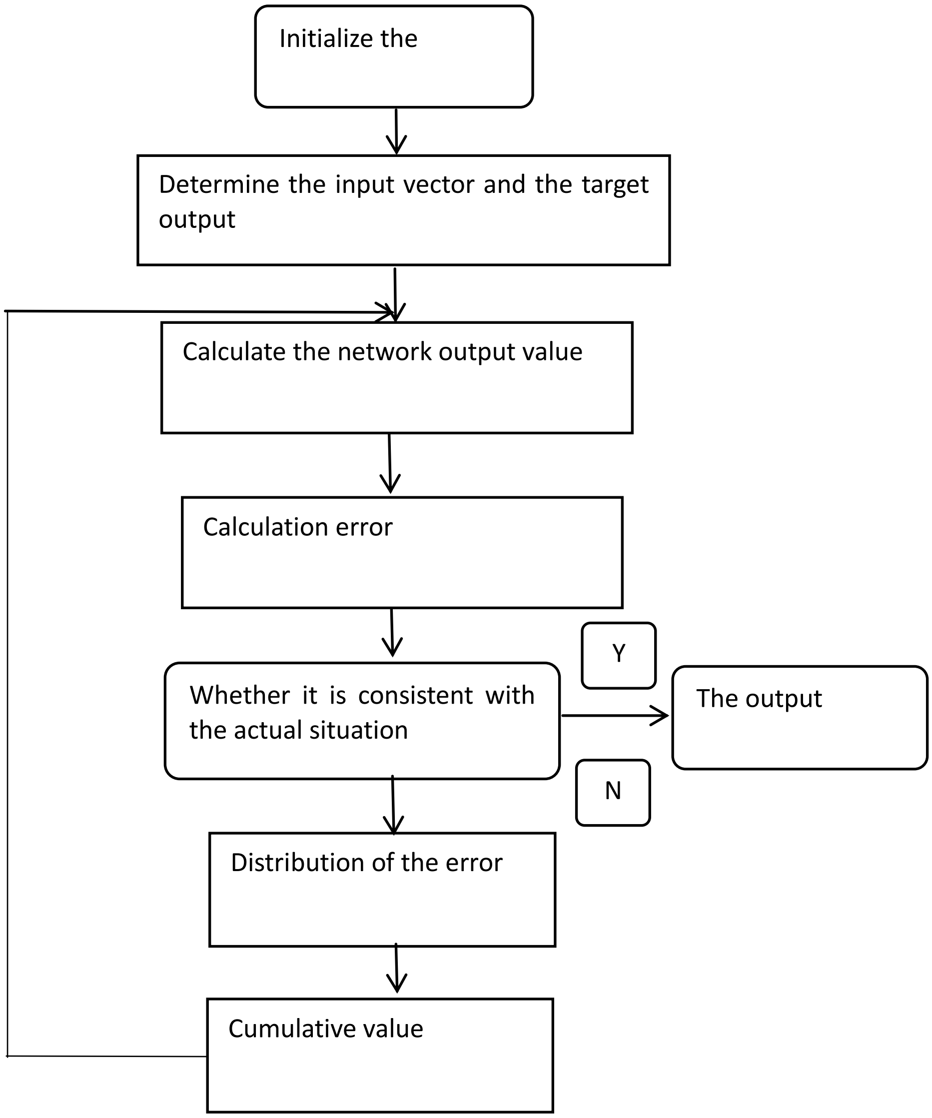

Figure 1. Artificial neural network training model

4.2. Prediction Model of Threats to Wildlife Living Environment Based on Convolutional Neural Network

After the CNN development environment is set up, the collected biomass samples are used to continuously conduct training parameter adjustment analysis, establish the convolution neural network structure, and diagnose and classify the data. Threat prediction involves the following steps:

(1) Collect threat data.

(2) The original threat data is preprocessed, normalized, and decomposed by wavelet to form a dangerous state matrix.

(3) Build a threat prediction model based on convolutional neural network. It includes 2 roll up layers, 2 pooling layers, 1 full connection layer and 1 classification layer; Adam algorithm optimizer is used for optimization.

(4) The threat type and location characteristics of the samples are binary coded to generate two types of tags, which are combined into a one-dimensional tag. Conduct training and test according to the proportion.

(5) Check whether it converges, otherwise continue to step 6.

(6) Back propagation, calculation of error, input in reverse order, continuous training, and adjustment of various parameters until the model output results meet the expectations.

(7) For threat prediction chart analysis, when the accuracy is high enough and the number of iterations is short enough.

4.3. Accuracy Evaluation of Artificial Neural Network Model

In order to test the generalization ability of the training model, the test samples other than those participating in the training are used for simulation calculation, and the simulation results are de normalized. According to the model evaluation indicators, the BP neural network biomass estimation models of six classes are simulated using the test samples not participating in the modeling in each class, and compared with the measured results. The evaluation results are shown in Table 3.

Table 3. Model accuracy evaluation results

Number of samples	MES	RNL
20	0.857	0.985
40	1.715	0.896
60	0.541	0.968
80	3.054	0.912

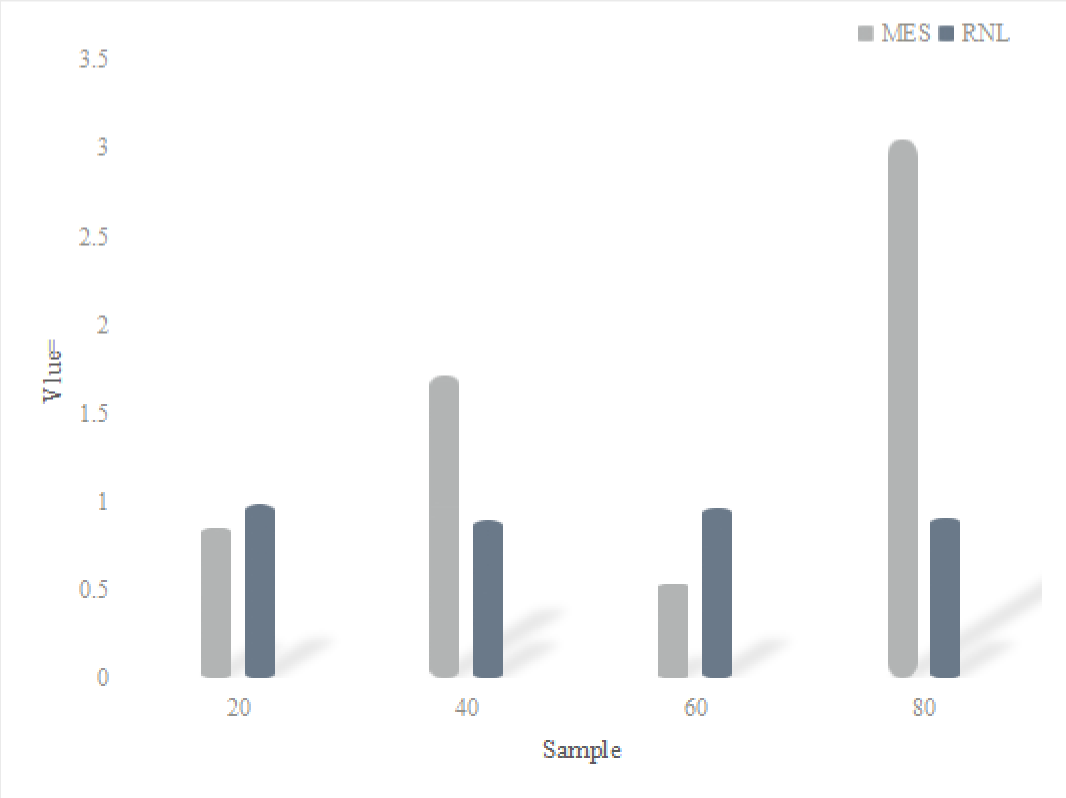

Figure 2. Comparison of model accuracy evaluation results

It can be seen from the data in Figure 2 that the mean square error (MES) and nonlinear fitting rate (RNL) of the neural network are 0.857 and 0.985 respectively when evaluating 20 wild biomass test samples. The nonlinear fitting rate (RNL) is close to 1, and the mean square error (MES) is also close to 1. It can be seen that the nonlinear fitting rate (RNL) is good, and its actual value is closer to the predicted value. When 60 wild biomass test samples were evaluated and predicted, the mean square error (MES) and nonlinear fitting rate (RNL) of the neural network were 0.541 and 0.968 respectively. The nonlinear fitting rate (RNL) is close to 1, while the value of mean square error (MES) is smaller than that of 20 samples. The mean square error (MES) and nonlinear fitting rate (RNL) of the neural network have good performance in the evaluation and prediction of 80 wild biomass test samples.

5. Conclusion

Therefore, in order to enrich the research on wildlife conservation, this paper firstly introduces the characteristics and values of wildlife species resources and the artificial neural network model. Based on the analysis and discussion of the feasibility technology of wildlife conservation based on artificial neural network, Based on the artificial neural network-based wild biomass assessment and threat prediction model, the study area profile and neural network parameters were investigated and designed. Secondly, the process structure of wild biomass assessment and threat prediction model of artificial neural network is designed and analyzed. Finally, the training accuracy of the algorithm proposed in this paper is compared and analyzed. The final experimental results verify the feasibility of the algorithm proposed in this paper in the nature conservation of wild life.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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