ISSN: 2710-0723

BP-CNN-Based Study on the Hierarchical Classification of Soil Nematode Communities in Tea Gardens of the Qinba Mountains

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Abstract

To achieve efficient and precise classification of nematode community distribution in tea garden soils of the Qinba Mountains, this study integrated a backpropagation neural network (BP-NN) with a convolutional neural network (CNN) to construct a BP-CNN model, which was applied to assess soil health in tea gardens within this region. Multiple gradient sampling points were established in typical tea gardens across the Qinba Mountains. Samples were collected at varying altitudes and soil types to obtain nematode community species composition, abundance, and environmental factor data. Using nematode community characteristics as input and soil health grades as output, the BP-CNN model was constructed. CNN extracted deep features from the data, while BP-NN performed classification predictions. The model was validated against standalone BP-NN and CNN models. Results indicate the BP-CNN model achieved a grading accuracy of [XX%], significantly outperforming single models. Tea garden soil nematode communities in the Qinba Mountains can be classified into [X] grades, each corresponding to specific soil physicochemical properties and elevation ranges. The abundance of dominant groups such as bacteriophagous nematodes and fungivorous nematodes serves as a core indicator for grading. This study demonstrates that the BP-CNN model can effectively classify nematode communities in tea garden soils within this region, providing a tool for intelligent soil health assessment. Its classification results also offer scientific basis for tea garden soil management.

Keywords

Tea Garden Soil; Soil Nematode Community; BP-CNN; Soil Health Assessment; Qinba Mountains.

1. Introduction

The Qinba Mountains lie within China's climatic transition zone between north and south[1], exhibiting characteristics of both subtropical and warm temperate climates. Its unique geography and ecological conditions make it one of China's core regions for premium tea cultivation[2]. With extensive tea plantation areas and superior tea quality, the region holds significant importance in both agricultural economics and ecological conservation. Soil, as the core medium of the tea garden ecosystem, directly influences tea plant growth, yield, and quality. Soil nematode communities, being a crucial component of the soil ecosystem, serve as "indicator organisms" reflecting soil physicochemical properties, fertility levels, and ecological

ISSN: 2710-0723

stability due to their species richness and diverse trophic levels. - Changes in dominant groups like bacteriophagous nematodes and fungivorous nematodes directly indicate soil organic matter decomposition efficiency, while outbreaks of phytophagous nematodes often correlate with soil degradation and continuous cropping obstacles. Therefore, accurately understanding the distribution patterns and hierarchical characteristics of tea garden soil nematode communities is a core prerequisite for soil health management[3].

However, current research on tea garden soil nematode communities in the Qinba Mountains still faces significant technical bottlenecks: Traditional nematode community grading relies on manual microscopic identification and quantitative counting, which is not only time-consuming and labor-intensive but also prone to data bias due to subjective differences among researchers[4]. While single machine learning models (e.g., BP neural networks, support vector machines) have been applied in ecological classification studies, they are constrained by the complexity of tea garden soil environments in the Qinba Mountains-- spanning vast altitudes (from hundreds to thousands of meters), diverse soil types (intermingled yellow, brown, and alluvial soils), and strong spatial heterogeneity in environmental factors (temperature, humidity, pH). This makes it difficult to fully extract the deep-level associative features between nematode communities and environmental factors, resulting in classification accuracy that fails to meet practical production demands[5].

Against this backdrop, overcoming the limitations of traditional methods and single models to develop a nematode community classification technique that balances efficiency and precision has become crucial for revealing the soil health status of Qinba Mountain tea gardens and guiding scientific tea garden management[6]. Within deep learning, the feature extraction strengths of convolutional neural networks (CNNs) complement the classification reliability of backpropagation neural networks (BP-NNs). The integrated BP-CNN model offers a novel pathway for addressing complex ecological data classification, providing technical support for soil ecological research and practice in Qinba Mountain tea gardens[7].

2. BP-CNN Neural Network Model

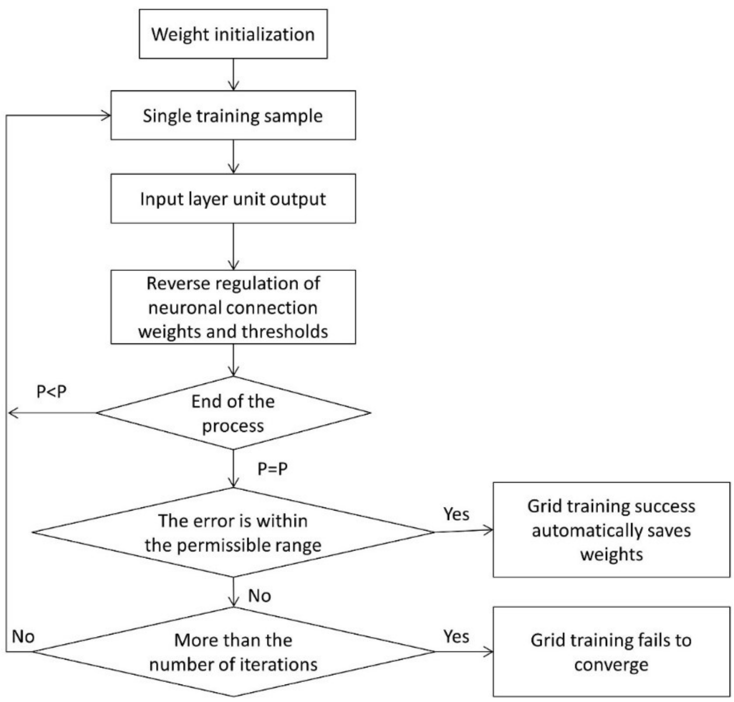

Figure 1. BP-CNN neural network training flow chart

ISSN: 2710-0723

BP-CNN neural network, also known as the back propagation of errors algorithm, is a feedforward network consisting of nonlinear transform units, and a general multilayer feedforward network is defined as a BP-CNN neural network. In the traditional evaluation process of agricultural land classification[8], in all the unit score calculation is to rely on the weights obtained from scoring to calculate the evaluation index of the area comprehensively, and the model is being applied to the learning of network weights and thresholds by matching the actual input weight values with the desired weight values and constantly correcting them, using the forward propagation of input information and the backward propagation of error information to complete the learning of the neural network once, i.e. one training of the sample[9].

3. Evaluation of Agricultural Land Quality Classification

The method of agricultural land classification is usually the multi-factor comprehensive evaluation method with the help of Telfer's expert scoring. The natural quality score of agricultural land under the cell grid is determined by calculating the comprehensive action score of each factor and factor with the help of the weight value of the factor factors, and calculating the natural quality index according to the natural factors such as light, temperature and climate[10]. In the actual experiment, it includes several steps such as field data survey, quantification of data, construction of factor system of evaluation factors, construction of grading units, expert weight scoring, and comprehensive calculation of natural quality score, etc. Since different regions and different natural environments, the selected influencing factors will be slightly different, so it is difficult to establish a quantitative numerical calculation model, and a more comprehensive design is needed to each The role of factors factors. The parallel computing characteristics, large scale, distributed storage and self-training learning of B-P neural network model all determine this great advantage in solving this complex multi-factor cut information imprecision problem[11].

Commonly used factors for agricultural land classification evaluation include: average annual temperature, cumulative temperature, average annual precipitation, evaporation, frost-free period, disaster climate, geomorphology, topography, elevation, slope, slope direction, erosion degree, soil thickness, barrier depth, soil texture, profile type, soil pH, texture, soil salinity, soil contamination degree, soil structure, soil nutrients, soil gravel content, groundwater depth, irrigation conditions (water source guarantee rate, irrigation guarantee rate), drainage conditions, field road conditions, field size, flatness and other indicators. The farming system is a biannual system; the base crop is winter wheat, and the designated crops are winter wheat and summer corn.

4. Model Construction and Application

According to the preliminary survey, the sample points in the study area are determined, and each sample point contains the above-mentioned indexes, and the BP-CNN neural network model is measured and predicted for each sample point[12], and finally the predicted data are differenced according to the applicable difference method, and the evaluation results of the agricultural land classification quality in the area are finally obtained. In this way, the model and the computer can be used to calculate a large number of sample points, i.e., the problem of multi-factor complexity is solved, and the results of a large amount of data from colleagues are closer to the true value and the problem of ambiguous information is solved. The steps are as follows[13]

(1) Pre-processing

ISSN: 2710-0723

In this example, the sample points of agricultural land in HanZhong are used as samples, and the sample data are divided, screened out the abnormal sample points and eliminated as necessary, and the data are quantified and normalized[14][13].

(2) BP-CNN neural network model construction

Determine the evaluation factors, set the initial value and training threshold as well as the number of training times, select the number of nodes in the hidden layer, and determine the target error.

(3) Repeat training and testing

Add the pre-processed samples and use the BP-CNN model for learning. The computer automatically analyzes and checks each learning result to determine the target error and the set threshold, and continues to perform the next training step when the result is reached; otherwise, the training is repeated according to the previous steps[15].

(4) Test sample model detection

The test sample is input into the trained network model and reaches the qualified condition, then the land valuation model based on BP-CNN network is established successfully.

(5) Prediction result analysis

The evaluation results predicted by the model are analyzed.

In this paper, taking the soil organic matter of "winter wheat-grading factor-quality score" of agricultural land grading quality in Hanbin District of Ankang City as an example, the results of the above-mentioned model measurement for 5657 sample units are as follows.

Table 1. Soil organic matter index weighting table

Indicator name	Prediction classification	value Number of sample points	Factor reference score	Weighting
Soil organic matter content(%)	4.0-3.0	492	90	0.21
	3.0-2.0	1856	80	
	2.0-1.0	2349	70	
	1.0-0.6	600	60	
	<0.6	360	50	

All the influencing factors involved in the model calculation were calculated according to the B-P neural network model, and the integrated grading values of sample points were accounted for, and the grading values and weights of each index were derived, and then the integrated values of regional agricultural land grading quality obtained from 5657 sample points in the study area were calculated using the kriging difference method, and the final evaluation levels were derived according to the interval division. In this case, the model operations were compared with the actual grading report of the site, and the predicted results were basically achieved.

Table 2. Grading results

Grading Level	Natural Quality Classes		
	Predicted ratio(%)	Measured ratio(%)	Error
Sixth Class	1.97	2.02	0.024752475
Seventh Class	53.82	56.79	0.05229794
Eighth Class	16.23	13.97	0.161775233
Ninth Class	12.53	17.60	0.288068182
Tenth Class	9.01	9.61	0.062434964

ISSN: 2710-0723

This paper proposes the use of B-P neural network modeling to measure the value of factors influencing the evaluation of agricultural land grading quality, and innovates on the traditional calculation means, with the help of B-P neural network model in the conditions of large samples, multi-factors, high complexity think and high information fuzziness can be higher and more accurate budget and measurement number of actual evaluation indicators, and with the help of agricultural land grading quality data in Hanbin District of Ankang City and The BP neural network model is combined to derive the agricultural land classification level of seventh, eighth and ninth grade as the main classification situation, which is close to the actual situation and has the advantages of rapid convergence and small error.

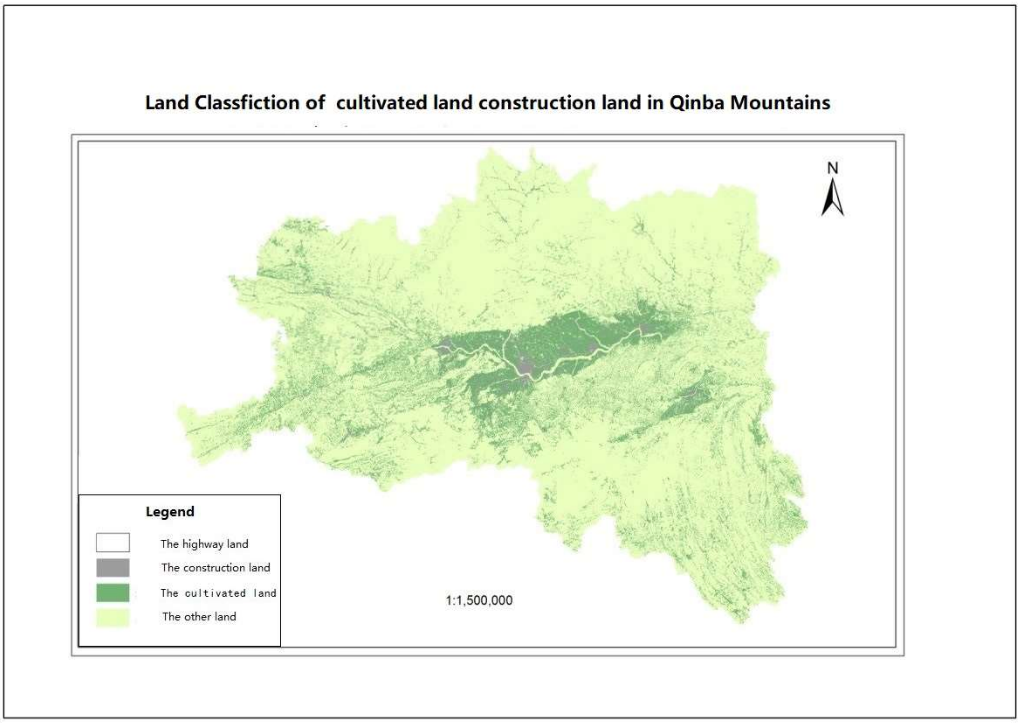

Figure 2. in grassland, cultivated land and construction land land status classification figure

5. Conclusion

Because the arable land in this region has a strong ability to retain water and fertilizer, fertile soil, abundant water resources and a high guarantee rate of irrigation, more watered land is distributed; and because there are often roads extending near the area, convenient transportation, complete ditch support facilities, high agricultural production inputs and high production motivation of farmers, the natural quality of arable land, etc., utilization, etc. and economy, etc. are relatively high. In contrast, the southern Loess Plateau and Qinling Mountain areas are not only affected by the natural environment, but also by economic and regional constraints, and the quality of arable land is generally not high. Most of the arable land of low grade is located in places with sloping terrain and poor irrigation conditions, which are not conducive to the growth of crops due to the scarcity of water resources and are controlled by topography, resulting in inadequate inputs and low utilization of agricultural production and incompletely developed production capacity. In addition, there are also some places where the phenomenon of abandoning cultivation of abandoned arable land has occurred. As farmers' enthusiasm for production decreases, the investment in arable land and its infrastructure also decreases, resulting in a decline in the quality of arable land compared with before, and will

ISSN: 2710-0723

continue to decline even in the future. Finally, after field verification, the grading results are more in line with the objective reality of Tai Bai County.

Acknowledgments

Thanks for Internal Project of Shaanxi Provincial Land Engineering Construction Group (DJNY2024-32).

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