RESEARCH ARTICLE

Simulation analysis of the effect of garden waste resource products on improving saline soil based on deep belief network

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To address the adverse effects of saline soil on landscaping, this research proposed a deep belief network (DBN) based simulation analysis method for analyzing the improvement effects of garden waste recycling products on saline soil using typical saline soils in Lianyungang, Jiangsu, China to collect key data on soil physical and chemical properties and garden waste recycling products. The proposed DBN model was trained to predict and evaluate the improvement effects with soil total salinity, pH, organic matter content as model inputs and the corresponding improved indicators as outputs. The results showed that the DBN model achieved a prediction accuracy of 94.8% with a mean square error of only 0.04, outperforming competing models such as support vector machines and random forests. Experimental validation showed that the recycling products reduced soil total salinity by an average of 35%, pH by 0.35 units, and increased organic matter content by 28%. Simulation results also indicated that the improvement effect was greater with higher application rates with the optimal application rate ranging from 2.0 to 2.5 kg/m². The DBN model demonstrated excellent adaptability and accuracy in predicting the improvement effects of saline soils, providing effective technical support for the scientific application of recycling products and soil ecological management.

Keywords: deep belief network; garden waste resource product; saline soil; improvement; simulation analysis.

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Introduction

Saline soil is a general term for saline soil, alkaline soil, and various salinized soils and alkaline soils [1]. Lianyungang (Jiangsu, China) is a coastal city with widespread saline-alkali land, and the problem of soil salinization and seriously restricts the development of local landscaping. The high concentration of soluble salts and alkaline substances in saline soils can adversely affect plant growth, resulting in poor plant growth or even death [2]. Therefore, improving the properties of saline soils and increasing soil fertility and plant habitability are the keys to achieving sustainable development of city's landscaping [3]. In recent years, extensive research has been conducted worldwide in the fields of saline-alkali land improvement and resource utilization of garden waste [4]. In terms of saline-alkali land improvement, many researchers have proposed different improvement technologies including physical, chemical, and biological methods [5]. Physical improvement measures include irrigation grouting, hidden pipe salt drainage, *etc*., which reduce salt damage by reducing soil salt content or improving soil structure [6]. Chemical improvement mainly reduces soil alkalinity by applying chemical amendments such as gypsum and phosphogypsum, which react chemically with sodium ions in the soil [7]. Biological improvement mainly improves soil properties by planting salt-tolerant plants and applying microbial agents, using the growth activities of plants and microorganisms [8]. However, these methods often have certain limitations in practical applications such as high costs, greater environmental risks, and insignificant improvement effects.

In terms of resource utilization of garden waste, related research mainly focuses on converting garden waste into organic fertilizers, soil conditioners, biofuels, *etc*. [9-11]. These studies provide multiple ways to utilize garden waste as a resource, but there are relatively few studies on its application in saline soil improvement and lack systematicity and in-depth research. Currently, the research on the application of garden waste resource products in saline and alkaline soil improvement is still in its infancy, and there are many shortcomings and challenges [12], which include lack of systematic research on the application of garden waste resource products in saline-alkaline soil improvement [13], lack of large-scale and long-term practical application cases for a comprehensive assessment of the feasibility and stability under actual conditions [14], and unclear of the interaction mechanism between the properties of garden waste resource products and saline-alkaline soil properties [15]. Therefore, conducting data-driven analysis on the improvement effect of garden waste resource products on saline-alkali soil is of great significance for the resource utilization of garden waste [16]. Research and evaluation of the improvement effect of garden waste resource products on saline-alkali soil will not only help improve the utilization rate and ecological benefits of saline-alkali soil but also provide a scientific basis for the resource utilization of garden waste and reduce environmental pollution [17, 18]. Previous studies mainly included the analysis of the basic characteristics of saline-alkali soil [19], the analysis of garden waste treatment methods, and the characteristics of resource products [20], the improvement effect analysis [21], and experimental simulation analysis [22]. The core goal of the simulation analysis of the improvement effect of garden waste resource products on saline soil is to quantitatively evaluate the improvement effect of garden waste resource products under different soil conditions and to deeply explore the mechanisms of their influence on the physical, chemical, and biological properties of saline soil [23]. Traditional approaches to soil improvement often rely on empirical trials with high costs and uncertain long-term outcomes. Deep belief network (DBN) is a deep learning method based on probabilistic generative models [24], and its structure usually consists of multiple hidden layers with each of them containing a certain number of neurons [25], which can be used to systematically assess the effect of garden waste resource products on saline soil improvement and provide innovative solutions for saline soil improvement. The integration of DBN into the research enables the systematic capture of complex, nonlinear interactions among soil physicochemical properties, waste-derived amendments, and environmental conditions, which will advance intelligent soil management strategies, offer researchers a scalable and transferable approach to other regions and soil types.

This research proposed a DBN based simulation analysis model to systematically analyze the improvement effect of garden waste resource products in soils with different salinity levels and explore its effect mechanism on soil physical, chemical, and biological properties. The proposed DBN model was experimentally verified for its accuracy and reliability in simulating the saline soil improvement process and optimized through experiments. This research would provide a reliable tool for simulating and predicting the improvement effects of garden waste resource products on saline soils and enrich the methodological repertoire of soil science and environmental management. Further, this research highlighted the dual benefits of promoting ecological restoration of saline soils and enhancing the sustainable utilization of urban garden waste, thereby bridging environmental engineering, waste recycling, and agricultural sciences. Ultimately, the findings of this study would facilitate the exploration of artificial intelligence approaches to ecological restoration and foster interdisciplinary collaborations between the computer science and soil science communities.

Materials and methods

DBN model structure

The DBN network structure included an input layer, multiple hidden layers, and an output layer. The input layer was used to receive the original data, while the hidden layers extracted the feature representations of the data layer by layer, and the output layer gave the result. The more hidden layers the DBN had, the better the model's ability to learn the features of the data, and the better it could capture the complex relationships in the data [26]. This study chose DBN model as the analysis and simulation tool to investigate the effect of garden waste resource products on saline soil improvement. The model application structure included the feature vectors that received the initial total salt amount of soil, pH value, organic matter content, soil texture, groundwater level, the type of garden waste resource products, and the amount of application in the input layer, the hidden layer as the core of the DBN model responsible for feature extraction and representation learning of the input data, the indicators prediction by the output layer including the whole salt amount, pH value, and organic matter content of the improved soil. The DBN model depth including the number of hidden layers and the width including the number of neurons per layer had a significant impact on the performance of the model [27]. Deeper networks learned more complex feature representations and increased the computational complexity and training time of the model. Wider networks could increase the representational power of the model but might lead to overfitting problems. In practice, the choice of model depth and width needed to be experimentally tested and adjusted according to the specific problem and data characteristics.

DBN learning algorithms

The learning process of DBN was divided into two stages including unsupervised pre-training and supervised fine-tuning. In the pre-training phase, each results-based management (RBM) was trained layer by layer to learn the feature representation of the data [28]. In the fine-tuning phase, the whole network was optimized by the back-propagation algorithm to improve the predict accuracy of the model.

Unsupervised pre-training was the first stage of the DBN model learning process to initialize the network weights and learn the feature representation of the data [29]. The weight matrix and bias vector of the RBM were randomly initialized. The input data was passed to the hidden layer of the RBM, and the activation state of the hidden layer neurons was calculated as the activation probability by using sigmoid function below.

$$p\left(h_j = 1 \mid v\right) = \sigma\left(\sum_{i=1}^{n} w_{ij} v_i + b_j\right) \quad (1)$$

where h_j was the activation state of each neuron in the j-th neuron of the hidden layer. v was the input vector. W_{ij} was the connection weight between the i-th neuron in the input layer and the j-th neuron in the hidden layer. b_j was the bias of each neuron in the j-th neuron of the hidden layer. σ was the activation function of sigmoid. According to the activation probability $p(h_j = 1|v)$, the states of the hidden layer neurons were sampled to obtain the binary state vector h. The hidden layer state h was then passed back to the input layer. The activation state of the neurons in the input layer was calculated with the activation probability being calculated by the sigmoid function below.

$$p\left(v_i = 1 \mid h\right) = \sigma\left(\sum_{j=1}^{m} w_{ij} h_i + a_i\right) \tag{2}$$

where v_i was the activation state of the i-th neuron in the input layer. a_i was the bias of the i-th neuron in the input layer. According to the activation probability $p(v_i = 1|h)$, the state of the neurons in the input layer was sampled to obtain the reconstructed input vector $v^{'}$. The reconstruction error was calculated and the weight matrix and bias vector of the RBM were updated based on the reconstruction error. A commonly used update rule was the contrastive divergence (CD) algorithm as follows.

$$\Delta w_{ij} = \varepsilon\left(\left\langle v_i h_j \right\rangle_{data} - \left\langle v_i h_j \right\rangle_{reconstruction}\right) \tag{3}$$

$$\Delta a_i = \varepsilon\left(\left\langle v_i \right\rangle_{data} - \left\langle v_i \right\rangle_{reconstruction}\right) \tag{4}$$

$$\Delta b_j = \varepsilon\left(\left\langle h_j \right\rangle_{data} - \left\langle h_j \right\rangle_{reconstruction}\right) \tag{5}$$

where ε was the learning rate. $\langle\cdot\rangle_{data}$ was the expected value on the original data. $\langle\cdot\rangle_{reconstruction}$ was the expected value on the reconstructed data. The above steps were repeated until the RBM converged, i.e., the reconstruction error was less than a preset threshold or the maximum number of iterations was reached. By training each RBM layer by layer, the DBN model was able to learn the feature representation of the data, providing good initial weights for subsequent supervised fine-tuning.

Supervised fine-tuning was the second stage of the DBN model learning process to optimize the prediction performance of the whole network using the label information [29]. The fine-tuning phase optimized the whole DBN model by back-propagation algorithm to adjust the weights and biases of all layers. The weights and biases obtained in the pre-training phase were used as the initial values. The input data was forward propagated through the DBN model to compute the predicted values for the output layer. The value of the loss function was calculated based on the predicted and true values, which included mean square error (MSE) and cross-entropy loss. The loss gradient was backpropagated layer by layer from the output layer to the input layer to calculate the gradient for each weight and bias. The weights and biases of the model were then updated based on the gradient information using optimization algorithms including stochastic gradient descent (SGD), Adam, and RMSprop. The above steps were repeated until the model converged, i.e., the loss function value was less than a preset threshold or the maximum number of iterations was reached. Through supervised fine-tuning, the DBN model could make full use of the label information to optimize the prediction performance and improve the accuracy and reliability of the model.

Cross-validation and independent test sets were applied to validate the accuracy and reliability of the proposed model and assess the generalization ability of the model. The trained DBN model was used to simulate and predict the saline soil improvement effect. Through the training process, the DBN model could effectively learn the complex relationships in the data and provide scientific and technical support for saline soil improvement.

Study area

Lianyungang (Jiangsu, China) located between 34°7′ - 34°54′N and 118°6′ - 119°30′E with the total area of 7,615 km^2, the terrain slopes from northwest to southeast, and plains and hills dominating the landscape was selected as the study area of this research. The climate was temperate monsoon with four distinct seasons, abundant rainfall, an average annual temperature of 14.5°C, annual precipitation of 972 mm, and an annual frost-free period of 220 days. The city had a variety of soil types with saline soil as one of the main soil types and mainly distributed in coastal areas and plains including two subclasses of salinized tidal soils and coastal saline soils. The total salt content of salinized tidal soil was generally between 1.0 and 6.0 g/kg, and the soil texture was mainly loamy. The total salt content of coastal salt soil usually exceeded 6.0 g/kg, and the soil texture was mainly clay and sandy soil. In addition, special types of saline soil such as blow-fill soils and salt ponds and shrimp ponds were also in some areas.

Data collection

The data were mainly collected from soil samples, garden waste resource products, field research and interviews, and literature reviewing. A total of 31 soil sampling points were deployed according to different soil types, salinization degree, and vegetation cover within the saline areas, which considered the heterogeneity and representativeness of the soil to ensure that the characteristics of saline soils in the study area could be fully reflected. The collected soil samples were sent to laboratories for physical and chemical property tests. The testing indexes included total salt, pH value, organic matter content, soil texture, hydrolysable nitrogen, quick-acting phosphorus, quick-acting potassium, and soil bulk weight. Different types of garden waste resource products were collected, which included compost, fermentation products, and crushed materials. The samples were analyzed for organic matter content, nitrogen, phosphorus, and potassium content, pH value, salt content, and texture following the relevant standards to ensure the accuracy and comparability of the data. In addition to laboratory tests, extensive field research and interviews were conducted [30], which covered the current situation of landscape greening including plant species, growth conditions, greening coverage, soil improvement measures including the implementation effects, costs and applicable conditions of different improvement measures, landscape waste treatment and utilization including the collection, transportation, and treatment processes of landscape waste, as well as the products of resourcing in the landscape greening application, interviews with relevant stakeholders including the collection of their opinions and suggestions on saline soil improvement and resource utilization of garden waste, and understanding the problems and needs in practical application. A large amount of domestic and international literature on saline soil improvement, resource utilization of garden waste, and the application of the DBN model was also reviewed.

Disposal methods and characteristics of garden waste resource products

Garden waste treatment methods were mainly based on the waste treatment process including composting, fermentation, and comminution [31]. Composting was the process of mixing garden waste such as twigs, leaves, grass clippings, *etc*. with microorganisms, fermenting them under certain temperature and humidity conditions, and converting them into fertilizers rich in organic matter. The composting process was usually divided into the stages of raw material preparation, stacking, fermentation, turning and aeration, ripening, and post-treatment. Fermentation was the process of using microorganisms to decompose organic materials in garden waste to produce organic fertilizer and biogas, which mainly included anaerobic fermentation and aerobic fermentation. Comminution was the process of mechanically crushing garden waste to make it into smaller particles or powder. The crushed material could be used for soil mulching as raw material for composting or fermentation or mixed with other materials to produce soil conditioners, biomass fuels, and so on. The characteristics of garden waste resource products mainly included organic matter content, nutrient composition, pH, salt content, texture, biological activity, stability, and environmental friendliness [32].

Model construction and modification

The model inputs included the initial total salt content of the soil, pH value, organic matter content, soil texture, water table, and the type and application amount of garden waste resource products, which provided rich information for the DBN model to accurately simulate the soil improvement process. The output of the model was the whole salt amount, pH value, organic matter content, and other indicators of the improved soil, which visually reflected the effect of soil improvement and provided a quantitative basis for evaluating the improvement effect of garden waste resource products on saline soil. The model was constructed through data pre-processing; determination of the number of neurons in the input, hidden, and output layers; model training and optimizing through unsupervised pre-training and supervised fine-tuning; model validation to prevent overfitting; and simulation test. The collected datasets were divided into 80% as training set and 20% as test set. The model included 3 hidden layers and 256 neurons per layer with learning rate of 0.01 and batch size of 64. The training iterations were set as 1,000 times. Sigmoid function was used for hidden layers, while linear functions were used in the output layer. The performance of the DBN model was compared with existing Random Forest, Support Vector Machine, and Linear Regression models and was evaluated by using mean square error (MSE), coefficient of determination (R^2), and accuracy as follows.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \quad (6)$$

where N was the sample size. y_i was the true value. $\hat{y}_i$ was the predicted value.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \bar{y}_i\right)^2} \quad (7)$$

where $\bar{y}_i$ was the average of the true values. The accuracy was the number of samples correctly predicted as a proportion of the total number of samples.

Results and discussion

Comparison of the total salt content of saline soil before and after the application of the garden waste resource product

The results demonstrated that all samples showed a significant decrease in total salt content after the amendment treatment with the average reduction of 35%. Some high salt samples with the initial salt content over 4.5 g/kg were reduced to below 2.5 g/kg after amending (Figure 1), indicating that the garden waste resource products had a significant dilution and replacement effect on high salt soils, which might be attributed to the organic matter and active microorganisms contained in the resource products to improve soil structure, enhance water permeability, migrate salt to the lower layers, thus reducing the salt concentration in the surface layer.

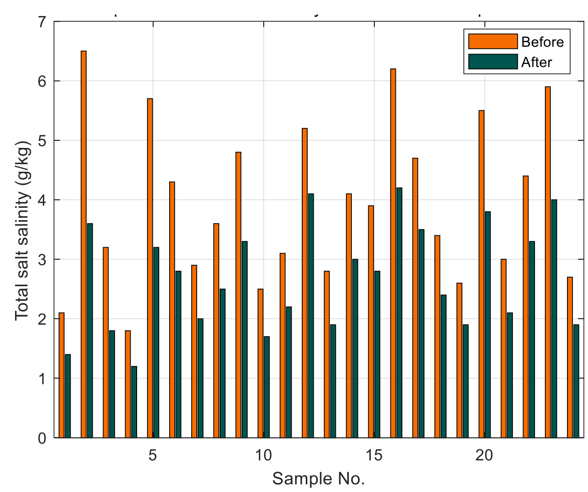

Figure 1. Comparison of total soil salinity before and after modification.

The trend line showed that most of the data points exhibited a consistent downward trend, indicating the stability and general applicability of the amendment effect. However, there were still some differences among samples, which might be affected by factors such as soil texture, water table, application rate, and type of amendment product. The results showed that, for samples with relatively low initial salinity at 2.0 - 3.0 g/kg, the decrease was slightly smaller, suggesting that the amelioration efficiency was relatively limited in low and medium salinity regions. Therefore, regulation of the application amount of the resource product according to the initial soil condition was needed to achieve a more precise and efficient amelioration goal.

Comparison of soil pH before and after amendment

The results showed that the pH values of almost all samples decreased to different degrees after the amendment treatment with an average decrease of about 0.35 units, indicating that the resource chemistry products had a significant effect in reducing soil alkalinity and improving the soil chemical environment (Figure 2). This pH adjustment helped to alleviate the toxic effects of sodium ions on plant roots in saline soils, thus creating a more suitable environment for plant growth. The higher the original pH value, the relatively larger the decrease, indicating that the garden waste resource products had a more pronounced effect on the regulation of heavily alkaline soils, which might be related to the slightly acidic properties of the products themselves. The average pH values of compost and fermentation products were 6.8 and 6.5, respectively, which were able to neutralize the alkaline components in the soil. Meanwhile, the rich organic matter might also stabilize the soil environment by enhancing the buffering capacity of the soil and reducing drastic pH fluctuations. Some samples demonstrated small or even flat pH changes, suggesting that the moderating effect of the resource chemistry products was limited under certain conditions, which might be related to factors such as insufficient application amount, compact soil texture, and excessive buffering. Therefore, it was necessary to combine the soil background characteristics, application techniques, and crop species to optimize the fertilizer application strategy to maximize the effect of soil pH regulation in practical applications.

Comparison of soil organic matter content before and after amendment

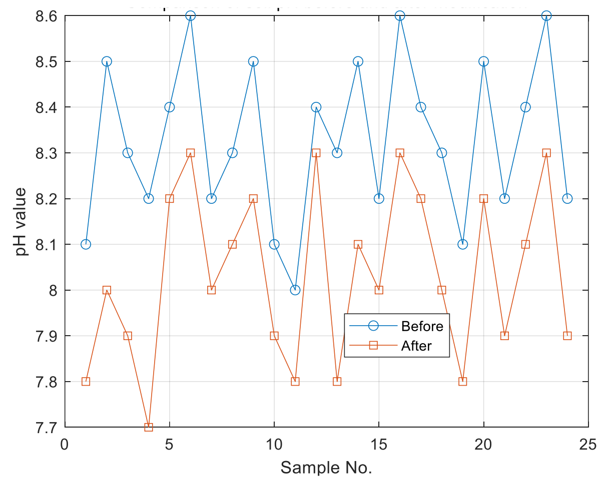

Figure 2. Comparison of soil pH before and after amendment.

The changes in soil organic matter contents before and after the application of garden waste resource products demonstrated that all samples showed a significant increase in organic matter contents after the amendment treatment with an average increase of 28%. The organic matter content of some soil samples was as low as below 10 g/kg before amendment, while it was generally enhanced to the range of 13 - 19 g/kg after amendment, showing that the resource-based products could significantly enhance the soil organic matter level in a short period of time (Figure 3). This effect was mainly because the garden waste resource product was rich in organic carbon and nutrients such as compost and fermentation products containing a large amount of humus, cellulose degradation products, microbial metabolites, and so on. These substances in the soil not only directly enhanced the content of organic matter, but also promoted the activity of soil microorganisms, thereby accelerating the transformation and accumulation of organic matter in the soil. In addition, the increase of organic matter also improved the soil granular structure, the ability of water and fertilizer retention, and provided a better environment for plant root growth. The variability also demonstrated that the effect of resource product application was closely related to the initial soil conditions and application strategy. The lower the initial organic matter contents of the sample, the more significant the improvement effect, indicating that the resource-based products were more effective in barren soils. Samples with good original organic matter contents had limited room for improvement and tend to stabilize, which suggested that, in the process of promotion, more attention should be paid to medium and low fertility soils. Through quantitative application and compound use, the improvement potential of garden waste resource products could be further released to achieve precise application and ecological restoration.

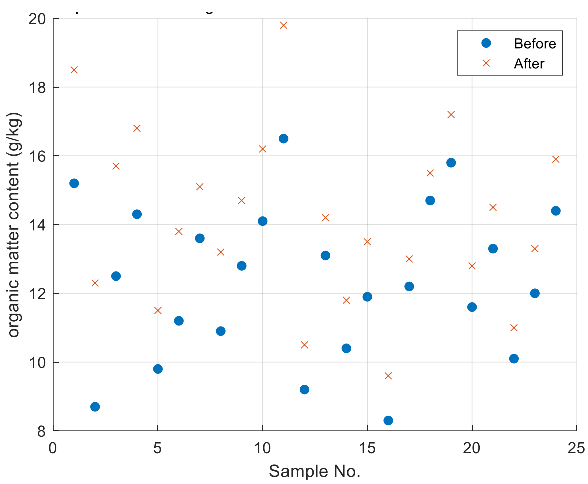

Figure 3. Comparison of soil organic matter contents before and after amendment.

DBN model predicted values vs. true values

The relationship between the predicted and the actual observed values based on the DBN model showed that most of the predicted values were distributed around the ideal diagonal line, indicating that the DBN model was able to restore key indicators such as total salinity, pH, and organic matter content of the amended soil more accurately, reflecting the model's comprehensive understanding of input characteristics and its accuracy. Fewer outliers and smaller error ranges further validated the robustness and generalizability of the DBN model in dealing with non-linear and multivariate relationships (Figure 4). The high quality of fit feature indicated that the model was highly adaptable to different types of soil improvement scenarios. The simulation outputs were highly consistent with the actual results, regardless of whether the soil was highly saline and alkaline or low fertility, which was attributed to the layer-by-layer unsupervised pre-training and supervised fine-tuning mechanism of DBN to effectively extract the deep features in the data and carry out structured learning, thus laying a solid model foundation for practical application.

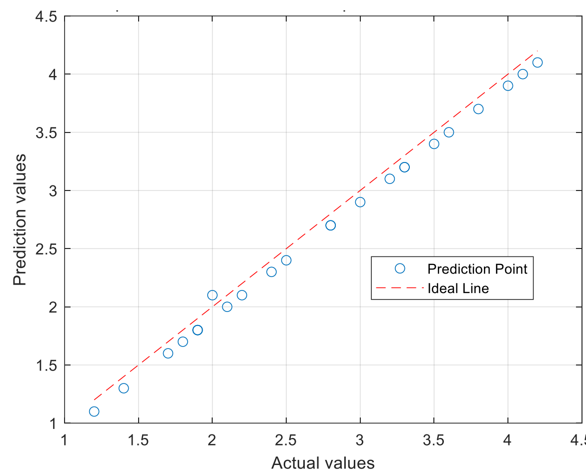

Figure 4. DBN model predicted values vs. true values.

Comparison of the performance of different models

The proposed DBN model showed a prediction accuracy of 94.8%, which was the highest one among the four compared models and significantly better than Random Forest (92.3%), Support Vector Machine (89.7%) and Linear Regression (85.2%). The results indicated that the DBN model was able to match the real observations more accurately and make correct predictions in most cases. The improvement in accuracy indicated that the model demonstrated a stronger ability to identify soil responses under different application conditions with advantages in modelling multivariate complex features. The MSE of DBN model was only 0.04, which was much lower than that of random forest (0.06), support vector machine (0.08) and linear

Table 1. Comparison of the performance of different models.

Model name	Accuracy (%)	mean square error (MSE)	Coefficient of determination (R^2)
Linear regression (math.)	85.2	0.12	0.78
Support vector machine	89.7	0.08	0.85
Random forest	92.3	0.06	0.89
DBN	94.8	0.04	0.93

regression (0.12). The results suggested that DBN not only predicted a high proportion of correct samples but also had a smaller bias for incorrect samples. A lower MSE indicated that the model was more robust to extreme values and had a more concentrated distribution of errors, which was especially critical for soil improvement field that was sensitive to numerical fluctuations. The R^2 value of DBN was 0.93, indicating that the proposed model was the most powerful one in explaining the data variability and more effective in capturing the complex non-linear relationships in the soil improvement process, making it the most reliable algorithmic choice for saline soil simulation tasks (Table 1). Overall, the results showed that the DBN model had the ability to minimize prediction error, while maintaining high accuracy, significantly outperforming traditional machine learning models. Its deep network structure could effectively capture nonlinear relationships, multivariate interactions, and implicit features, making it a preferred method for dealing with garden waste resource products in the simulation of saline soil improvement.

Comparison of soil indicators before and after improvement.

The results demonstrated three key indicators including total salt (g/kg), pH value, and organic matter content (g/kg) of the 10 samples before and after the application of garden waste resource product to evaluate the effectiveness of the amelioration. All samples showed different degrees of total salinity decrease after improvement, reflecting the positive effect of the resource products in reducing the accumulation of soil salts. The average whole salt content of the 10 samples was 3.94 g/kg before improvement and 2.35 g/kg after improvement with an average decrease of nearly 40%. The results suggested that the organic matter and microbial activity in the resourcing products might promote salt migration and sodium ion replacement, thereby reducing the surface salt concentration and alleviating salt stress. The improvement showed a decreasing pH trend with an average decrease of about 0.3 units, suggesting that the resourcing products had a neutralizing effect on the alkaline environment. Considering that resourcing products were usually slightly acidic or neutral and rich in humus with buffering capacity, this reduction in pH could effectively improve the alkaline environment in saline soils that was unfavorable to plant uptake and help to improve crop suitability and root vigor. The changes in organic matter content increased significantly in all samples after amendment with the enhancement generally ranging from 2.0 to 4.0 g/kg (Table 2). The results indicated that the garden waste resource products had a good soil fertility enhancement effect in the short term, enhancing the soil microbiological environment, improving the granular structure, and increasing the water and fertilizer retention capacity. The results also confirmed the good practical prospects and ecological benefits of the improvement program, supported the reasonableness of the model prediction results, and provided empirical evidence for the development of differentiated application strategies.

Relationship between the application rate of garden waste resource products and the improvement effects

The effects of garden waste resource products on soil improvement at different application rates (0.5 - 2.5 kg/m²) showed that, With the increase

Table 2. Comparison of soil indicators before and after improvement.

Sample number	Total salt (g/kg)		pH value		Organic matter (g/kg)	
	Before	After	Before	After	Before	After
1	2.1	1.4	8.1	7.8	15.2	18.5
2	6.5	3.6	8.5	8.0	8.7	12.3
3	3.2	1.8	8.3	7.9	12.5	15.7
4	1.8	1.2	8.2	7.7	14.3	16.8
5	5.7	3.2	8.4	8.2	9.8	11.5
6	4.3	2.8	8.6	8.3	11.2	13.8
7	2.9	2.0	8.2	8.0	13.6	15.1
8	3.6	2.5	8.3	8.1	10.9	13.2
9	4.8	3.3	8.5	8.2	12.8	14.7
10	2.5	1.7	8.1	7.9	14.1	16.2

Table 3. Relationship between the application rate of garden waste resource products and the improvement effects.

Application rate (kg/m²)	Total salt after modification (g/kg)	Modified pH	Improved organic matter (g/kg)
0.5	2.3	8.2	16.5
1.0	1.9	8.0	17.2
1.5	1.6	7.9	17.8
2.0	1.4	7.8	18.5
2.5	1.3	7.7	19.0

of application amount, the total salt amount of soil gradually decreased from 2.3 g/kg to 1.3 g/kg, while the pH value decreased from 8.2 to 7.7, and the organic matter content increased from 16.5 g/kg to 19.0 g/kg (Table 3). The results demonstrated a clear dose-dependent trend, which suggested that increasing the application rate within a reasonable range could enhance the amelioration effect, improve soil fertility, and alleviate salinity stress.

Conclusion

This study used a deep belief network (DBN) to comprehensively construct and evaluate a simulation analysis method for the effect of garden waste resource products on saline-alkali land improvement. The results showed that the DBN model could effectively simulate and predict the saline-alkaline soil improvement effect of garden waste resource products under different conditions, providing scientific basis and technical support for the ecological recovery and sustainable use of saline-alkaline land. Garden waste resource products demonstrated significant effects in lowering the total salt content and pH value of the soil, as well as increasing the organic matter content of the soil. The DBN model was able to better capture complex non-linear relationships in the soil improvement process, providing a powerful tool for the optimization of soil improvement measures. Although the proposed DBN-based simulation method achieved good results in predicting the saline soil improvement effect, there were still some shortcomings, which included the limited number of study samples and lacked wider regional representation that might affect the generalization ability of the model. Further, the input variables had not yet covered all the factors that might affect the amelioration effect such as rainfall and soil microbial community structure, *etc*. Furthermore, this study focused on short-term improvement effects and lacked long-term dynamic monitoring and validation, which made it impossible to comprehensively assess the impact of resource products on sustainable soil improvement. Future research should expand the sample area and type, construct a multi-region and multi-type soil database, and improve the adaptability and popularity of the model. More ecological and environmental factors such as soil enzyme activity, microbial diversity, *etc*. should be explored to improve the comprehensive prediction ability of the model. Further, medium- and long-term field experiments should be carried out to assess the long-term effects of garden waste resource products on saline soils including changes in soil fertility, biodiversity, and ecosystem services and verify the effect of sustained improvement in different application modes and time scales, while the Internet of Things and remote sensing technology may be combined to achieve intelligent and visual management of soil improvement and promote the efficient application of resource products in the ecological restoration of saline and alkaline land.

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