RESEARCH ARTICLE

The role of agricultural ecotourism in promoting the development of health industry under the background of deep learning

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With the advancement of the global health industry, agricultural ecotourism has emerged as an innovative tourism model that integrates agriculture, ecology, and public well-being. This study aimed to investigate the role of agricultural ecotourism in promoting the development of the health industry by leveraging deep learning technologies. A multi-dimensional dataset comprising environmental attributes of ecotourism destinations, tourist health profiles, and regional health industry indicators was collected. Deep learning algorithms including MLP, CNN, and LSTM were applied to predict market demand and assess health impacts. The results revealed a strong positive correlation between agricultural ecotourism participation and the demand for health-related products and services, especially among middle-aged tourists in high-quality ecological environments. The findings provided empirical evidence for the integration of agricultural ecotourism and the health industry, offering practical insights for policymakers, local governments, and tourism enterprises to enhance regional health outcomes and sustainable economic development.

Keywords: deep learning; agricultural ecotourism; health industry.

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Introduction

With the rapid development of social economy, the health industry promotes economic growth and improves people's quality of life. Agritourism integrates the new industrial form of agriculture, ecology, and tourism and gradually becomes a force to promote the development of health industry. In the context of urban-rural integration, agricultural ecotourism can promote the modernization and sustainable development of agriculture and provide people with a healthy lifestyle and tourism experience. The application of deep learning technology in various fields has deepened, providing new technical support for the optimization of agricultural ecotourism and the promotion of health industry. In recent years, the application of deep learning technology in many fields has gradually attracted attention.

Einstein *et al*. explored the potential of deep learning in the field of geriatric mental health, emphasizing the technology's ability to process complex cognitive data to provide precise diagnostic support [1]. Estrada-Molina *et al*. systematically reviewed the application of deep learning in open learning and suggested that this technology could promote the transformation of education model and was increasingly widely used in personalized learning path design and adaptive learning systems [2]. In the medical field, AbuSalim *et al*. analyzed deep learning technology in dental informatics and believed that this technology could improve the accuracy of dental diagnosis [3]. Himeur *et al*. discussed the use of deep learning and transfer learning for mask detection in a smart city environment [4]. Aiming at the health industry, Iqbal *et al*. analyzed the application of deep learning in the classification and detection of breast cancer data sets, demonstrating its potential in medical imaging diagnosis [5]. Vasconcelos *et al*. indicated the great potential of deep learning technology in emergency response and disaster prevention in their research on deep learning application in the field of fire detection [6]. In the field of ecotourism, Rosmadi *et al*. discussed how meaningful gamification could promote the awareness of environmental protection in ecotourism, arguing that this method could motivate tourists to participate in ecological protection behavior [7]. Hosseini and Paydar studied the impact of discount and advertising strategies in the ecotourism supply chain and found that appropriate marketing means could effectively enhance consumer engagement and behavior change [8]. Shi and Chen studied the impact of environmental value, face culture, and emotional intelligence on ecotourism intention from the perspective of China, emphasizing the moderating role of emotional intelligence in ecotourism decision making [9]. Wondirad explored whether ecotourism could truly promote sustainable destination development through meta-analysis, revealing the multiple controversies and complexities of ecotourism [10].

This study aimed to evaluate the health benefits of agricultural ecotourism and analyze its contribution to improving population health outcomes. The research proposed a deep learning-based predictive model to optimize the design of agricultural ecotourism related products and enhance their role in driving the health industry by using deep learning technology to collect and analyze relevant data of agricultural ecotourism, which would promote the development of health industry. Environmental data, tourist data, and health industry data related to agricultural ecotourism were used for data pre-processing and cleaning to ensure the accuracy and reliability of data. A variety of deep learning models were constructed, optimized, and evaluated. The best models for analysis and application were then selected [11]. This study provided empirical data and scientific evidence to support policymakers in facilitating the integration of agricultural ecotourism and the health industry.

Materials and methods

Data resources

The data sources of this study included environmental data related to agricultural ecotourism, tourist data, and multi-dimensional data related to health industry. The environmental data collected from the China Meteorological Data Service Center (http://data.cma.cn) including climate, land use, and vegetation indices of agricultural ecotourism sites across five provinces, which provided a basis for analyzing the natural environmental conditions of agricultural ecotourism and its impact on the development of health industry. The tourist data that acquired through structured questionnaires conducted at local agricultural ecotourism sites and archived visitor records provided by tourism bureaus in Mudanjiang, (Heilongjiang, China), Yichun (Jiangxi, China), Dali (Yunnan, China), Anji (Zhejiang, China), and Lijiang (Yunnan, China) and the China National Tourism Data Center (http://www.ctaweb.org) related to basic information about tourists including age, gender, and frequency of travel, travel behavior including activity preferences and engagement, and their health status including physical change and health satisfaction [12]. The health industry related data that were retrieved from China Health Statistics Yearbook published by National Health Commission (Beijing, China) and supplemented with regional health market reports available *via* Wind Economic Database (http://www.wind.com.cn) contained the development indicators of the health industry including the market size of the health industry, the sales data of health products, and the level of public health. Data were collected through on-site questionnaire survey, operation data records of tourist attractions, and health industry development reports. In cooperation with agricultural ecotourism scenic spots, the operation data of scenic spots and the participation of tourists were obtained [13]. The feedback information from tourists was collected by issuing questionnaires and combining with the online platform survey. The contents of the questionnaire mainly focused on the basic information, travel experience, and health changes of tourists. The public reports issued by relevant government departments and industry associations were referred to obtain macro health industry-related data.

Sample selection

The sample selection followed the principle of scientific and misrepresentations, covering different types of agricultural ecotourism regions and various tourist groups. The areas with high development potential of agro-industry were selected, which had relatively perfect agro-industry infrastructure, rich natural resources, and good tourist reception capacity [14]. To ensure the comprehensiveness and misrepresentations of the data, ten agricultural ecotourism scenic spots in five provinces were selected as research samples, which were distributed in different geographical areas including agricultural tourism, agricultural experience, and ecological recuperation types. Various factors were considered during tourist samples selection, which included age, gender, and health status. The sample age distribution of this study ranged from 18 to 65 years old, covering young, middle-aged, and elderly groups [15]. The proportion of males and females involved in this study was relatively balanced, ensuring that the sample was representative of a broad group of tourists [16]. The survey of health status included people with good health status and people with certain health problems, so that the impact of agricultural ecotourism on tourists under different health conditions could be analyzed. This study involved three main categories of data samples including environmental samples from 10 agricultural ecotourism sites, 1,000 tourist response records, and health industry data from five provinces of China. The agricultural ecotourism sites were Jingpo Lake Scenic Area (Mudanjiang) and Wuhua Mountain Agricultural Park (Jixi) in Heilongjiang province, Wuyuan Rural Culture Zone (Shangrao) and Yichun Health Eco-Park (Yichun) in Jiangxi province, Shaxi Ancient Town (Dali) and Lijiang Ecological Leisure Zone (Lijiang) in Yunnan province, Anji Bamboo Forest Retreat (Anji) in Zhejiang province, Dujiangyan Agro-Ecology Demonstration Zone (Chengdu) and Mount Qingcheng Eco-Agriculture Base (Dujiangyan) in Sichuan province.

Data preprocessing and cleaning

There were missing values, outliers, and inconsistencies in the original data. The mean and regression filling methods were used to process the missing data in some fields to ensure the integrity of the data. The outliers were detected using the Box-Plot method, which removed or corrected samples that deviated significantly from normal values [17]. Data consistency checks mainly standardized data formats to ensure that field names and data types of different data sources were consistent. After data cleaning, all variables were standardized and converted to the same dimension to avoid differences between different dimensions affecting subsequent analysis results [18]. The abnormal outliers were further checked and processed by data interpolation or elimination to ensure the validity and rationality of the data set. The processed datasets provided high-quality input for subsequent model construction and analysis.

Model selection

Several common deep learning models were selected to build a model of the relationship between agricultural ecotourism and health industry, which included the multi-layer perceptron (MLP) model, constitutional neural network (CNN), and long short-term memory network (LSTM) model. These models had their own characteristics, modeling and forecasting the promotional effect of agricultural ecotourism on health industry from different angles. The MLP model could effectively capture nonlinear relationships in data and was suitable for dealing with structured data, basic information of tourists, and health status. CNN model was good at processing data with spatial characteristics, extracting effective features from the image data of agricultural ecotourism scenic spots and analyzing the impact of scenic spot environment on tourists' health [20]. The LSTM model had a strong ability to process time series data, which was suitable for analyzing the health changes of tourists in different time periods and modeling the health change trend of tourists in long-term ecotourism activities. By comparing the prediction effect of different models, the deep learning model that was most suitable for the data characteristics and prediction target of this research was determined. The deep learning models used in this study were implemented using TensorFlow 2.11 and Keras (http://www.tensorflow.org). All modeling was performed using servers located at the High-Performance Computing Center, Mudanjiang Normal University (Mudanjiang, Heilongjiang, China).

Model training and optimization

The model was trained by supervised learning and annotated dataset. To improve the accuracy and robustness of the model, a variety of optimization methods were adopted. In the data preprocessing stage, the input data was standardized and normalized to avoid the influence of data of different dimensions on the model training process. The appropriate loss function and optimization algorithm for each model were selected. In the MLP and CNN models, the cross-entropy loss function and the Adam optimizer were used, while the mean square error loss function and the Apropos optimizer were used in the LSTM model. These optimization methods helped the model to converge quickly and avoid over fitting during training. During the training process, the model was iterated several times, each time adjusting the hyper parameters to improve performance. The learning rate, batch size, number of hidden layers, and number of nodes of different models were adjusted in several rounds. In the optimization process, the performance of the model was evaluated by cross-validation method to ensure that the model had good generalization ability. A total of 1,000 tourist demographic and behavior data records with 800 records for training and 200 for validation, 3,000 annotated images of environmental image data including scenic spot images with 2,400 for training and 600 for testing, and 100 series of health industry temporal trend data with 80 for training and 20 for testing from 5 provinces in 5-year sequences were used in this study.

Model tuning process

Various techniques were used to improve the performance of the model in the process of model tuning. The hyper parameters were systematically adjusted by grid search method. The adjusted hyper parameters included learning rate, batch size, number of hidden layers, and number of nodes. Different search scopes were selected for different deep learning models. For MLP and CNN models, the learning rate was adjusted from 0.0001 to 0.01, while, for LSTM models, the learning rate was limited to 0.0005 to 0.002. The optimal training configuration was found by adjusting the parameters of batch size and number of hidden layers. In the process of hyper parameter tuning, early stop technique was adopted to avoid over training of the model. The early stop technique automatically stopped the training when the error on the verification set started to rise, which reduced the over fitting phenomenon. To improve the generalization ability of the model, the data enhancement method was adopted in the training. In the CNN model, the diversity of training data was increased by random clipping, flipping, and rotating, and the robustness of the model was improved.

Selection and application of deep learning algorithm

In specific applications, MLP model was used to analyze the relationship between tourists' basic information and health status, while CNN model was used to extract potential features from the image data of agricultural ecotourism scenic spots, and LSTM model was mainly used to analyze the health changes of tourists in different time periods, especially the impact of a long tourism cycle. Each model had its own advantages, depending on the type of data and analysis objectives. To evaluate the effect of the model, the loss function was used as the standard to measure the performance of the model. For the classification problem, the cross-entropy loss function was chosen, and for the regression problem, the mean square error loss function was used. The loss functions of MLP, CNN, and LSTM were common standards for this type of task. The loss function (*L*) was calculated as follows.

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

where y_i was the true value. $\hat{y}_i$ was the predicted value. *N* was the number of samples. In terms of activation function, Lure activation function was used in MLP and LSTM models, and Zsigmondy activation function was used in CNN model. The activation function (*A*) was shown below.

$$A(x) = 1/(1+e^{-x}) \tag{2}$$

Model evaluation index

To comprehensively evaluate the performance of the constructed deep learning model, a variety of evaluation indicators were selected, which could ensure the accuracy, robustness, and generalization ability of the model and their suitableness for the analysis of the relationship between agricultural ecotourism and health industry. The index of accuracy, precision, recall rate, F1 score, and area under the curve (AUC) value were employed. The accuracy measured the proportion of model predictions that were correct. Precision was used to evaluate the proportion of samples that were positive among the samples predicted by the model. Recall reflected the ability of the model to identify positive samples. The F1 score was the harmonic average of accuracy and recall rate. The balance of the model on positive and negative class sample recognition was evaluated comprehensively. The AUC value represented the overall differentiation ability of the model, and the closer the value was to 1, the stronger the classification ability of the model was. For a variety of models in this study, the cross-validation method was used to comprehensively evaluate the above indicators to ensure the robustness of the evaluation results. The performance of each model's evaluation index under multiple breaks was recorded for the final model selection.

Model verification process

To verify the validity and robustness of the selected model, the model verification method was adopted including the division of training set and verification set and cross-verification. In the training process, 80% of the data was used for training, and 20% of the data was used to verify the effect of the model. The model was adjusted according to the performance of the verification set during the training process, and the model was finally evaluated through the test set after the training. Accuracy was the most used classification evaluation indicator, calculating the proportion of samples correctly predicted to the total sample and was calculated as follows.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

where *TP* was true positive. *TN* was true negative. *FP* was false positive. *FN* was false negative. Recall and F1 scores were also used to evaluate the performance of the model in the case of class imbalance. The recall rate was calculated by the proportion of all positive samples identified by the model as follows.

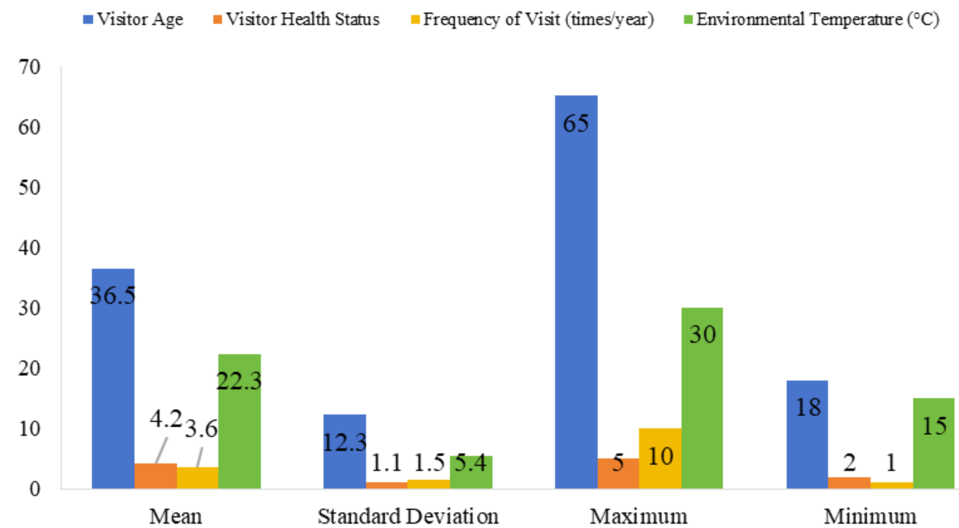

Figure 1. Descriptive statistics of the samples.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

The F1 score was the harmonic average of accuracy and recall as shown below.

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

Results and discussion

Descriptive statistics of data

The descriptive statistics of data mainly summarized the basic characteristics of the sample through the mean value, standard deviation, maximum value, and minimum value indexes. The age, gender, health status, and tourism frequency variables of tourists were statistically analyzed to understand the basic distribution of samples. In terms of health industry data, the market size, product category, and public health status indicators of health industry in different provinces were calculated [19]. For the environmental data of agro-industry areas, the mean and standard deviation of climate and soil quality environmental indicators were calculated to assess the impact on tourists' health and tourism experience (Figure 1).

Results of data analysis

The data distribution analysis in this study focused on several variables related to agricultural ecotourism and the health industry to identify the distribution characteristics of these variables and provide a basis for subsequent modeling and analysis. The age, health status, frequency of visits, environmental quality of scenic spots, and market size factors of the health industry were analyzed. The analysis of tourists' age showed that the majority of tourists were between 25 and 50 years old with the tourists between 35 and 45 years old as the largest proportion. Most of the tourists in this age group were middle-aged and young people with strong health awareness. They had a strong interest in eco-tourism, especially in the context of improving their own health, and were more inclined to participate in agricultural ecotourism activities. A small number of visitors were over the age of 60 with a relatively weak health status and a relatively low frequency of participation in agricultural ecotourism. In terms of health status, most tourists had a high health score, and agricultural ecotourism attracted a more health-conscious group of tourists. Most of the tourists' health scores were above 4 points out of 5, reflecting the tourists' positive attitude towards health management and health promotion. In the distribution of visit frequency, the data

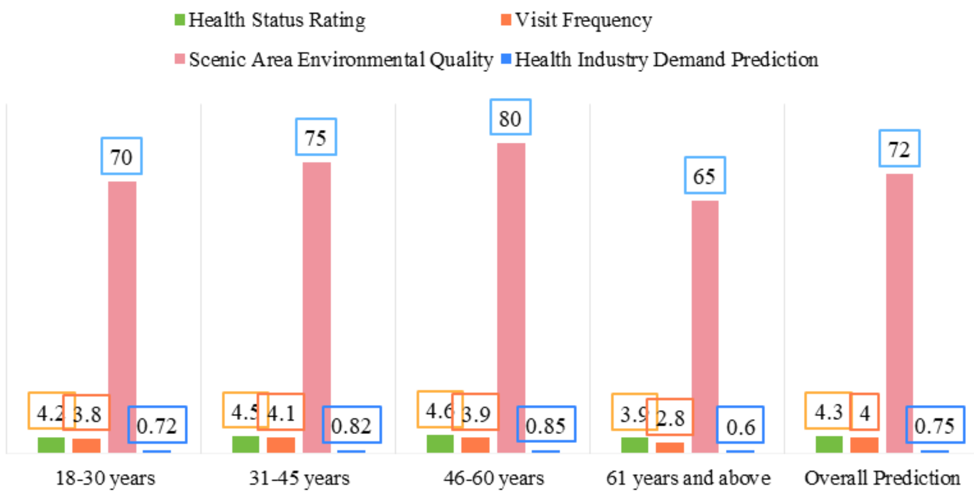

Figure 2. Model prediction results summary.

showed an obvious skewed distribution with a small number of tourists participating in ecotourism at a very high frequency (more than 10 times per year), while the majority of tourists participating at a low frequency, concentrated between 1 and 3 times. Agritourism was highly attractive to some tourists, while most tourists were in a relatively low-frequency state of participation. The age distribution of tourists indicated that individuals aged 35 to 45 constituted the largest proportion of 42.6% followed by those aged 25 to 34 of 31.7%, suggesting that middle-aged adults exhibited the highest participation in agricultural ecotourism. Only 8.2% of respondents were over 60 years old, indicating relatively low engagement among elderly individuals. Regarding health status, 65.4% of respondents rated their health between 4 and 5 on a 5-point scale, showing high self-perceived health levels among participants. The majority of tourists traveled 1 to 3 times annually (58.1%), while only 6.7% exceeded 10 visits per year, reflecting a generally low-frequency travel pattern. As for environmental quality, 71.2% of the evaluated agricultural ecotourism sites scored above 80 out of 100, indicating a high ecological quality, while only 9.3% scored below 60. These findings supported the idea that tourists preferred destinations with better ecological environments, which in turn increased their engagement in health-related consumption, which suggested a strong potential for leveraging environmental quality as a strategic asset in health industry development.

Model prediction results

The predicted results of the model mainly reflected the role of agricultural ecotourism in promoting the health industry and its performance in different tourist groups. The CNN model was used to predict that in various market segments of the health industry (Figure 2). There was a correlation between the participation degree of agricultural ecotourism and the health status of tourists, the frequency of visits and the environmental quality of scenic spots. The health status of tourists had a direct impact on the consumption of health industry, and tourists with better health status were more inclined to buy health products and services. The frequency of tourists' visits and the environmental quality of scenic spots were also closely related to the market demand of the health industry. Tourists who frequently participated in agricultural ecotourism paid more attention to the health industry, and in high-quality ecological scenic spots, tourists' willingness to consume health was significantly enhanced. There were differences in the demand for health industry among tourists of different age groups, and middle-aged tourists of 30 - 50 years old had the strongest demand for health industry. The

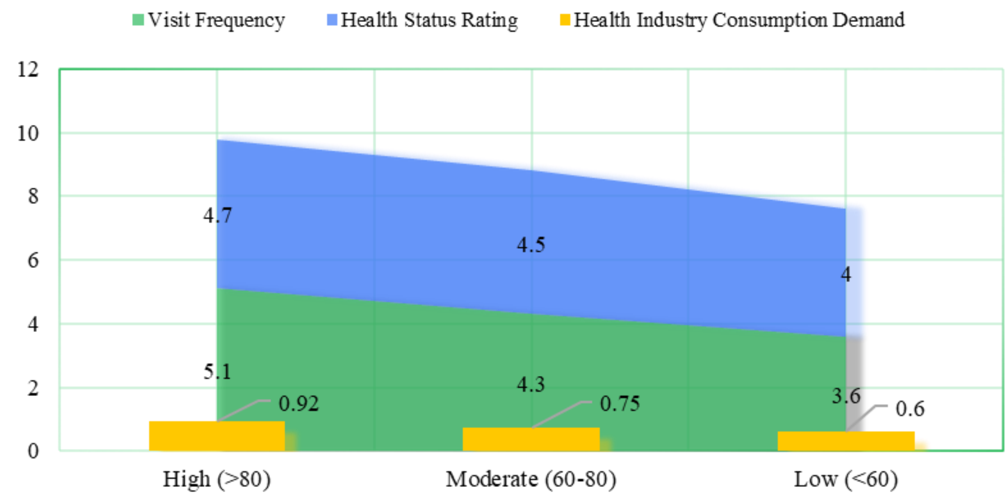

Figure 3. Relationship between agricultural ecotourism and health industry development.

correlation coefficients derived from the CNN model outputs revealed significant associations between the participation in agricultural ecotourism and various health-related variables. Specifically, the Pearson correlation coefficient between scenic environmental quality scores and predicted demand for health products was r = 0.61 ($P < 0.01$). The correlation between visit frequency and health industry engagement was r = 0.54 ($P < 0.05$), while health status scores and demand levels were positively correlated with r = 0.49 ($P < 0.05$). These values substantiated the claim of moderate-to-strong correlations between agricultural ecotourism variables and health industry growth.

Analysis of the relationship between agricultural ecotourism and health industry

Through the analysis of the relationship between agricultural ecotourism and health industry, the study revealed the promotional effect of agricultural ecotourism on health industry. The growth of health industry was closely related to the frequency of tourists participating in agricultural ecotourism and their health status, and tourists with better health status had stronger demand for related health products and services. The results showed that the impact of agricultural ecotourism on the health industry was not limited to product consumption, but extended to service demand such as health management, nutrition guidance, and health tourism (Figure 3). After experiencing the health benefits of the natural environment in ecotourism, tourists tended to continue to pay attention to health-related industries. The consumption potential of tourists in the health industry was positively correlated with their visit frequency and the environmental quality of scenic spots, which verified the effective prediction of the deep learning model to the data. Afro-ecotourism promoted the overall development of the health industry by improving the health level and environmental awareness of tourists, which implied that agricultural ecotourism participation not only reflected tourists' existing health awareness but might also act as a reinforcing driver of continued health-related behavior and consumption, supporting the integration of green tourism with public wellness strategies.

Practical significance and application scenarios of the results

The results of this study provided insight into the integration of agricultural ecotourism and health industry and revealed the role of ecotourism activities in promoting the development of health industry. The age, health status, and environmental quality of tourists directly affected the participation of agricultural ecotourism and the consumption demand of

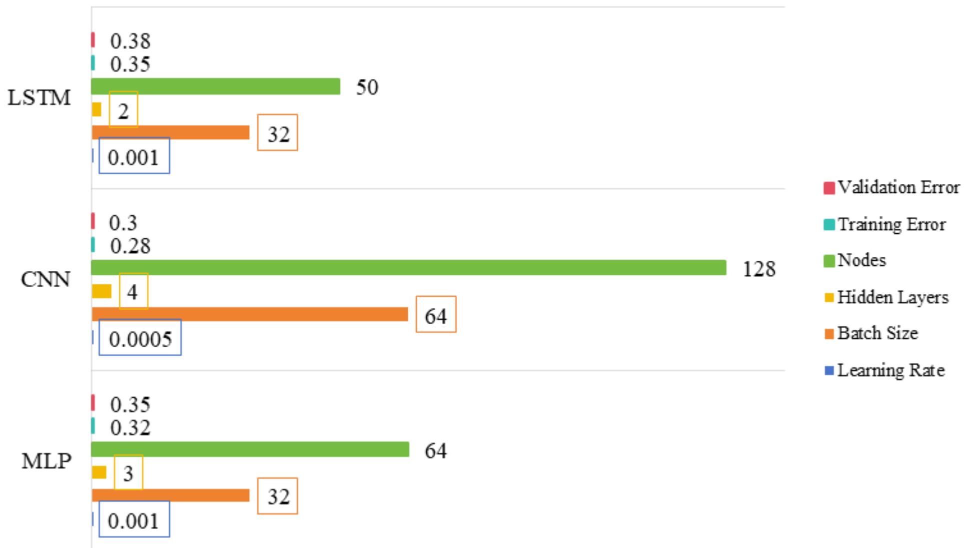

Figure 4. Model parameters and training results.

health industry (Figure 4). The high-quality ecological environment and high health assessment score increased the frequency of tourists' participation and enhanced the market demand of the health industry. In the middle-aged and elderly groups, the demand for health management was relatively strong, which provided a broad market space for the expansion of the health industry. In terms of application scenarios, it provided practical reference for local governments and tourism enterprises. The optimization of scenic environment and the targeted design of health industry products could enhance the participation of tourists and promote the sustainable development of local economy. Health industry enterprises could design more personalized products and services according to the health needs of tourists to improve consumer satisfaction. For health management organizations, in-depth understanding of the health status and changes in needs of tourist groups could help to develop more targeted service strategies. This observation suggested a demographic targeting opportunity for health industry stakeholders, particularly in tailoring services and marketing strategies toward the 30 – 50 age group, who were both health-aware and financially capable. Grid search revealed optimal hyperparameters with a learning rate of 0.001, batch size of 64, three hidden layers, and 128 nodes per layer. These settings ensured convergence and minimized overfitting. The evaluation results showed that the CNN model performed well on several indicators, outperforming other models in accuracy and AUC values, showing stronger classification capabilities and better generalization performance. The evaluation results of MLP and LSTM models also showed better results, which were slightly inferior to that of CNN model. Therefore, the CNN model was selected as the main analysis tool (Figure 5).

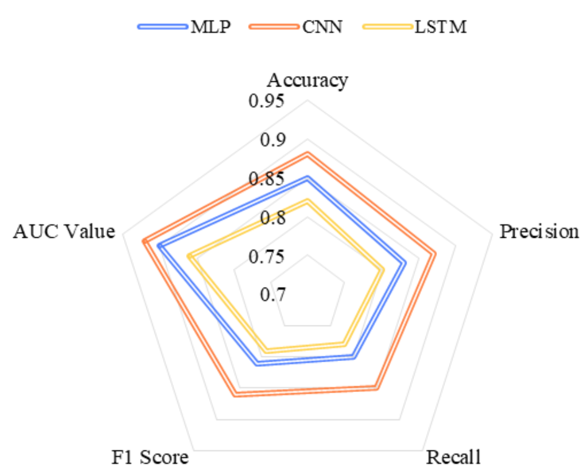

Figure 5. Model evaluation results.

Because the regional differences of the data were large, the participation of agricultural ecotourism in some regions was low, and the misrepresentations of the samples was insufficient, the generalization ability of the model might be affected. In some economically backward areas, the infrastructure of agricultural ecotourism was not perfect, and the participation of tourists was low, which could not fully reflect the development trend of health industry in different regions. There were some limitations in the data sources for the market size of the health industry. The market size data in some regions were incomplete and lacked a unified measurement standard, and the scale of the health industry was difficult to quantify and compare, which affected the accuracy of the research conclusions. The result of model prediction and analysis was limited by the imperfection or inconsistency of relevant data. The deep learning algorithm used in the study had a strong dependence on data, and the data multiprocessing and cleaning work had tried to reduce the interference of noisy data. However, it was still difficult to avoid some potential data bias. In terms of data collection, future research should expand the geographical scope of samples, increase the diversity of data samples, improve the universality of research conclusions, strengthen cooperation with local governments and enterprises, and ensure the acquisition of more representative and accurate health industry data, especially in the quantification of health industry scale and market demand. Further, future research could optimize algorithms for deep learning models to improve adaptability and processing power for different data types. In view of data noise and deviation, data calibration and correction measures should be added to ensure data quality and improve the prediction accuracy of the model. The cross-domain migration ability of the model was also worthy of attention, and the study results should be applied to different countries or regions to conduct cross-cultural and cross-regional comparative studies. Future research should pay more attention to the interaction between agricultural ecotourism and health industry. Combining the behavioral data of tourists, the demand for health management and the supply chain of the tourism industry, this research explored the synergies between the two from a deeper level and explored how agricultural ecotourism could promote the development of the health industry through innovative products and services and promote the growth of local economy. This study demonstrated that agricultural ecotourism could serve as a significant driver of growth within the health industry. The application of deep learning models such as CNN and LSTM allowed for robust predictions and analysis, highlighting that frequent tourist participation, superior environmental quality, and positive health perception were strongly correlated with increased demand for health-related products and services. These findings suggested that agricultural ecotourism not only benefited tourists' well-being but also stimulated market development in health-related sectors, forming a self-reinforcing cycle of ecological and economic sustainability. Despite the limitations in regional data representativeness and health industry measurement, the results offered actionable insights for policymakers and enterprises seeking to promote integrated development. Future research should refine model generalizability and expand data acquisition across broader cultural and geographic contexts to support a more comprehensive understanding of the synergy between tourism and public health.

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