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Research Article

Cultural Creativity, Industrial Scale, Management Methods, and Their Roles in Rural Revitalization from the Perspective of Big Data

Yiqing Huang[1] and Wei Wang[2]

[1]*School of Digital Economy & Trade, Wenzhou Polytechnic, Wenzhou 325000, Zhejiang, China*
[2]*School of Information and Statistics, Guangxi University of Finance and Economics, Nanning 530000, Guangxi, China*

Correspondence should be addressed to Wei Wang; 2020110014@gxufe.edu.cn

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Rural revitalization, as a significant element of the national economy, has become a hot topic at present. The development of digital economies makes big data play become more significant for the national economy. To accelerate the process of rural revitalization, using up big data is vital. To mine the relationship between factors, such as cultural creativity, industrial scale, management methods, and rural revitalization from big data, this study adopts a neural network method. Based on the proposed neural network, a scheme to analyze the relationship between cultural creativity, industrial scale, management methods and the level of rural revitalization is presented. Through case studies, the effectiveness of analyzing the influence of cultural creativity, industrial scale, and management methods on rural revitalization based on big data is demonstrated. Moreover, the results validate that the proposed neural network has good prediction accuracy, which indicates that it is reliable to use neural networks to analyze the relationship between the impacting factors and the rural revitalization level with the assistance of big data.

1. Introduction

The digital economy has become a powerful driving force for national economic growth [1, 2]. Big data is the product of the development of information technology and a new stage of the informatization process, its development is an important factor in the formation and prosperity of the digital economy [3]. So big data technology is vital in national economic development. Economic development is an important element of rural revitalization, so big data technology can accelerate the process of rural revitalization [4]. Currently, big data technology has played a boosting role in many aspects of rural revitalization. It can not only promote the rational management of land resources and the effective use of rural land, but also improve modern agricultural production and efficient circulation of agricultural products. Moreover, big data technology improves the agricultural management efficiency and ability of comprehensive rural governance [5]. Therefore, big data technology is conducive to improving the fusion of artificial intelligence and rural development.

Rural revitalization is affected by many factors, such as culture, economy, management strategies, etc. [6]. Advanced culture is the embodiment of social soft power and the spiritual driving force of social development [7]. So, the development of advanced culture and improvement in the creative level of culture can promote the realization of rural revitalization, which is inseparable from economic development. The economy is the foundation of social development [8]. The development of rural economies can be achieved through the development of land economy and agricultural factories. Among them, the scale of land economies and agricultural factories are important factors affecting the development of rural economies, which is also related to the process of rural revitalization. With the expansion and variety of rural industries, management strategies play an increasingly important role in the process of rural revitalization [9]. In the process of land production and economic crop cultivation, reasonable management strategies can mobilize the enthusiasm of laborers and increase crop yields. In factory production, excellent management strategies can improve product quality and production efficiency and can also reduce the probability of production accidents. Promoting the diversification and targeted development of management strategies is conducive to the full utilization of the labor force and the improvement in production efficiency. Actually, there are more factors affecting rural revitalization, which are not listed in detail here to save space.

Computers have been applied in many areas, and big data technology has realized vigorous development in recent years [10, 11]. Network interconnection, the application of smart products, etc., are generating many data all the time. To analyze the objective development law of corresponding objects with data, big data technology came into being. By analyzing data, big data technology can obtain the intrinsic relationship between the inducement factors and the results [12]. The ability of big data technology to solve the relationship of variables directly through data makes up for the defects caused by insufficient human experience in some fields, which not only makes the analysis results more objective and credible, but also saves a lot of labor costs [13]. In addition, big data technology does not need to establish specific control equations for the analysis object, which broadens the application scope of big data technology, especially in some complex systems or scenarios where it is difficult to construct control equations. For rural revitalization, it is difficult to establish an effective control equation between the various factors and the level of rural revitalization. Moreover, if the importance of each development factor to rural revitalization is evaluated based on expert experience, differences in expert experience can lead to highly subjective results, which is unfavorable for further improving the development strategy of rural revitalization. Considering the aforementioned characteristics of big data technology, it is feasible to establish the relationship between various factors and rural revitalization through big data technology.

To establish the relationship between various development factors and rural revitalization, this study adopts the neural network method [14]. Neural network methods are a branch of big data technology. Compared with other traditional big data algorithms, neural network methods have advantages in data mining. The bigger the size of data, the better the performance of neural network methods, while the performance of traditional big data algorithms tends to be saturated with the increase of data scale [15]. In the process of using the neural network method to establish the relationship between the influencing factors and rural revitalization level, statistical parameters, for example relative error, and correlation coefficient are used to evaluate the accuracy of the mapping relationship established by the neural network method.

This study is organized as follows: Section 1 describes the effect of various factors on rural revitalization and the importance of big data technology in rural revitalization. Section 2 describes the development of related research works on rural revitalization. Section 3 presents the fully connected neural network adopted in this study. Section 4 presents the data preparation for the case study. Section 5 analyzes the feasibility and accuracy of the fully connected neural network according to the results of case studies. Section 6 is the conclusion of this study.

2. Related Work

As a significant element of the national economy, rural revitalization has received national concern over the years.

Since the fast development of computer technology, researchers have applied big data technology to rural revitalization in an attempt to promote the rapid development of rural revitalization. From the perspective of data mining, Zhou [16] built an intelligent platform for macroeconomic analysis in rural revitalization. With the intelligent platform, it is possible to process and analyze data collected by computers. Through data processing and analysis, feature information that characterizes rural revitalization can be extracted from the data. The performance of the proposed intelligent platform is explored by simulation experiments. Considering the development of e-commerce under big data, Xiong and Liu [17] put forward strategies to promote rural revitalization by analyzing the role of e-commerce in rural areas. With the improvement in rural knowledge levels, e-commerce has great development potential in the rural market. One of the reasons is that with the assistance of big data technology, e-commerce can achieve precise marketing. In addition, big data analysis in e-commerce can accelerate the circulation of agricultural products, thereby increasing farmers' income. Therefore, by leveraging the big data advantages of e-commerce, the process of rural revitalization can be accelerated. Influenced by the vigorous development of big data technology in today's era, Zhao et al. [18] analyzed the impact of big data on rural revitalization from three aspects, namely e-commerce, smart agriculture, and rural governance platform. In terms of e-commerce, big data technology enhances the sales efficiency of agricultural products and increases farmers' income levels. In smart agriculture, big data technology enables rural areas to more scientifically manage crops. In terms of rural governance platforms, relying on big data, cadres can obtain information more efficiently, thereby improving work efficiency. By analyzing the application of big data technology in these three aspects, strategies to accelerate rural revitalization are analyzed. To make the concentration of big data in rural revitalization higher, Liu et al. [19] built a big data-driven intelligent platform for rural revitalization. The platform can realize the evaluation, sharing, and real-time monitoring of the rural governance level. At the same time, an efficient data processing technique is adopted for data clustering, thereby improving the accuracy and efficiency of data analysis.

To analyze the impact of cultural creative, industrial scale, and management methods on rural revitalization, Duxbury [20] analyzed the importance of cultural vitality to rural development and discussed how to strengthen rural cultural and creative work through rural creative economy and creative entrepreneurship. Moreover, with big data, Tang [21] analyzed the impact of rural tourism on rural revitalization and used BP neural network to predict the development trend in rural tourism. Based on the results of the BP neural network, the factors affecting the development of rural tourism are analyzed. In addition, the strategies for promoting rural revitalization are also presented.

According to the above description, big data technology has been widely applied to rural revitalization currently. Moreover, many researchers have recognized the importance of cultural creative, industrial scale, and management methods to rural revitalization.

3. Methodology

3.1. Formulation of the Relationship between Factors and Rural Revitalization. Rural revitalization is affected by many factors, such as cultural creativity, industrial scale, and management methods. To explore the importance of each factor to rural revitalization, the relationship formulation is established between factors and the level of rural revitalization, and the expression is as follows:

$$LRR = F(X), \tag{1}$$

where LRR represents the level of rural revitalization, $X = \{x_1, x_2, \ldots, x_n\}$ represents factors that affect the level of rural revitalization. Since the relationship between various factors and the level of rural revitalization is difficult to express through exact functions or empirical formulas, this study attempts to learn the relationship between factors and the level of rural revitalization through the neural network method. With the learned relationship $F(\cdot)$, the importance of each factor to the level of rural revitalization can be inferred, thereby the development scheme of each factor can be improved, and ultimately, the process of rural revitalization can be accelerated.

To establish the relationship between factors and the level of rural revitalization more easily, each factor and the level of rural revitalization are quantified. In this study, percentile scores are used for quantitative processing, and the score interval is set to [0, 100]. That is, the value range of LRR and x_i is [0, 100], $i = 1, 2, \ldots, n$.

3.2. Architecture of the Proposed Neural Network. To learn the relationship between various factors and the level of rural revitalization, this study adopts a neural network method. Neural networks are a branch of big data. With big data, neural networks can extract features of the data and infer the interaction between various variables.

According to equation (1), the purpose of this study is to explore the functional relationship between factor "X" and the level of rural revitalization "LRR." Considering the dimensions of variables X and LRR, this study establishes a fully connected neural network to learn the relationship between X and LRR. The established fully connected neural network is shown in Figure 1. The established fully connected neural network mainly includes fully connected layers, dropout layers, and batch normalization layers. Next, the principle of each network layer and the necessity of its existence are introduced in detail.

3.2.1. Fully Connected Layer. The fully connected layer is the basic network layer in the neural network, and its structure is shown in Figure 2, where $X = \{x_1, x_2, x_3\}$ and $O = \{o_1, o_2, o_3\}$ represent the input and output of fully connected layers, respectively. Input neurons and output neurons of the fully connected layer are all connected by weights, and the weights are gradually updated during network training to maximize the extraction of feature information from the input. Based on these weight connections, the fully connected layer can extract the interaction features between each neuron, thereby obtaining the implicit information contained in the input.

The fully connected layer realizes the mapping from input to output through weight connection, and its mathematical expression is as follows:

$$full_k = f\left(\sum_{n=1}^{N} x_n w_{n,k} + b_k\right), \tag{2}$$

where $full_k$ is the kth neuron output in the output layer, x_n is the input of the nth neuron in the input layer, $W_{n,k}$ is the weight corresponding to the kth neuron in the output layer, b_k is the bias corresponding to the kth neuron in the output layer, and $f(\cdot)$ is the activation function. Sigmoid function and tan$h$ function are frequently used; moreover, rectifier linear unit (ReLU) and exponential linear unit (ELU) are newly emerging activation functions recently [22]. Since the sigmoid function and tan$h$ function have the problem of gradient anomalies, the application of the ReLU function and ELU function is becoming more and more extensive. The mathematical expressions of the ReLU function and ELU function are given in equations (3) and (4), respectively.

$$y = \begin{cases} 0 \ (x \leq 0) \\ x \ (x > 0) \end{cases}, \tag{3}$$

$$y = \begin{cases} \alpha\left(e^x - 1\right)(x \leq 0) \\ x\,(x > 0) \end{cases}, \tag{4}$$

where α is a nonzero constant. Although the ReLU activation function alleviates the problem of gradient anomalies, the output distribution of the ReLU function is not zero-centered, which limits the training speed of neural networks [23]. While ELU is still not equal to 0 when $x < 0$, the output of ELU is closer to the distribution of zero-centered. Therefore, the ELU function can not only alleviate gradient anomalies in the process of neural network training, but also make the output distribution of the network layer close to zero-centered, thereby improving the training efficiency of the neural network. Based on the above analysis, this study adopts ELU as the activation function in each network layer.

3.2.2. Dropout Layer. As can be seen from the structure of the fully connected layer, two neurons in the two adjacent layers are connected by weights, which makes it necessary to

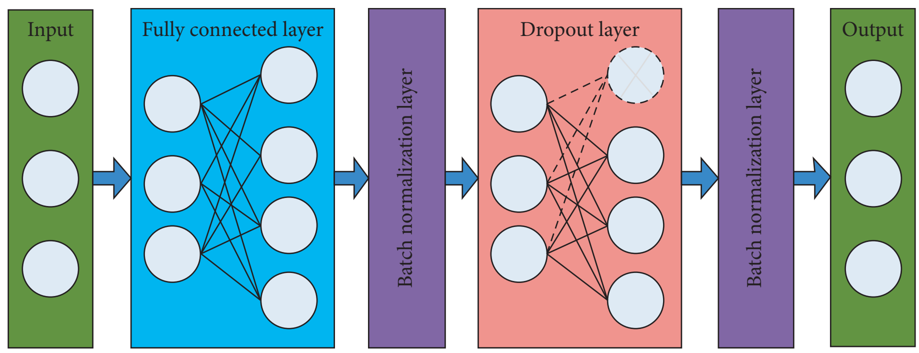

Figure 1: Structure of the established fully connected neural network.

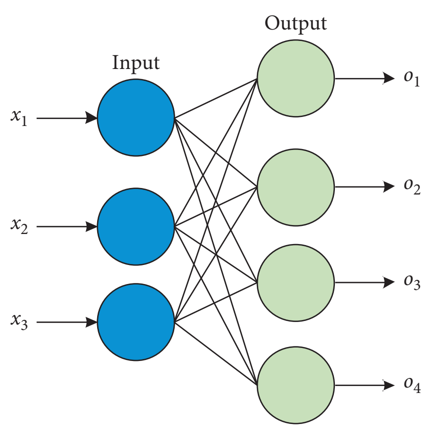

Figure 2: Structure of the fully connected layer.

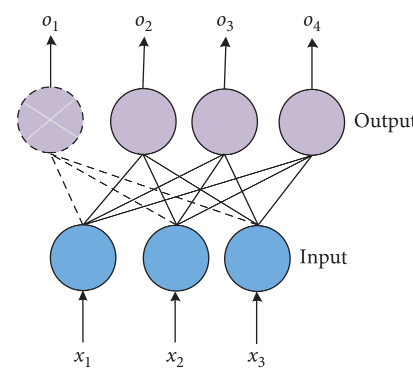

Figure 3: Structure of the dropout layer.

learn numerous parameters during the neural network training process, which increases the training cost, and the overfitting phenomenon may also occur [24]. To improve the training efficiency of the network and suppress the overfitting phenomenon in the network training process, this study adds a dropout layer to the fully connected neural network. Actually, the dropout layer in this study is a fully connected layer with dropout rules applied. The structure of the dropout layer is shown in Figure 3, which corresponds to the scenario of applying dropout in the output layer. Comparing Figures 2 and 3, it can be seen that the dropout rule deactivates some neurons in the output layer. Note that after applying the dropout rule, the deactivation of neurons is random, and the number of deactivated neurons can be adjusted by setting different dropout hyper-parameters.

According to the characteristics of the dropout layer, some neurons will be deactivated in each training step, which reduces the time of each training step. Moreover, by randomly deactivating neurons, uncertainty information in the input can be extracted, thereby improving the generalization performance of the trained neural network.

3.2.3. Batch Normalization Layer. Based on the characteristics of the ELU function, although the output of each network layer basically meets the zero-centered distribution, the output may still be very large, which may lead to gradient explosion during network training. To cope with gradient explosion, this study adds a batch normalization layer between every two fully connected networks. The mathematical expression of the batch normalization layer is as follows:

$$\mu_{\mathrm{B}} = \frac{1}{m}\sum_{i=1}^{m} x_i, \tag{5}$$

$$\sigma_{\mathrm{B}} = \frac{1}{m}\sum_{i=1}^{m} \left(x_i - \mu_{\mathrm{B}}\right)^2, \tag{6}$$

$$\widehat{x}_i = \frac{x_i - \mu_{\mathrm{B}}}{\sqrt{\sigma_{\mathrm{B}}^{\ 2} + \varepsilon}}, \tag{7}$$

$$BN_i = \gamma\widehat{x} + \beta, \tag{8}$$

where $\mathbf{B} = \{x_1, x_2, \ldots, x_m\}$ represents the input of the batch normalization layer, $\mu_{\mathbf{B}}$ and $\sigma_{\mathbf{B}}$ represent the mean and variance of the vector $\mathbf{B}$, respectively, ε is a positive number close to 0, which is used to ensure that $\sigma_{\mathbf{B}} + \varepsilon > 0$. γ and β are parameters to be trained in the batch normalization layer, and BN_i represents the ith output of the batch normalization layer. Equation (7) performs normalization on vector $\mathbf{B}$, whose output is a vector with mean 0 and variance 1.

With the batch normalization layer, the input of each fully connected layer is a standard normal distribution. As indicated in Reference [25], the standard normal distribution is more suitable for network training, so batch normalization layers improve the training efficiency of the fully connected neural network.

3.3. Training of the Established Fully Connected Neural Network

3.3.1. Data Processing Methodology. In this subsection, the methodology of data processing is introduced to better illustrate the following neural network training process. When applying the neural network method to learn the relationship between factors and the level of rural revitalization, big data is needed. For the obtained rural revitalization-related data, the level of rural revitalization and its influencing factors, cultural creativity, industrial scale, management methods, etc., are presented in this study in percentile scores. Before using the collected data as the input of the neural network, data processing is required, because when the input of each network layer of the neural network is normally distributed, the network training can achieve higher efficiency [25].

In this study, the Z-score standardization method is used to standardize the data corresponding to each factor. The mathematical expression for normalizing the data is as follows:

$$N = \frac{X - \mu}{\sigma}, \tag{9}$$

where $X = \{x_1, x_2, \ldots, x_n\}$ represents the score corresponding to each factor, μ is the mean of the vector X, and σ is the standard deviation of the vector X. After Z-score standardization, the processed data obey the standard normal distribution.

3.3.2. Training of the Established Fully Connected Neural Network. After data processing, the distribution of the data is a standard normal distribution. Next, the established fully connected neural network can be trained based on the processed data.

In this study, the back-propagation algorithm [26] is used to train the network. The training steps of the network are mainly divided into four steps: first, calculating the loss function of the neural network based on the forward propagation algorithm. In this study, the mean square error (MSE) function is used as the loss function of the established neural network. The mathematical expression of MSE is

$$MSE = \frac{1}{N} \sum \left(y_{\text{pre}} - y_{\text{real}}\right)^2, \tag{10}$$

where y_{pre} and y_{real} represent the neural network prediction and the real rural revitalization level, respectively, and N represents the number of samples; second, calculating the gradient of the loss function to the trainable parameters based on the chain rule; third, updating trainable parameters in each network layer; and finally, repeat step (1) to step (3) until the prediction result of the neural network meets the preset accuracy or reaches the maximum training epochs.

3.4. Scheme for Predicting the Level of Rural Revitalization. Based on the above description, this subsection presents a scheme for predicting the level of rural revitalization, and its flowchart is depicted in Figure 4. The specific details are as below:

(i) Data collection and data processing. Since the collected data reflecting various factors and the level of rural revitalization may have missing data or inappropriate ranges, which will affect the training efficiency of the neural network, data processing is necessary.

(ii) Division of the processed data. The processed dataset is divided into the training set, validation set, and testing set. Among them, the training set and validation set are used for training the neural network; the testing set is used to evaluate the generalization performance of the trained neural network.

(iii) Training of the neural network. The neural network is trained and evaluated based on the divided dataset.

(iv) Prediction of rural revitalization level. First, the newly collected data reflecting various factors are processed. Then, the newly processed data are input to the trained neural network, and its output is recorded as the rural revitalization level corresponding to these factors.

4. Case Study

To explore the effectiveness of the fully connected neural network proposed in this study in predicting the level of rural revitalization, an experiment is conducted using the survey results of a city as a dataset.

The variables in the collected data mainly include three impacting factors affecting rural revitalization and the level of rural revitalization, which are cultural creativity, industrial scale, and management methods. To analyze the relationship between these three factors and the level of rural revitalization, the data corresponding to these three factors are prepared as the input of the proposed neural network, and the level of rural revitalization is utilized as outputs of the proposed neural network.

According to the description in Section 3.4, first, data processing is performed on the collected data. During the survey, the data collected included the development status of many villages. For convenience, these villages are divided into 20 regions based on the distance from the city center "d," that is, 20 datasets are obtained. Each dataset contains 700 samples, and each sample contains 4 variables, which can quantify the levels of rural revitalization and its influencing factors of a village. The variables in samples are composed of (x_1, x_2, x_3, and y), where x_1, x_2, and x_3 represent the quantitative scores of cultural creativity, industrial scale, and management methods, respectively, and y represents the quantitative score of rural revitalization level. After data processing, the data distributions corresponding to the three factors are all standard normal distributions. Second, the

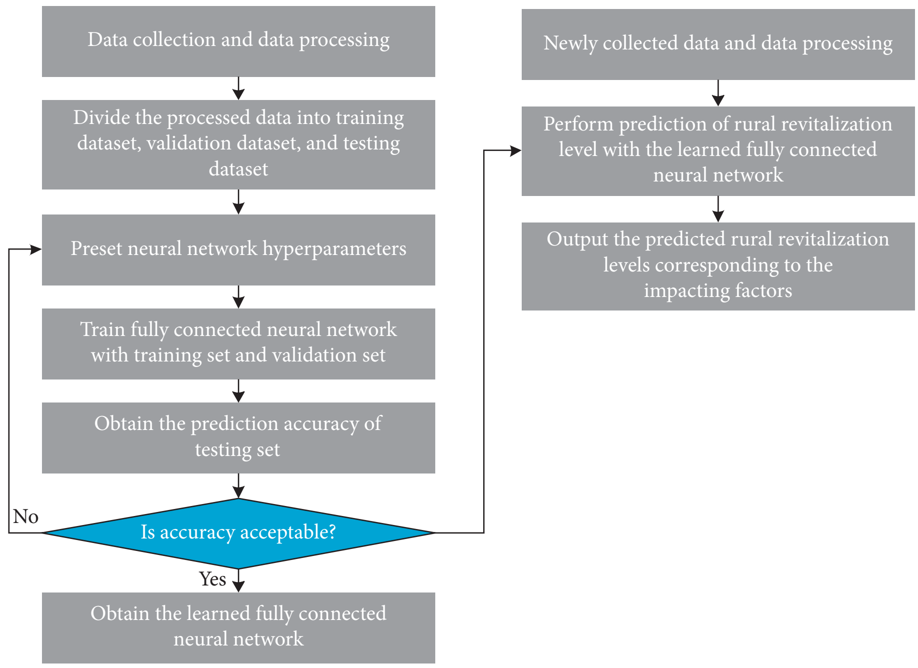

Figure 4: Flowchart of predicting the level of rural revitalization based on the proposed neural network.

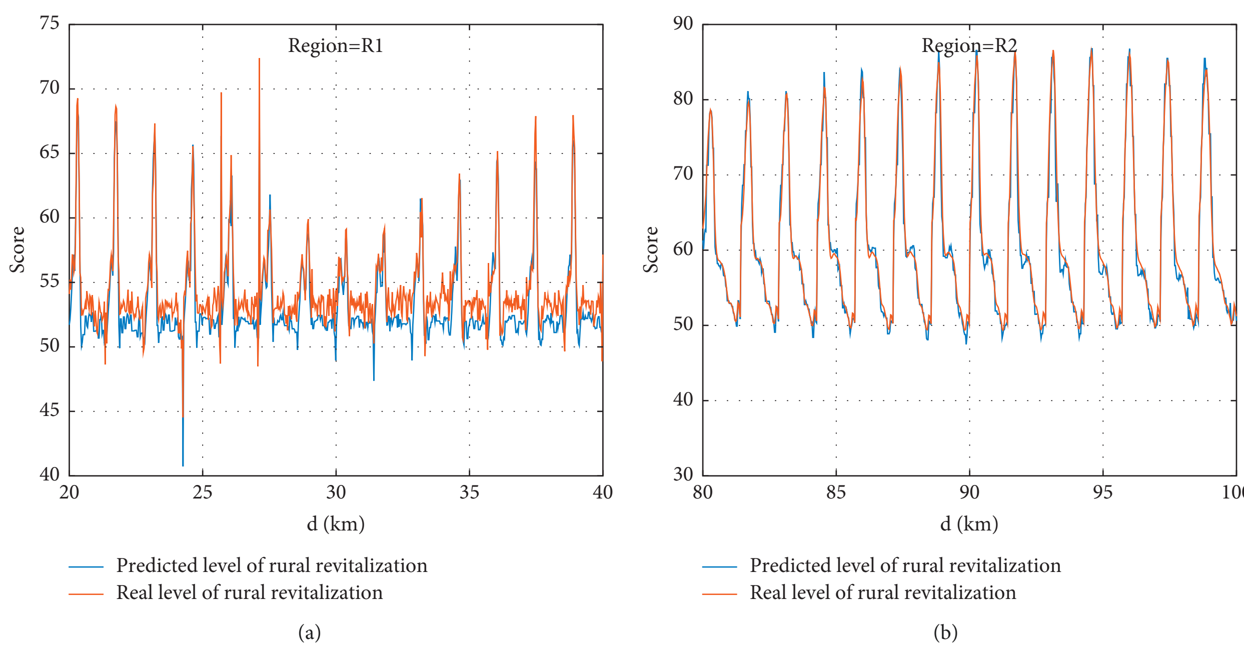

Figure 5: Comparison of neural network predicted and real rural revitalization levels in different regions.

processed data are divided into the training set, validation set, and testing set, which contain 16, 2, and 2 datasets, respectively. Besides, the hyper-parameters of the fully connected network are set as [100, 100, 0.5], where the first two "100" represent the number of neurons in fully connected layers, and 0.5 is the probability in the dropout layer. Based on the divided datasets and preset hyper-parameters, the training and performance evaluation of the proposed neural network can be performed.

5. Results and Discussion

5.1. Evaluation of the Performance of Proposed Neural Networks. Based on the training results of the neural network, this section analyzes the effectiveness of the proposed neural network for fitting the relationship between the impacting factors and the level of rural revitalization.

Under the two regions of R1 and R2 in the testing set, the rural revitalization level predicted by the neural network and the real rural revitalization level are depicted in Figure 5,

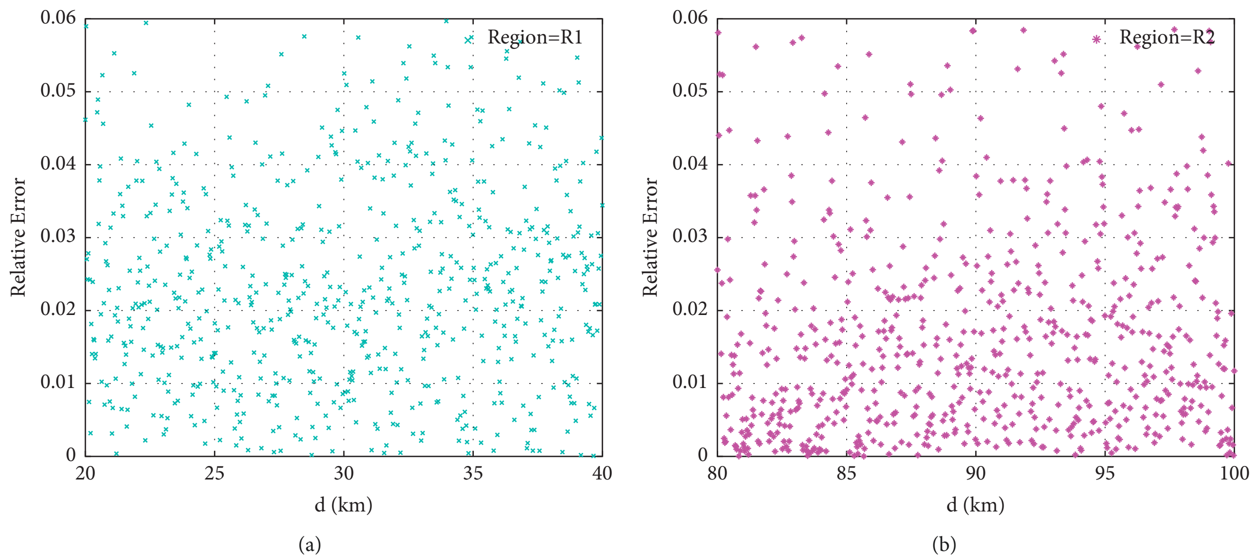

FIGURE 6: Relative errors between the neural network predicted and real rural revitalization levels in different regions.

where the Score represents the quantitative score of the rural revitalization level, and the horizontal axis "d" represents the distance between the village and the center of the city. Figure 5 shows that the neural network can predict the rural revitalization level in each region well. Moreover, Figure 6 shows the relative errors between the neural network predicted and real rural revitalization levels in the R1 and R2 regions, and the mathematical expression for the relative error is as follows:

$$\mathrm{RE} = \mathrm{abs}\left(y_{\mathrm{pre}} - y_{\mathrm{real}}\right)/y_{\mathrm{real}}, \tag{11}$$

where y_{pre} and y_{real} represent the neural network predicted and real rural revitalization levels, respectively, and abs(·) denote the operation to obtain the absolute value. It can be seen from Figure 6 that the relative errors between the predicted and real rural revitalization levels are mostly within 5% in both regions. The result indicates that the predicted and real rural revitalization levels are in good agreement.

Figure 7 shows the average relative errors between the predicted and real rural revitalization levels, and the average relative error is the mean of relative errors in Figure 6. It can be seen that in both R1 and R2 regions, the prediction error of the neural network is less than 2.53%, and even in the $R2$ region, the average relative error value reaches 1.78%, which shows that the trained neural network still has good predictive performance on the testing set. There are differences in the prediction accuracy of neural networks in different regions, it can be explained as follows. Due to geographical location, there may be some differences in the development characteristics of villages in different regions, and there may be certain errors in data collection.

According to the above analysis, the rural revitalization level predicted by the proposed neural network is in good agreement with the real level, which shows that the neural network can well analyze the relationship between the impacting factors and the level of rural revitalization. Therefore, the corresponding level of rural revitalization can be well inferred with the impacting factors by applying the proposed neural network.

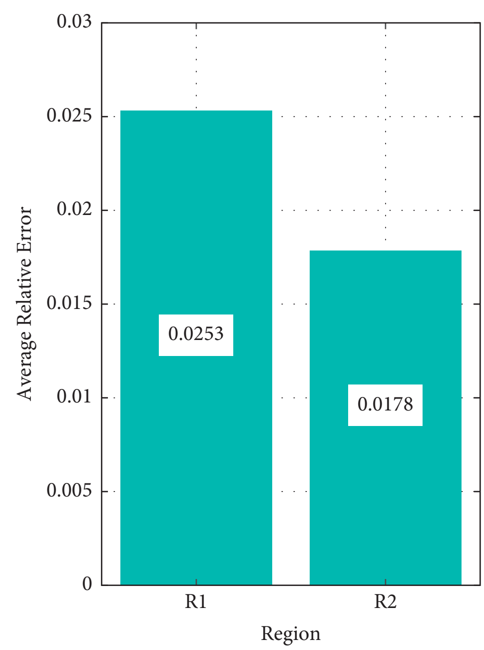

FIGURE 7: Average relative errors between neural network predicted and real rural revitalization levels in different regions.

5.2. Statistical Analysis. To further verify the performance of the proposed neural network in predicting the rural revitalization level according to the impacting factors, the statistical analysis of results on the testing set is carried out in this subsection. The statistical indicators analyzed are MSE and linear correlation.

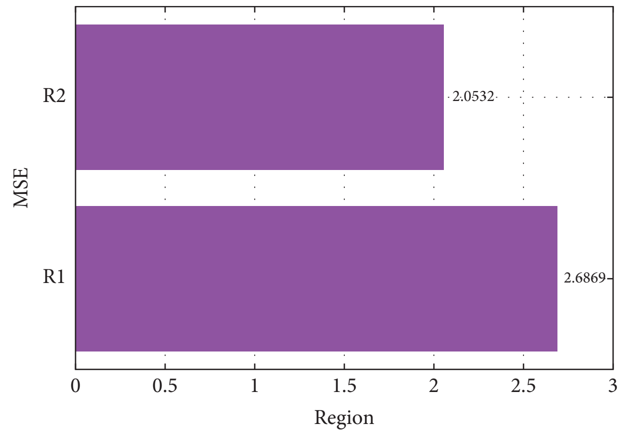

Figure 8: MSE between neural network predicted and real rural revitalization levels in different regions.

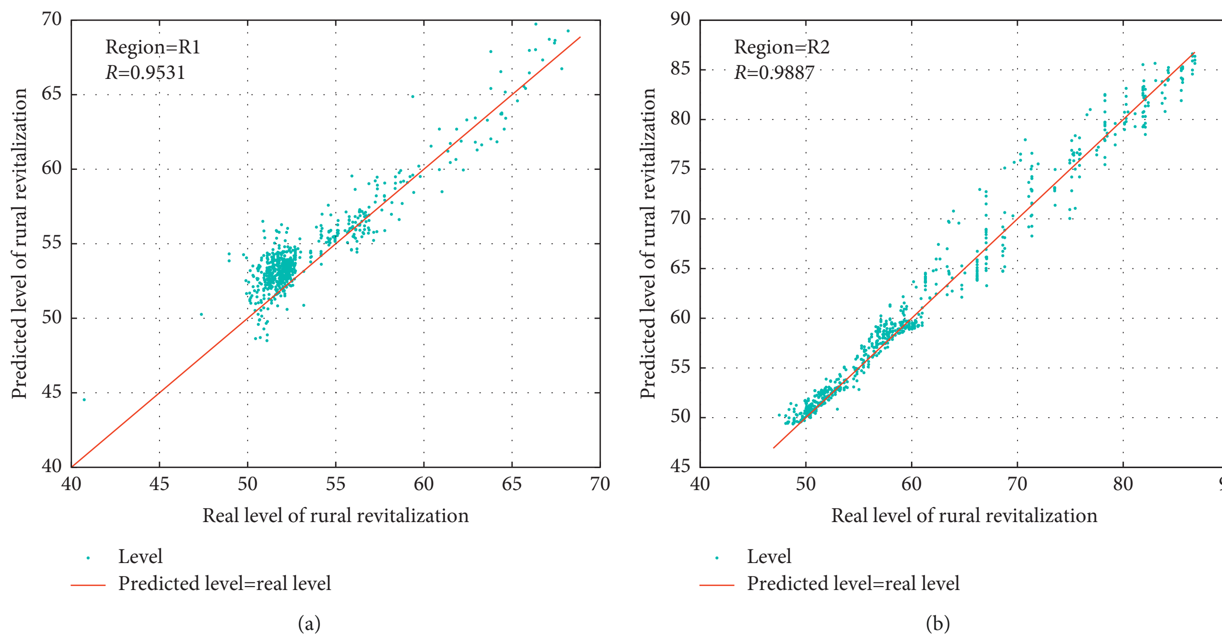

Figure 9: Linear correlations between neural network predicted and real rural revitalization levels in different regions.

In the testing set, the MSE indicators between the rural revitalization level predicted by the neural network and the real level under regions R1 and R2 are displayed in Figure 8. In this figure, MSE values corresponding to two regions R1 and R2 are all less than 2.6869, and the calculation formula of the MSE is equation (10). Since the score range of rural revitalization levels is [0, 100], the MSE in Figure 8 shows that the gap between the neural network predicted and the real rural revitalization level is small.

The linear correlation is further analyzed to explore the gap between the predicted and real rural revitalization levels. To show the correlation between the predicted and real rural revitalization levels more intuitively, Figure 9 shows the distribution of the predicted and real rural revitalization levels and the line of $y = x$. It can be seen that points corresponding to the predicted and real levels are very close to the line of $y = x$. Moreover, the correlation coefficients between the predicted and real rural revitalization levels are also presented in Figure 9. The correlation coefficients corresponding to the two regions R1 and R2 are 0.9531 and 0.9887, respectively. The calculation results of the correlation coefficient further show that there is a strong correlation between the neural network predicted and real rural revitalization levels.

According to the statistical analysis of the results, it is further confirmed that the proposed neural network has good performance in predicting the level of rural revitalization according to the impacting factors.

6. Conclusions

This study focuses on analyzing the relationship between factors, such as cultural creativity, industrial scale, management methods, etc., and the level of rural revitalization in the background of big data, and deduces the importance of each impacting factor to rural revitalization according to the results. This study proposes a fully connected neural network. With a case study, the performance of the proposed neural network in predicting the level of rural revitalization based on impacting factors is analyzed. The obtained results are summarized below.

Comparing the neural network predicted and real rural revitalization levels, in the R1 and R2 regions corresponding to the testing set, relative errors between the predicted and real rural revitalization levels are mostly within 5%, and average relative errors corresponding to these two regions are at most 2.53%. The comparison results show that the rural revitalization level predicted by the proposed neural network is in good agreement with the real level.

According to the statistical results, in both R1 and R2 regions, the mean square errors between the neural network predicted and real rural revitalization level are both less than 2.6869. Moreover, the linear correlation coefficients corresponding to the two regions are 0.9531 and 0.9887, respectively, and the points corresponding to the predicted and real levels are very close to the line of $y = x$. Hence, the statistical analysis results further indicate that the proposed neural network has good performance in predicting the level of rural revitalization according to the impacting factors.

Therefore, according to the results of case studies, the proposed neural network can well analyze the relationship between factors, such as cultural creativity, industrial scale, management methods, etc., and the level of rural revitalization in the background of big data. Ultimately, with the proposed neural network, the importance of each factor to rural revitalization can be obtained.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have conflicts of interest or personal relationships that could have appeared to influence the work reported in this article.

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