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Assessment of the Exterior Quality of Traditional Residences: A Genetic Algorithm–Backpropagation Approach

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Abstract: The visual aesthetics of villages are remarkably affected by the exterior quality of traditional residences, influencing the impression and assessment of local culture. A proper scientific assessment of exterior quality can protect traditional cultures and improve the development of villages. This research was conducted in a village consisting of 115 residences (Mengjinglai village, which is on the border between China and Myanmar). The backpropagation (BP) neural network model with genetic algorithm (GA) was applied to evaluate the quality of the dwellings. All the evaluation values of the dwellings were defined by scores. Meanwhile, the score of each residence was affected by three main factors: architectural spatial elements, architectural construction elements, and historical and cultural elements. The results show that the village's dwellings are well preserved and clearly express the traditional Dai style. Moreover, the GA–BP approach is more suitable than the traditional BP method for the assessment of the exterior quality. The quantitative machine learning model would be useful for other aspects of the assessment of similar villages in the future.

Keywords: traditional village; exterior quality assessment; GA–BP neural network model; residential conservation

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1. Introduction

Traditional villages are settlements that possess cultural heritage in both tangible and intangible forms and have strong historical, cultural, scientific, artistic, social, and economic values. With the rapid development of global industrialization and urbanization, the phenomenon of the decline and disappearance of traditional villages is intensifying, and to resist this, it is necessary to strengthen their conservation and development [1]. Although efforts to preserve the heritage of traditional villages are gradually increasing, there is also a need for more innovation in theoretical research and research methods [2]. The conservation of traditional villages involves changes in spatial patterns, social and cultural loss, the ecological deterioration of landscapes, the loss of populations, the preservation of vernacular architecture habitats, and the development of traditional cultural and social relations [3]. Therefore, the conservation and development strategies, renewal strategies, and value assessments of traditional villages have gradually become areas of concern for scholars [4].

Interpreting, measuring, quantifying, and delineating the value of traditional villages, and determining weights, make this a relatively complex issue for scholars. Thus, traditional village evaluation has a strong component of interdisciplinary research, including architecture, urban and rural planning, geographic science, sociology, tourism, and statistics [5]. Most of the current research on village value-assessment systems for evaluation purposes is based on merit assessment and graded protection. The evaluation methods have gradually developed from mainly qualitative to combining some quantitative methods, such as hierarchical analysis, the entropy weight method, the Delphi method, the fuzzy evaluation method, and the material element analysis method [6]. In addition, artificial intelligence has been applied in various fields, and machine learning, one of the branches of artificial intelligence, is capable of supervised learning for the evaluation of the architectural quality of traditional villages. However, building quality is influenced by a combination of influencing factors and is not in a purely linear relationship, while neural networks are suitable for processing non-linear information problems influenced by multiple factors [7]. Therefore, the use of neural networks is suitable for the comprehensive evaluation of the quality of traditional buildings.

The BP neural network is a multilayer feed-forward network with a multilayer neural network structure that is more mature than traditional neural networks in theory and application. It is widely used, but also has disadvantages, such as its easy formation of local minimum and no global optimum, low efficiency, slow convergence rate, etc. [8]. Therefore, the optimization of neural networks is receiving increasing attention. Among various optimization methods, GA has the advantages of better global search capability, fast solution space search, and strong robustness [9]. Since a single genetic algorithm code does not fully represent the constraints of the optimization problem, the solution needs to be considered using thresholds, which in turn increases the workload and solution time [10]. In order to fully circumvent the above disadvantages, GA and BP are combined to take advantage of each other's strengths and learn from existing research achievements to identify improved solutions. Gonzalo combined the supervised and unsupervised optimization of genetic algorithms to assess the quality of water over five years, determine quality classes, and demonstrate confidence [11]. Zhang proposed an optimization method based on genetic algorithms combined with the energy requirements in classrooms and applied it to a school building [12]. Yousef investigated a BP neural network classifier for extracting the external quality features of dates and grading and ranking them accurately by date [13]. Lin applied GA–BP to knowledge-fusion risk assessment, constructing an innovative ecosystem knowledge-fusion risk-assessment index system, thereby providing a new practical approach [14]. Li applied GA–BP to assess the risk of tunnel cavern surge and tunnel karst [15]. Zhu compared GA–BP with PSO–BP and the initial BP neural networks to assess the risk of rainfall-induced landslides [16]. Dai used the AHP–FCE and GA–BP methods to assess an intelligent learning environment in higher education and concluded that the GA–BP model could simplify the assessment process and improve fault tolerance [17].

A genetic algorithm is an adaptive search algorithm, proposed by J. H. Holland in 1975, that is able to find optimal solutions in a global space [18]. The optimal network weights and thresholds are used as the initial network models, which can not only overcome the problem that the prediction results of the traditional BP neural networks are easily influenced by initial weights and thresholds and easily fall into the local optimum, but also greatly improve the accuracy of model evaluation [19]. The GA–BP neural network shares the advantages of both the global convergence of GA and the local search of BP, which can significantly improve the performance of the neural network model. The GA–BP model guides the sensitivity to the initial values of weight and thresholds, which may reduce the influence of human subjectivity to a certain extent, and serves as a reference for other scholars to apply the neural network in the field of village assessment. Therefore, the GA–BP neural network model can be applied to effectively evaluate the quality of traditional residential buildings using the connection weights optimized by the genetic algorithm [20]. It is clear from the aforementioned literature that GA–BP is applicable to quality rating assessments, except that there is a large gap in current research on external quality, particularly that of traditional buildings. This study focuses on an assessment of Mengjinglai village in Yunnan province as a case study, constructs an evaluation index system applicable to the traditional architecture of this village, and applies the GA–BP neural network model to conduct a comprehensive evaluation of the exterior quality.

2. Materials and Methods

2.1. Study Area

The dynamic distribution of the external building evaluation results enables more challenging and more accurate verification of artificial intelligence assessment methods. On the border between Yunnan Province and Myanmar, there are a number of villages with a mixture of architectural cultures. Mengjinglai village, known as the "The First Village of China–Myanmar", is rich in cultural features and has both traditional and modern architectural forms. Mengjinglai village is located within the jurisdiction of Daluo Town, Menghai County, Xishuangbanna Dai Autonomous Prefecture, Yunnan Province, across the river from Myanmar, with a village area of approximately 5.6 km^2 and a total of 115 households [21,22]. The village is surrounded by mountains on all sides, is situated close to water sources, and features a beautiful natural environment. The terrain is a low-mountain hilly area, and the climate is characterized by a typical northern tropical climate. In order to adapt to the hot and humid natural environment, the Dai people have developed unique stilt-style architecture (Figure 1).

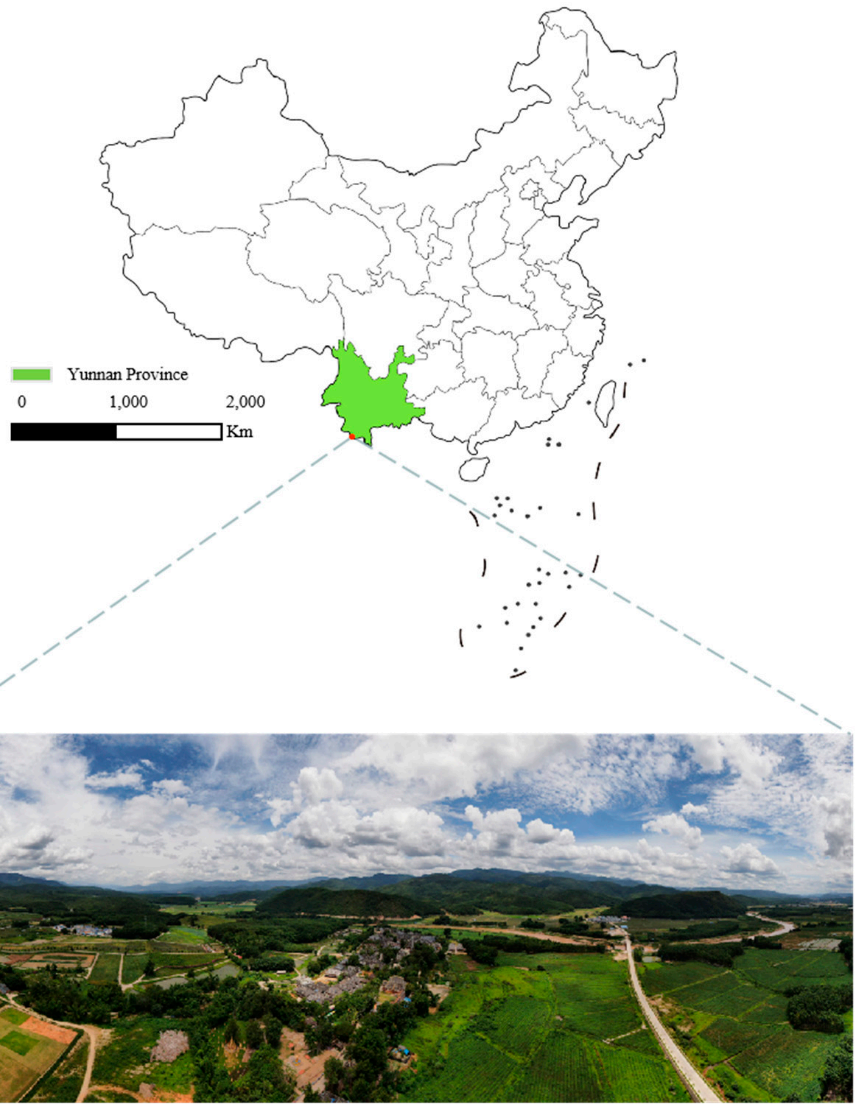

Figure 1. Location of Mengjinglai village in Yunnan, China.

Mengjinglai is typical of traditional Dai villages, whose populations have historically had frequent contact with Burmese residents and intermarried with them, creating a rare form of mixed settlement. The buildings in the village are all built according to the terrain, with an overall fan-shaped distribution. The layout of the village harmoniously unites human architecture with nature, forming a unique architectural style [23].

2.2. Data Sources

The rural settlement data used in this study consisted mainly of remotely detected image data, and economic, demographic, and historical village information data [24]. Satellite map data of Mengjinglai village were obtained through Google Earth Engine. Economic and population data were obtained from the Menghai County Statistical Yearbook and the monthly report of the Bureau of Statistics on the Menghai County People's Government website. Information on the history of Mengjinglai village was obtained from Menghai County Records [25]. Photographs of buildings, water systems, mountains, roads, interior spaces, and other details were obtained by the author through fieldwork in 2021 (Figure 2). During the site survey, each of the 115 traditional residences was scored and the actual condition of the architectural space, the architectural constructional elements, and the historical and cultural elements were recorded (Table 1).

Figure 2. Selected photographs of traditional residences.

Table 1. Construction of an exterior quality assessment indicator system.

Primary Indicators	Secondary Indicators		Scoring Criteria			References
			1 Point	2 Points	3 Points	
A—Architectural spatial elements	A1	Void deck	Substantial replacement of timber-frame materials with modern materials and untidy interiors	Partly timber-framed materials and largely furnished interiors	Complete with timber-frame materials and well-furnished interior of the space	[26]
	A2	Landscape space	The interior and exterior are largely devoid of landscaped surroundings	Interior and exterior design with partially landscaped surroundings	Interior and exterior design with good landscape setting	[27]
	A3	Interior space	Less use of timber-frame materials, confusing interior layout, and poor lighting and ventilation	Partly timber-framed materials, average interior layout, average lighting and ventilation	Well-preserved timber-frame materials, good interior layout, good lighting and ventilation	[28]
B—Architectural construction elements	B1	Building materials	The materials used are heavily influenced by the overall Dai style of the dwelling	The materials used have a lighter influence on the overall Dai style of the dwelling	The materials used largely do not detract from the overall Dai style of the dwelling	[29]
	B2	Architectural form	A lighter representation of the characteristic Dai style of dwelling	A larger display of the characteristic Dai residential style	A full display of the characteristic Dai style of dwelling	[30]
	B3	Roof frame	Traditional materials are less well preserved and more rarely used	General conservation, mostly in traditional materials	Well-preserved and largely traditional materials	[31]
C—Historical and cultural elements	C1	Architectural style	Fairly well preserved and not very in keeping with the style of the village	More uniformly preserved and in keeping with the style of the village	The overall architectural style is uniform and in complete harmony with the village	[32]
	C2	Cultural value	Has fewer cultural elements	Has general cultural elements	Has significant cultural elements	[33]
	C3	Historical value	Has fewer historical elements	Has general historical elements	Has very strong historical elements	[34]

2.3. Exterior Quality Evaluation of Traditional Residences and Value Grading

The 115 dwellings in the village, which generally include the typical buildings of Mengjinglai village, were selected for rating. The reaction to the quality of the appearance of traditional buildings is the most direct response of visitors and researchers. The ratings of village dwellings were judged to facilitate quick improvements in the image of villages [35]. Therefore, this study focuses on the architectural methodology proposed by İpekoğlu to assess the exterior characteristics of buildings, with some adaptations, by integrating indicators of Dai elements, depending on where on the border the Mengjinglai village buildings were located [36]. After scoring each indicator, the exterior characteristics of the traditional dwellings were calculated using the entropy method to find the desired value.

According to the results of the field surveys, data collection, expert consultations, indicators, and grades, the quantitative value classifications of traditional rural dwellings were determined based on their location in Mengjinglai village. The three main indicators were: architectural spatial elements (A), architectural construction elements (B), and historical and cultural elements (C). The nine secondary indicators were: void deck (A1), landscape space (A2), interior space (A3), building materials (B1), architectural form (B2), roof frame (B3), architectural style (C1), cultural value (C2), and historical value (C3). The values of the traditional buildings were quantified in a comprehensive way using the corresponding scoring criteria (1–3 points). The quality of the buildings was divided into 4 levels: (1) Grade I: top 10% of the residential dwellings, indicating very high quality; (2) Grade II: top 20% of the residential dwellings, indicating high quality; (3) Grade III: top 30% of the residential dwellings, indicating fair quality; (4) Grade IV: top 40% of the residential dwellings, indicating poor quality [6].

According to the evaluation samples and indicators of the exterior quality of the traditional residences, let X_{ij}, $i = 1, \ldots, 115;\ j = 1, \ldots, 9$, denote the jth indicator of the ith dwellings. First, we standardize nine indicators in order to eliminate the impact of the dimension and the different variation results in

$$Y_{ij} = \frac{X_{ij} - min\left(X_j\right)}{max\left(X_j\right) - min\left(X_j\right)} \tag{1}$$

$$Y_{ij} = \frac{min\left(X_j\right) - X_{ij}}{max\left(X_j\right) - min\left(X_j\right)} \tag{2}$$

where $Y_{ij} \in [0, 1]$ represents the value of the indicator after standardizing the jth indicator and ith sample; $min\left(X_j\right)$ and $max\left(X_j\right)$ represent the minimum and maximum values of the jth indicator. Subsequently, the entropy value e_j results in

$$e_j = -\frac{1}{\ln\ 115}\sum\nolimits_{i=1}^{115} P_{ij} \ln\ P_{ij} \tag{3}$$

where $P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{115} Y_{ij}}$. If $P_{ij} = 0$, it is replaced with $P_{ij} = 10^{-6}$, which makes the logarithmic function valid. It should be noted that the value of 10^{-6} is small enough not to affect the result. Finally, the comprehensive score of the evaluated target of different dwellings is computed by

$$s_i = \sum_{i=1}^{9} w_j P_{ij} \tag{4}$$

where the weight $w_j = \frac{1-e_j}{\sum_{j=1}^{9}(1-e_j)}$. The larger the s_i, the higher the evaluation score of the exterior quality [6].

2.4. GA–BP Neural Network

The scores of the 115 traditional buildings were first calculated using the entropy method, and were used as the output values for the neural network model training. The scores were compared with those of the BP and GA–BP neural network models. The most reasonable approach was chosen to recalculate the scores of 115 buildings, which were divided into four classifications. Finally, the results were analyzed and discussed.

2.4.1. GA–BP Neural Network Process

The BP neural network is an information processing system designed in the basis of the structure and function of simulated neural networks. The BP algorithm is more efficient at capturing the non-linear relationship between factors and output. Repeated network learning is very accurate at correcting training errors. The general BP neural network model consists of three layers: the input layer, the hidden layer, and the output layer. The exterior information is received through each node in the input layer and passed to the hidden layer, where the information is processed and transformed before becoming the output value. Training is finished if the training error reaches the expected error. Otherwise, the training error reverses into the network and the iteration process is repeated [37].

The use of the genetic algorithm to optimize the neural network connection weights consists of two main parts: firstly, the genetic algorithm is used to optimize the initial weights of the network; and secondly, the optimized values provided from the GA are assigned to obtain an optimized BP neural network to predict the output accurately. Throughout the evolutionary process, the neural network structure, including the number of layers in the hidden layer, the number of nodes in the hidden layer, and the connections between the nodes, is fixed [38]. The corresponding GA–BP neural network flow is shown in Figures 3 and 4.

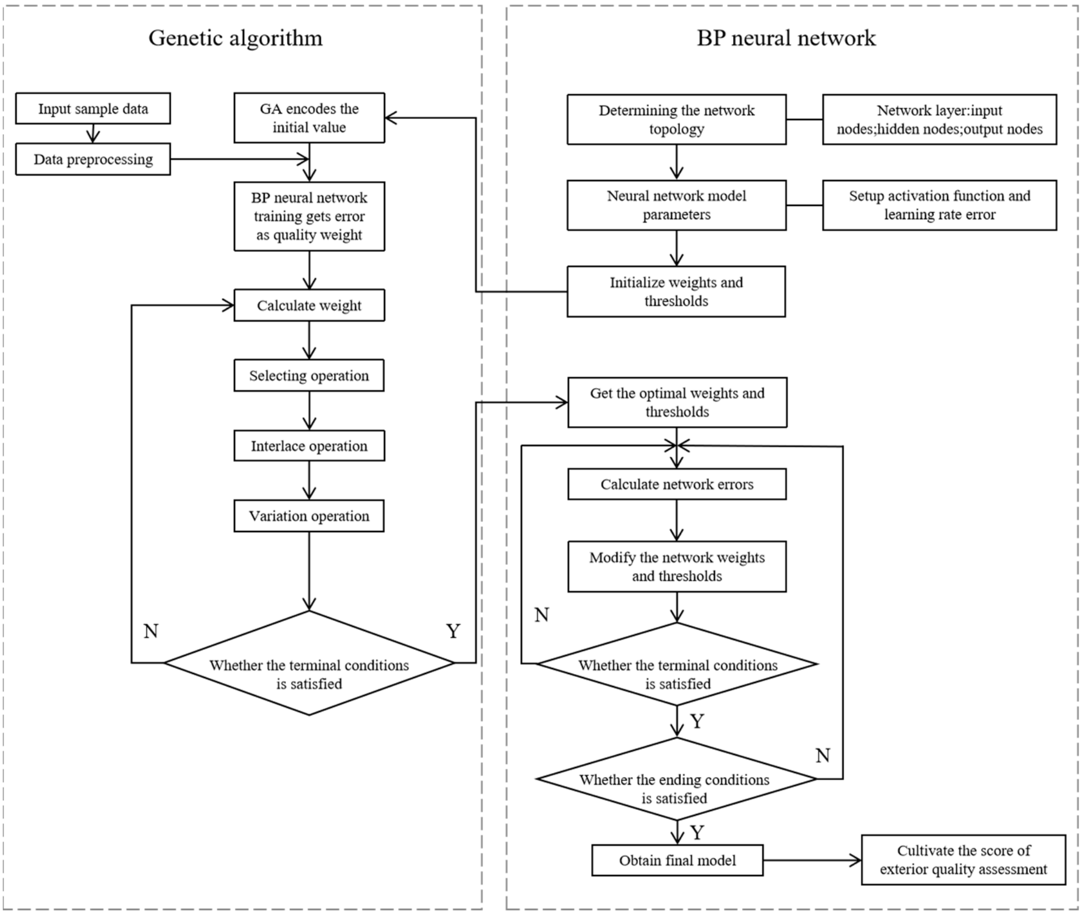

Figure 3. The flow of the GA–BP neural network model.

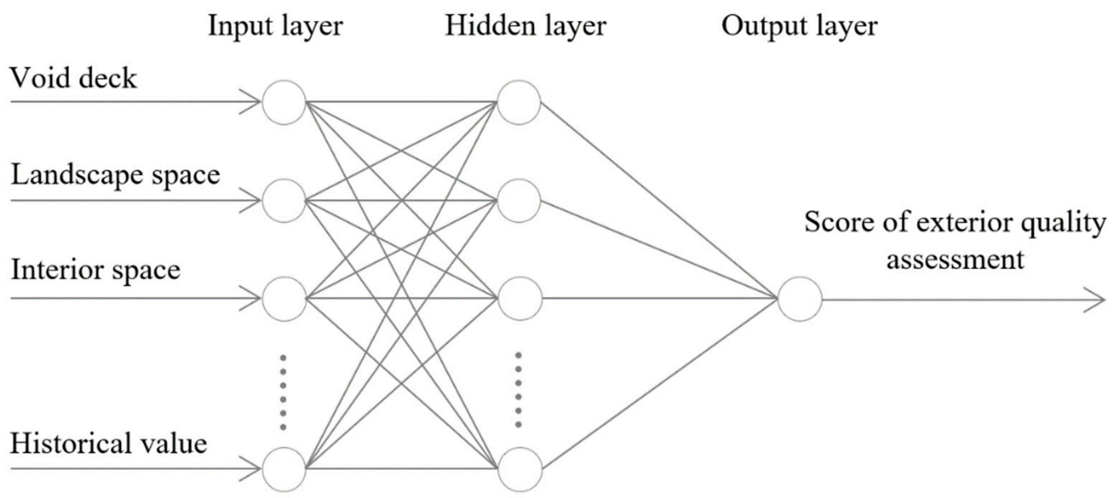

Figure 4. BP neural network structure for the exterior quality assessment.

2.4.2. Design of GA–BP Neural Network Model

1. Correlation analysis of indicators

In order to measure the statistical relationship between two random indicators, a Spearman's rank correlation, which is a non-parametric correlation between the ranking of two random indicators, is applied here. The closer the correlation is to 1, the stronger the relationship between the two indicators. The following formula is used to calculate the Spearman's rank correlation:

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i}{n(n^2 - 1)} \quad (5)$$

where d_i denotes the difference between two ranks of corresponding indicators and n is the number of observations. In particular, we have $n = 115$. Figure 5 displays the Spearman's rank correlation between each indicator. The greater the correlation, the larger the points in the figure. In particular, a strong correlation corresponds to large points. The results show that all correlations are less than 0.5, which indicates that there is no strong correlation and a small probability of the presence of multicollinearity. Moreover, we also compute the condition number to diagnose multicollinearity. By using the Spearman's rank correlation matrix, the condition number is equal to 8.617, which is less than 10, which indicates the absence of multicollinearity. Thus, all nine indicators should be considered in the GA–BP neural network model [39].

2. BP neural network model setup

The BP neural network structure in this paper consists of an input layer, a hidden layer, and an output layer, of which the hidden layer is one layer. According to the correlation analysis, we selected nine indicators to assess the exterior quality of traditional dwellings in Mengjinglai village. Thus, the input layer has nine nodes. According to the assessment requirements of exterior quality, one output node can effectively differentiate house quality, i.e., there is one node in the output layer. For the nodes in the hidden layer, we make a preliminary determination of the number of nodes according to Equation (6), and finally determine the number of nodes in the hidden layer of the final neural network model by the model training error. Based on empirical studies, Cheng proposed that the number of nodes N_{hid} in the hidden layer can be initially determined by the following formula [40]:

$$N_{hid} = \sqrt{N_{in} + N_{out}} + a \quad (6)$$

where N_{in} is the number of nodes in the input layer; N_{out} is the number of nodes in the output layer, and a is a constant in the interval $[1,\ 10]$. Thus, in our case $N_{hid} = \sqrt{9+1} + a = 3.162 + a$. In Figure 6, the number of iterations and mean square error (MSE) in the BP neural network model are computed to choose the number of nodes in the hidden layer, where the MSE is formulated as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{7}$$

where y_i is the true value of the outputs and $\hat{y}_i$ is the predictor of the outputs. Figure 6 evaluates the variation in the number of iterations and MSE for choosing the number of nodes in the hidden layer of the BP model. The x-axis represents the number of nodes in the hidden layer. The left side of the y-axis displays the iteration of the algorithm, while the right side of the y-axis exhibits the MSE. Moreover, it should be noted that by increasing one node in the hidden layer, there are 11 more parameters in the model. If too many hidden layer nodes are chosen, overfitting is likely to occur. Therefore, considering the number of parameters, the number of iterations, and MSE, we choose seven nodes in the hidden layer. By accumulating the results of the correlation analysis, the input layer should be included for all nine indicators. In addition, our interested output is only the evaluation value of the dwellings. Therefore, the structure of the neural network model determined in this paper is "9–7–1", i.e., nine nodes in the input layer, seven nodes in the hidden layer, and one node in the output layer. The parameters to be estimated in the BP neural network are $9 \times 7 + 7 + 7 \times 1 + 1 = 78$.

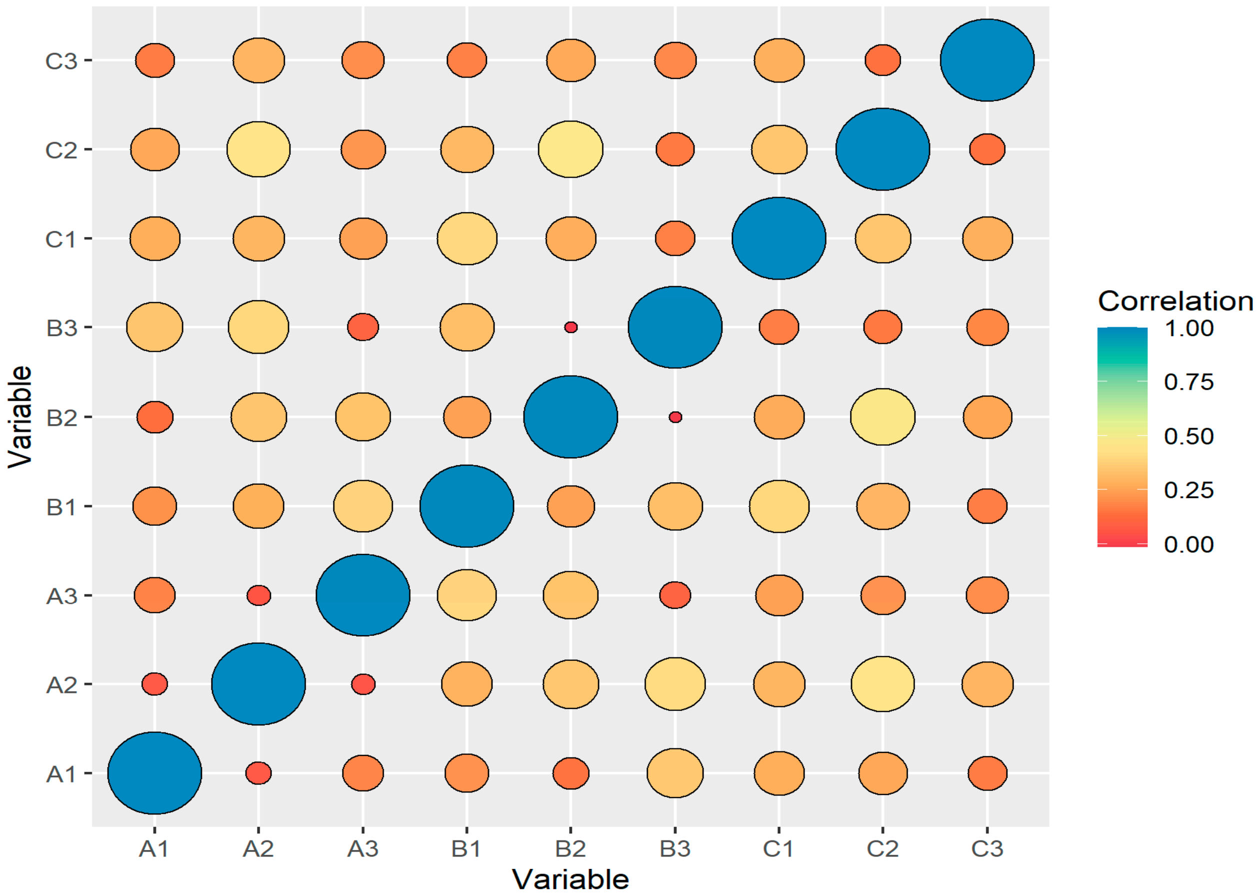

Figure 5. Spearman rank correlation between variables.

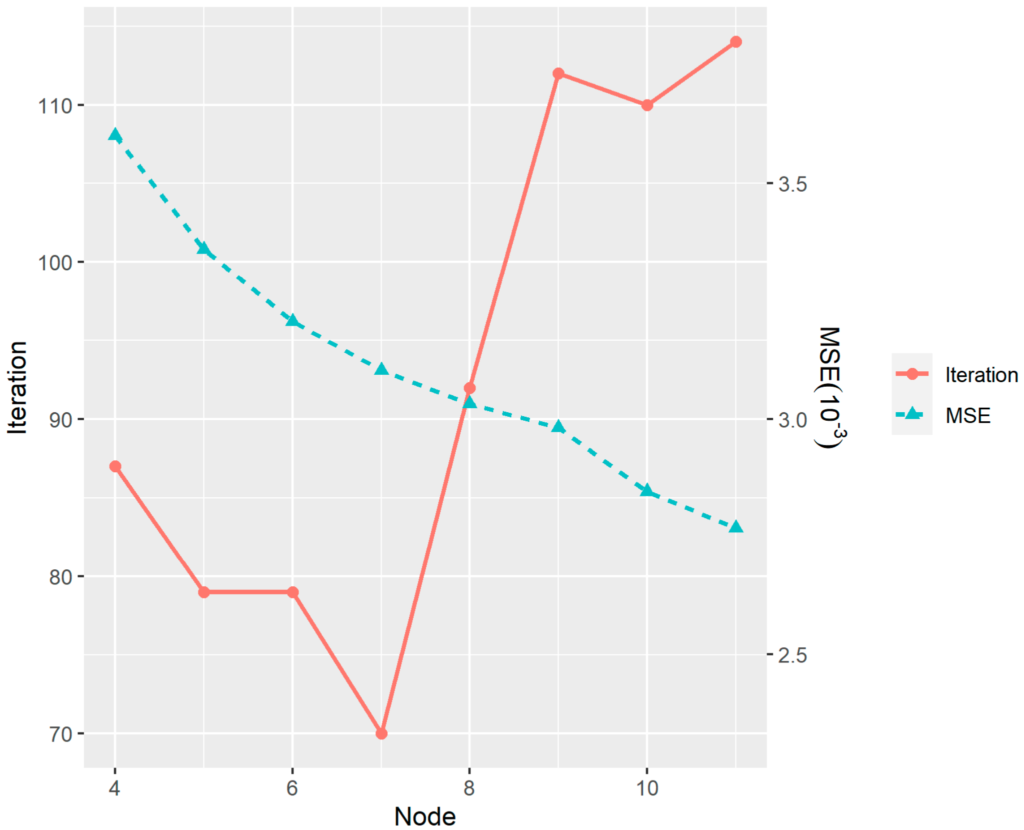

Figure 6. The number of iterations and MSE of BP model in the hidden layer.

3. GA Setting

The genetic algorithm consists of four main parts: coding, selection, crossover, and mutation. At first, coding is performed, followed by selection, crossover, and mutation. All three operations are evaluated by the fitness value calculated from the fitness function, where a higher value means that the individual is more adaptable and should have a higher probability of reaching a higher value, which makes it more likely that the individual is to be selected to pass on its advantages. The BP neural network designed in this paper has a 9–7–1 structure, and, by using binary coding, can easily cause the coding string to be too long, leading to a decrease in the operation rate; thus, real number coding is used. The output of the evaluation of the exterior quality of the traditional residential buildings in Mengjinglai village is required to be non-negative, the inverse of the MSE can be used as the adaptation function, and the adaptation function takes the form of 1/MSE. A roulette wheel is used to select some individuals to form a new population and to eliminate some individuals with lower target values [41]. Crossover is a process whereby two paired chromosomes exchange some of their genes in some way based on the crossover probability, thus forming two new individuals, and variation is a process whereby some gene values in the coding string of an individual are replaced with other gene values based on the variation probability to form a new individual. The crossover and variance probabilities are set at 0.7 and 0.05, respectively [42].

3.1. Selection and Learning of Training Samples

To increase the credibility of the model, the 115 samples were randomly divided into training and testing samples in a 6:4 ratio. In total, 69 samples were randomly selected for training according to the ratio, and the model parameters were trained. The remaining 46 were used as testing samples to evaluate the model and to calculate the quality weight values of the appearance of the residential dwellings. All calculations in this paper were implemented in R and Python; the GA–BP neural network results were obtained using the

TensorFlow module in Python, with an optimized learning rate of 0.1 [43]. The learning rate, a hyper-parameter, was used to control the rate of the GA–BP algorithm, which updated the learning values of the parameter of interest.

3.2. Analysis of Evaluation Results

In order to build a highly accurate model between the 9 indicators and the exterior quality evaluation of traditional residential buildings, 69 training data were first used to train the models to obtain the estimate of the model's parameters. Next, the training model was used to compute the 115 predictors of the exterior quality evaluation value. In order to assess the performance of BP and GA–BP algorithms, we also computed the training MSE and the iterations of BP and GA–BP algorithms. In particular, in the BP algorithm, the 115 iterations were needed to train the model with the training MSE 2.548×10^{-3}, while the GA–BP algorithm only needed 100 iterations and reduces the training MSE to 0.714×10^{-3}, which was much smaller than that of the BP algorithm. This result confirms that the training error of the GA–BP neural network model is significantly smaller than that of the BP network, and the GA–BP neural network algorithm can reduce the number of iterations for model training [44,45]. In this sense, it can be concluded that the GA–BP neural network is more stable and better adapted than the BP neural network model. Figure 7 presents further comparable details and shows that the predicted values of the evaluation value in different residences in the GA–BP model are closer to the true values than those of the BP model, which indicates that the points of the GA–BP are closer to the diagonal line.

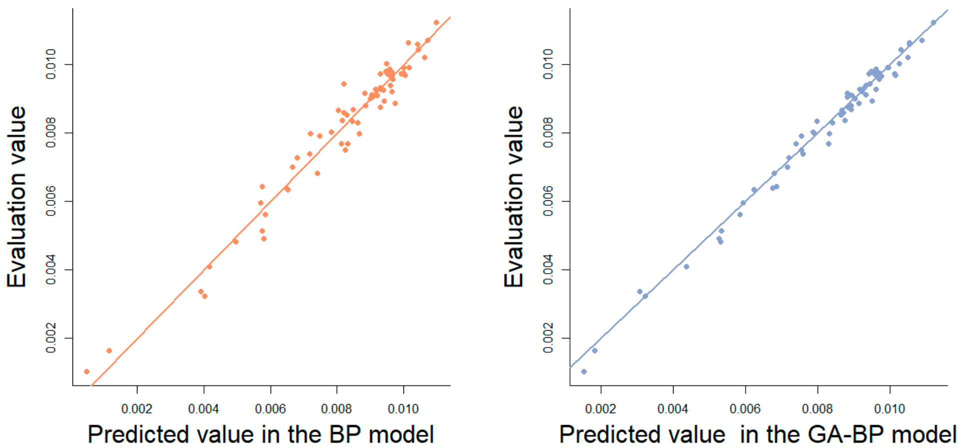

Figure 7. Predicted values in different residences of the BP model and GA–BP model.

According to the evaluation results, the final exterior quality of the dwellings was divided into four grades, with proportions of 10%, 20%, 30%, and 40% corresponding to Grade I, Grade II, Grade III, and Grade IV, respectively. The scatter plot of the evaluation values of the exterior quality of the different dwellings is shown in Figure 8. The four grades of 115 dwellings in Mengjinglai village are distributed in Figure 9. As can be seen from the diagram, most of the Grade I dwellings are located in the center of the village, with a well-preserved appearance and good architectural space, and the history and culture are well displayed; the Grade II dwellings are concentrated in the central part of the village, with good preservation of the original style in terms of building materials, but with a certain commercial space; the Grade III dwellings are scattered in various parts of the village, with a certain amount of renovation, in terms of appearance; the Grade IV dwellings are mainly located at the edge of the village, and most were recently renovated or have a strong commercial space.

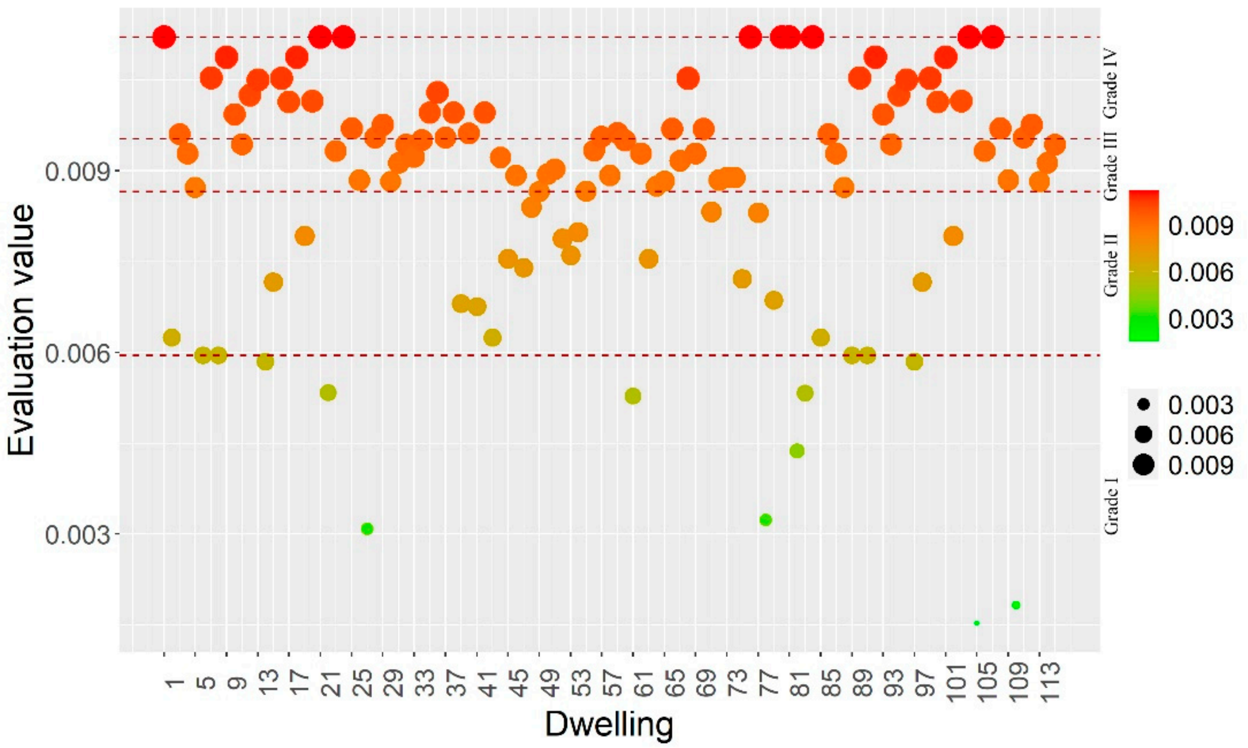

Figure 8. Scatter plot of the evaluation values of different residences.

Figure 9. Distribution of residential grades in Mengjinglai village.

4. Discussion

The evaluation of the quality of the appearance of traditional residential dwellings is currently not unified due to the resistance to variation and the diversity of elements that make up the quality of the appearance of buildings. The exterior quality of traditional dwellings is one of the most direct forms of contact for tourists and scholars, and also affects the direct impression of villages, while good exterior quality can also better convey and promote the culture of villages. Most studies on the architecture of villages still focus on spatial form, development and evolution, community satisfaction, and public participation. In this work, the external quality of the dwellings was assessed by using machine learning approaches, and the results can be used to help in the planning and design of villages. Architects can select the design priorities for renovation based on the assessment levels and can influence the design ideas based on the results of the different assessment factors; for example, increasing the use of local timber and tiles leads to better assessment results. Traditional houses can be assessed using the GA–BP method, but also the external quality of urban buildings or other aspects of quality.

The GA–BP neural network model is significantly more efficient than the BP network, reducing the number of iterations for model training, and is more effective in terms of global search capability. The GA–BP neural network model is more stable and adapts better than the BP neural network model. The focus of this paper is on how machine learning can quantify the assessment of the exterior quality of traditional residential buildings, and more work is needed to apply the assessment system and provide an analysis of exterior quality. More elements of assessment could be added in future studies to make the results more accurate, and further research could be conducted on the subject of predicting future trends in external quality.

5. Conclusions

This paper took Mengjinglai village as a case study and applied the GA–BP neural network model to evaluate the exterior quality of residential houses based on the respective advantages of the BP neural network and the GA, classified the quality levels, and compared and analyzed the results of the BP neural network model and the GA–BP neural network model. The main conclusions are as follows: (1) The GA–BP network model is less error-prone and more efficient than the traditional standard BP neural network. Using the GA–BP network model in the exterior quality evaluation of traditional residential houses can lead to a more rational and scientific approach to village assessment, and provide a reference for other, similar studies. (2) The overall exterior quality of Mengjinglai village is well preserved, highlighting the traditional Dai architectural style, and there was little difference in the scores of the four classifications assessed. However, the village's architecture still needs to be combined with local policies and customs to reflect the traditional culture.

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