

Using Combined Weighting and BP Neural Networks for Relative Poverty Measurement and its Evaluation

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Abstract—This study addresses the challenges of measuring and evaluating relative poverty by introducing a comprehensive evaluation model based on the Analytic Hierarchy Process (AHP)-entropy method and BP neural networks. A multidimensional evaluation index system was constructed through expert consultation and literature review. The AHP-entropy method was then employed to determine the weights of the evaluation indicators, ensuring objectivity and scientific validity. Additionally, the BP neural network model was integrated to leverage self-learning and adaptive mechanisms for efficient and accurate poverty assessment. Empirical analysis shows that the model maintains a calculation error within 3.9%, demonstrating high precision and wide applicability. This research provides a novel approach that combines qualitative analysis with quantitative evaluation, offering a practical tool for governmental agencies to design effective poverty alleviation strategies. Moreover, the model opens new pathways for future research in regional poverty assessment, especially in enhancing cross-cultural adaptability and advancing intelligent evaluation models.

Keywords—Analytic hierarchy process (AHP); entropy method; BP neural network model; relative poverty measurement

I. INTRODUCTION

With the rapid development of the socioeconomic landscape, the issue of relative poverty has gradually become a crucial indicator for measuring social equity and harmony. Traditional poverty measurement methods, which predominantly rely on single income indicators, often fail to comprehensively capture the multidimensional characteristics of poverty. Therefore, research on poverty measurement in the context of the new era has shifted from a single income dimension to a comprehensive multidimensional assessment [1-2]. Multidimensional poverty encompasses not only economic income but also aspects such as education, health, and environment, reflecting a holistic understanding and in-depth analysis of poverty. How to achieve relative poverty measurement across multiple dimensions is an important topic in social science research, playing a significant role in achieving targeted poverty alleviation, promoting social equity, and improving people's living standards [3].

Past studies on relative poverty have often emphasized qualitative analysis [4-6], limiting their capacity for scientific quantitative assessments [7-8]. In response, some scholars have utilized the traditional Alkire-Foster (A-F) method. For example, Qin et al. [9] applied the A-F method to analyze multidimensional relative poverty in six regions of Xinjiang,

while Gan et al. [10] combined the A-F method, Dagum Gini coefficient, and Kernel density estimation to examine multidimensional poverty and regional disparities across 31 provinces in China between 2013 and 2019. Similarly, Guo [11] employed CFPS data and a modified A-F method with subjective and objective weighting techniques to assess multidimensional poverty in China. Despite its widespread use, the A-F method has limitations, such as difficulties in precisely quantifying non-economic dimensions of poverty [12-13] and inherent subjectivity.

Regression analysis has also been explored as an alternative. Zhu et al. [14], for instance, employed logistic regression to identify factors influencing rural household poverty in western China, while Tian et al. [15] analyzed multidimensional poverty and its mechanisms in Henan Province using the A-F model and binary logistic regression. However, traditional mathematical approaches face challenges, including difficulties in constructing evaluation indicators, susceptibility to subjective bias, and computational complexity.

In contrast, the Analytic Hierarchy Process (AHP) offers significant advantages in quantifying and evaluating poverty. For instance, Dong [16] applied AHP and intergenerational income elasticity coefficients to explore factors affecting intergenerational poverty transmission. Luo and Cao [17] used AHP to construct a multidimensional indicator system for measuring urban household poverty in China. Zhu et al. [18] combined an AHP-improved A-F method to measure and decompose multidimensional relative poverty. Tao [19] established a multidimensional evaluation system with 14 indicators across five dimensions, using AHP and entropy-based weighting to determine indicator weights. Similarly, Chen [20] applied AHP to assess urban poverty during China's transition period, determining weights for various poverty dimensions.

Despite its utility, AHP has limitations, including subjectivity, high consistency requirements, potential complexity in hierarchical structures, challenges in determining weights, limited sensitivity analysis for parameter variations, constrained applicability, and significant computational demands.

To overcome these challenges, this study proposes a comprehensive evaluation model integrating AHP, the entropy method, and BP neural networks. The model begins by analyzing the factors influencing relative poverty and constructing a corresponding evaluation index system. Next,

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indicator weights are determined using AHP and the entropy method, which are then applied to score the relative poverty population. A BP neural network model is subsequently developed, trained, and tested using MATLAB. The BP neural network model proposed in this study provides more accurate evaluation results compared to traditional mathematical models and fuzzy mathematical theory. Through self-learning and adaptive adjustment, it effectively addresses the shortcomings of traditional evaluation methods in handling dimensional diversity and imprecise problem quantification.

By combining AHP and entropy-based weighting with BP neural networks, this study enhances the scientific validity and precision of poverty measurement while providing robust tools for poverty alleviation policy development and implementation. Continuous innovation and deeper research in this field can make meaningful contributions to reducing relative poverty, fostering social equity, and improving living standards.

II. METHODS

A. Construction of the Multidimensional Poverty Measurement, Evaluation System and Establishment of Data Samples

1) *Construction of the measurement indicator system*: The development of a multidimensional poverty measurement and evaluation system must adhere to the principles of scientific objectivity, comprehensiveness, feasibility, and representativeness [21]. For example, Huang et al. [22] classified poverty into seven dimensions: income standards, the "three guarantees" (education, healthcare, and housing), food and nutrition structure, social relations, and mental state. Similarly, Liao et al. [23] categorized poverty into dimensions such as living standards, production resources, income, health, education, political participation, sanitation facilities, and household assets. Thus, constructing a scientifically robust and rational evaluation indicator system is critical for addressing poverty measurement, with the design of these indicators being the core challenge.

At present, no unified standard exists for relative poverty evaluation systems. Therefore, this study develops its indicator system by interpreting the concept of relative poverty and utilizing statistical data from sources such as the China Statistical Yearbook and CFPS2020. Indicators with unavailable data were excluded. The finalized system reflects the practical context of China's economic development. It comprises five secondary indicators—basic living security, capabilities, social security, development opportunities, and economic conditions—and 14 tertiary indicators, as detailed in Table I.

2) *Data sources*: The quality of the sample used for learning plays a crucial role in determining the performance of the neural network model. Therefore, this study utilizes data from CFPS2020 (China Family Panel Studies). The data collection process adhered to rigorous scientific methods, tracking data across three levels: individual, household, and community. This approach ensured both the

comprehensiveness and depth of the study. The broad geographic coverage, spanning 25 provinces, municipalities, and autonomous regions, further strengthened the generalizability and applicability of the findings. For data processing, STATA software, a widely recognized statistical tool, was employed to ensure accuracy and validity. During the processing, survey data were carefully filtered according to the dimensions of relative poverty measurement, resulting in 4,594 valid responses, thereby ensuring the study's precision and reliability.

3) *Quantitative processing of the indicator system*: Following data integration, the data were sequentially organized and transformed into the format shown in Table II, where each column represents the score of an individual respondent across 14 dimensions. A base score of 60 was assigned to each indicator, with specific values assigned according to the actual context, as outlined in Table II. This process finalized the quantitative analysis of each indicator.

TABLE I MULTIDIMENSIONAL RELATIVE POVERTY MEASUREMENT AND EVALUATION SYSTEM

Primary Indicators	Secondary Indicators	Tertiary Indicators
Multidimensional Relative Poverty Measurement and Evaluation System (A)	Living Security (W1)	Adequate Food and Clothing (W11)
		Drinking Water Supply (W12)
		Housing Conditions (W13)
	Economic Conditions (W2)	Per Capita Household Income (W21)
		Proportion of Transfer Income (W22)
	Feasible Capability (W3)	Education Level of Household Head (W31)
		Number of Laborers (W32)
		Health Status (W33)
	Development Opportunities (W4)	Access to Bank Loans (W41)
		Job Satisfaction (W42)
		Proportion of Migrant Laborers (W43)
	Social Security (W5)	Satisfaction with Medical Conditions (W51)
		Medical Insurance and Assistance (W52)
		Satisfaction with Education (W53)

B. Empowerment of the Multidimensional Poverty Measurement and Evaluation System

1) *AHP-based empowerment of evaluation indicators*: The Analytic Hierarchy Process (AHP) is a method that integrates both quantitative and qualitative analysis, enabling a comprehensive assessment of the research problem [18]. In this study, AHP is employed to determine the weight coefficients of each indicator. To minimize the randomness introduced by evaluators' subjective preferences and prior knowledge, a panel of experts was convened to provide a collective empowerment judgment. The expert panel constructed a criterion-level judgment matrix using the 1–9 scale method, as illustrated in Table III.

TABLE II QUANTITATIVE PROCESSING OF THE MULTIDIMENSIONAL RELATIVE POVERTY MEASUREMENT INDICATOR SYSTEM

Primary Indicators	Secondary Indicators	Tertiary Indicators	Tertiary Indicator Weights
Multidimensional Relative Poverty Measurement and Evaluation System (A)	Living Security (W1)	Adequate Food and Clothing (W11)	The total expenditure on food and clothing exceeds 2300, assign a value of 90; between 1380 and 2300, assign a value of 70; less than 1380, assign a value of 60.
		Drinking Water Supply (W12)	Tap water/bottled water/purified water/filtered water, assign a value of 90; well water, assign a value of 80; river/lake/pond spring water, assign a value of 70; others, assign a value of 60.
		Housing Conditions (W13)	Courtyards, villas, and townhouses, assign a value of 90; small buildings, assign a value of 80; unit apartments, assign a value of 70; single-story houses, assign a value of 60.
	Economic Conditions (W2)	Per Capita Household Income (W21)	Household per capita non-operating income below 50% of the median, assign a value of 60; between 50%–80% of the median, assign a value of 70; between 80%–100% of the median, assign a value of 80; above the median, assign a value of 90.
		Proportion of Transfer Income (W22)	Household savings below 50% of the median, assign a value of 60; between 50%–80% of the median, assign a value of 70; between 80%–100% of the median, assign a value of 80; above the median, assign a value of 90.
	Feasible Capability (W3)	Education Level of Household Head (W31)	Bachelor's degree or higher (including associate degree), assign a value of 90; high school/vocational school/technical school/secondary technical school, assign a value of 80; middle school, assign a value of 70; primary school or below, assign a value of 60.
		Number of Laborers (W32)	If the respondent's comprehension ability is weak and judged as very poor, assign a value of 60; otherwise, assign a value of 90.
		Health Status (W33)	If the respondent feels unhealthy, assign a value of 60; otherwise, assign a value of 90.
	Development Opportunities (W4)	Access to Bank Loans (W41)	If yes, assign a value of 60; if no, assign a value of 90.
		Job Satisfaction (W42)	Very satisfied, assign a value of 90; fairly satisfied, assign a value of 80; somewhat dissatisfied/average, assign a value of 70; very dissatisfied, assign a value of 60.
		Proportion of Migrant Laborers (W43)	If the respondent's information level about their future is below 50% of the median, assign a value of 60; between 50%–80% of the median, assign a value of 70; between 80%–100% of the median, assign a value of 80; above the median, assign a value of 90.
	Social Security (W5)	Satisfaction with Medical Conditions (W51)	Very satisfied, assign a value of 90; fairly satisfied, assign a value of 80; somewhat dissatisfied/average, assign a value of 70; very dissatisfied, assign a value of 60.
		Medical Insurance and Assistance (W52)	None, assign a value of 60; if yes, assign a value of 90.
		Satisfaction with Education (W53)	Very satisfied, assign a value of 90; fairly satisfied, assign a value of 80; somewhat dissatisfied/average, assign a value of 70; very dissatisfied, assign a value of 60.

TABLE III CRITERION-LEVEL JUDGMENT MATRIX

A	W1	W2	W3	W4	W5	Weight
W1	1	2	4	4	2	0.36
W2	0.5	1	5	4	2	0.28
W3	0.25	0.2	1	2	0.25	0.08
W4	0.25	0.25	0.5	1	0.2	0.06
W5	0.5	0.5	4	5	1	0.22

The matrix is solved, yielding a maximum eigenvalue of $\lambda_{Max} = 5.23$. The corresponding eigenvector is $W_i = (0.36, 0.28, 0.08, 0.06, 0.22)$. A consistency test is then conducted on W_i , as shown in Eq. (1):

$$CI = \frac{\lambda_{Max} - n}{n - 1} = 0.0585 \quad (1)$$

According to the table, when $n=5$, the value of $RI=1.12$. Therefore, the relative consistency index can be calculated, as shown in Eq. (2):

$$CR = \frac{CI}{RI} = 0.05226 < 0.1 \quad (2)$$

The calculations demonstrate that the matrix achieves satisfactory consistency, meaning that the weight vector W_i is

both objective and acceptable. Similarly, applying the same method to solve the other matrices results in the judgment matrices presented in Table IV to Table VII.

Table IV presents the weight distribution for the multidimensional relative poverty measurement indicator system. The weight of the secondary indicators represents their share within the overall evaluation system, while the weight of the tertiary indicators reflects their share within the corresponding secondary indicators. The comprehensive weight is the weighted average of both secondary and tertiary indicator weights, indicating their relative importance within the entire evaluation framework.

TABLE IV HP-BASED WEIGHT DISTRIBUTION FOR THE MULTIDIMENSIONAL RELATIVE POVERTY MEASUREMENT AND EVALUATION SYSTEM

Primary Indicators	Secondary Indicators	Secondary Indicator Weights	Tertiary Indicators	Tertiary Indicator Weights	Comprehensive Weight
Multidimensional Relative Poverty Measurement and Evaluation System (A)	Living Security (W1)	0.36	Adequate Food and Clothing (W11)	0.1	0.04
			Drinking Water Supply (W12)	0.23	0.08
			Housing Conditions (W13)	0.67	0.24
	Economic Conditions (W2)	0.28	Per Capita Household Income (W21)	0.8	0.22
			Proportion of Transfer Income (W22)	0.2	0.06
	Feasible Capability (W3)	0.08	Education Level of Household Head (W31)	0.09	0.01
			Number of Laborers (W32)	0.27	0.02
			Health Status (W33)	0.64	0.05
	Development Opportunities (W4)	0.06	Access to Bank Loans (W41)	0.12	0.01
			Job Satisfaction (W42)	0.68	0.04
			Proportion of Migrant Laborers (W43)	0.2	0.01
	Social Security (W5)	0.22	Satisfaction with Medical Conditions (W51)	0.26	0.06
			Medical Insurance and Assistance (W52)	0.63	0.14
			Satisfaction with Education (W53)	0.11	0.04

2) *Entropy method for weight assignment to evaluation indicators*: The entropy method is an objective weighting approach that assigns weights based on the degree of variation in indicator values. Its main advantage is that it avoids the subjective biases inherent in the Analytic Hierarchy Process (AHP), thereby improving both the objectivity and accuracy of weight assignment. This method is particularly effective for situations where indicators exhibit high variability, randomness, and disorder, providing a more accurate representation of each indicator's true significance within the evaluation system. Consequently, this study employs the entropy method to objectively assign weights to the evaluation indicators, following the steps outlined below:

a) Let A denote the j -th indicator of the i -th household. The corresponding attribute decision matrix is as shown in Eq. (3):

$$M = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (3)$$

b) Data standardization is performed to eliminate the influence of different units on the evaluation indicators. In this study, the mean normalization method is applied for standardization, and the calculation is as shown in Eq. (4):

$$y_{ij} = \frac{x_{ij}}{\bar{x}_j} \quad (4)$$

c) The contribution of the i -th sample under the j -th indicator, denoted as p_{ij} , is calculated as shown in Eq. (5):

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^m y_{ij}} \quad (5)$$

d) The total contribution of the j -th indicator is calculated as its information entropy value, as shown in Eq. (6):

$$E_j = -k \sum_{i=1}^m p_{ij} \ln(p_{ij}) \quad (6)$$

In the equation, $k = \frac{1}{\ln(m)}$.

e) Calculate the coefficient of variation for the contributions of each sample under the j -th indicator, as shown in Eq. (7):

$$d_j = 1 - E_j \quad (7)$$

f) Calculate the weight corresponding to the j -th indicator, as shown in Eq. (8):

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (8)$$

The weights calculated using the entropy method, based on the data from Section II B and analyzed with the R software, are summarized in the Table V.

3) *Comprehensive weighting approach integrating AHP and the entropy method*: The Analytic Hierarchy Process (AHP) is highly subjective, relying heavily on qualitative components and limited quantitative data, which reduces its credibility. In contrast, the entropy method lacks the ability to compare indicators across dimensions. To address these limitations, a combined weighting method is employed, which considers the intrinsic statistical properties and authoritative values of the indicators. This method integrates subjective and objective weighting approaches, balancing their respective strengths and weaknesses. The corresponding equation is as shown in Eq. (9):

$$W_j = \frac{\sqrt{\alpha_j \beta_j}}{\sum_{j=1}^n \sqrt{\alpha_j \beta_j}} \quad (9)$$

Among these, α_j denotes the weight values derived from the Analytic Hierarchy Process (AHP), while β_j represents the weight values obtained using the entropy method.

The combined weights are calculated using the combined weighting formula, based on the subjective and objective weight values obtained from the Analytic Hierarchy Process (AHP) and the entropy method. The corresponding weighting results are presented in Table VI.

TABLE V WEIGHT DISTRIBUTION FOR THE MULTIDIMENSIONAL RELATIVE POVERTY MEASUREMENT AND EVALUATION SYSTEM BASED ON THE ENTROPY METHOD

Primary Indicators	Secondary Indicators	Tertiary Indicators	Entropy Weight
Multidimensional Relative Poverty Measurement and Evaluation System (A)	Living Security (W1)	Adequate Food and Clothing (W11)	0.08
		Drinking Water Supply (W12)	0.02
		Housing Conditions (W13)	0.08
	Economic Conditions (W2)	Per Capita Household Income (W21)	0.02
		Proportion of Transfer Income (W22)	0.04
	Feasible Capability (W3)	Education Level of Household Head (W31)	0.12
		Number of Laborers (W32)	0.04
		Health Status (W33)	0.06
	Development Opportunities (W4)	Access to Bank Loans (W41)	0.09
		Job Satisfaction (W42)	0.05
		Proportion of Migrant Laborers (W43)	0.06
	Social Security (W5)	Satisfaction with Medical Conditions (W51)	0.03
		Medical Insurance and Assistance (W52)	0.24
		Satisfaction with Education (W53)	0.06

TABLE VI COMPREHENSIVE WEIGHT DISTRIBUTION FOR THE MULTIDIMENSIONAL RELATIVE POVERTY MEASUREMENT AND EVALUATION SYSTEM BASED ON AHP & ENTROPY METHOD

Primary Indicators	Secondary Indicators	Tertiary Indicators	Subjective Weight	Objective Weight	Comprehensive Weight
Multidimensional Relative Poverty Measurement and Evaluation System (A)	Living Security (W1)	Adequate Food and Clothing (W11)	0.04	0.08	0.07
		Drinking Water Supply (W12)	0.08	0.02	0.05
		Housing Conditions (W13)	0.24	0.08	0.16
	Economic Conditions (W2)	Per Capita Household Income (W21)	0.22	0.02	0.08
		Proportion of Transfer Income (W22)	0.06	0.04	0.06
	Feasible Capability (W3)	Education Level of Household Head (W31)	0.01	0.12	0.04
		Number of Laborers (W32)	0.02	0.04	0.03
		Health Status (W33)	0.05	0.06	0.07
	Development Opportunities (W4)	Access to Bank Loans (W41)	0.01	0.09	0.04
		Job Satisfaction (W42)	0.04	0.05	0.05
		Proportion of Migrant Laborers (W43)	0.01	0.06	0.03
	Social Security (W5)	Satisfaction with Medical Conditions (W51)	0.06	0.03	0.05
		Medical Insurance and Assistance (W52)	0.14	0.24	0.22
		Satisfaction with Education (W53)	0.04	0.06	0.06

C. Development of the BP Neural Network Model

1) *Determining the fundamental parameters of the BP neural network:* To construct a BP neural network, key parameters such as the number of layers, the number of neurons, the activation function, and the learning rate must be determined. Generally, increasing the number of layers enhances computational accuracy; however, this also results in longer training times and may increase the risk of overfitting. Alternatively, computational accuracy can be improved by adding more hidden nodes without expanding the network layers. Consequently, this study employs a three-layer BP neural network with a single hidden layer.

The number of neurons in each layer is determined as follows: the 14 tertiary indicators from the multidimensional relative poverty measurement system serve as input neurons, while the system's poverty scores are used as output neurons, resulting in $n = 14$ and $l = 1$. Based on Eq. (10), the range of values for the hidden layer nodes is $[4, 8]$. Therefore, this study sets the number of hidden layer nodes m to the higher value of 8 to enhance computational accuracy.

$$\sqrt{n} \leq m \leq \sqrt{n(l+3)} + 1 \quad (10)$$

In this study, the activation function for the input layer is defined as the hyperbolic tangent function, as shown in Eq. (11):

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (11)$$

The activation function for the output layer is the Sigmoid function, as shown in Eq. (12):

$$f(x) = \frac{1}{1 + e^{-x}} \quad (12)$$

The learning rate governs the adjustment of synaptic values during the neural network training process. If the learning rate is too high or too low, it can lead to system instability. To maintain stability during training, the learning rate (denoted as η) should be within the range of 0.01 to 0.1. In this study, η is set to 0.55. Based on these considerations, the topology of the BP neural network used in this study is shown in Fig. 1.

2) *Parameter settings for the BP neural network model:* To train the BP neural network model, the initial network parameters must be determined. These parameters typically include the weights for each layer and the activation thresholds. The weights and thresholds are initialized to small random values. In this study, the initial values are randomly selected within the range of $[-1/12, 1/12]$ prior to training. Additionally, 70% of the data is designated as the training sample, with $x(m) = [x_{m1}, \dots, x_{m16}]$ representing the input data for the input layer, y_m representing the desired output, and m representing the sample index.

Once the initial parameters and training samples are set, the outputs of the hidden and output layers can be calculated. The induced local domain for a particular neuron in the hidden layer, as used in this study, is shown in Eq. (13):

$$v_j(m) = \sum_{i=1}^n w_{ij}x_{ij} - \theta_j \quad (13)$$

The induced local domain of a specific neuron k in the output layer is shown in Eq. (14):

$$v_k(m) = \sum_{j=1}^s w_{jk}v_j(m) - \theta_k \quad (14)$$

In the equation, n and s denote the number of neurons in the input and hidden layers, respectively.

Based on the induced local domain outlined above, the output of neuron j in the hidden layer at time m is as shown in Eq. (15):

$$y_j(m) = \frac{e^{v_j(m)} - e^{-v_j(m)}}{e^{v_j(m)} + e^{-v_j(m)}} \quad (15)$$

At this stage, the output of neuron k in the output layer is as shown in Eq. (16):

$$y_k(m) = \frac{1}{1 + e^{-v_k(m)}} \quad (16)$$

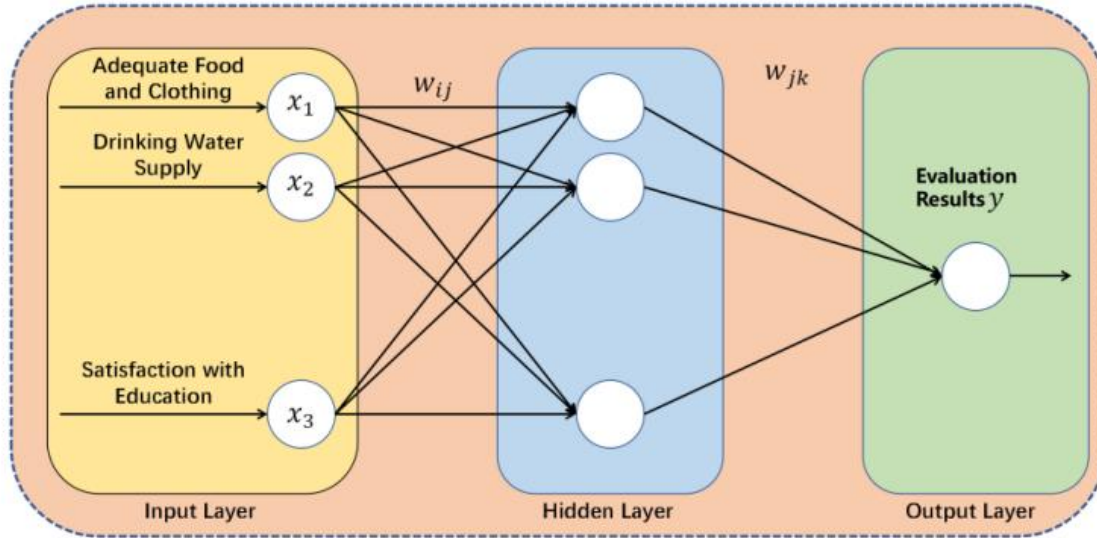


Fig. 1. Multidimensional relative poverty measurement and evaluation system model.

III. RESULTS AND DISCUSSION

A. Model Training

After constructing the model as outlined above, 70% of the integrated data was used for training, with 15% allocated as training samples and the remaining 15% as testing and validation data. Fig. 2 illustrates the regression of the target relative to the output. The R-values for the training set, validation set, test set, and all data are 0.98371, 0.985, 0.97912, and 0.98313, respectively. These results suggest that the neural network model demonstrates a high degree of linearity and exhibits strong fitting performance.

B. Empirical Analysis

After training the neural network model, 20 sets of integrated data were selected for testing. The test results, compared with the comprehensive weighted calculations, are presented in Table VII (excerpt). The comparison reveals that the average relative error for the 20 test samples is 0.89%, with a maximum relative error of 3.90%. These results suggest that the model achieves high prediction accuracy. Furthermore, the use of the neural network model for multidimensional relative poverty measurement is simple, significantly reducing computational costs and demonstrating strong feasibility. The fitted curve is shown in Fig. 3.

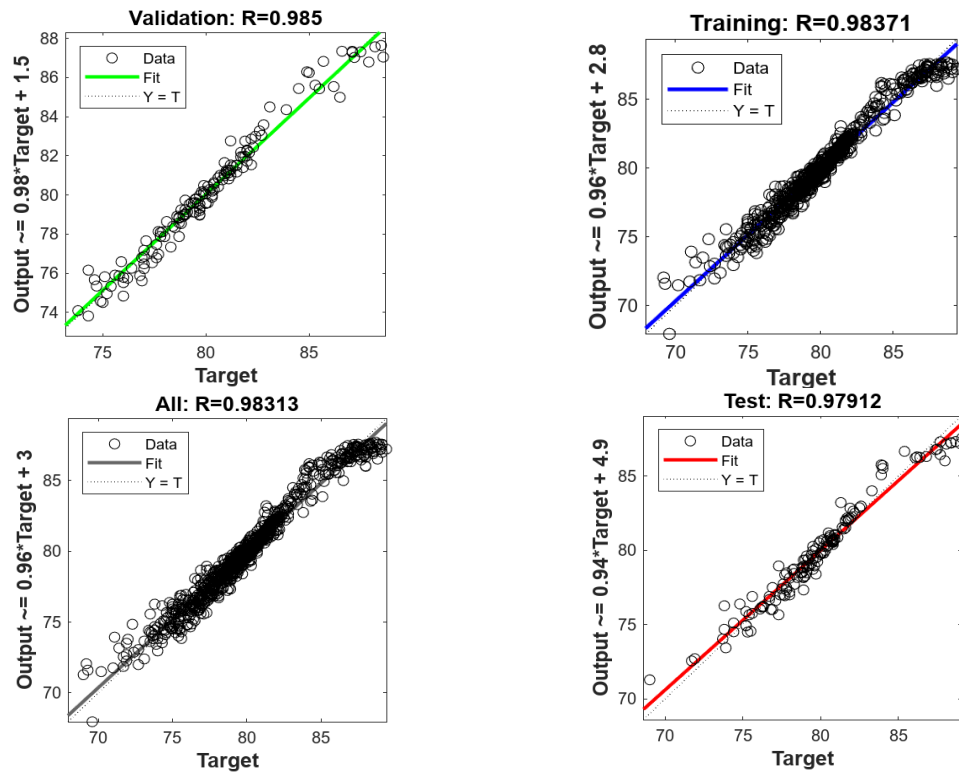


Fig. 2. Regression of the target relative to the output.

TABLE VII BP NEURAL NETWORK CALCULATION RESULTS AND COMPREHENSIVE WEIGHTING EVALUATION RESULTS

Serial Number	Expected Output	BP Predicted Value	Relative Error	Serial Number	Expected Output	BP Predicted Value	Relative Error
1	86.1	86.8574	0.88%	11	84.4	84.6768	0.33%
2	72.7	72.5812	0.16%	12	71.9	73.6172	2.39%
3	78.7	78.5607	0.18%	13	80.4	80.5731	0.22%
4	73.8	73.3003	0.68%	14	80.7	79.4826	1.51%
5	85.6	87.1798	1.85%	15	79.5	79.1354	0.46%
6	74.7	74.0416	0.88%	16	74.5	74.6252	0.17%
7	74.5	72.9669	2.06%	17	87.8	88.1500	0.40%
8	72	69.1954	3.90%	18	76.5	76.2431	0.34%
9	76.7	76.4779	0.29%	19	81.1	80.9983	0.13%
10	77.3	77.0135	0.37%	20	78.4	77.8524	0.70%

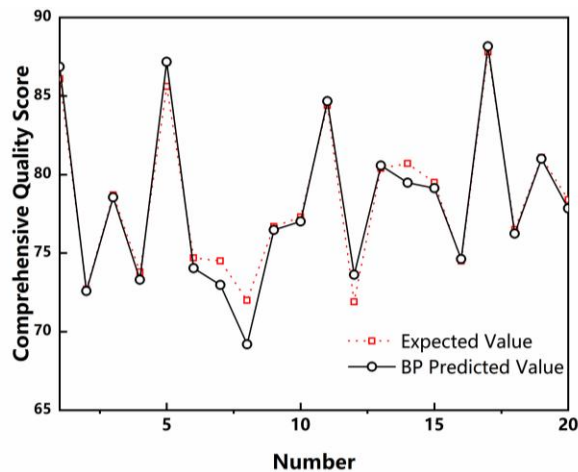


Fig. 3. Comparison curve of expected output and BP predicted value.

IV. CONCLUSIONS

This study develops a multidimensional relative poverty measurement evaluation system based on the AHP and entropy weight method, offering a quantitative analysis-based evaluation approach. To enhance the convenience of comprehensive quality assessment, a model combining the AHP and entropy weight method with the BP neural network is also proposed. The main conclusions are as follows:

This study employs the AHP-entropy method to allocate comprehensive weights to evaluation indicators, establishing a scientific and rational multidimensional relative poverty assessment system. The development of this framework provides governments with a quantitative and systematic evaluation tool during the implementation of multidimensional poverty assessment, thereby enhancing the objectivity and scientific rigor of the evaluation process.

The research demonstrates that the BP neural network-based relative poverty measurement model exhibits significant advantages in addressing complex nonlinear problems. The application of this model not only improves evaluation efficiency and reduces computational costs but also validates its feasibility and effectiveness in practical poverty population assessment through empirical analysis.

The BP neural network model proposed in this study holds broad application prospects in the field of poverty population assessment. This methodology enables more objective and equitable evaluation of multidimensional relative poverty, facilitating better implementation of poverty eradication policies by government departments and promoting comprehensive national development.

CONFLICTS OF INTEREST

The authors declare no potential conflict of interest.

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