Artificial Intelligence-Driven Genetic Algorithm Optimization for Language Learning and Assessment in Medical Research

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Abstract: Establishing a sound and efficient evaluation system for balanced indicators of compulsory education is the key to promoting the balanced development of compulsory education. The study aims to establish a data mining algorithm based on a university Spanish education and assessment system for the problems in university Spanish education and assessment. The study first constructs the data elements of university Spanish education and assessment, second establishes a genetic algorithm-based BP neural network optimization algorithm (GA-BP), and finally analyzes its effect. The final research proves that the GA-BP completes the 10-time stated objective in the evolutionary, and its adaptation degree reaches the set expectation. Then, the relevant threshold and weight value are gained, and finally, the model gets 10-6 errors in the training 100 times, which achieves the expected accuracy. The distinction between the desired and actual value is primarily in [-0.06693,0.07434]; The training set Ris 0.99283 is close to 1. The fit is high, and the average GA-BP accuracy is around 97.5%, significantly better than other algorithms. The proposed GA-BP has outstanding application in university Spanish education and assessment.

Keywords: GA-BP model, educational quality assessment, BPNN, Spanish language teaching, Artificial Intelligence, Medical Research.
DOI: https://doi.org/10.14733/cadaps.2024.S24.89-104

1 INTRODUCTION

The 2017 edition of the Spanish Language Curriculum Standards states that "the value of teaching Spanish depends on the diversity of the students and that the teaching of Spanish should be primarily aimed at ensuring that students have basic competence in Spanish [25]." When creating the language environment, designing classroom activities, and implementing them, it is essential to make them diverse and selective, according to the characteristics of the students, for all scholars, but also to take into account the needs and interests of different students, so that their natural development, their cultural awareness and their ability to learn, etc., are enhanced [30]. Therefore, the teaching of Spanish must change its philosophy, improve its teaching methods, and use them flexibly to match the new curriculum standards and make them compatible with the teaching of Spanish. In such an environment, it is of great importance to teach the Spanish language classroom effectively [26]. Teaching and learning Spanish languages is less comprehensive than high-stakes subjects such as languages, mathematics, and English. Although Spanish is part of the curriculum standards, there must be a clear distinction between the assessment systems for teaching and learning Spanish in multiple subjects [22]. Therefore, this study aims to construct a system built on a data mining algorithm for the assessment of teaching and learning of Spanish at university and to make it, proposing a BPNN model based on an improved genetic algorithm (GA-BP) [6] to optimize the system for the education and assessment of Spanish at university. Enhanced the assessment model for teaching and learning Spanish at university, enabling a diverse teaching and learning assessment approach.

The study first expounds on the current research status of worldwide language education evaluation, establishes the data elements of college Spanish education, introduces the application of GA-BP, and eventually discusses the application of the improved neural network algorithm (INN) in Spain. Analysis of the application effect in language education and assessment. Research can expound on the importance of some language courses and provide clear goals for college students. Still, it should not make students slack on other homework; it will also help college students' enthusiasm for learning. The first part of the paper mainly explains the context and significance. Part 2 establishes a Spanish university education evaluation model combining GA and BPNN. The third part is to design and carry out a simulation experiment to verify the effectiveness of the developed evaluation model. The fourth part summarizes the complete text, especially the experimental results, and points out the direction of future research.

2 RELATED WORK

The balanced development of compulsory education is the key to balancing education supply and demand, which requires a scientific and practical education evaluation system. Its complexity is directly connected to the complexity of the compulsory education evaluation system. In recent years, the balanced development of compulsory education in China has attracted extensive attention from scholars, and some scholars have also studied the teaching evaluation model of minority languages such as Spanish. Yz A et al. raised a hybrid recommendation model built on network structure characteristics by combining the characteristics of neural networks, graphical neural networks, user interaction, tensor decomposition, and other methods. Compared with different network and matrix decomposition methods based on xSVD++, RTTF, DSE, etc., it has lower and higher prediction accuracy [42]. Okoye K et al. introduced the education process and data mining (EPDM+ML) model based on student teaching evaluation (SET) data and designed a verification experiment based on the design data set. It shows that the model can quickly output the classification results of student teaching evaluation data and can be used to improve teachers' behavior. In addition, the model can also be used to identify significant factors that affect student assessment and teacher recommendations, as well as the growing demand to promote and support teaching plans. [19]. On this basis, Yang X et al. used BPNN to evaluate the BP network and used PSO to advance the weight and threshold of the BP network to achieve its overall optimization. Through example verification, this improved BP using PSO to optimize the weights and thresholds of the BP network has the same prediction results of university teaching management evaluation indicators compared with traditional machine learning algorithms such as simple BP algorithm, random forest algorithm, and logical regression algorithm. However, the prediction accuracy of the method designed in this study is slightly higher. Because PSO optimizes BP algorithm parameters, the process and difficulty of the training algorithm are significantly reduced. These show that it has an excellent practical application prospect [40]. By Lu Y et al., the multimedia teaching evaluation reasoning model is applied to the effect and trend prediction of reasoning teaching, and a reasoning model simulating the process of LTV-IFLA based on accurate intuition is proposed. This teaching reasoning model combined with multimedia technology can accurately predict the teaching effect of fundamental courses and the absorption of students' knowledge. Still, some significant things could be improved, such as the low computational efficiency of this algorithm, especially when processing a large number of data samples, and the computational speed is plodding [14]. Luo Y and others discussed the information processing problem in CAI courseware. They used a simulated annealing algorithm to train the weight parameters of each neuron of the BPNN algorithm to propose an improved hybrid BPNN. The efficiency of this algorithm in processing CAI courseware information is significantly higher than that of similar algorithms widely used in the world, and the calculation accuracy has no significant difference compared with the comparison methods; it has a specific market application value, but due to the limited experimental conditions, the calculation effect and application value of the improved algorithm could not be tested on more real data sets. The author intends to supplement and correct this deficiency in subsequent research [15].

Sun Qiang et al. found few evaluation and analysis models for students' online Chinese curriculum evaluation data in the current educational world. Therefore, according to the characteristics of the data, a unique evaluation model for analyzing online Chinese curriculum evaluation data in colleges and universities was built using the Fast RCNN algorithm. It can output the overall evaluation grade of students on a course according to the multidimensional evaluation data of students on a course. So teachers can improve their teaching methods and details more efficiently [13]. Hou J et al. proposed a multidimensional data processing method and compared it with other shallow models. This neural network algorithm and traditional machine learning algorithms such as linear regression, logical regression, and naive Bayes can effectively evaluate higher education institutions' education quality and process a large amount of data before the model is improved [7]. Huang W et al. used a machine learning method based on Gaussian processes. This paper proposes an improved machine learning algorithm based on the mixture of Gaussian and sparse Bayesian, which is used to extract students' evaluation attitudes and improvement suggestions from English curriculum teaching evaluation data. A test experiment was also designed and carried out in the research. The test results show that the algorithm can effectively remove invalid information, emotional garbage information, etc., from the original data set and extract and construct relevant information to form the final evaluation to create the final evaluation results. The output of the final assessment is more accurate than the comparison algorithm. This experiment proves the advantages of the algorithm designed in this study in English intelligent teaching evaluation [9].

Through comparative analysis, the paper finds out the main factors that affect the quality of network teaching, including the teaching state of teachers, students' learning ability, teaching textbooks, teaching aids, etc. This paper uses descriptive statistics, analysis of variance, Pearson correlation analysis, and other methods to verify the proposed hypothesis. It combines PSO and BPNN to build a PSO-BP algorithm to address the features of datasets that affect the quality of network teaching. The PSO-BP model has significantly higher prediction accuracy and faster calculation speed than other methods, only slightly slower than the XGBoost algorithm model [10], compared with other standard network teaching evaluation algorithm models. Yang L et al. used the improved CNN Dempster Shafer model to combine the different results of each ICNN module and apply it to the teaching quality evaluation (TQE) of various courses. Then, the superiority of ICNN's DS integration mode in the system is proved through simulation experiments. Moreover, the ICNN’s DS comprehensive evaluation model is the best among the various TQE indicators currently studied. Still, the stability of the calculation results is slightly worse than that of comparison models[39].

Few studies use data mining algorithms in teaching evaluation mode, and the use of data mining algorithms in Spanish teaching evaluation is even rarer. This paper introduces them to the Spanish teaching evaluation system.

3 THE PROPOSED GA-BP SYSTEM

3.1 Establishment of Data Elements for the Education and Assessment of Spanish at the University

This article analyzes Spanish teaching from the perspective of improving the quality of Spanish teaching, as shown in Figure 1 [18].

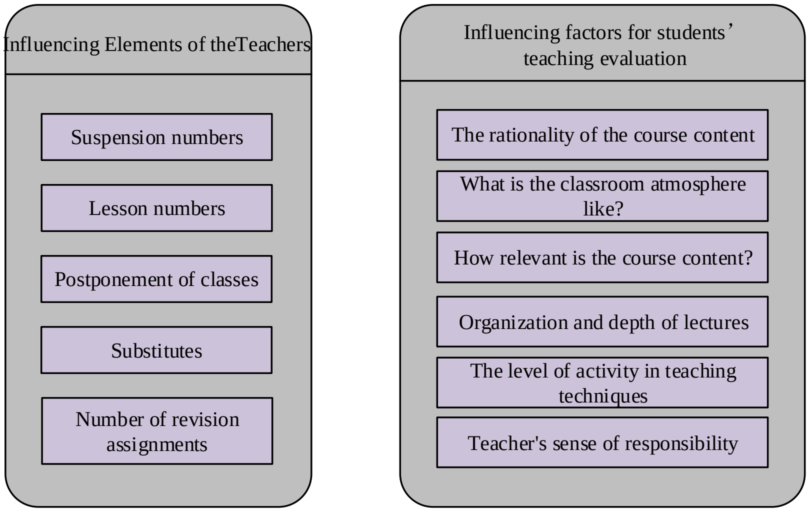

Figure 1: Influencing elements: TQE in institutions of higher education.

As can be seen in Figure 2, the study addresses the influencing factors of teachers themselves. It is evident from the figure that the dark black boxes are the influencing factors that the study establishes to select for the assessment of teaching quality in higher education, which are then labeled in order [32]. These ten are utilized as the input variable acquired for the model, explicitly labeled in equation (1).

$$x = (X_1, X_2, \cdots, X_n)^T \qquad (n = 10) \tag{1}$$

As Eq.(1), x is the vector of influencing elements; X_i is the value based on the relevant factors of Spanish evaluation in Fig.1 [45]; the level of teaching quality of each institution is derived by the experts based on each influencing factor, the construction of the model of the results is obtained through the analysis of each influencing factor, and the adaptive genetic algorithm of evolution is applied to the fuzzy level and output level weights The initial values, learning rates, and dynamic coefficients were optimized [44]. Then, the node numbers in the neural network are used to determine that in the hidden layer[37].. In teaching and evaluating Spanish, neural networks are employed until the expected training bias is completed.

3.2 Improvement of Ga-Based Bpnn Algorithm

There is a certain similarity in the characteristics of BPNN and human neurons, which can store large amounts of massive data without understanding the mapping relationships between variables and can train the inputs and outputs directly on the network[36]. The primary BPNN thought is to use the gradient decreasing method to make the prediction results close to the actual situation by backward correcting the deviation of the prediction of the output layer from the actual data[38], and Fig.2 shows its three-layer network structure.

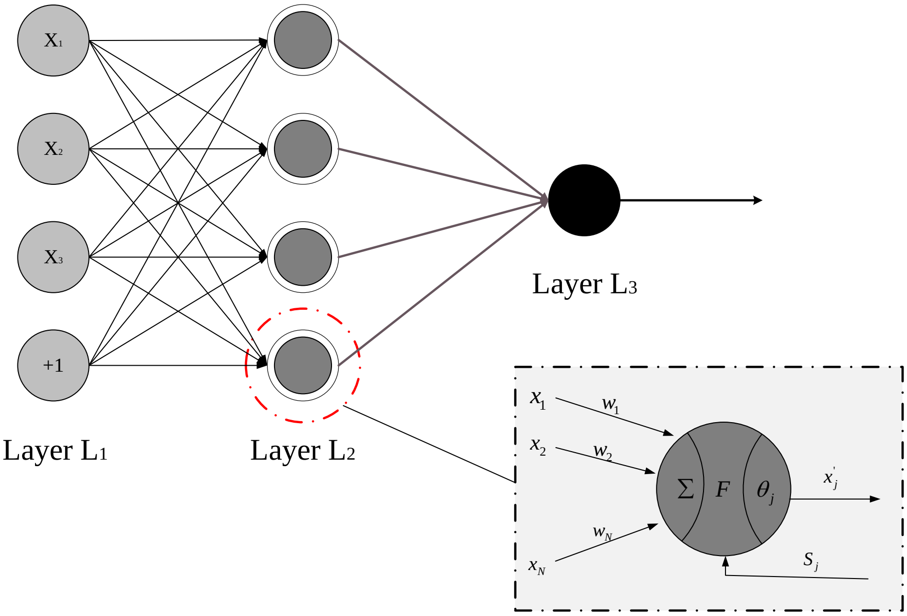

Figure 2: Neural network topology.

In Fig.2, the BPNN is segmented into two stages [12]: pre-activation is the weighted sum of signals transmitted by the upper layer network, while the activation stage substitutes the pre-activation result [35]. The details are displayed in equations (2) ~(3).

$$g(x) = w_{ij}x_i + b_j \tag{2}$$

$$h(x) = f(g(x)) \tag{3}$$

As equations (2) and (3), $x_1, x_2, \cdots, x_N$ represents the output value of the x_i in the previous layer; w_{ij} is the weight of the j in the upper and the i in the previous [2]; b_j means the critical threshold. The formula between the x_j' and n is Shown in Eq. (4)[41].

$$X_j = \sum_{i=1}^{N} w_i \cdot x_i + S_j \tag{4}$$

In equation (4), S_j is the feedback signal. The BPNN is iterated once from both the anterior and posterior [33], i.e., beginning at the input layer by carrying out successive operations on the current parameters and then sending them along the forward direction of the network to the output layer with a forecast of its real-loss[4]. The backward transmission means the deviation between the estimates obtained from the previous time and the actual losses[31], using a gradient-decreasing method to correct each parameter in each layer in the reverse direction until the deviation between the estimates and the substantial losses are both on target[16]. The backward propagation is the loss-error of the predicted and actual values gained from the previous time. From the output level, the gradient decreasing method is used to reversely correct each layer's parameters until each layer's loss error is the target[24],[23], as shown in Figure 3.

The implicit layer output variables are Eq.(5).

$$h_j = (h_1, h_2 \cdots, h_p) = f(\sum_{i=1}^{n} w_{ij}x_i + a_j), j = 1,2, \cdots, p \tag{5}$$

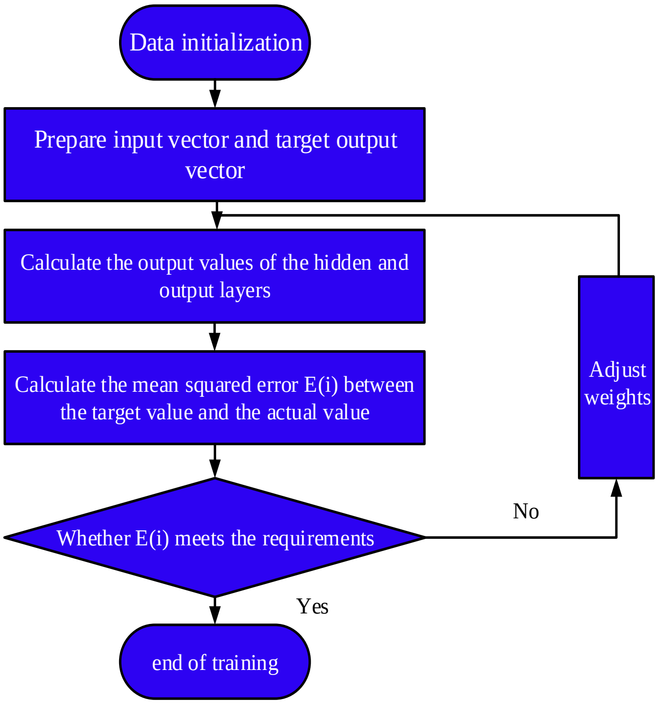

Figure 3: Flow chart of BPNN training.

In equation (5), a_j is the bias. The actual output variable is Eq.(6).

$$y_k = (y_1, y_2, \cdots, y_q) = \sum_{j=1}^{p} h_j w_{jk} + b_k, k = 1,2, \cdots, q \tag{6}$$

In Eq. (7), w_{jk} is the weight of the implicit and output layers. b_k means the bias. The expected output variable is exhibited in Eq.(8).

$$d_k = (d_1, d_2, \cdots, d_q), k = 1,2, \cdots, q \tag{7}$$

The error function is Eq.(8).

$$E = \frac{1}{2}\sum_{k=1}^{q}(d_k - y_k)^2 \tag{8}$$

M-specimens' Gauss function is Eq.(9).

$$E = \frac{1}{2m}\sum_{l=1}^{m}\sum_{k=1}^{q}(d_k(l) - y_k(l))^2 \tag{9}$$

Eq.(10) is the formula for updating weight values.

$$\begin{cases} w_{ij} = w_{ij} + \eta h_j(1 - h_j)x_i \sum_{k=1}^{q} w_{jk}(d_k - y_k) \\ w_{jk} = w_{jk} + \eta h_j(d_k - y_k) \end{cases} \tag{10}$$

In equation (10), η is the learning rate, and the bias is updated as Eq.(11).

$$\begin{cases} a_j = a_j + \eta h_j(1 - h_j) \sum_{k=1}^{q} w_{jk}(d_k - y_k) \\ b_k = b_k + \eta(d_k - y_k) \end{cases} \tag{11}$$

GA has the advantage of global search, while BPNN has a more significant local search capacity [21]. Nevertheless, since BPNNs are endowed with initial weights at random, this can lead to a situation where the number of training sessions and the final weights can be different after each BP training session is completed[20]. The study proposes a GA-BP method for modeling a university Spanish education and assessment system to make the final results more accurate, practical, and reasonable[29]. First, the P-group is initialized through the initialization algorithm to confirm the size. Next, the individual with a specific probability value is classified by the fitness function of each individual [46], and Eq.(12) is the selection method.

$$P_i = f(i)/\sum_{i=1}^{n} f(i) \tag{12}$$

In Eq.(12), $f(i)$ is the fitness. In step 3, a new individual generation is cultivated by changing the individual's genes, and the individuals that do not meet the standard are eliminated[43]. The 4th-step is to insert the new ones into P and execute fitness analysis. Determine the required conditions according to the neural network error. If it is satisfied, perform step 6. On this basis, each person is used as the weight, and it is calculated. The possibility of selecting i is Eq.(13).

$$T_i = f_i/\sum_{k=1}^{M} f_k \tag{13}$$

In equation (13)。 after getting the probability of each individual, use random numbers of 0 and 1 to decide which individual to mate with. Since the relationship between crossover and encoding is substantial, and it can be seen from the above that the floating-point encoding method is used, this article only discusses the floating-point encoding method; its arithmetic crossover method is shown in Equation (14).

$$\begin{cases} X_A^{t+1} = \partial X_B^t + (1-\partial) X_A^t \\ X_B^{t+1} = \partial X_A^t + (1-\partial) X_B^t \end{cases} \tag{14}$$

In Eq.(14), X refers to a unit. ∂ It is a parameter. If it=constant, then it= equation operation. If it is confirmed by evolutionary algebra, then it is inconsistent [17]. The last type of variation uses homogeneous variation. Homogeneous variation involves displacing all the gene values on a chromosome with a certain probability to a random number consistent with an even distribution[47]. The genes on each chromosome are viewed as a changing point. Depending on it, the GA is initialized and terminated by repeating iterations with fitness calculations, replication and crossover, and genetic operations, such as mutations, in each iteration until the end condition is finished. Otherwise, the repetition does not stop[5]. Regarding the current condition, different Apps will have disparate end situations. In this paper, however, the end condition is that the iteration will cease when the iterations are reached [34].

In Fig. 4, using the initial value and threshold of the BPNN and using the inversion of the training error function of the BPNN [3], any discrete random groups can be obtained to select the optimal individuals; new populations are obtained through crossover and mutation till the optimization target. Next, the genetic operation will be repeated until the GA completes its iteration. The optimal initial values and thresholds of the BPNN can be obtained through the optimization of the GA [1]. Eventually, the mean cross entropy is obtained, and the verification set with the smallest entropy is used as the final evaluation mode(Song Cet al. 2022) [28], as shown in equation (15).

$$Acc = \frac{1}{k}\sum_{i=1}^{k} acc_i \; (i = 1,2,\ldots,k) \tag{15}$$

acc_i in Eq.(15) refers to the i validation set error. The study notates the accuracy of the quality assessment rubric for teaching in Spanish as equation (16).

$$P = \frac{N_{right}}{N_{all}} * 100\% \tag{16}$$

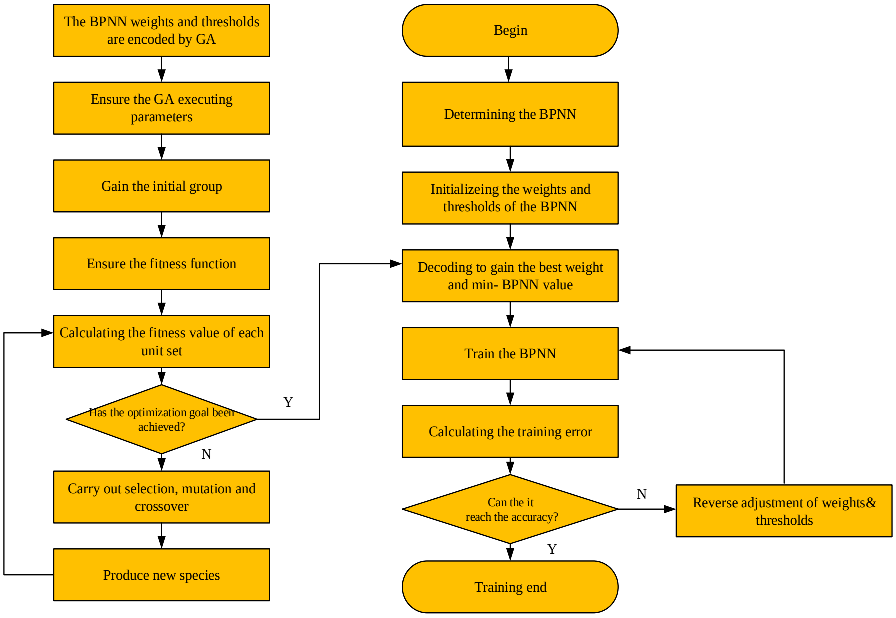

Figure 4: GA-BP flow chart.

In equation (16)。 N_{right} is the number of factors assessed as high in the quality of teaching in Spanish, $and\ N_{all}$ is the sum of items in the test group (Singhrova Aet al. 2021) [27].

4 PERFORMANCE ANALYSIS

4.1 Analysis of the Effectiveness of Inn in Spanish Language Education and Assessment

This paper used ten assessment indexes from 5 universities as the input data, and their time was vectorized to acquire the related teaching determination score. The scale of each indicator distinction led to differences in the decreasing rate of each indicator. Using the same learning rate made it challenging to achieve an optimal solution for network training and, simultaneously, to avoid the data of indicators with too large values causing gradient explosion and indicators with too small values being swallowed up. The training of BPNN is the basis for establishing the BPNN model. This paper adopts a unified standardization criterion and normalizes its data, see Table 1.

-	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
S 1	*0.26*	*0.08*	*0.54*	*0.54*	*0.43*	*0.19*	*0.55*	*0.61*	*0.54*	*0.63*
S2	*0.13*	*0.04*	*0.32*	*0.38*	*0.13*	*0.36*	*0.19*	*0.35*	*0.64*	*0.38*
S 3	*0.68*	*0.18*	*0.48*	*0.21*	*0.23*	*0.81*	*0.81*	*0.31*	*0.94*	*0.72*
S4	*0.61*	*0.16*	*0.11*	*0.69*	*0.48*	*0.16*	*0.52*	*0.25*	*0.15*	*0.14*
S 5	*0.54*	*0.09*	*0.21*	*0.64*	*0.46*	*0.64*	*0.64*	*0.12*	*0.11*	*0.52*

Table 1: Normalized data.

In model establishment, the choice of activation function is crucial; the Sigmoid and tanh are the input data in [0,1], the activation state has a small area of action, and the data on both sides are mostly suppressed. The differentiation interval<1. The gradient value declined as the network depth rose. Relu is active as the input value>0. It has an extensive range of activation intervals and can advertise the disappear gradient. Neither the function nor differentiation of Reluc has been subjected to any complex mathematical operations. They are set directly to 0, thus averting the involvement of the constrained neurons and making them learn faster. Nevertheless, the neuron's original status is 0, therefore preventing it from damaging the neuron. A modification to the Relu function by Leaky_Relu can be an excellent way to mitigate the weaknesses of the neural network. This calls for constant adjustment by training. The α is complex to be mastered. Therefore, two methods, Relu and Leaky_Relu, are used as the hidden layer activation function of the BPNN. Distinctive training errors and times are gained through 5 network trainings.

-	*Relu*		*Leaky_Relu*	
	TE	*TT*	*TE*	*TT*
time-1st	*0.0218*	*105*	*0.0238*	*118*
time-2nd	*0.0235*	*102*	*0.0240*	*123*
time-3rd	*0.0216*	*101*	*0.0209*	*109*
time-4th	*0.0211*	*102*	*0.0210*	*115*
time-5th	*0.0219*	*103*	*0.0256*	*117*

Table 2: Comparison of actual and leaky_relu.

Note: training error=TE; training time=TT.

Using the 5xBP to perform the Relu and Leaky_Relu algorithms, it is found that the training error of the 5xBP neural network on the Relu is very similar to the Leaky_Relu. Thus, the initial value Relu of the BPNN can be used as the hidden layer of the BPNN. The BPNN has a higher classification probability in [0, 1]. The teaching quality gradient of BPNN in grades 0-8 and the start function of its output layer are usually soft mapping functions. It is possible to reflect multi-neurons' outputs into the (0,1), the gross neuron possibility=1. After assuring the GA-BP, the standardized data is introduced for later research. Then, the training error curve is first obtained; see Fig. 5 and Fig. 6.

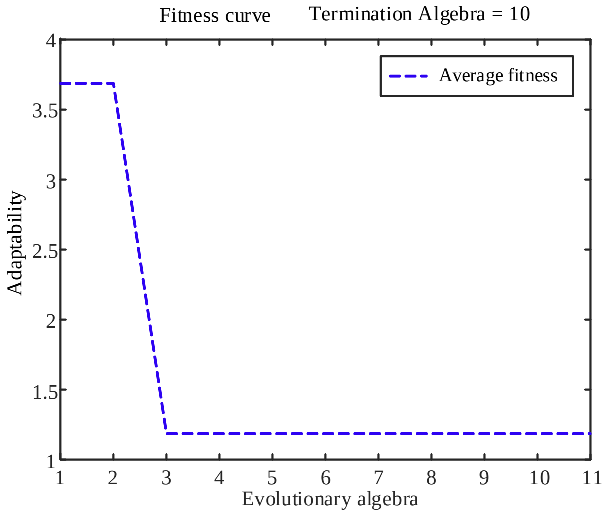

Figure 5: Statistical chart of training fitness of GA-BP.

As shown in Fig.1 and the fitness chart in Fig.5, the BPNN of the GA has obtained the desired accuracy. GA-BP achieved the set value when the evolutionary generation amounts =10. The corresponding threshold and weight values are obtained.

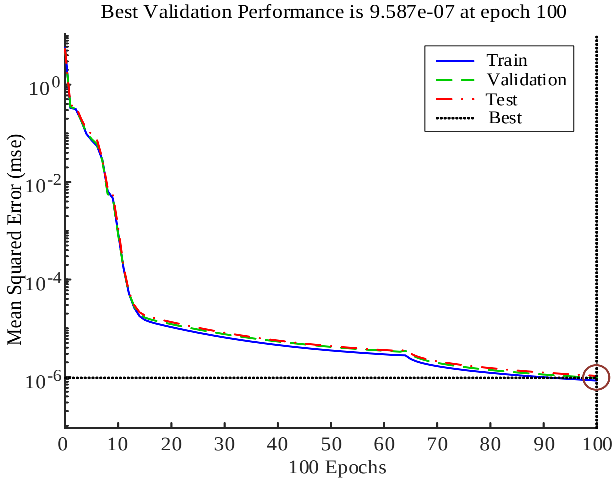

Figure 6: Statistics of MSE of GA-BP training.

In Fig.6, the threshold and weight are replaced for repetitive iterations. At last, the model completed the expected accuracy when trained 100 times. The model reached 10-6 errors, achieving the desired accuracy. The Fig.7 shows the error histogram for each of its sets.

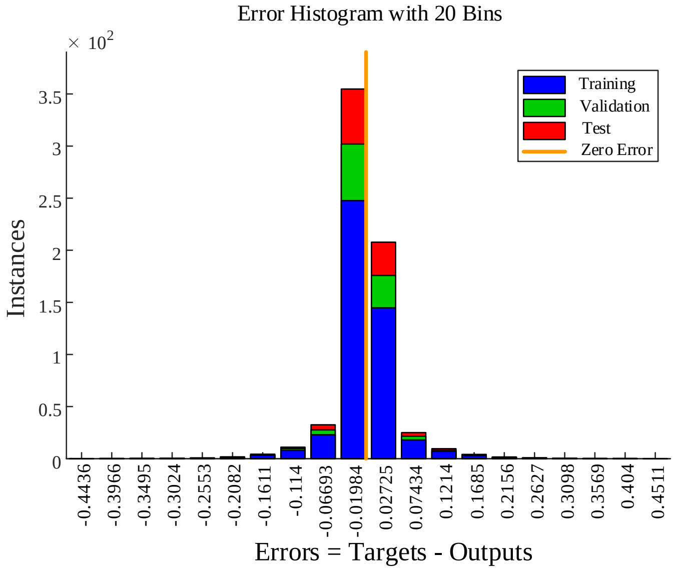

Figure 7: The TE of GA-BP histogram.

Figure 7 shows the distribution of model errors. The mistakes of the three sets are mainly distributed around the zero value, and the distinction between the two values is primarily spread in the [-0.06693,0.07434]. This means that the model's predicted performance is solid, the GA-BP evaluation model has a fast learning speed, and its performance is more stable.

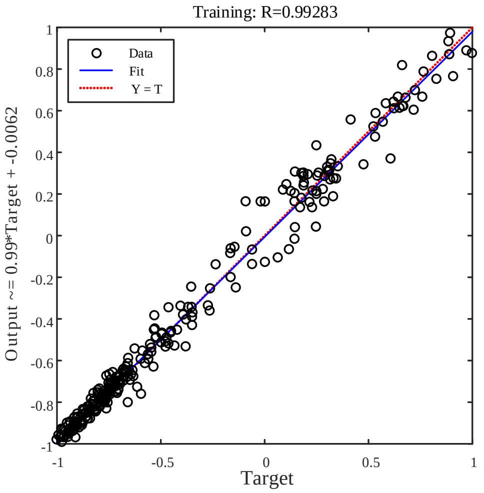

Figure 8: Fitted curve after training.

From Fig.8, the training set prediction values are high, with deviations in some rare instances. The R-values for each of its sets hover around 0.99, which is a good fit. and that for the training set is 0.99283, which is very close to 1. So, the established GA-BP has a high degree of fitting. Finally, this paper compares the BPNN and GA-BP with the literature[18] and gives the corresponding calculation results.

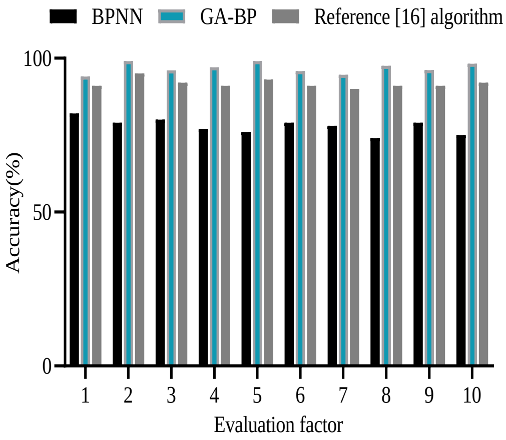

Figure 9: Accuracy of TQA in colleges and universities.

From the chart, the average distribution of the GA-BP algorithm reaches 97.5%, and the estimation accuracy of the BPNN is above 80%. This is due to the BPNN's adaptive ability, which can quickly match the corresponding thresholds and weights. Therefore, the described GA-BP has obtained more significant results in evaluating Spanish teaching. The model has a fast learning speed, high prediction accuracy, and stable performance.

4.2 Engineering Applications

It would be hasty to verify the stability of the model only by taking a university Spanish education as the research object. Therefore, the study obtained the academic performance of the 2020-level software engineering undergraduates and carried out noise reduction, redundant features, and other predictions. Processed and obtained relevant experimental data. This data set covers the academic achievements of 278 software engineering majors in 35 basic subjects and majors and provides relevant scholarship information. "Get scholarship" as the target variable, take each subject as a categorical variable, and the importance of each subject is shown in Figure 10 (only nine subjects are listed here)[11][8].

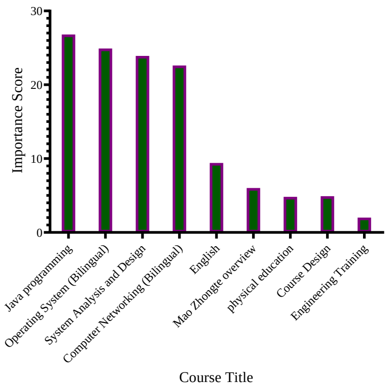

Figure 10: Statistics of curriculum importance coefficient with "failure or not" characteristics.

As shown in Figure 10, in terms of "fail or not," the three most important subjects are Java programming (importance score 26.05), the operating system course (importance score 24.39), and the system analysis and design course (importance score 22.12).

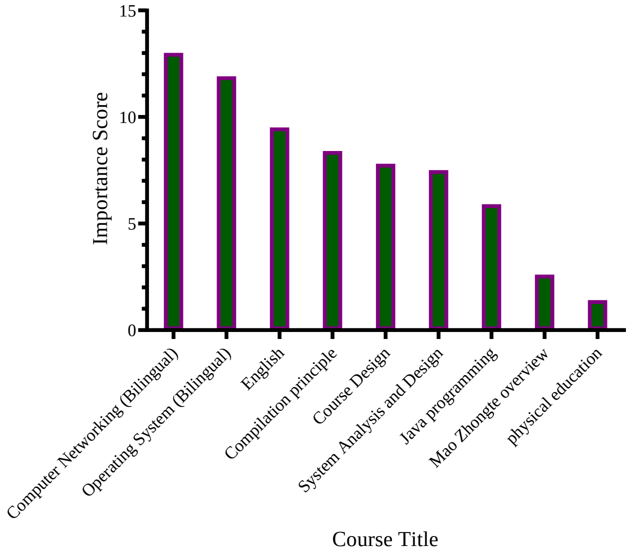

Figure 11: Statistics of importance coefficient of "scholarship" feature.

From Fig.11, in the aspect of "whether to obtain a scholarship," the performance of computer networks, operating systems, and English is the most prominent. In contrast, computer networks, Operating systems, and English are critical in software engineering. Students who have mastered this knowledge also showed better learning effects on the whole, so the conclusion of this study is consistent with the subjective analysis.

5 CONCLUSION AND THE FUTURE WORK

Education is both a measure of a country's soft power and an essential platform for measuring a nation's culture. To achieve equity in compulsory education and to strengthen the concept of "high quality, high connotation, and strong characteristics," China continues to promote the reform and development of the education system, especially the evaluation of the quality of school education, which is critical. In this study, a model is constructed to evaluate the quality of Spanish language education in five selected universities. After confirming the GA-BP, the normalized data were imported for further study. This model reached the set expectations in terms of fitness when the number of evolutionary generations reached 10, and the corresponding thresholds and weights were obtained for repeated training iterations. The model eventually reached 10-6 when it reached 100. The error of the three sets was mainly distributed around the zero value; the model has good forecasting ability, the learning speed of the model is fast, and the performance is good. The R for this training set is 0.99283, which is a good choice. Through the comparison of the three models, the prediction accuracy of the GA-BP can reach 95%, which has significant advantages compared with other methods.

Due to the limited nature of the data used in the study, only some simple and different experimental results were obtained, which clarified the importance of some professional courses and provided direction for students to focus on learning. Still, it should not cause students to relax while studying other courses. Due to the limited data, only some simple results were obtained. By horizontally comparing the learning effects of students of different majors in different universities, other results may be obtained, showing the exploration value of data mining technology in education. The fusion of AI, genetic algorithms, and language learning holds immense promise for advancing the capabilities of medical professionals, fostering better communication, and ultimately improving healthcare outcomes for patients globally.

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