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Research Article

Research on Expert System of Japanese Auxiliary Teaching Based on BP Neural Network

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College Japanese teaching is the cradle of Japanese professional development. With the rising frequency of interactions with Japan in our country in the fields of politics, economy, trade, and other fields, Japanese as a professional discipline is exhibiting popularization, universalization, and folkization features. However, the ever-emerging trend of Japanese as an application tool for worldwide communication has rendered professional Japanese instruction in colleges insufficient. To meet the needs and growth of society, as well as to address the problems of teacher shortages and a lack of attention to students' fundamental knowledge in the reform of Japanese language teaching in colleges, the study uses an expert system as the theoretical foundation and combines BP neural network technology to design an auxiliary teaching system with a friendly interface, strong versatility, and extensibility for Japanese language teachers and students. Teachers can use this technique to organize the test by classifying and summarizing the test questions based on the knowledge points and complexity of the questions. Students can utilize this system to learn on their own, and by identifying weak links in their knowledge points, they can practice more effectively and create a multiplier impact with half the work. Finally, the whole system is designed and implemented in accordance with the software development process. It has been demonstrated that the system can provide realistic results and has good application value after a huge quantity of data testing and operation.

1. Introduction

The need for foreign language talents has increasingly evolved from one foreign language to "bilingual" and "multilingual" due to the rapid growth of the domestic economy and the accelerating pace of internationalization. Foreign language majors in colleges and universities should seek to develop not just their second foreign language skills but also their professional foreign language skills. Japanese has risen to the top of the list of second foreign language options for college students. In particular, since the turn of the century, exchanges between China and Japan have grown in frequency, the two countries' import and export commerce has steadily increased, and economic and cultural exchanges have accelerated. As a result, the focus of Japanese language teaching has shifted to students' comprehensive Japanese application ability, self-learning ability, and improving cultural self-cultivation [1, 2]. Therefore, Japanese teaching resources are becoming increasingly unable to satisfy the objectives of social growth, and the highly competitive job market has imposed ever-increasing demands on graduates. Thanks to the advancement of AI and network technology, intelligent auxiliary teaching systems have evolved with the times, attracting substantial research. There are many intelligent teaching assistance systems based on networks in use at the moment, both at home and abroad, but their intelligence is low [3, 4]. Given the numerous problems with the current Japanese auxiliary teaching system, it is necessary to expand research into an artificial intelligence-based Japanese auxiliary teaching system.

The notion of expert systems may be dated back to the 1960s as an essential branch of AI. The DENDRAL expert system, created by Stanford University in 1965, is regarded as a milestone in the evolution of expert systems [5]. Expert systems have now become one of the most active, valuable, and productive scientific fields in artificial intelligence [6]. It can efficiently utilize the valuable experience and expertise collected by experts over a long period of time and solve problems that demand expert solutions by simulating expert thought processes. Medical, military, geological exploration, teaching, chemical, and other fields can all benefit from expert systems. Since 2000, people's research on expert systems has undergone a certain change, and the research has turned to expert systems combined with fuzzy technology, real-time operation technology, and neural network knowledge base technology and has made breakthroughs in new technologies. Many fault diagnosis expert systems based on BP neural network have been developed. Reference [7] optimized the BP neural network as the expert system diagnostic and reasoning module using the Sparrow Search Algorithm (SSA) and analyzed and diagnosed the defect of the rubber-wheeled vehicle using the built fault diagnosis system. The results demonstrate that the system is both accurate and quick to complete diagnostic tasks. Reference [8] took the slow convergence speed of the BP neural network algorithm as the starting point and finally increased the convergence rate by introducing the steepness factor, combined with the introduction of the momentum factor and the adaptive step selection method. Furthermore, they improved the efficiency of tamping vehicles in fault diagnosis applications. Reference [9] was based on the feedforward network learning algorithm of the BP neural network and utilized the LabVIEW tool to create a teaching quality evaluation model that automatically divides into five categories: excellent, good, medium, qualified, and unqualified, avoiding the impact of artificially subjective weight ratio settings on the evaluation conclusion. Reference [10] built a gearbox fault diagnosis system based on BP neural network to diagnose the cement vertical mill gearbox, planetary gearbox gears, and bearings in the cement plant and give the diagnosis conclusion.

The above research shows that the expert system based on BP neural network plays the role of prediction, diagnosis, troubleshooting, monitoring, control, and interpretation in various fields. However, since AI technology has been widely utilized in the area of education, the expert auxiliary teaching system based on AI has been steadily applied to intelligent teaching in colleges, which is firmly linked to educational modernization. In other areas of education, the artificial intelligence-based expert auxiliary teaching system also has a variety of applications, including the development of human reasoning model learning aids, which is becoming increasingly popular. For example, the internal medicine diagnosis expert system is an expert-assisted teaching system that can identify and diagnose the patient's symptoms through a series of rules of the patient's symptom attributes [11]. In view of this, the study takes the actual needs of Japanese teaching in the age of intelligence as the starting point and proposes a set of solutions to the problems of insufficient teachers and a lack of attention to students' fundamental knowledge that currently plague Japanese teaching in colleges. It can address the obstacles that students face in their independent Japanese learning at colleges. Moreover, it can address the issue that teachers find it difficult to participate in their students' independent learning. Therefore, with the support of this system, it may not only help students consolidate and master basic knowledge but also improve their independent learning ability, minimize teachers' teaching burden, and improve teaching quality. Researchers integrated BP neural network technology with expert system theory to produce a set of Japanese auxiliary teaching expert systems that are interactive and easy to maintain and extend and can share resources for Japanese teachers and students. The innovative work of this article includes the following:

(1) First of all, the system generally adopts the B/S three-layer structure system and integrates the features of Japanese teaching, resulting in some functions of the Japanese auxiliary teaching expert system being more perfected and humanized.

(2) Secondly, according to the different users, the system integrates teaching evaluation and autonomous learning and provides an English-assisted teaching module and a student's autonomous learning module. The former is primarily aimed at teachers, and it uses the knowledge expression method to classify and summarize Japanese knowledge points by combining frame type and production type. Japanese teachers can use this system to diagnose the entire class and determine the students' comprehension of fundamental knowledge, which can then be used to guide the teaching. The latter analyzes the relationship between the knowledge points of the exam questions using the BP neural network algorithm, creates the student's self-learning module, and performs self-diagnosis and other activities on the basis of the individual student.

(3) Finally, the whole system is designed and implemented in accordance with the software development process. It has been demonstrated that the system can provide realistic results and has good application value after a huge quantity of data testing and operation.

2. Related Concepts and Theories

2.1. The Basic Principle of BP Neural Network. Rumelhalt et al. presented the BP artificial neural network in 1986, which represents a new era in the optimization of artificial neural networks for associative memory [12]. It is one of the most extensively used and successful artificial neural network algorithm models. Backpropagation (or "BP") neural networks are multilayer feedforward neural networks trained to utilize error backpropagation approach [13], which is frequently utilized in systematic evaluation in a variety of domains [14–16].

The forward and backpropagation procedures are used in BP neural network training. A signal propagates forward from the input layer to the hidden layer to the output layer, where it is transformed nonlinearly layer by layer to produce the output signal. The condition of neurons in one layer has no bearing on the condition of neurons in the next layer. If the actual result generated at the output layer does not reach the expectation, the error is propagated backward. At the error feedback step, the error signal is carried from the

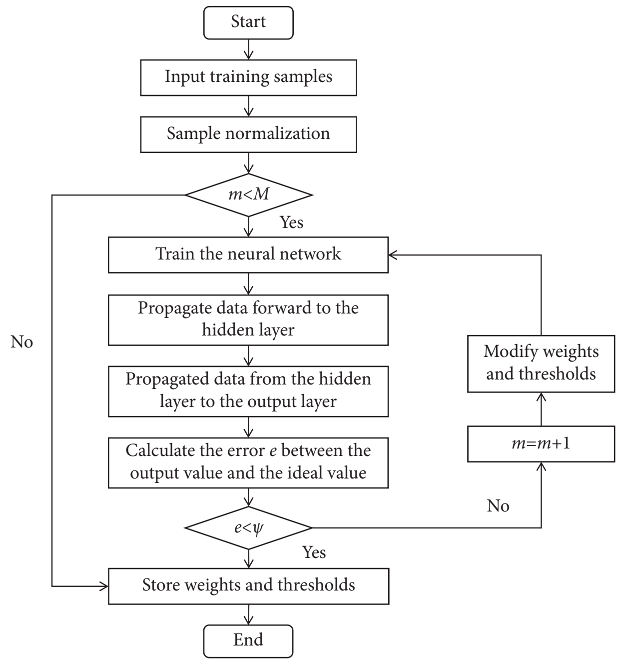

Figure 1: The construction flowchart of the BP neural network.

output to the hidden to the input direction, and the error is spread to all neurons in each layer. The weights and thresholds of each neuron in this layer are changed based on the error received in each layer to reduce the error in the gradient direction. The BP neural network is built when the network has been repeatedly trained until the output error or the number of training times meets the predetermined value. Figure 1 depicts the entire procedure.

As illustrated in Figure 1, by training the network with input training samples, the BP neural network may build a nonlinear mapping connection from input to output. Because of its simple structure and strong adaptability, it has a strong ability of repetition in functions such as nonlinear approximation [17]. Considering the computational complexity and other factors, the article utilizes a BP neural network to mine the mastery of a certain knowledge point by Japanese majors in colleges, despite the fact that there are higher-performance algorithms or network structures such as convolutional neural networks [18]. An expert system model of Japanese auxiliary teaching was built based on this so as to help teachers to analyze students' learning situation intuitively and to better serve Japanese teaching.

2.2. Expert System. The expert system primarily performs problem diagnosis based on knowledge stored in the knowledge base, which is acquired by interviewing experts, experienced maintenance employees, or studying literature materials. However, there may be omissions, resulting in inadequate fault diagnostic findings. The weights and thresholds determine the network's steady state, and the stable neural network becomes the neural network expert system's knowledge base [19]. As a result, this article considers combining the two to solve the tough challenge of expert system knowledge acquisition while also enabling expert system defect diagnostics through quantitative analysis.

The human-machine interface, database, knowledge base, inference engine, and interpreter are the basic components of an expert system [20]. The human-machine interface (HMI) is an interactive window that allows users to log in and operate the system. The database stores the user's personal information and receives the collected data that has been standardized. The rule knowledge, trained neural network structure, and modified weights and thresholds are all stored in the knowledge base. The inference engine's reasoning process is carried out by depending on the knowledge base's rules or by combining the collected and processed data with the trained neural network for diagnosis and then clearly exhibiting the diagnosis results through the interpretation. Figure 2 exhibits the expert system's structure.

Then combined with Figure 2, each component of the new system built in this study is introduced in detail.

2.2.1. The Design of Knowledge Base. The knowledge base is divided into two sections: the ability to submit and handle information and the ability to store information using the expert model, which makes it simple to maintain. There are two forms of knowledge in the Japanese teaching assistant expert system's knowledge base: static knowledge base and dynamic knowledge base. The former combines fixed vocabulary and grammar in Japanese learning that is stored hierarchically in the static knowledge base after extensive conversation and summation by subject experts and knowledge engineers. The latter refers to the rules input by domain experts, which can be added, modified, and deleted.

The Japanese auxiliary teaching expert system, which includes the qualities of causal, logical, process, and structural, is mostly used to examine students' understanding of knowledge points in a given test. As a result, the system proposed in our study uses a hybrid knowledge expression method based on rules and frameworks, which can fully exploit the benefits of both knowledge expressions, learn from each other's strengths and weaknesses, improve knowledge expression ability, and improve reasoning efficiency. The following is how the hybrid knowledge representation can be defined:

The frame name:

Slot 1: Side 1 (IF (Choice A) THEN (Conclusion 1), CF)
Side 2 (IF (Choice B) THEN (Conclusion 2), CF)
...
Slot 1: Side 1 (IF (Choice A) THEN (Conclusion 1), CF)
Side 2 (IF (Choice B) THEN (Conclusion 2), CF)
...

where the options of A, B, etc represent the set of judgment sates, the conclusions represent the set of inferred conclusions, and CF refers to the degree of certainty. CF is independent of the judgment condition set and the inferred conclusion set, and they have no direct relationship.

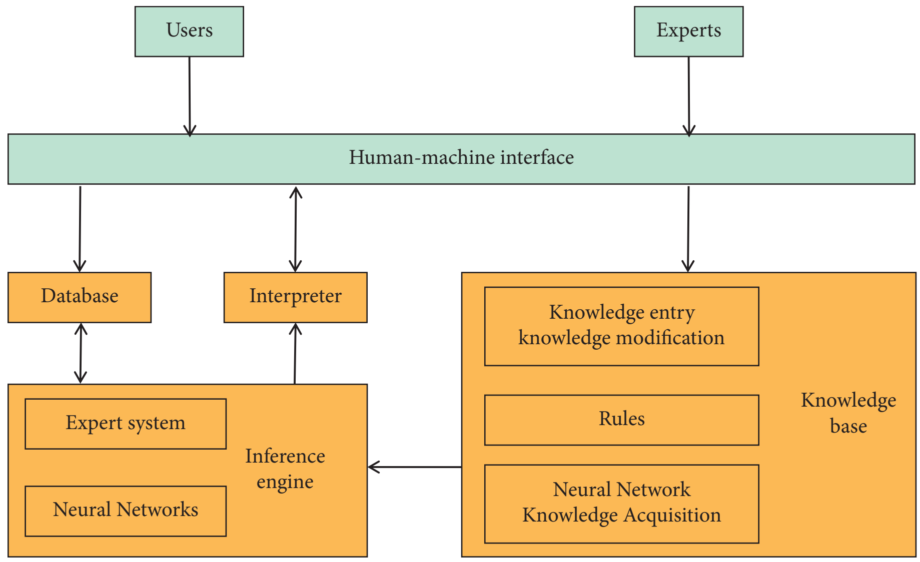

Figure 2: The structure diagram of the expert system based on a neural network.

2.2.2. Inference Engine. An expert system, which is just a collection of computer programs [21], is incomplete without an inference engine. This system employs a method of reasoning that combines forward and backward reasoning. Forward rule reasoning is used to match known facts with the knowledge base. The knowledge points contained in the examinations are picked after analyzing and resolving disputes. Reverse uncertainty reasoning is then applied to determine the learners' mastery of the knowledge item.

(1) Forward rule reasoning

A rule-based representation with multiple inputs and outputs that can be broken down into individual inputs and outputs is known as forward rule reasoning. The detailed definition is shown in the following formula:

$$R(i)\text{: if } x_i \text{ then } y_i \text{ is } (y_i, c_i)\,(i = (1, 2, \ldots, M))\text{: } CF(y_i), \tag{1}$$

where $R\ (i)$ represents the $i \in R$-th rule, $X = \{x_1, x_2, \ldots, x_m\}$is the input vector of the system, $Y = \{y_1, y_2, \ldots, y_n\}$ is the output vector of forward inference, and y_i stands for the knowledge. The rule conclusion $Y \in V$ is the output of the forward reasoning of the system, and c_i is the certainty of y_i. M refers to the number of rules. CF (y_i) is the credibility of the i-th knowledge mastery. It reflects the degree to which domain experts are uncertain about the increase or decrease of trust, and the larger the value, the more accurate the analysis of y_i.

(2) Inverse uncertainty reasoning

The rules in the knowledge base of the proposed system are based on credibility. As a result, the uncertainty inference engine is implemented using the uncertainty inference approach. Then, the system's fuzzy relational formula is established:

Table 1: Numerical representation of credibility fuzzy quantifiers.

Fuzzy quantifier	Value
Absolutely credible	1
Very credible	0.9
Strong credibility	0.7
General credibility	0.5
Less credible	0.3
Weak credibility	0.1
Not credible	0

$$\mu_z = \{\mu_i \cdot W\} \lim_{x \longrightarrow \infty}, \tag{2}$$

where μ_z is the conclusion vector.

Solve formula (2) to obtain its reasoning mode.

$$\mu_i \longrightarrow \mu_{CF} \longrightarrow \mu_z. \tag{3}$$

Suppose $\mu_Y = [\mu_{Y_1}, \mu_{Y_2}, \ldots \mu_{Y_N}]^T$, which refers to the quantized vector of the forward reasoning conclusion y. $W = [w_1, w_2, \ldots, w_n]$ is the weight vector. Let $\mu_p = \mu_y \cdot W$. Assuming that μ_p is a weighted logical formula, it can be expressed as follows:

$$\mu_p = \sum_{i=1}^{n} w_i \cdot \mu_y. \tag{4}$$

The truth degree of formula (4) is the weighted cumulative sum of the truth degrees of each subitem. Therefore, the truth degree of the whole formula increases with the increase of the truth degree of each subform.

μ_{CF} is the confidence level of the conclusion $(0 \le \mu_{\mathrm{CF}} \le 1)$. The credibility of the conclusion is obtained by the superposition and quantification of the credibility of the rules and then the transmission of reverse reasoning. In this system, μ_{CF} is actually the credibility of the y vector in the whole analysis, that is, the proportion of the occurrence times of the knowledge points corresponding to y_k in the whole

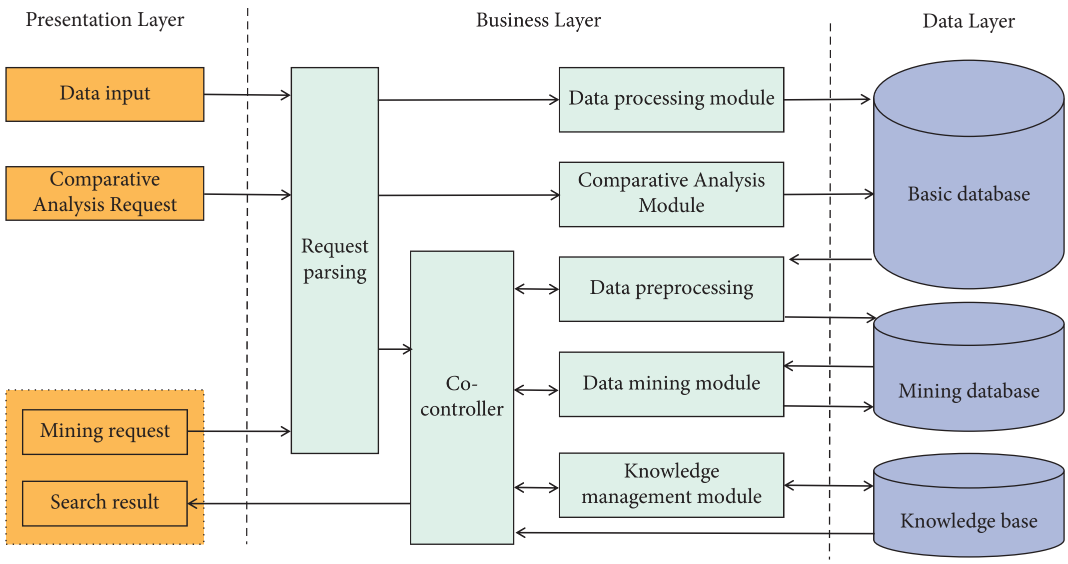

Figure 3: Architecture diagram of the whole system.

analysis question. Some fuzzy quantifiers and quantitative representations to describe credibility are specified in advance for users' benefit, together with the expertise of specialists in the area, as indicated in Table 1.

2.2.3. Interpreter. After the Japanese teacher submits the learners' answers files locally, the system displays the reasoning results in the form of a table to the teacher user. The interpreter includes two parts: first, the system gives the knowledge point name in the form of knowledge point representation based on the diagnostic conclusion obtained by the test results uploaded by the user. Then, it will provide a timely analysis of the diagnosis fault knowledge points and confirm the conclusion's credibility. The result is presented in ascending order based on learner's test results.

3. Construction of Japanese Auxiliary Teaching Expert System Based on BP Neural Network

The system is built on a three-layer Browser/Server (B/S) architecture. The B/S structure is a rather nebulous idea, and there is no universal design standard. It mainly includes the presentation layer, business layer, and data layer. Figure 3 depicts the system's complete architecture.

A presentation layer serves as the user's interface with the system. Users can communicate data with the business layer through the presentation layer, which requires ease of use and strong interaction. The business layer is the connecting layer between the presentation and data layers. It includes data processing module, comparative analysis module, data preprocessing module, and data mining module. Both the first layer and the last layer can only exchange data through the middle layer. The data layer stores the data required by the system during operation, as well as some temporary data generated during operation.

To make the system diagnosis more accurate and personalized, the study combines the neural network with the expert system in the data mining module so that intuitive thinking and logical thinking complement each other. The system transforms the experience and knowledge of Japanese experts into a nonlinear problem so that the diagnosis process realizes the nonlinear mapping of input and output and then uses the neural network to obtain the final diagnosis result.

3.1. Implicit Knowledge Base Based on Neural Network. The representation of neural network knowledge is implicit [22], and it corresponds to image knowledge. The collection of weight coefficients and thresholds acquired after learning in the manner of internal coding are mostly transformed from domain experts' subjects and rule tables in this system. The network structure and weights are stored in the knowledge base. This kind of knowledge is obtained through the neural network learning module and belongs to the metaknowledge acquired by the system, which provides information for reasoning and judgment. The representation of knowledge is defined as follows:

$$\begin{aligned} \text{If } \left(x_1, x_2, \ldots, x_n\right)^T &= (1, 0, \ldots, 0)^T \text{ Then } \left(y_1, y_2, \ldots, y_m\right)^T \\ &= (0, 1, \ldots, 0)^T, \end{aligned} \tag{5}$$

where $(x_1, x_2, \ldots, x_n)^T$ represents the description of the knowledge point after some questions in the question bank are converted; $(y_1, y_2, \ldots, y_m)^T$ refers to the diagnosis result of the knowledge point.

According to the knowledge provided by domain experts, Japanese knowledge is divided into 15 knowledge points, and Japanese experts add questions for these 15 knowledge points as the test question bank of the sample database. The selection of knowledge points should be representative, and the training and testing samples are selected from this database. When the network has been

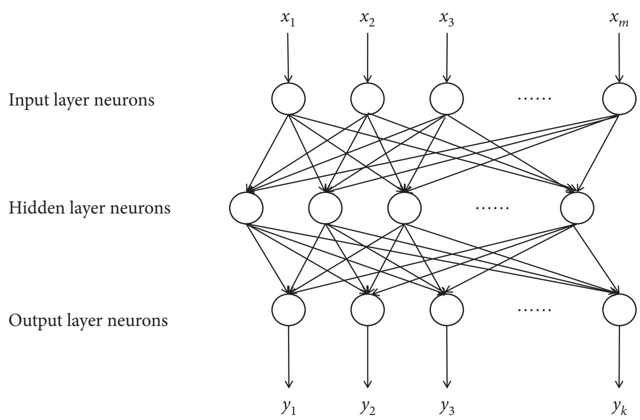

Figure 4: Structure diagram of BP neural network.

trained and students want to test themselves, they also extract test questions from this database for self-testing.

3.2. Training of BP Neural Network Model. The fault diagnosis of each student's knowledge point is actually the evaluation of their mastery of knowledge points. The forward multilayer network is the most extensively used and effective in the field of defect diagnosis [23]. It is also known as a BP network since it uses the BP algorithm in the learning process. Figure 4 illustrates the network's structure.

Assuming that the system adopts the three-layer neural network structure training model in Figure 4, and its learning procedure is as follows.

Suppose the input layer contains M neurons, the hidden layer contains N neurons, and the output layer contains K neurons. The input vector is $X = \{x_1, x_2, \ldots, x_m\}$, the output vector of the hidden layer is $H = \{h_1, h_2, \ldots, h_n\}$, and the target output of the output layer is $Y_{\text{target}} = \{b_1, b_2, \ldots, b_j\}$, and the actual output of the output layer is $Y_{\text{real}} = \{y_1, y_2, \ldots, y_k\}$. From the input layer to the hidden layer, the weight matrix is defined as U, and from the hidden layer to the output layer, the weight matrix is defined as V. μ_n and δ_k represent the neuron biases of the hidden layer and output layer, respectively, and f and g are the sigmoid functions, respectively.

(1) The output of the hidden layer is as follows:

$$h_n = f\left(\sum_{n=1}^{N} U_{mn} x_m - \mu_n\right), \; n = 1, 2, \ldots, N. \tag{6}$$

(2) The actual output of the output layer is as follows:

$$y_k = g\left(\sum_{n=1}^{N} V_{nk} h_n - \delta_k\right), \; k = 1, 2, \ldots, K. \tag{7}$$

(3) Calculate the error between the target output and the actual output of the output layer as follows:

$$e = \frac{1}{2} \sum_{k=1}^{K} \left(y_k - b_k\right)^2. \tag{8}$$

It is important to note that the number of neurons in the hidden layer is not determined at random. In the study, the numbers of neurons in the input and output layers are predetermined, and the number of neurons in the hidden layer can be calculated using the following formula [24]:

$$N = \sqrt{M + K} + a, \; (\text{a is a constant between } 1 - 10). \tag{9}$$

According to the previous analysis, the detailed training procedure of the BP neural network contains the following steps:

Step 1: Determine the network structure. Set $M = 150$, $K = 4$; then according to formula (9), we can get $N = 20$.

Step 2: Preset all connection weights w_{ij} to random values between [−1, +1]. w_{ij} is the weighted value between the node of this layer and the node of the next layer.

Step 3: Formalize the training samples. That is, respectively, initialize the input vector x_p ($p = 1, 2, \ldots, 150$) and the target output vector b_p ($p = 1, 2, \ldots, 150$).

Step 4: Training phase: do the following for each sample:

(a) Use formulas (6) and (7), respectively, to calculate h_n and y_k.
(b) Use formula (8) to calculate the output error.
(c) Modify the weights and thresholds according to the following formula:

$$w_{ji}^{n}(k+1) = w_{ji}^{n}(k) + \mu \delta_{pj}^{n} y_{pi}^{n-1} - a\left(w_{ji}^{n}(k) - w_{ji}^{n}(k-1)\right). \tag{10}$$

(d) If $|y_{pj}^{n}(k+1) - y_{pj}^{n}(k)| < \xi$, then go to (e); otherwise, return to Step 4.
(e) If $|y_{pj}^{n}(k) - b_{pj}(k)| < \phi$, then go to (f); otherwise, return to Step 2.
(f) End of training.

The training process corresponding to the algorithm is illustrated in Figure 5.

4. System Performance Test and Analysis

To analyze how the Japanese auxiliary teaching expert system works in actual teaching, we illustrate it with an example.

4.1. System Environment Configuration. The operating system is Windows 10 × 64 bits, the CPU is Intel(R) Core(TM) i7-9700 CPU @ 3.00 GHz, the web server uses Internet Information Server (IIS) 6.0, and the development software uses ASP.NET. The backend database uses SQL Server 2000. For the convenience of development, configure the database server and the web server on the same computer.

4.2. System Performance and Analysis. Case: a Japanese test has 30 participants, and the teacher wishes to assess the results of ten questions. First, use the user interface to enter these ten questions and their associated rules into the database. The knowledge points contained in the ten questions selected in the test are then distributed on nine separate grammar points following systematic reasoning and

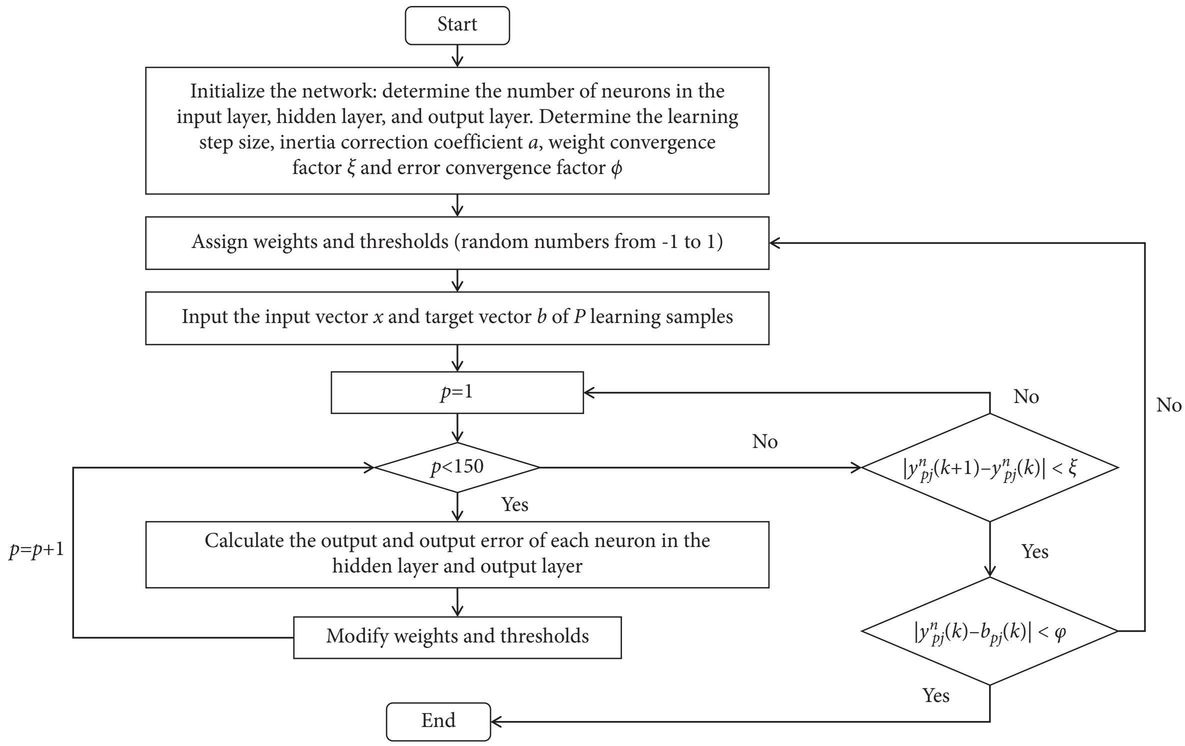

Figure 5: Detailed flowchart of the key algorithm in this paper.

Table 2: The y vector corresponding to the nine grammar points.

y vector	Grammar points
y_1	Adverbs, conjunctions, etc.
y_2	Auxiliary words and auxiliary verbs
y_3	Adjective verbs
y_4	Adjectives
y_5	Verbs
y_6	Nouns, numerals, pronouns
y_7	Word order
y_8	Sentence pattern
y_9	Tense

Table 3: Students' answers.

Question number	A	B	C	D
1	14	4	5	7
2	10	6	9	5
3	12	2	11	4
4	8	9	9	4
5	9	9	3	8
6	13	0	7	10
7	6	7	8	2
8	10	11	2	5
9	5	2	5	17
10	9	6	7	4

analysis. As indicated in Table 2, define the y vector as these nine grammar points.

After the exam, the teacher uploads the students' answers. Table 3 presents the statistical findings.

The system combines the obtained answer samples of 30 students, stores the sorted data in the database, and matches the rules defined in the knowledge base. In a comprehensive evaluation of the nine grammar points, quantize y to get μ_y as follows:

$$\mu_{y_k} = \frac{x}{n}, \tag{11}$$

where x represents the frequency of the knowledge point y_k among all the student answers and n is the sum of the questions answered by all students. After obtaining this expression, weight μ_y. Define the weighted vector as W; the weighting rule is as follows:

Suppose the credibility vector is $C = \{c_1, c_2, \ldots, c_n\}\,(0 \le c_i \le 1)$. In the samples to be detected, the weighted value w_i corresponding to each knowledge point is weighted and superimposed by the confidence vector C. The credibility is determined by the rules in the system and is defined by domain experts. The value of the weighting vector is decremented in steps of 2^n. The weighted μ_y is represented by μ_p, and the results are illustrated in Table 4.

The credibility of the conclusion is represented by the μ_{CF} vector, and the results are shown in Table 5.

It can be seen from the above analysis that if all the students in the class choose the option that the answer attribute is "we have mastered this knowledge point," and the answer is a deterministic answer, its weighted value μ_{yk} is the smallest, and its value is 0. If all the students in the class choose the option with the answer attribute of "we have not mastered this knowledge point" and the answers are deterministic, the weighted value μ_{yk} is the max, up to 30. As shown in Table 4, the weighted value of the knowledge point of "verbs" is the largest, reaching 21. It can be concluded that through this test,

Table 4: The weighted μ_y.

μ_{p1}	μ_{p2}	μ_{p3}	μ_{p4}	μ_{p5}	μ_{p6}	μ_{p7}	μ_{p8}	μ_{p9}
3.5	0	5	16	21	8	3	7.5	0

Table 5: The vector μ_{CF}.

μ_{CF1}	μ_{CF2}	μ_{CF3}	μ_{CF4}	μ_{CF5}	μ_{CF6}	μ_{CF7}	μ_{CF8}	μ_{CF9}
0.65	0.125	0.175	0.575	0.5	0.35	0.375	0	0

Table 6: The analysis results of the class examination given by the system.

Knowledge point	The situation	The credibility
Verbs	Poor	General credibility
Adjectives	Poor	General credibility
Nouns, numerals, pronouns	Good	Weak credibility
Sentence pattern	Good	Not credible
Adjective verbs	Good	Less credible
Tense	Good	Not credible
Auxiliary words and auxiliary verbs	Good	Less credible
Adverbs, conjunctions, etc.	Good	Credible
Word order	Unknown	Weak credibility

the knowledge of "verbs" is the worst in the whole class. Secondly, the knowledge points of "adjectives" are also poorly grasped. The weighted values of "auxiliary words and auxiliary verbs" and "sentence pattern" are both 0, indicating that students have the best grasp of these two knowledge points. By comparing the data in Table 5 and the credibility measures defined by the system in Table 1, the credibility of the conclusions of each knowledge point can be obtained.

Finally, for the examination situation, the system also gives an overall analysis of the examination situation of the class, as shown in Table 6.

Observing the analysis results in Table 6, the mastery of the knowledge point "word order" is "unknown." This is because, in the process of answering the questions, more than 25% of the students did not answer the questions corresponding to this knowledge point. Therefore, the system data is incomplete, and reasonable reasoning cannot be given. According to this situation, teachers can conduct the next test or focus on explaining this knowledge point in the teaching process.

To summarize, it has been demonstrated that the Japanese teaching auxiliary expert system integrating BP neural network built in the research may provide appropriate findings and has good application value after testing and processing a huge quantity of data. To complete the basic evaluation of college Japanese teachers' mastery of knowledge points in student groups, it employs a combination of production and frame-based knowledge expression methods and uncertain reasoning technology. At the same time, based on the evaluation results, the system may identify weak connections in knowledge points and present students with tailored tasks. This not only relieves teachers' workloads but also improves the quality of Japanese education.

5. Conclusion

In the age of Intelligence 2.0, the application of AI technologies to foreign language instruction has sparked the interest of a growing number of scholars, and it has become an unavoidable trend in the future growth of foreign language education. It may be argued that the integration, development, design, and application of artificial intelligence and foreign language teaching courses, as well as their management and evaluation, will usher in a new revolution in language technology and foreign language teaching. In today's college classrooms, the utilization of intelligent auxiliary teaching systems is unavoidable. The approach of instruction that combines Japanese majors with science and technology is steadily being introduced. The Japanese auxiliary teaching expert system integrating the artificial intelligence algorithm presented in the study supports the development potential of intelligent technology in the area of education, and this learning technique will become more brilliant in the future. The system's test results show that it has good application value. However, because the system is relatively new, it is still in the experimental and theoretical stages and has not been widely used. As a result, we must work hard in the future and improve in the following areas. The Japanese auxiliary teaching expert system proposed in this study is on the basis of minimizing the acquisition of basic knowledge under the reformation of Japanese teaching in colleges and assists the teaching of basic knowledge. Currently, the system only diagnoses faults for codified knowledge points. It only enables the entry and judgment of objective questions when choosing a question database and neural network sample database. To make the Japanese auxiliary teaching expert system more useful and intelligent, it needs further to assist students in the training of subjective questions like reading comprehension, translation, and composition. Meanwhile, future work practices will need to address the system's reliability and intelligence level.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Huanhuan Chu contributed to the writing of the manuscript and data analysis. Yifan Meng supervised the work and designed the study. Yifan Meng provided great help in the revision of the final draft, agreed to be included in the author list of the article. All unanimously agreed to the above arrangement. All the authors have read and agreed the final version to be published.

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