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Research Article

Design of an Artificial Intelligence Algorithm Teaching System for Universities Based on Probabilistic Neuronal Network Model

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Intelligence is gradually becoming an important tool for solving difficult problems with the development of computers. This article takes the design of university teaching systems as the research context to establish an artificial intelligence network research and learning platform. A probabilistic process neuron network model is proposed, which combines the Bayesian probabilistic classification mechanism with the dynamic signal processing method of process neuron networks, and achieves dynamic classification based on Bayesian rules by adding a pattern unit layer to the feed-forward process neuron network as well as adopting a normalised exponential excitation function. Artificial intelligence prediction based on probabilistic neural networks is verified by MATLAB as having good convergence and fault tolerance as well as data processing capability. The article also analyses the functions of the university intelligent teaching system and realises the optimal design of the university intelligent teaching system.

1. Introduction

With the continuous improvement of science and technology, intelligent management has become one of the future development directions of universities, and the design and implementation of intelligent systems in universities can not only enable universities to carry out better education work but also effectively improve their own management level and achieve more efficient cultivation of talents. Among the many scientific technologies, artificial intelligence algorithms lay a profound foundation for the design and implementation of intelligent systems in colleges and universities. Through the application of this technology in the intelligent system of colleges and universities, it can realise the integrated management of various management functions in colleges and universities and strengthen the information interaction between various departments in colleges and universities. The artificial intelligence algorithm creates good conditions for the scientific design of the intelligent system in colleges and universities, realizes the optimal choice for the design of the intelligent system in colleges and universities, and improves the operation performance of the system.

Online learning is gradually penetrating into various industries. In the learning exchange process, network teaching breaks through the bottleneck on time and space. At the same time, e-learning systems allow students to transition into the system without additional learning by virtualising real campus facilities and resources. In the Internet era, using artificial intelligence technology, the intelligent teaching system can automatically diagnose the learning level of students according to their cognitive ability, identify problems in the learning process, propose solutions in the context of the current learning situation, and finally provide targeted feedback and suggestions. The system overcomes the shortcomings of traditional education. The system provides students with various teaching resources and shares good teachers, which greatly improves the quality of teaching and learning. It allows students to be taught and learn randomly on the system. The ITS provides a highly personalised and intelligent learning experience for students based on their cognitive development level and learning style.

Probabilistic neural networks were proposed by Specht [1] is closely related to many concepts. We know that probabilistic neural networks are based on Bayesian decision theory and are gradually gaining widespread attention due to their unique form of uncertainty knowledge representation and the incremental learning of integrated prior knowledge, among other properties. Its basic idea is to estimate the known class conditional probabilities and prior probabilities by Bayesian formulae to obtain the posterior probabilities and then classify the decisions [2]. Many studies have shown that probabilistic neural networks are easy to train, converge quickly, and their judgment surfaces are close to the optimal Bayesian criterion surfaces. At present, probabilistic neural networks have been widely used in pattern classification [3], signal processing [4], target tracking [5], and other fields.

Process neuron networks can directly use time-varying processes as input and output signals, which is an extension in the time domain [6–8]. For the simulation modeling, system identification, process simulation, and generalized function approximation of complex nonlinear dynamic systems that lack prior knowledge and models, process neuron networks have shown obvious advantages and have been successfully applied in pattern recognition [9], fault diagnosis [10], and prediction [11]. A process probabilistic network model is proposed and built by fusing the time-varying (function) with the probabilistic neural network in the literature [12], and the corresponding learning algorithm is designed.

In the era of big data, the technology and theories of artificial intelligence are getting better and better, and its application areas are expanding, integrating into almost all walks of life. The development of artificial intelligence is an important factor in leading various fields to the forefront, and the Internet plus education has become a trend in society, with machine learning becoming the most important application of artificial intelligence technology in education [13–15]. In 21st century, with the development of machine learning, knowledge representation, processing of natural language, and computer visualisation and other technologies continue to face new challenges. This study combines the current situation of teaching systems in education with data mining techniques combined with student behaviour analysis to design a personalised cognitive student model and develop an intelligent, personalised, educational environment.

This article predicts learners' interest in learning by analysing their learning behaviours. It is mainly based on learner behaviours, such as browsing, saving, downloading, printing, and favouriting. The study uses keyword lists and topic searches to construct learner interests and uses keyword lists and topic searches to construct models of learner interests. The teaching system design simulation development process is divided into three phases: the first phase is the primitive phase, which is simply processing; the second phase is the development of test technology and sensing technology, which focuses on signal processing; and the third phase is the intelligent simulation technology, processing, and prediction data phase, which enables the rapid development of simulation [16] for various systems. In this study, data mining techniques are used to obtain data on learners' learning behaviour, model students, and develop an intelligent system by designing a personalised cognitive student model, which provides learners with more valuable learning resources. This article is aimed at university students and teachers and provides a reference communication simulation for modern university media from the perspective of political culture.

2. Introduction to Relevant Theories

2.1. Artificial Intelligence Techniques. With the introduction of artificial intelligence, a multidisciplinary science, it has been used to study, develop, simulate, and extend the theoretical techniques of human intelligence and has led to the creation of probabilistic neural networks [17]. According to Deyi Li, the study of how to make intelligence to complete complex problems that humans need to solve, theories, and technologies that mimic human intelligent behaviour, and the intelligent systems built that can incorporate human needs, think like humans, and further enhance human intelligence [18]. In the field of artificial intelligence, it usually uses machine learning for algorithmic computing, and deep learning is an algorithm or method to implement machine learning [19]; therefore, the academic community regards artificial intelligence, machine learning, and deep learning as an approximate inclusion relationship.

In the context of big data, the development of information technology in schools is receiving a lot of attention in the education sector, which is trying to adopt a "problem-oriented" approach to teaching and learning, so that students can receive new knowledge outside of the "tutorial learning" process. The main focus of education in the 21st century will be on intelligent learning, using technology to optimise teaching and learning. Therefore, the combination of AI technology and teaching systems is a hot topic of research in the education sector. The use of AI technology in teaching can develop students' problem-solving skills, personalise online education, meet individual learners, and realise the meaning of teaching according to their abilities. Based on a review of the literature, the study summarises the shortcomings of traditional education and uses AI technology to combine the design principles and objectives of intelligent teaching systems to provide students with a highly personalised and intelligent teaching system [20–22]. The study also aims to provide a highly personalised and intelligent teaching system for students.

The use of online teaching resources and the prerequisite of basic theoretical knowledge has effectively increased the "gold standard" of the physical classroom, reflecting the advanced, innovative, and challenging nature of teaching. On the one hand, students have familiarised themselves with the process of producing different types of television news through a number of well-designed practical training projects and are now able to produce different types of television news independently, thus achieving the objective of linking with the actual workplace. On the other hand, the self-reflection and summary after the practical training, the mutual evaluation of the group, and the teacher's comments have made the teaching and learning interactive and effective, so that the students' learning initiative is obviously enhanced. The teaching and learning activities have been enhanced.

Using artificial intelligence algorithms to abstract the design tasks of university intelligent systems, the interference caused by surface phenomena to the system design is avoided, so that the root of the system design problems can be identified, and a normative representation of the overall functions and conditions of use of university intelligent systems can be achieved.

2.2. Intelligent Teaching and Learning Systems. The concept of intelligent teaching and learning systems originated in 1982 from computer-assisted instruction, which is an adaptive teaching system that uses artificial intelligence technology to allow computers to take on the role of teachers to deliver individualised instruction to learners and provide guidance [23]. "Intelligent teaching" means that the teaching provided is personalised to meet the needs of the learner. Based on this, the intelligent teaching system can provide learners with suitable learning resources and teaching strategies, expand teaching time and space, and improve teachers' teaching effectiveness by combining learners' cognitive level and learning interests. It can also improve teachers' effectiveness and students' learning efficiency [24]. The intelligent system is designed to provide learners with personalised teaching guidance through question formulation and answer analysis, providing learners with a personalised and intelligent learning experience. It provides an effective teaching approach for the cultivation of 21st century core talents in education effectively cultivates students' problem-solving skills, realises individualised teaching and learning, and provides personalised guidance and feedback to students.

This article combines the current state of research on the application of AI in education and teaching systems, along with the principles of system design, to design an intelligent and personalised learning environment. The research in this study includes the following aspects:

(1) Using data mining technology to analyse student behaviour information in the e-learning platform, design and implement a learning interest submodel and a learning-style submodel and propose a personalised cognitive student model containing two submodels of learning interest and student learning style.

(2) Design and implement a triple randomized automatic question building algorithm based on a unitary knowledge domain and also design and implement a testing algorithm that incorporates an expert question bank and a self-built question bank by combining the authority of a specific expert question bank.

(3) Design and implement a simple web-based intelligent teaching system, use the personalised cognitive student model to model students, use the expert question bank and self-built question bank to test students' learning, and provide the system with a basis for students' next steps in learning.

2.3. Bayes' Theorem. Bayes Thomas, in his article "On the solution of the doctrine of chance problem," proposed a theory of inductive inference in which the "Bayes' theorem (or Bayes' formula)" gives the formula for calculating the conditional probability (posterior probability) of all causes C after the outcome E is known [25, 26], which can be regarded as one of the earliest statistical inference procedure. The basic element is that the posterior probability $P(A \mid B)$ is estimated from the prior probability $P(A)$ and the conditional probability $P(B \mid A)$.

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}. \tag{1}$$

2.4. Bayesian Determination Strategy. The accepted criterion for a decision rule or strategy for pattern classification is that it minimizes the expected risk in some sense [27]. Such a strategy is called a Bayesian strategy. As an example, let the mode state P be P_A or p_B. Based on a set of measurements described by the n dimensional vector $X = [x_1, x_2, \ldots, x_n]$, the Bayesian decision rule for decision $p = P_A$ or $p = P_B$ becomes

$$d(X) = \begin{cases} P_A, h_A i_A f_A(X) > h_B i_B f_B(X) \\ p_B, h_A i_A f_A(X) < h_B i_B f_B(X) \end{cases}, \tag{2}$$

where $f_A(X)$ and $f_B(X)$ are the probability density functions for A and B, respectively. l_A is the loss function for determining $d(X) = p_B$ at $p = P_A$. l_B is the loss function for determining $p = P_B$ at $p = P_B$ (loss at correct determination equals 0). h_A is the prior probability at $p = P_A$ and $h_B = 1 - h_A$ is the prior probability at $p = P_B$.

The bound between the region of Bayesian decision rule $d(X) = p_A$ and the region of Bayesian decision rule $d(X) = p_B$ can be found by the following equation:

$$f_A(X) = K f_A(X), \tag{3}$$

where $K = (h_B l_B / h_A l_A)$.

The key to using equation (3) is the ability to estimate the probability density function based on the sample pattern. Usually, the prior probability is known or the loss function can be estimated accurately requiring a subjective estimate [28]. However, if the probability density function of a pattern is unknown and a set of training patterns (training samples) is given, the only clues to derive the probability density function are these samples.

2.5. Probability Density Function Estimation Methods. The accuracy of the discriminant boundary depends on the accuracy of the probability density function estimation. Parzen proposed a cluster valuation formula for *f(X)*.

$$f_n(X) = \frac{1}{n\lambda}\sum_{i=1}^{n}\omega\left(\frac{X - X_{Ai}}{\lambda}\right). \quad (4)$$

At the same time, Parzen proves that $\lim_{n\longrightarrow\infty} |f_n(X) - f(X)|^2 = 0$.

Cacoullos extends Parzen's results, and in the special case of the Gaussian kernel, the multivariate estimate can be expressed as follows:

$$f_1(X) = \frac{1}{(2\pi)^{P/2}\sigma^P}\cdot\frac{1}{m}\sum_{i=1}^{m}\exp\left[-\frac{(X - X_{Ai})^T(X - X_{Ai})}{2\sigma^2}\right], \quad (5)$$

where i denotes the sample number, and m denotes the total number of training samples. X_{Ai} denotes the ith sample of category p_A. σ denotes the smoothing parameter, and p denotes the dimension of the metric space.

3. Probabilistic Process Neuron Networks

3.1. Probabilistic Process Neuron Model. In many time-varying dynamic signal processing problems affected by a variety of nonlinear perturbations, coupling between signals and noise, the results of a comprehensive evaluation cannot give a completely accurate answer of yes (taking the value of 1) or no (taking the value of 0); instead, there is often some degree of yes or no, i.e., the evaluation results show a certain degree of probability or ambiguity. The solution to such problems awaits the emergence of a new model [29].

The probabilistic process neuron (PPN) proposed in this paper is similar to the ordinary process neuron model. The model is composed of time-varying signal inputs, spatio-temporal weighted aggregation, and stimulated output operations. The model is shown in Figure 1.

The $x_1(t), x_2(t), \ldots, x_n(t)$ is the process input at time [0, T], $w_1(t), w_2(t), \ldots, w_n(t)$ is the weighting function for each dimensional input, and y is the output. In contrast to the Sigmoid-type excitation function used by ordinary process neurons, this model uses an exponential excitation function with probabilistic statistical properties.

$$g(x) = \exp\left[\frac{x^{-1}}{\sigma^2}\right], \quad (6)$$

where σ is the distribution of $g(x)$ for the smoothing parameter $\sigma = 0.4$ and is shown in Figure 2.

From Figure 2, it can be seen that when $x \in [-1, 1]$, $g(x) \in (0, 3]$. Therefore it has the significance of calculating probability for the independent variable x. The input-output relationship of the probabilistic process neuron is given as

$$y = \exp\left[\frac{\int_0^T W(t)X(t)dt - 1}{\sigma^2}\right] = \exp\left[\frac{\int_0^T \sum_{i=1}^{n} w_i(t)x_i(t)dt - 1}{\sigma^2}\right]. \quad (7)$$

3.2. Probabilistic Process Neuron Network Model. The PPNN model is shown in Figure 3.

The training speed of PPNN will be much faster than that of ordinary feed forward neural networks [30]. However,

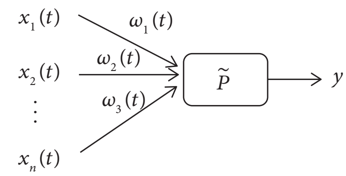

Figure 1: Probabilistic process neuron model.

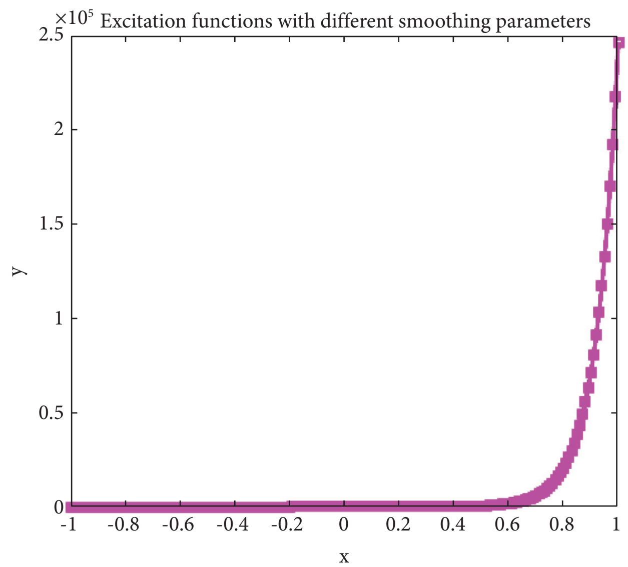

Figure 2: Image of the activation function $g(x)$.

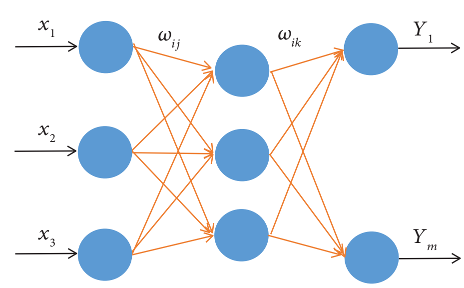

Figure 3: Structure of the probabilistic process neural network model.

due to the summation of the pattern layers, the outputs corresponding to the pattern layers have large values and are guaranteed to be clearly distinguishable from each other. In this way, there is no "rejection" of the sample at the output, thus ensuring that the PPNN has a strong discriminatory power.

If we let the input be $X(t) = [x_1(t), x_2(t), \ldots x_n(t)]$, then the formula for the hidden layer output $H = [h_1, h_2, \ldots h_K]$ is

$$h_j = \exp\left[\frac{\int_0^T \sum_{i=1}^{n} w_{ij}(t)x_i(t)dt - 1}{\sigma_j^2}\right], \quad (8)$$

where δ_j is the parameter of the jth neuron; then, the initial value can be

$$\sigma = \frac{d_{\max}}{\sqrt{H}}, \tag{9}$$

where $d_{\max}$ is the maximum Euclidean distance between each cluster centre vector of the training sample, and H is the number of centres. The output layer is

$$p_k = \sum_{j\in\Omega_k} h_j\,(k = 1, 2, \ldots, m), \tag{10}$$

where m is the actual number of class patterns of the sample and Ω_k is the set of hidden node serial numbers contained in the kth pattern.

The final output of the network is

$$\begin{aligned} y_k &= \sum_{j=1}^{m} v_{jk} p_k \\ &= \sum_{j=1}^{m} v_{jk} \sum_{s\in\Omega_j} \exp\left[\frac{\int_0^T \sum_{i=1}^n w_{is}(t)x_i(t)dt - 1}{\sigma_s^2}\right], \quad k = 1, 2, \cdots, m, \end{aligned} \tag{11}$$

where v_{jk} is the output layer connection right.

The probabilistic process neuron uses the exponential function defined in (1) as the excitation function, and the network structure is similar to that of a general probabilistic neural network. Therefore, the classification mechanism of this network is consistent with Bayesian decision theory. In fact, the nonlinear process of the model is mainly done in the hidden layer, if we let $W_j(t)$ be equal to some $X(t)$ in the training set, and both $W_j(t)$ and $X(t)$ have been specified into unit lengths.

$$\begin{aligned} \int_0^T \left(W_j(t)\right)^2 dt &= \sum_{i=1}^n \int_0^T \left(w_{ij}(t)\right)^2 dt = 1, \\ \int_0^T (X(t))^2 dt &= \sum_{i=1}^n \int_0^T \int (x_i(t))^2 dt = 1. \end{aligned} \tag{12}$$

Therefore, there is

$$\begin{aligned} \sum_{i=1}^n \int_0^T \int_{w_{ij}} (t)x_i(t)dt &\geq -\frac{1}{2}\left(\sum_{i=1}^n \int_0^T \int_i \left(w_{ij}(t)\right)^2 dt + \sum_{i=1}^n \int_0^T \int (x_i(t))^2 dt\right) = -1, \\ -1 \leq Z_j &= \sum_{i=1}^n \int_0^T \int_i \left(w_{ij}(t)\right) x_i(t)dt \leq 1. \end{aligned} \tag{13}$$

According to the excitation function, the summation unit simply accumulates the outputs of the hidden layer and then, after weighted aggregation, gives real values in the interval [0, 1] at the output layer to determine the final mode class, which obviously presents a certain probability of the output results.

4. Experimental Analysis

As the knowledge base of functional carriers has many economic technical parameters, when building this knowledge base, we need to ensure the integrity of the functional carriers so that the knowledge can be searched by function and name. The knowledge can be retrieved by function and name. In order for the AI algorithms to generate solution solutions, it is necessary to retrieve the corresponding functional vectors according to the subfunctions of the functional structure and binary encoding of the subfunctions, and then, linking the function carriers of the different subfunctions codes are joined first and last to construct individual chromosomes. In this way, randomly generate a group of chromosomes so that each chromosome can have a separate solution and use genetic manipulation to evolve these populations of solutions until the best solution. In addition, from the perspective of the genetic algorithm of the AI algorithm from the perspective of genetic algorithms for artificial intelligence algorithms, each solution in each chromosome needs to be evaluated for fitness. The genetic manipulation is used to evolve these solutions. The evaluation of each chromosome solution is carried out by means of economic and technical evaluations.

There are a number of problems with neural network modeling; it is important to include sufficient information in the features. A learning system is built into the neural network to incorporate quantification of data processing so that a reasonably quantifiable understanding of social relationships, modern rationality, knowledge systems, and values can be achieved through training. Then predict trends based on the information results, anticipate their development, and then propose appropriate countermeasures. The 33*4 dimensional matrix data collected was used as network training samples before selecting multiple samples and some samples as validation samples, and the simulation type codes corresponding to as in Table 1.

The results of the data clustering used are shown in Figure 4.

After a modern media perspective on the creation of a bionic algorithm for a classification prediction model for university instructional design systems, a two-layer network algorithm was created through MATLAB-a classification layer (cluster) and a competition layer. PPNN network was created; a

Table 1: Category labels for the type of simulation.

Forecast type	Category
Worst	1
Less favourable	2
Commonly used	3
General	4
Excellent	5

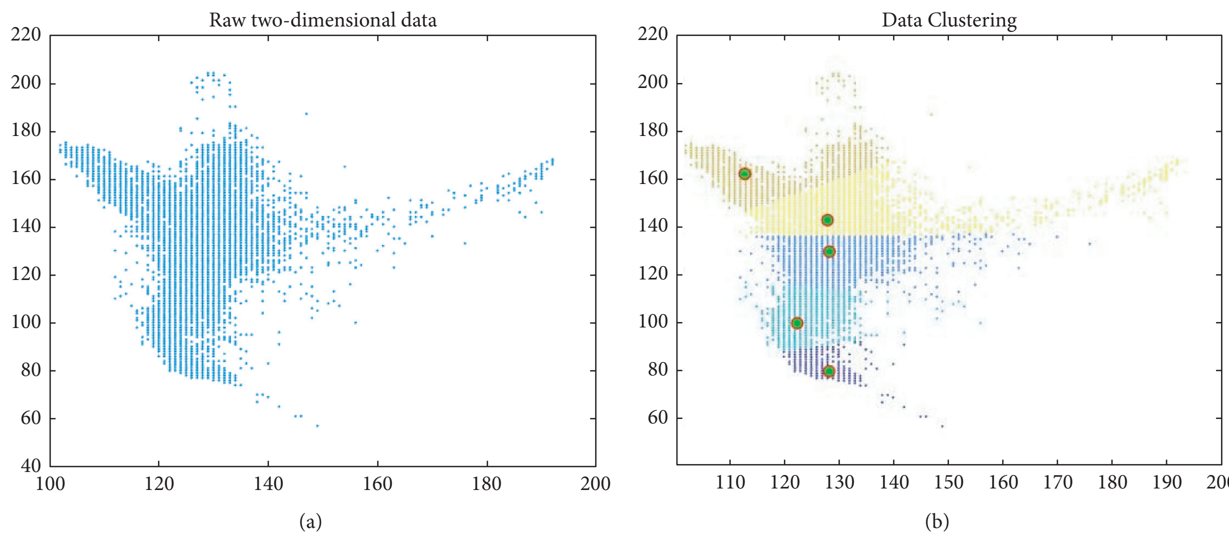

Figure 4: 2D raw data and clustering result display. (a) 2D data display. (b) Image clustering.

Table 2: Prediction results for target data.

Sample number	Classification results	Actual classification	Actual results
1	5	5	5
2	1	1	1
3	4	4	3
4	5	5	5
5	3	3	3
6	3	3	3
7	4	4	3
8	3	3	3
9	3	3	3
10	1	1	1

threshold is set to pre-process the input vector, and the pre-processed vector is fed into the function for calculation.

The algorithm is robust to the problems and the prediction results are shown in Table 2.

The predicted results for the target data can be displayed directly in Figure 5.

Details of the training process for neural network classification are shown in Figure 6.

The following grid search algorithm (GS_PPNN) was used to optimise the classification results, and the optimized classification accuracies are shown in Table 3 and compared with the unoptimized results.

Histograms of the classifier results for the three probabilistic neural networks are shown in Figure 7.

The grid search algorithm uses cross-validation to find the best pair of parameters for the PPNN and finally uses the best pair of parameters to bring into the model for classification, thus improving the classification results. Although the grid search algorithm can find the optimal combination of parameters by searching all parameter pairs, this process usually takes a lot of time, which greatly reduces the efficiency of classification. In the article, PCA is used to reduce the dimensionality of the data and extract the most representative low-dimensional features for classification. The effects of different principal components on classification time and classification accuracy are given in Tables 4 and 5.

A comparative graph of the effect of different principal components on classification accuracy is given in

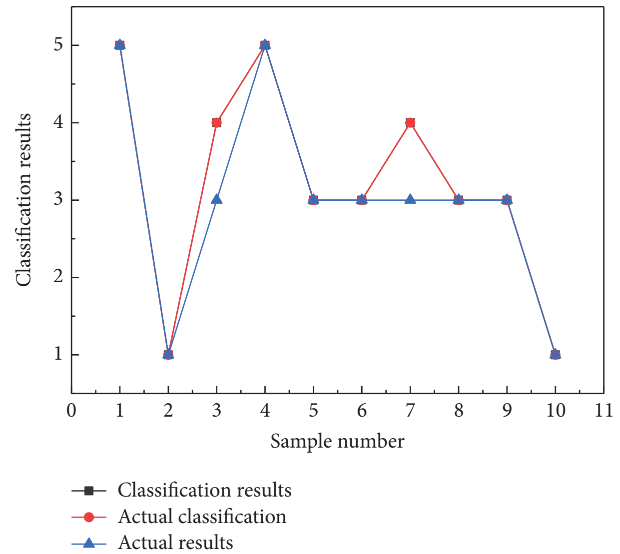

FIGURE 5: Predicted classification results for the target data to be classified versus the actual categories.

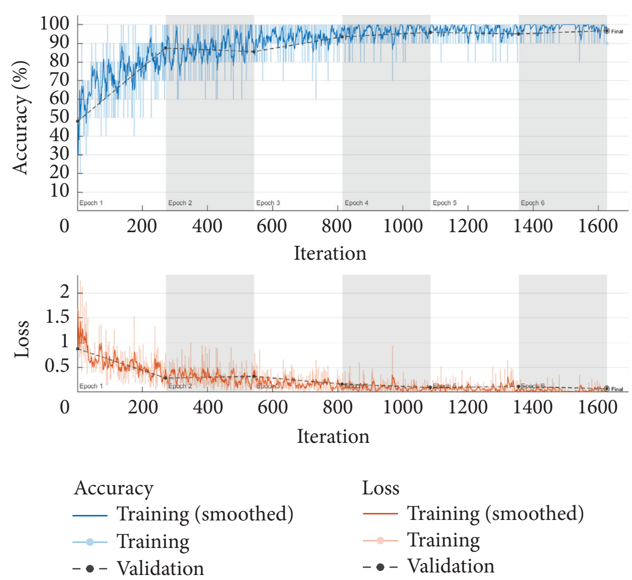

FIGURE 6: Neural network training process.

TABLE 3: Optimization results for different probabilistic neural networks and grid search algorithms.

Category	Category 1	Category 2	Category 3	Category 4	Category 5
			Classification accuracy (%)		
PNN	86.56	89.36	85.46	84.25	81.05
PPNN	89.23	90.12	88.65	87.54	85.21
GS_PPNN	91.87	93.26	90.26	91.48	89.57

Figure 8, and the effect of classification time with different principal components is shown in Figure 9. The information in Tables 4 and 5 shows that the highest classification accuracy is achieved with a principal component of 50% and the classification time is acceptable at this time, so the article uses a principal component of 50% for the optimisation of the grid search algorithm in the data for the teaching system design study, which in turn gives the best classification results and a higher classification rate.

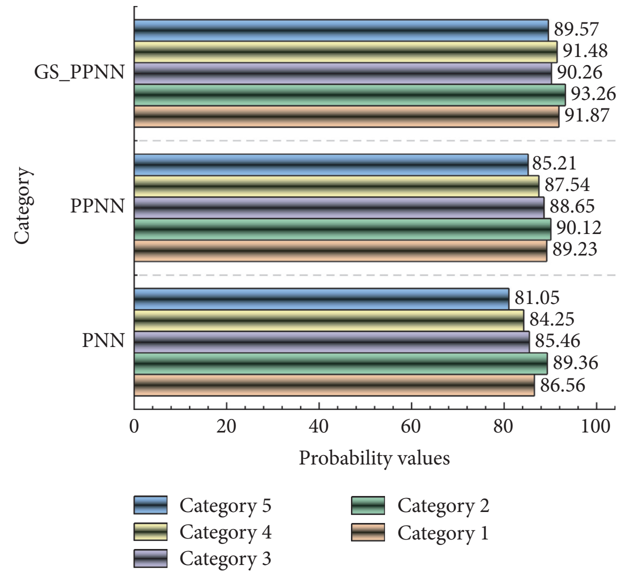

Figure 7: Histogram comparison of the optimisation results of different probabilistic neural networks and grid search algorithms.

Table 4: Effect of different principal components on classification accuracy.

Classification accuracy (%)	Principal component analysis		
Proportion	25%	50%	75%
PPNN	84.25	88.56	85.62
GS_PPNN	85.79	91.28	89.46

Table 5: Effect of different principal components on classification time.

Classification time (s)	Principal component analysis		
Proportion	25%	50%	75%
PPNN	25.65	28.62	32.45
GS_PPNN	45.36	51.63	65.26

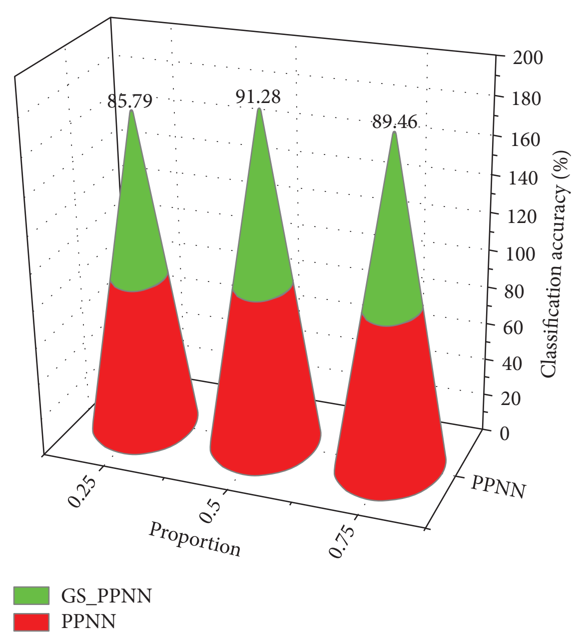

Figure 8: Comparison of the effect of different principal components on classification accuracy.

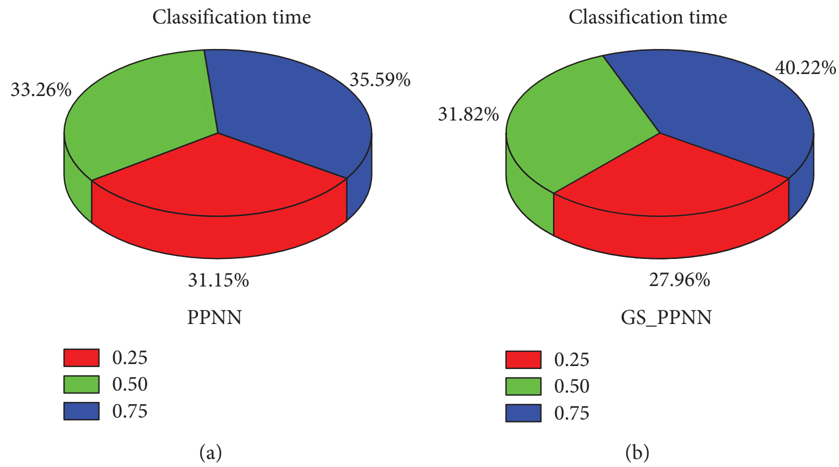

FIGURE 9: Comparison of the effect of classification time under different principal components.

5. Conclusion

In this article, a probabilistic process neuronal network model and a classification algorithm have been proposed. The algorithm is considered as a deterministic algorithm in terms of the approximation ability of the neural network. However, the model uses an exponential excitation function with probabilistic meaning in the hidden layer, which makes the model possess some characteristics of a stochastic algorithm at the same time. The probabilistic process neuron network uses process-like inputs, which effectively broadens the scope of application of ordinary PNN. The model is suitable for real-time processing of information due to its small number of adjustable parameters and fast convergence rate. The experimental results show that the model and algorithm have certain potential in pattern classification. It can substantially improve the efficiency of university intelligent teaching systems and also scientifically evaluate multiple design solutions of university intelligent systems, so as to achieve the optimal design of university intelligent teaching systems. The design of the artificial intelligence algorithm teaching system for universities based on the probabilistic neuronal network model proposed in the article deserves further research due to the relatively single parameter under ideal conditions, and in future practical applications, more factors should be considered for the influence of the model.

Data Availability

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

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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