International Journal of e-Collaboration
Volume 20 • Issue 1

A Model Based on Fuzzy Neural Networks for Sharing Digital Educational Resources in English

Xian Yang, Hubei College of Chinese Medicine, China

Haiying Wang, Xi'an Technological University, China*

ABSTRACT

The ineffective digitization of core English course resources, due to limited autonomy, fragmentation, and inadequate management, has prompted the development of digital teacher libraries using multimedia and Internet technologies. Fuzzy neural networks (FNNs), combining fuzzy and neural network controls, have emerged as a promising approach for mathematical modeling. This paper presents an FNN-based model for sharing digital English educational resources and proposes an effective guidance mechanism for sharing digital science education resources. Experimental results show that the FNN outperforms the Apriori algorithm in training sample error by 0.02069 and reduces running time by 0.0034 seconds on average. This indicates the FNN's superior approximation capabilities with appropriate initial fuzzy rules. Consequently, the FNN-based model enhances the value and quality of educational resources, expands the capacity of information resource libraries, and effectively mitigates the creation of low-quality resources.

KEYWORDS

Apriori Algorithm, Digital English Educational Resources, FNN-Based Collaborative Model, Fuzzy Neural Network (FNN)

In the current era of the internet, the integration of online platforms has become increasingly essential across all academic disciplines (Zhu et al., 2020). The implementation of recent national curriculum reforms has raised teachers' awareness of the vital necessity to develop curriculum resources (Luo et al., 2023). Within educational contexts, "points of knowledge" or "topics" represent the fundamental units of subject content, characterized by their interactive, diverse, open, and autonomous nature (Khan et al., 2024). With the expanding scope of education, universities confront a scarcity of educational resources, directly impacting undergraduate education quality (Ravichandran & Keikhosrokiani, 2023). Schools are urged to enhance English curricula quality and effectiveness by sourcing teaching materials from the internet, extracting valuable content, and establishing a robust digital English curriculum resource base in response to this challenge (Hashmi et al., 2024).

DOI: 10.4018/IJeC.344456
*Corresponding Author

The advancement of information technology (IT), with computer networks at its core, has provided crucial technical support for educational reform, emphasizing the integration of advanced IT into traditional teaching methods (Liao, 2022). Consequently, digital teaching methods based on computers and networks have emerged as a predominant trend in English classroom teaching reform; these methods align with the ongoing evolution of English teaching methodologies. Although the effective sharing and utilization of educational resources play a pivotal role in enhancing the quality and efficiency of education, challenges persist in the digitization of core English course educational resources. Issues such as low autonomy, fragmentation, and inadequate management systems have hindered seamless sharing and access to vital educational materials (Zhang, et al., 2024). To address these obstacles, the development of digital teacher libraries integrating multimedia and internet technologies has emerged as a promising solution to facilitate broader access to educational resources.

In recent years, the integration of fuzzy control and neural network techniques has garnered significant attention across diverse research fields owing to their effectiveness in modeling nonlinear systems. The fusion of these approaches has given rise to the development of a unified system known as a fuzzy neural network (FNN) or neuro-fuzzy system, offering a powerful tool for research and practical applications in diverse domains (Balakrishnan et al., 2023). This paper introduces an FNN-based model designed specifically for sharing digital English educational resources, with a focus on promoting effective mechanisms for comprehensive guidance in resource sharing. Through empirical evidence, the superiority of the FNN model over traditional algorithms, such as the Apriori algorithm, is demonstrated in terms of training sample error and running time, underscoring its efficacy in approximating complex systems with enhanced performance (Shen et al., 2023). By leveraging the proposed FNN-based collaborative model, educational institutions have the opportunity to elevate the value and quality of educational resources, expand the capacity of educational information libraries, and deter the production of low-quality materials (Lanjewar & Panchbhai,2023). Given the evolving landscape of education informatization and the emphasis on leveraging advanced technologies for educational transformation, the adoption of innovative models, such as the FNN-based digital English educational sources sharing model, is crucial for fostering sustainable development in education resource construction (Singh et al., 2024).

Compared with traditional methods, FNNs offer the ability to model nonlinear systems effectively. Traditional methods may struggle with complex nonlinear relationships present in educational resource sharing. The integration of fuzzy systems and neural networks in the FNN model results in a powerful tool for research and practical applications. This integration allows for more nuanced and flexible modeling compared with traditional approaches. Unlike traditional methods, FNN models possess learning and adaptive capabilities. These capabilities allow FNN models to adapt and learn from data, thereby making them more suitable for dynamic environments, such as educational resource sharing. The FNN-based collaborative model has demonstrated superior performance compared with traditional algorithms, such as the Apriori algorithm, in terms of training sample error and running time. This finding suggests that FNN can provide a more efficient and effective solution for sharing digital English educational resources. The FNN model leverages collaborative filtering techniques, such as deep neural network-based collaborative filtering, for course recommendation in e-learning platforms. This collaborative approach enhances the quality and relevance of shared educational resources.

Therefore, in this study, we advocate for the implementation of the FNN-based model as a strategic approach to enhance resource management practices, achieve optimal resource allocation across schools, drive cost efficiencies, and maximize the overall effectiveness of educational resources in the digital era.

RELATED WORKS

In the era of the "internet+", a plethora of diverse resources is available. In the field of education, online classes, flipped classes, and numerous mobile learning applications saturate the internet, offering a wide array of learning resources. Prioritizing open education and personalized teaching methods enables seamless connection of the four key components—platform, teacher, learner, and learning resources—across temporal and spatial boundaries. Integrating the creation of digital educational materials with the teaching process aims to foster online interaction among teachers, facilitate resource sharing, enable collaborative research in networked teaching activities, and emphasize active student learning, thereby guiding the development of digital educational sources.

According to Kong (2019), the concept of curriculum resources has a broad and narrow meaning. Curriculum resources in the broad sense refer to the factors that contribute to the achievement of curriculum goals, whereas curriculum resources in the narrow sense refer only to the sources of direct factors that form the curriculum (Kong, 2019). Cui and Wang (2021) argued that curriculum resources, also called educational sources, are the sources of curriculum and teaching information, or all material and human resources that are useful for curriculum and teaching (Cui & Wang, 2021). Khodabandelou and Ebadzadeh (2019) discussed the symbiosis of shared digital educational sources in universities based on the perspective of symbiosis theory; these researchers analyzed the impact of the theory of symbiotic strategies for digitized sources and shared universities (Khodabandelou & Ebadzadeh, 2019). In the context of learning-based curriculum, Zheng et al. (2021) defined it as the factors and conditions of implementation that support and sustain the occurrence and development of learning activities.

Hui and Aiyuan (2021) proposed a systematic approach for an English education model based on the neural network algorithm. Their study focused on optimizing English teaching methods using neural networks, which aligns with the goal of enhancing English education in the present study. The findings of this study may offer insights into the application of neural network algorithms in the educational context. Zhang (2023) presented an IoT-based English translation and teaching approach using particle swarm optimization and neural network algorithms. This research explored the use of advanced optimization techniques in language teaching. Although different in focus, the utilization of neural network algorithms in language education provides valuable insights for the development of the proposed model. Ansari et al. (2017) developed an FNN-based framework to discover user access patterns from web log data. This framework demonstrated the effectiveness of FNNs for pattern recognition and analysis.

Fuzzy models use good knowledge expression and reasoning, similar to human thinking, but they depend too much on human subjective factors and lack learning and adaptive capabilities. FNN structure is variable, but it is unable to express structural knowledge; FNN network parameters also lack physical meaning and are prone to local extremes in the learning process (El-Nasr et al., 2000). Chen and Huang (2021) proposed modified rules for excitatory and inhibitory neurons and neuronal connection strengths, and their results still serve as the basis for many studies of neural network models. Singh (2019) proposed various fuzzy neuron models, including fuzzy neuron models similar to those mentioned above, as well as fuzzy neurons with fuzzy weighting coefficients and the ability to input fuzzy quantities. Zhang et al. (2020) attempted to use teacher signals to train perceptrons and simulate the cognitive and learning abilities of the human brain. This experiment aroused the interest of many scholars and triggered the first leap in neural network research. Zubatyuk et al. (2021) identified the fuzzy features of human thinking by imitating the fuzzy information processing ability and comprehensive judgment ability of humans. These researchers solved the fuzzy information processing issues that are hard to be addressed by conventional mathematical approaches. Those who needed to solve problem areas could only do so with the help of human experience (Zubatyuk et al., 2021). Duan and Wang (2018) introduced the concept of energy functions, proposed criteria for network stability, and presented a new method for associative memory and optimization calculations. Vedavathi and Anil Kumar (2022) used a deep neural network-based collaborative filtering technique for course recommendation in an e-learning platform.

The FNN-based model for sharing digital English educational resources yields quantifiable benefits in terms of improved accuracy, efficiency, and resource quality. It aligns with and advances the state of the art in educational technology research. It also responds to the evolving demands of online learning environments, curriculum reform, personalized education, and sustainable resource management. The increasing importance of online platforms in education (Zhu et al., 2023) highlights the necessity for sophisticated tools such as the FNN model to manage and distribute digital resources effectively. As learning shifts to digital environments, the proposed model responds to the need for efficient, adaptive, and intelligent systems that can handle the complexity and scale of online resource sharing. National curriculum reforms (Luo et al., 2023) emphasize the critical role of developing and utilizing high-quality resources. The FNN model directly addresses this requirement by facilitating the identification, organization, and distribution of relevant, up-to-date, and engaging digital English materials that support contemporary pedagogical goals. The "internet+" era promotes personalized teaching methods and open education (Fan, 2024), thus emphasizing seamless connections between learners, teachers, platforms, and resources. The FNN-based model, with its capacity for adaptive learning and collaborative filtering, supports these trends by tailoring resource recommendations to individual learners and fostering a collaborative ecosystem where resources are easily accessible and shared across temporal and spatial boundaries. The importance of sustainable development in education resource construction (Snekha & Ayyanathan, 2023) underscores the need for models such as the FNN that promote efficient use, continuous improvement, and equitable access to educational materials. By optimizing resource allocation, reducing redundancy, and enhancing resource quality, the FNN model contributes to the long-term sustainability of educational ecosystems.

These studies demonstrate the growing interest in neural network algorithms, collaborative filtering techniques, and related approaches for various applications, including language education, information management, and decision support systems. Although limited research specifically focuses on sharing digital English educational resources, the insights gained from these studies can be applied to the development of the proposed FNN-based model. By leveraging the strengths of neural networks and collaborative techniques, this model has the potential to address the challenges associated with resource sharing and improve the efficiency and effectiveness of English education.

IDEAS OF BUILDING AND SHARING DIGITAL ENGLISH EDUCATIONAL SOURCES BASED ON FNN

An Introduction to FNN

FNNs represent a fusion of two powerful computational paradigms: fuzzy logic and artificial neural networks (ANNs). FNNs integrate the ability of fuzzy logic to handle uncertainty and imprecision with the learning and generalization capabilities of neural networks. At their core, FNNs consist of layers of interconnected neurons, including input, hidden, and output layers. Each neuron applies fuzzy logic operations to its inputs before passing the result to the next layer. This integration allows FNNs to process and learn from data that are inherently fuzzy or imprecise. The operation of FNNs involves learning fuzzy rules from training data, where each rule captures a relationship between input and output variables expressed in linguistic terms. Learning algorithms such as backpropagation are used to adjust the connection weights between neurons, minimizing the error between predicted and actual outputs. FNNs excel at handling uncertainty and imprecision in data, making them suitable for applications such as pattern recognition, control systems, and decision support systems. They offer interpretability because fuzzy rules can be easily understood and modified by domain experts to incorporate new knowledge. In summary, FNNs offer a versatile and powerful framework for addressing complex real-world problems by integrating the complementary strengths of fuzzy logic and neural networks.

In the context of developing an FNN-based model for sharing digital English educational sources, teachers must continuously update and expand their information knowledge structure. Additionally, teachers should be able to use IT flexibly. This combination of knowledge and skills is crucial for effectively implementing and managing educational resources in the digital age. The design of the database for the FNN-based model is a critical aspect that directly impacts the overall performance of the model. The database includes components such as the affiliation function of each linguistic variable, scale change factor, and the number of sublevels in the fuzzy space. The choice of database and the design of data structure are fundamental in ensuring the successful realization of the model. Fuzzy sets play a significant role in the FNN-based model, serving as an extension of classical sets. The affiliation function, which is a key component of fuzzy sets, extends the concept of the characteristic function. Understanding the principles of fuzzy sets and affiliation functions is essential for effectively building and sharing digital educational sources. By integrating the FNN-based model into a comprehensive digital platform, educational institutions can enhance resource management practices, optimize allocation, and maximize the effectiveness of educational resources in the digital age. This approach not only improves resource construction and management but also facilitates optimal resource allocation, cost reduction, and overall resource effectiveness.

The FNN-based model offers a systematic approach to address challenges in traditional English education models, such as digitization limitations and inadequate management systems. By leveraging this model, educators can access high-quality educational resources, contributing to the sustainable development of English education material construction.

Construction of Digital English Educational Sources Co-Build and Share Model

The main role of the digital English educational sources sharing model is that in a connected network environment, within a certain area, the application of the influential rule search scheme (IRSS) (Chatterjee & Rakshit, 2004) can facilitate different schools, departments, and individuals to share high-quality digital software educational sources in a targeted, personalized and convenient way, to interoperate and achieve the purpose of sharing high-quality resources. For teachers, students can be encouraged to use various educational sources and be brave enough to combine their own experience in using them to propose modifications to teachers. Figure 1 shows the physical structure of the teaching resource sharing model.

First, the hardware structure of the model includes the physical hosts running the FTP server, the database server, and various application servers, in addition to the PCs running the client programs. Because the fuzzy controller processes data based on a fuzzy set approach, fuzzifying the input data is an essential step. In addition to studying the representation of uncertain and imprecise knowledge, imprecise inference methods are also explored. The formula to calculate the output of each neuron in the implicit and output layers of the network is shown in equation (1).

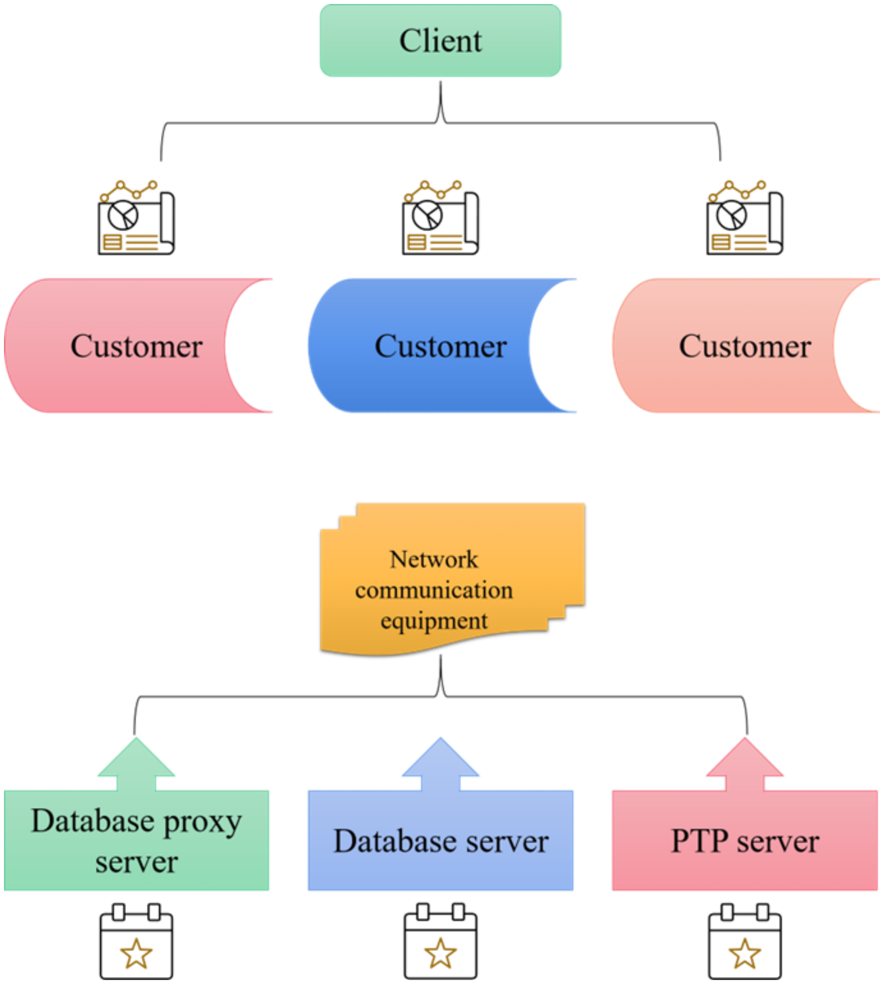
$$O_{Pj}^{l} = fi(\sum_{j} w_{ji}^{l} O_{i}^{l-1} - \theta_{j}^{1}) \tag{1}$$

The traditional approach is to use a measure of proximity, expressed in most cases as a sum of squared errors (SSE). The SSE is defined as shown in equations (2) and (3).

$$\mathrm{SSE} = \sum_{i=1}^{\mathrm{k}} \sum_{\lambda \in c_i} dis(v_i, x) \tag{2}$$

$$C_i = \frac{1}{m_i} \sum_{\lambda \in c_i} x \tag{3}$$

Figure 1. Physical Structure Diagram of Teaching Resource Sharing Model



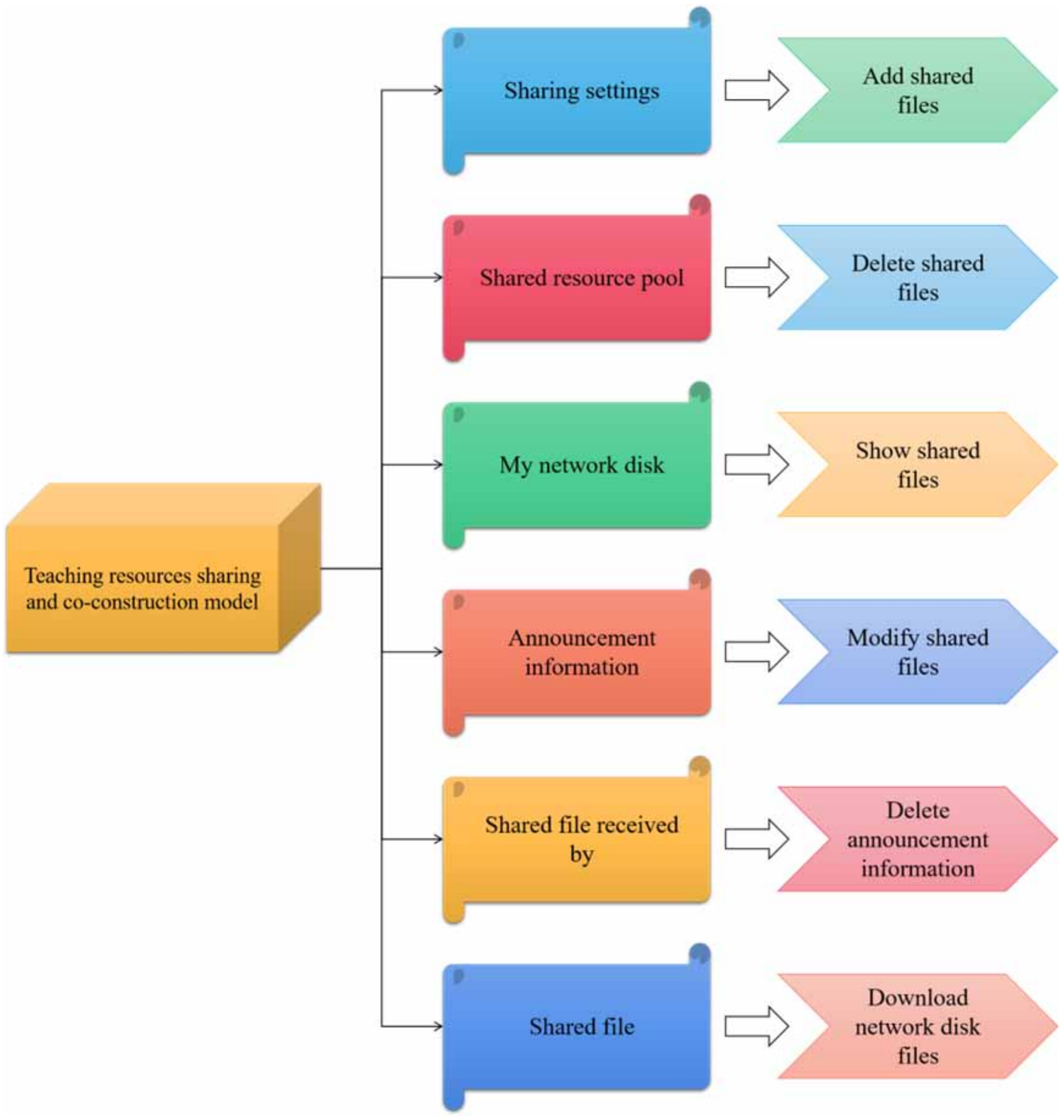
In these equations, k = number of clusters, c_i = class i, m_i = number of samples, v_i = center point, and x = clustered samples.

Conditional curriculum resources are characterized by their role in the curriculum, but they do not become a direct source of the curriculum. However, they do determine to a large extent the scope and level of implementation of the curriculum. Within the range of possible curriculum resources and with due consideration of the cost of the curriculum, the material curriculum resources that are decisive for the lifelong development of students are selected and prioritized for use. The aggregated features at each moment are obtained by concatenating feature words at different granularities at that moment, and the results are shown in equation (4).

$$c_i = \left[c_i^1; c_i^2; \ldots c_i^k\right] \tag{4}$$

In equation (4), c_i^k, the convolution window of the i word, is the characteristic representation of k.

Figure 2. The Functional Module Diagram of Teaching Resource Sharing Model Client



Schools also need to set up a special evaluation and management organization for English digital educational sources to dynamically monitor, track, evaluate, and improve the sharing of English digital educational sources. This step will promote the relevance and standardization of the shared English digital educational sources and improve the management efficiency. Users can set default parameters for the sharing function modules according to their personal preferences, such as size limit or sharing length limit. Its detailed functional modules are divided as shown in Figure 2.

Second, to speed up the server's response to requests and data processing and improve its operational efficiency, the server-side work is partitioned into independent application servers distributed on different physical hosts with the exception of the FTP server and database server as independent functions. Neuronal models are commonly described by first-order differential equations, which can model the change of FNN synaptic membrane potential with time, as shown in equation (5).

$$\begin{cases} y_i(t) = f[u_i(t)] \\ \tau \dfrac{du}{dt} = -u_i(t) + \sum w_{ij} x_j(t) \end{cases} \tag{5}$$

In equation (5), u_i = the internal state of neurons, θ = the threshold, and x_i = the input signal.

The exact amount needed for detection performs scalar processing, transforms the range of the input quantity into the corresponding domain for fuzzification, and converts the input data into an appropriate fuzzy quantity. It mainly consists of several sections, such as listening problem-solving skills, listening questions for English III and IV exams, listening simulation training for foreign secretarial exams, listening simulation training for BEC exams, self-testing aptitude tests, audio recordings of working scenes in various industries, and listening recordings of texts in accompanying textbooks. On-campus curriculum resources are the most direct and convenient resources to achieve the curriculum and teaching objectives. Therefore, they should be in the leading position of curriculum resources development, whereas off-campus curriculum resources are currently in the secondary position of curriculum resources development owing to the limitation of time and space. If appropriate goals are to be set for a given educational audience, considering both what they have already learned and their existing knowledge and skills is necessary.

Finally, the software structure of the model contains several functional modules, and the client side is in the form of application software providing the user with the corresponding operating interface. On the server side, it takes the form of partitioned services, distributed deployment and parallel processing. The aim is to obtain the most appropriate affiliation function for the control purpose in that it has not yet been proved what shape of the affiliation function is optimal for a certain control objective; that is, generating the output produced by each rule corresponding to the input is a normalized computation, as shown in equation (6).

$$f = \sum_{\mathrm{i}=1}^{p} u_i \tag{6}$$

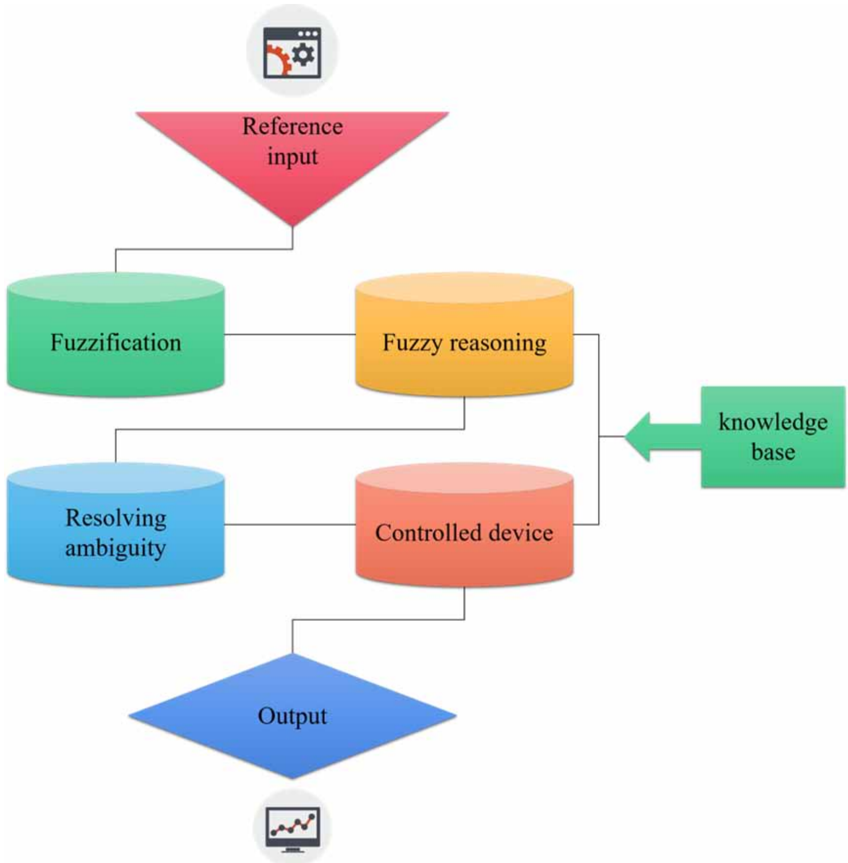
Therefore, the affiliation function mostly relies on experience or is selected considering the convenience of processing. The curriculum materials should be exploited and treated with an open mind to all the achievements of civilization created by human beings, and all possible curriculum resources that are beneficial to educational and teaching activities should be developed and utilized as much as possible. Information-based teaching puts forward higher requirements for English teachers, who should not only update and expand their information knowledge structure but also be able to use IT flexibly.

Database Design of FNN-Based Model

Data are the core of a model, and whether the choice of database and the design of data structure are reasonable or not directly affects the realization of the overall performance of the model. The database includes the affiliation function of each linguistic variable, the scale change factor, and the number of sublevels in the fuzzy space. When the Euclidean distance is chosen as the non-similarity index between the vectors in the group and the corresponding clustering centers, the objective function can be chosen as shown in equation (7).

$$J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \left(\sum\nolimits_{k, x_k \in G_i} \left\| x_k - c_i \right\|^2 \right) \tag{7}$$

Figure 3. Structure Diagram of FNN Database



In equation (7), J_i = objective function.

The FNN database is often obtained from the affiliation function or look-up table, and the commonly used fuzzification methods are single-point fuzzy set method and triangular fuzzy set method. The structure of the FNN database is shown in Figure 3.

First, the shared file information database is used to store the file information records shared by users in the model. Educators should "revitalize" junior high school English teaching materials with "task-based" teaching approaches, actively develop literature curriculum resources, and carry out classroom English poetry teaching strategies. The model is used to correlate different granularity features with each other and to obtain their representations through weighted summation, as shown in equation (8).

$$\alpha_{\mathrm{i}}^{t} = \frac{\exp(U_i^{tT} u_w)}{\sum_t \exp(U_i^{tT} u_w)} \tag{8}$$

In equation (8), c_i^t = the i word characterization of the t th feature.

Most runs of the actual control model illustrate that the execution process is not sensitive to the shape of the affiliation function when the division width is the same. Much of the information provided to the decision-maker is incomplete, imprecise, and subjective. Therefore, the decision-maker is required to use fuzzy set theory and techniques to deal with the objectives and constraints to make reasonable and correct decisions under fuzzy environment conditions. Although the traditional feedback neural network evaluates only the posterior probability (that is, the network weights and radial basis function parameters are determined), the output of FNN can be expressed as shown in equation (9).

$$y_j = \sum_{i=1}^{h} \omega_{ij} \exp\left(-\frac{\left\|x_p - c_i\right\|^2}{2\sigma^2}\right), j = 1,2,3,\ldots,n \tag{9}$$

In equation (9), ω_{ij} = the weight of the hidden layer and output.

With the city network and campus network as the platform, the education management department in the region will take the lead in pooling education information resources construction funds. Encourage educational software developers to cooperate with schools so that they can complement each other in resource construction and jointly build digital educational information resources that meet the needs of teaching and learning.

Second, the shared file access control database is used to store records of access rights of files corresponding to different users. In the development of course resources, developers need to follow the principles of systematicity, selectivity, reference, and school-basedness. The rule base includes a series of control rules expressed in fuzzy language variables. These rules reflect the experience and knowledge of control experts, in accordance with certain fuzzy control rules, combined with an appropriate reasoning mechanism. This rule base results in a fuzzy control method that is transformed into a control algorithm for controlling the controlled object. After the interaction process, the correlation coefficient matrix of the evaluation index is calculated, as shown in equation (10).

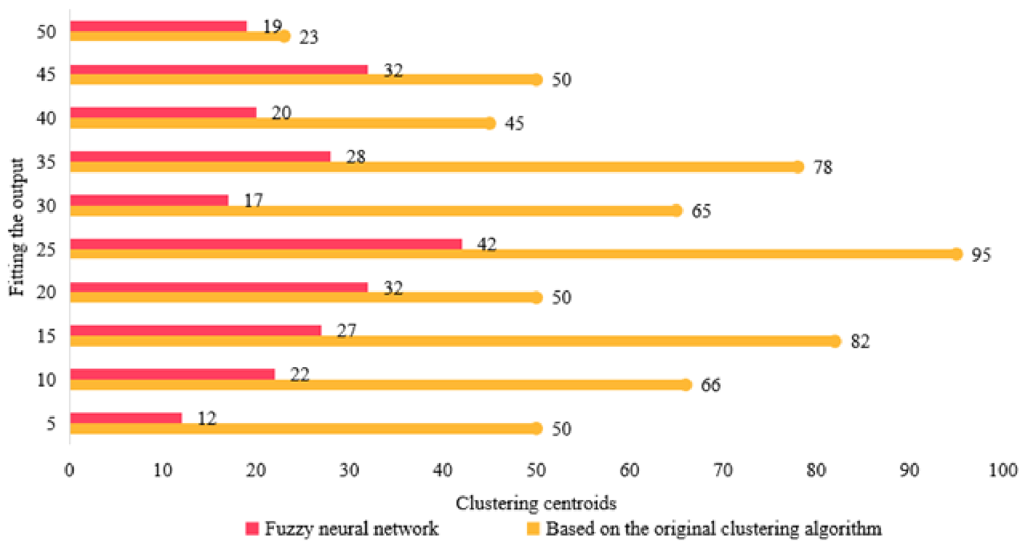
$$R = (r_{ij})_{p\times p} \tag{10}$$

In equation (10), R_{ij} = the correlation coefficient between the i teaching quality evaluation sample and the j index.

The mechanism of lateral inhibition or excitation between neurons in the same layer can be realized by interconnecting neurons within the layer. Thus, the number of neurons that can act simultaneously within a layer can be limited, or the neurons within a layer can be divided into several groups. By sharing educational information resources, educators can realize the reasonable allocation of educational sources in the region, fully share various educational resources in the region, and avoid duplicate investment and construction of educational information resources.

Finally, the shared file download information database is used to store the corresponding records generated when users perform download operations on shared files. English material-based resources can be divided into on-campus resources and off-campus resources according to their sources, and cultural resources and educational sources according to their contents. Therefore, the input variables first undergo a scale change (transforming them to the corresponding theoretical domain range) and then undergo a fuzzification process so that the original exact input quantity becomes a fuzzy quantity. The change is represented by the corresponding fuzzy set. The FNN is composed of a large number of nonlinear processing units that provide it with strong nonlinear characteristics and enable it to simulate many nonlinear models. Through the initiative of regional education authorities to concentrate their financial resources on building a regional central educational resource library, the capacity of educational information resources is expanded, the quality of educational information

Figure 4. Comparison of Fitting Effects of Two Methods



resources is improved, the presentation of educational information resources is enriched, the network connectivity and access speed between schools and the resource library are enhanced, and the effective use of online educational information resources is promoted.

APPLICATION ANALYSIS OF FNN'S DIGITAL ENGLISH EDUCATIONAL SOURCES CO-BUILD AND SHARE MODEL

Analysis of Fuzzy Nearest Neighbor Learning Algorithm

The fuzzy nearest neighbor learning algorithm performs clustering iterations based on the input information of samples to determine the center of affiliation. To better promote the construction and application of digitized sources and to maximize the advantages of digitized sources, resource sharing becomes an inevitable way to reach this goal. Because the model runs on a network basis, analyzing the fuzzy nearest neighbor learning algorithm is important. For example, the model accepts a user's input, from which some scripting language should be filtered out to avoid some more common script injection to destroy the operation of the model and steal user information. To verify the effectiveness of this model, we compared the original clustering-based algorithm with the FNN approach. The results are shown in Figure 4.

First, we created an initial fuzzy rule base from the input-output data pairs. It has the ability to simulate human reasoning based on fuzzy concepts, and its role is to apply fuzzy implication and inference rules according to the rules and the given facts to arrive at a reasonable output or conclusion. Thousands of new resources appear every second, but the storage capacity of transmission media is limited, and the limitations of human experience make absorbing all digital educational resources impossible; only selective ingestion can be done. The affiliation function greatly increases the order of the model because it deteriorates the distribution of data points in the input space, generating many blind spots and consequently having to generate new clustering centers. The comparison of the clustering effects of the simulation examples is shown in Table 1.

Therefore, an FNN can be trained by the data provided by the model, and the trained network has the ability to simulate the inherent laws of the training data. A specialized institution or organization

Table 1. Comparison of Clustering Effects of Simulation Examples

Sampling data 1,000			
	H	F	Center Point
Original clustering algorithm	7.2231e-2	8.26158	271
Fuzzy neural network	6.2415e-1	9.22512	142

may be able to develop a better resource service model to provide subscriptionable resource services for other platforms in an open or fee-based way and to upgrade and maintain it well.

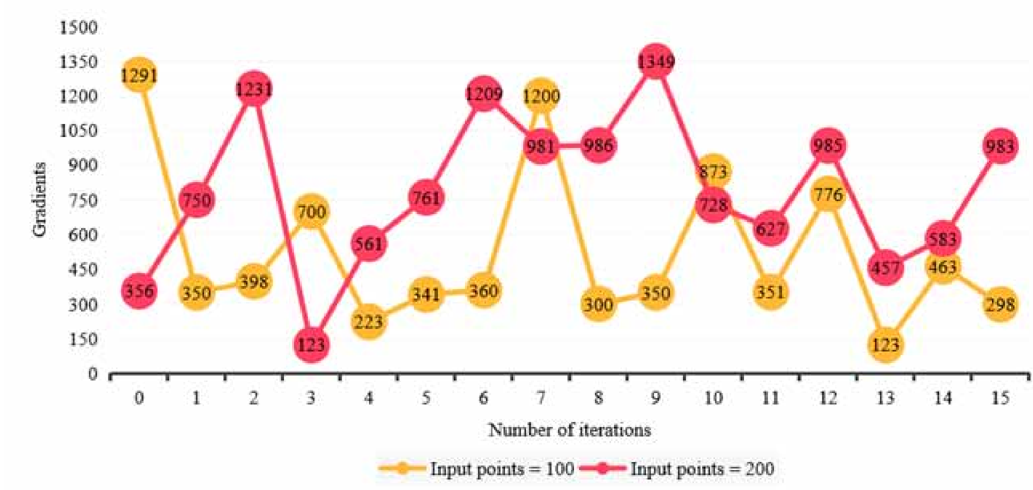
Next, we adjusted the parameters in the rule base to obtain an ideal, accurate fuzzy rule base. What is obtained by fuzzy inference is a fuzzy quantity, whereas for the actual control, this fuzzy quantity must be converted into a clear quantity. The inverse fuzzifier must complete this task by mapping a fuzzy set on the output space to a definite point, which can be regarded as the inverse process of fuzzification. Learners can provide feedback to the resource manager according to their needs in the process of using, and these opinions are incorporated into the system of resource construction, so the use of digital education resources is a two-way process. By identifying this function to compare the operation effect of the two learning algorithms, we were able to analyze the trend of the variation of the norm of the gradient of the error function and the error function about the weight. The error functions and the variation curves of the gradient of the input points of the training samples for 100 and 200 are shown in Figures 5 and Figure 6.

FNNs can be simulated not only by software but also by integrated circuits. Therefore, the neural network has fast and large-scale data processing capability. It can expand the coverage and utilization of educational resources, give full play to the role of high-quality educational resources, and meet the usage needs of applicants to the greatest extent.

Finally, the number of rules for selecting the optimal fuzzy logic model is equal to the number of input-output data pairs in the sample set so that one rule corresponds to one input-output data pair. With the organizational management mechanism as the coordination and effective incentive policy as the promotion, the coordination and linkage of the three levels of construction subjects are realized in the implementation process to break the bottleneck of regional education information resources

Figure 5. Error Function Curve

Figure 6. Gradient Norm Change Curve



building and sharing. In the fuzzy set of fuzzy reasoning results, the element with the largest affiliation degree is taken as the output value. If one institution completes this knowledge point and participates in sharing it in these thousand school areas, other units can share and use this knowledge point, while saving the cost of resource construction. The fuzzy inference machine infers fuzzy conclusions (i.e., fuzzy sets on the domain), based on the fuzzy inference knowledge in the fuzzy rule base and the fuzzy sets generated by the fuzzy generator, and feeds them to the anti-fuzzifier.

Application Analysis of FNN Model in Resource Co-Construction and Sharing

Most of the current FNN models are multilayer forward network structures, which are related to the unidirectional nature of fuzzy inference, and different types of FNNs emerge owing to the different neurons and different incorporation of fuzzy components.

First, the node in the first layer is the input node, which represents the input language variables. It plays the role of transmitting the input values to the next layer. It is a feed-forward, tutorless learning algorithm whose content is such that if two neurons are excited at the same time (i.e., activated at the same time), the synaptic connection between them is strengthened. We conducted numerical experiments on the FNN model and used the error function variation curves corresponding to different learning rates, as shown in Figure 7.

The FNN model can effectively promote the teachers and students in regional schools to actively obtain high-quality educational sources, help teachers and students to develop information literacy, and improve the quality of teaching and school effectiveness. The choice of fuzzy generator, fuzzy reasoner, and anti-fuzzifier has a large degree of freedom. Therefore, when a fuzzy logic system is used to solve some special problems, the optimal fuzzy logic system can be selected through a learning approach so that it can effectively use both data and linguistic information.

The fuzzification layer is next. Each node represents a linguistic variable value. Its function is to calculate the affiliation function of each input component belonging to each linguistic variable value fuzzy set. In other words, the degree of subordination can be used to quantitatively describe the degree of compliance of the elements in the domain with the fuzzy concept, which realizes the expansion of the absolute subordination relationship in the classical set so that the fuzzy set is represented by the subordination function and the fuzzy concept is represented by the fuzzy set. Using 20 fuzzy rules, we randomly generated the initial parameters of the network between 10 and 30, and the experimental results of the Apriori algorithm and the FNN's discriminative Gabor function are shown in Table 2.

Figure 7. Curve of Error Function Corresponding to Different Learning Rates

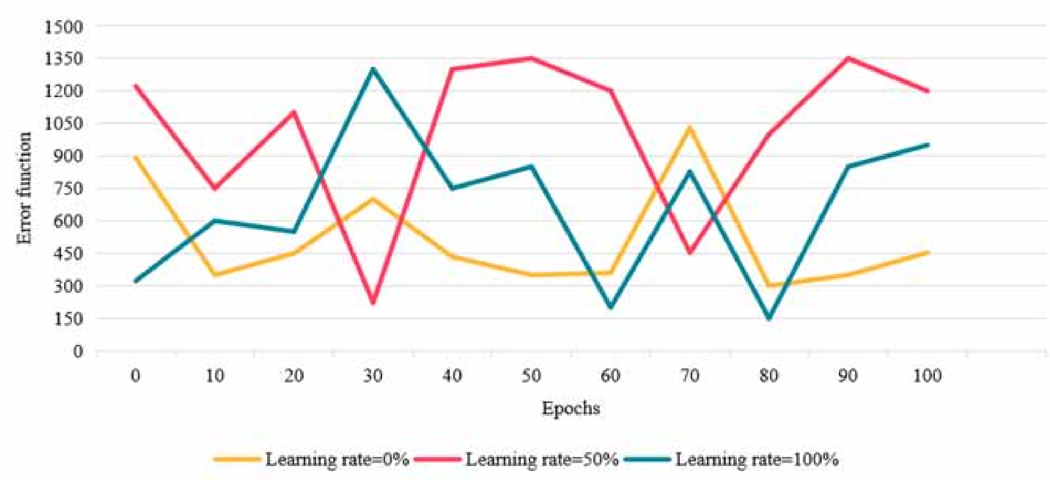


Table 2. Experimental Results of Identifying Gabor Function

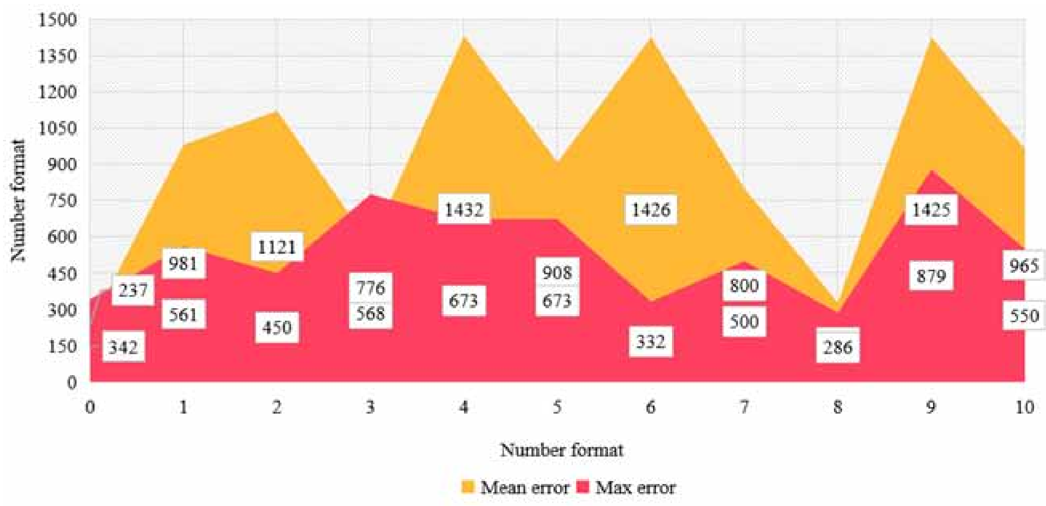
Algorithm	FNN	Apriori
Training steps	12,000	12,000
Training sample error	0.00251	0.02347
Average running time per step(s)	0.0034	0.0068

With suitable initial fuzzy rules, the training sample error of the FNN is reduced by 0.00251, and the average running time is reduced by 0.0034 s, compared with the Apriori algorithm, so the FNN has a good approximation effect.

We interpret this as the components of building and sharing educational information resources, and how they interact and influence each other. This includes the relationships among information resource providers, managers, and users involved in constructing and sharing educational information resources. It also encompasses how these resources are developed, applied, and operate. It provides a generalized model for quantifying expert linguistic information and systematically using such linguistic information under fuzzy logic rules. However, it has the disadvantage that the input and output are fuzzy sets, which are not easy to be used by most engineering systems. The results were recorded statistically throughout the test using a fixed-point format and repeated with a variety of smaller representation and lower precision data formats. The computational errors of the network in different numerical formats are shown in Figure 8.

Finally, the nodes in the third layer are rule nodes representing fuzzy logic rules. The connections in this layer are used to generate fuzzy logic rules and conditional or antecedent matches. That is, the degree of applicability of each rule is calculated. The difference in teaching philosophy, teaching methods, and teaching staff between regions makes some students not enjoy quality resources, and consequently, they cannot really share resources. Therefore, the fuzzy set can be considered a conceptual extension of the classical set, and the classical set is a special form of the fuzzy set, whereas the affiliation function is an extension of the characteristic function, and the characteristic function is just a special case of the affiliation function. The intrinsic motivation is the shortcomings of digital educational sources that cannot be effectively built and shared. Thus, educators should understand users' needs and motives in the teaching process, let users take the initiative and truly participate in the production activities of digital educational sources, and meet users' needs for sharing and

Figure 8. Network Calculation Errors in Different Numerical Formats



communication of educational sources. These measures enable network users to access the required information resources anytime and anywhere through network terminals, regardless of the location and distance of resource storage. The FNN's output can be precisely determined by the affiliation functions of the variables in the rule base and the output of the rules (conclusion part). Therefore, the parameters of the system can be determined by the system identification method.

Quantifiable Outcomes

The proposed FNN-based model for sharing digital English educational resources represents a significant advance in addressing the challenges associated with ineffective digitization and resource management in the field of English language instruction. The experimental evaluation of the FNN model against the Apriori algorithm yields compelling evidence of its superiority in several key performance metrics. The FNN model exhibits a significantly lower training sample error (0.00251) compared with the Apriori algorithm (0.02347). This 0.02096 reduction in error signifies a substantial improvement in the model's accuracy in processing and learning from training data, indicating a higher capacity for accurate identification and classification of digital English educational resources. The FNN-based model demonstrates a marked advantage in computational speed, with an average running time per step of 0.0034 seconds, compared with 0.0068 seconds for the Apriori algorithm. This 50% decrease in running time underscores the FNN's efficiency in processing large volumes of data and executing resource-sharing tasks, translating into faster response times and enhanced user experience on e-learning platforms. The adoption of deep neural network-based collaborative filtering within the FNN model contributes to improved course recommendations, enhancing the relevance and quality of shared resources for learners. This feature not only increases user satisfaction but also promotes more targeted and effective learning experiences, ultimately contributing to better learning outcomes. Implementation of the FNN-based model is expected to result in optimized resource management practices, enabling schools to achieve more efficient resource allocation and cost savings. The model's adaptability and learning capabilities allow it to dynamically respond to changing user needs and resource availability, ensuring that resources are distributed and utilized in the most effective manner. By virtue of its superior approximation capabilities and ability to identify and prioritize high-quality resources, the FNN model effectively curbs the proliferation of low-quality digital English educational materials. This leads to a higher overall quality standard within information resource libraries and supports the establishment of a robust, reliable, and valuable resource pool for educators and learners alike.

CONCLUSION

The proposed FNN-based model for sharing digital English educational resources holds promise as a potential tool to address the persistent challenges encountered in traditional English education models, including digitization limitations, autonomy constraints, fragmentation, and inadequate management systems. The FNN model is conceptually promising in its ability to integrate fuzzy logic and neural network principles for resource sharing.

Regarding optimized allocation, we posit that the FNN model can distribute resources more efficiently. Quantitative data or case studies showcasing the model's ability to balance resource demand, minimize redundancy, and cater to diverse learning needs would be crucial in substantiating the claim of optimized allocation. With regard to cost efficiencies, we assert that the FNN-based approach can lead to cost savings. On the issue of maximizing resource effectiveness, the paper highlights the potential for improved learning experiences through enhanced course recommendations and targeted resource provisioning. Lastly, we suggest that the FNN model offers a systematic approach to tackling the challenges of digital English education resource sharing.

This paper presents an innovative FNN-based model with the potential to revolutionize digital English education resource sharing. However, it falls short in providing comprehensive evidence to substantiate the full extent of its claims regarding enhancements to resource management, optimized allocation, cost efficiency, resource effectiveness, and the systematic nature of the proposed solution. Future research should aim to address these gaps by furnishing empirical data, comparative analyses, cost-benefit assessments, and detailed implementation frameworks to more confidently assert the model's transformative potential in the realm of digital English education.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

We declare that there are no conflicts of interest.

FUNDING

This project was funded by the Hubei Vocational and Technical Education Association, grant number ZJGA202228.

PROCESS DATES

Received: March 11, 2024, Revision: April 2, 2024, Accepted: April 2, 2024

CORRESPONDING AUTHOR

Correspondence should be addressed to Haiying Wang; Jessica_why@163.com

ACKNOWLEDGMENT

We would like to show sincere thanks to the developers of the techniques that have contributed to this research.

REFERENCES

Ansari, Z. A., Sattar, S. A., & Babu, A. V. (2017). A fuzzy neural network based framework to discover user access patterns from web log data. *Advances in Data Analysis and Classification*, *11*(3), 519–546. doi:10.1007/s11634-015-0228-4

Balakrishnan, M., Rajendran, V., Prajwal, S. J., & Indiran, T. (2023). Neural network-based Hammerstein model identification of a lab-scale batch reactor. *ACS Omega*, *9*(1), 1762–1769. doi:10.1021/acsomega.3c05406 PMID:38222548

Chatterjee, A., & Rakshit, A. (2004). Influential rule search scheme (IRSS)—A new fuzzy pattern classifier. *IEEE Transactions on Knowledge and Data Engineering*, *16*(8), 881–893. doi:10.1109/TKDE.2004.26

Chen, H., & Huang, J. (2021). Research and application of the interactive English online teaching system based on the internet of things. *Scientific Programming*, *2021*(3636533), 1–10. doi:10.1155/2021/3636533

Cui, X., & Wang, X. (2021). Research on the online college English teaching mode from the perspective of autonomous learning. *Journal of Contemporary Educational Research*, *5*(11), 114–117. doi:10.26689/jcer.v5i11.2689

Duan, T., & Wang, A. (2018). Fuzzy neural network learning based on hierarchical agglomerative TS fuzzy inference. [IJRIS]. *International Journal of Reasoning-Based Intelligent Systems*, *10*(2), 83–89. doi:10.1504/IJRIS.2018.092209

El-Nasr, M. S., Yen, J., & Ioerger, T. R. (2000). Flame—Fuzzy logic adaptive model of emotions. *Autonomous Agents and Multi-Agent Systems*, *3*(3), 219–257. doi:10.1023/A:1010030809960

Fan, J. (2024). A big data and neural networks driven approach to design students management system. *Soft Computing*, *28*(2), 1255–1276. doi:10.1007/s00500-023-09524-8

Hashmi, M. B., Mansouri, M., Fentaye, A. D., Ahsan, S., & Kyprianidis, K. (2024). An artificial neural network-based fault diagnostics approach for hydrogen-fueled micro gas turbines. *Energies*, *17*(3), 719. doi:10.3390/en17030719

Hui, W., & Aiyuan, L. (2021). A systematic approach for English education model based on the neural network algorithm. *Journal of Intelligent & Fuzzy Systems*, *40*(2), 3455–3466. doi:10.3233/JIFS-189383

Khan, S., Khan, M. A., & Alnazzawi, N. (2024). Artificial neural network-based mechanism to detect security threats in wireless sensor networks. *Sensors (Basel)*, *24*(5), 1641. doi:10.3390/s24051641 PMID:38475178

Khodabandelou, G., & Ebadzadeh, M. M. (2019). Fuzzy neural network with support vector-based learning for classification and regression. *Soft Computing*, *23*(23), 12153–12168. doi:10.1007/s00500-019-04116-x

Kong, S. (2019). Practice of college English teaching reform based on online open course. *English Language Teaching*, *12*(5), 156–160. doi:10.5539/elt.v12n5p156

Lanjewar, M. G., & Panchbhai, K. G. (2023). Convolutional neural network based tea leaf disease prediction system on smart phone using PAAS cloud. *Neural Computing & Applications*, *35*(3), 2755–2771. doi:10.1007/s00521-022-07743-y

Liao, D. (2022). Retracted: Development and utilization of English online course resources based on fuzzy neural network. *Journal of Sensors, 2022*, 1795446. (Retraction published 2023, *Sensors, 2023*, 9808615)10.1155/2023/9808615

Luo, S. (2023). The current landscape and future direction of curriculum reform in China. *Future in Educational Research*, *1*(1), 5–16. doi:10.1002/fer3.8

Luo, W., Huang, H., Yan, W., Wang, D., Yang, M., Zhang, Z., Zhang, X., Pan, M., Kong, L., & Zhang, G. (2023). A graph neural network-based digital assessment method for vocational education level of specific regions. *Journal of Circuits, Systems, and Computers*, *32*(15), 2350262. doi:10.1142/S0218126623502626

Ravichandran, B. D., & Keikhosrokiani, P. (2023). Classification of Covid-19 misinformation on social media based on neuro-fuzzy and neural network: A systematic review. *Neural Computing & Applications*, *35*(1), 699–717. doi:10.1007/s00521-022-07797-y PMID:36159189

Shen, Y., Li, H., Zhang, B., Cao, Y., Guo, Z., Gao, X., & Chen, Y. (2023). An artificial neural network-based data filling approach for smart operation of digital wastewater treatment plants. *Environmental Research*, *224*, 115549. doi:10.1016/j.envres.2023.115549 PMID:36822533

Singh, A. P., Singh, A., Kumar, A., Agarwal, H., Yadav, S., & Gupta, M. (2024). Development of an artificial neural network-based image retrieval system for lung disease classification and identification. *Engineering Proceedings*, *62*(1), 2. doi:10.3390/engproc2024062002

Singh, N. K. (2019). Detection of postural balance degradation using fuzzy neural network. *International Journal of Bioinformatics Research and Applications*, *15*(4), 371–394. doi:10.1504/IJBRA.2019.103788

Snekha, S., & Ayyanathan, N. (2023). An educational CRM chatbot for learning management system. *Shanlax International Journal of Education*, *11*(4), 58–62. doi:10.34293/education.v11i4.6360

Vedavathi, N., & Anil Kumar, K. M. (2022). SentiWordNet ontology and deep neural network based collaborative filtering technique for course recommendation in an e-learning platform. *International Journal of Uncertainty, Fuzziness and Knowledge-based Systems*, *30*(04), 709–732. doi:10.1142/S0218488522500192

Zhang, H., Wang, Y., Zhang, M., Song, Y., Qiu, C., Lei, Y., Jia, P., Liang, L., Zhang, J., Qin, L., Ning, Y., & Wang, L. (2024). Deep neural network-based phase-modulated continuous-wave LiDAR. *Sensors (Basel)*, *24*(5), 1617. doi:10.3390/s24051617 PMID:38475153

Zhang, L. (2023). An IoT-based English translation and teaching using particle swarm optimization and neural network algorithm. *Soft Computing*, *27*(19), 14431–14450. doi:10.1007/s00500-023-09032-9

Zhang, Y., Jin, Z., & Chen, Y. (2020). Hybrid teaching–learning-based optimization and neural network algorithm for engineering design optimization problems. *Knowledge-Based Systems*, *187*, 104836. doi:10.1016/j.knosys.2019.07.007

Zheng, K., Zhang, Q., Hu, Y., & Wu, B. (2021). Design of fuzzy system-fuzzy neural network-backstepping control for complex robot system. *Information Sciences*, *546*, 1230–1255. doi:10.1016/j.ins.2020.08.110

Zhu, S., Yu, T., Xu, T., Chen, H., Dustdar, S., Gigan, S., Gunduz, D., Hossain, E., Jin, Y., Lin, F., Liu, B., Wan, Z., Zhang, J., Zhao, Z., Zhu, W., Chen, Z., Durrani, T., Wang, H., Wu, J., Zhang, T., & Pan, Y. (2023). Intelligent computing: The latest advances, challenges, and future. *Intelligent Computing, 2*, 0006. 10.34133/icomputing.0006

Zhu, Y., Lu, H., Qiu, P., Shi, K., Chambua, J., & Niu, Z. (2020). Heterogeneous teaching evaluation network based offline course recommendation with graph learning and tensor factorization. *Neurocomputing*, *415*, 84–95. doi:10.1016/j.neucom.2020.07.064

Zubatyuk, R., Smith, J. S., Nebgen, B. T., Tretiak, S., & Isayev, O. (2021). Teaching a neural network to attach and detach electrons from molecules. *Nature Communications*, *12*(1), 4870. doi:10.1038/s41467-021-24904-0 PMID:34381051