Hindawi
Advances in Multimedia
Volume 2022, Article ID 4452393, 10 pages
https://doi.org/10.1155/2022/4452393

Research Article

A Scalable Blockchain Framework for ELA Assessment

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Received 19 May 2022; Revised 26 June 2022; Accepted 5 July 2022; Published 12 September 2022

Academic Editor: Qiangyi Li

As a popular technology in the information age, blockchain is having a profound impact on various industries, including the field of education. Blockchain technology can accelerate the modernization of education in China, adapt to the new situation of epidemic prevention and control needs, and promote the renewal of the management and training modes of college students. Blockchain technology is decentralized, tamper-proof, traceable, trackable, open and transparent, which is conducive to the realization of individual student-centered teaching and learning, as well as an open, and transparent teaching process, which can motivate the learning motivation of English majors and improve the effectiveness of the student management and training models. To address the problem of low accuracy of the traditional English proficiency classification methods, this article aims to explore the application of blockchain technology in the management and training model of English majors and its feasibility. We propose a proficiency evaluation model based on a Discrete Hopfield Neural Network (DHNN). Firstly, the hierarchical analysis method is used to construct the evaluation index system of students' English ability, and then the ability classification indexes are divided into 5 levels.The network achieves the classification of students' English proficiency through the associative memory of the classification criteria, and the classification results are compared with those of the BPNN model. The simulation results show that the classification accuracy of the BPNN model is 80.0% and that of the DHNN model is 100.0%. The DHNN model has improved the classification accuracy and generalization ability, and the model establishment process is simple and the results are intuitive, which verifies the effectiveness of the proposed model

1. Introduction

Blockchain technology is an emerging technology that has attracted much attention in recent years, and has been widely used in the financial industry, business services, and other fields, and has also brought new atmosphere and possibilities to the education field. Blockchain can play its unique technical advantages to provide a strong guarantee in such aspects as college entrance examinations, credentialing, degree certificates, and transcript records. Correctly classifying English levels can both objectively assess students' abilities and provide a basis for teachers to develop graded teaching plans [1]. Traditional English assessment methods are generally divided in a linear pattern, but the presence of multiple factors has led to a high-dimensional and nonlinear posture in the assessment of English proficiency. The assessment results of traditional assessment methods differ greatly from reality and are difficult to meet the requirements of engineering applications. In recent years, due to the rapid development of ANN technology, using neural networks for English learning is a new way of learning [2]. Among the various neural networks, BPNN is the most representative and widely used network model at present. In the existing literature, the BPNN method has been used to evaluate English and improve the classification results to a large extent. However, BP neural networks are characterized by difficulty in determining the topology, slow convergence speed, and the learning process is easy to fall into local optimum. Since Hopfield neural networks have rich practical experience in association and memory, they have been widely used in pattern recognition. To address the problem that the traditional classification accuracy is not high, this paper categorizes and evaluates them using discrete HopfieldNeuralNetwork (DHNN) and compares them with BPNN model to test the correctness of the model [3].

Currently, blockchain technology is developing at a rapid pace and three different application models, public chain, alliance chain, and proprietary chain, have been formed according to the actual application and needs. In medicine, Philips is using blockchain technology for the verification of medical records and confidentiality of personal data [4]. In IoT, IBM and Samsung have introduced an Ethernet blockchain architecture for IoT solutions that is highly redundant and fault-tolerant, enabling secure and stable data transfer without the need for a central server and system management. Although blockchain technology has been widely used in the financial and service industries worldwide, its application in education has received little attention.

From the global perspective of education, Yi-Fu Jin made an in-depth analysis of the application of blockchain technology in the field of education, and proposed the architecture of "blockchain+education" and gave a hybrid deployment model based on local decentralization [5]. Li et al. believe that the future development direction of "blockchain+education" can be divided into six directions, namely, distributed learning record storage, online education certificate system, copyright protection of curriculum resources and academic results, intelligent contract and accumulation of educational contracts, decentralized global knowledge base, and knowledge circulation and society.

In terms of curriculum and teaching, Xu Tao summarized the existing research and practice, pointing out that there are three main applications of blockchain technology in education and teaching: transcripts, learner resources, and learning ledgers [6]. Xue Yue et al. believe that the most promising ones to rapidly spread in the education industry are learning records and certificates. Educational institutions like Sony and MIT's Media Lab have made some attempts at this [7].

In terms of applications for comprehensive teaching, Professor Xue and others have analyzed the advantages and features of blockchain technology in the evaluation of student behavior in colleges and universities, and based on this, designed a blockchain-based student behavior assessment system to achieve a comprehensive and holistic record and evaluation of college students' academic performance [8].

As a compulsory public course with a wide audience, long running time and rich learning channels and platforms, college English course needs objective, scientific, innovative and continuous learning evaluation methods, and the learning process assessment based on blockchain technology is a new direction worthy of consideration and exploration.

2. State of the Art

With the continuous popularization of quality education and the deepening of the new curriculum reform, education and teaching are no longer just about simply imparting knowledge, but about improving students' independence. English is an important course in university, and its mode of thinking and learning methods are very different from those of other subjects, so it is necessary to cultivate students' independent learning ability.

Different views and opinions exist among scholars at home and abroad about learning ability [9]. In this paper, we start from studying the learning ability of people and further understand the components and composition of learning ability. Professor Shan points out that students' learning ability is mainly composed of various psychological factors, physical and mental factors, behavioral factors, and certain direct environmental factors. Students' learning ability is divided into two levels: real and potential.

Professor Chongde Lin believes that the nature and cultivation of learning ability should be approached from the perspective of disciplinary ability [10]. He believes that learning ability refers to the synthesis of students' intelligence and ability with a particular discipline. According to Lin, subject competence, usually has three meanings: first, it refers to students' mastery of the overall knowledge of a subject; second, it refers to the intellectual activities performed in learning the knowledge and skills of a subject; and third, it is learning ability, i.e., the learning strategies and ways in which students learn a subject.

Bivarin proposes the information processing orientation learning ability, which is created and developed in the learning process, and it is a personality characteristic with the ability to obtain information independently, process and use it, and analyze and solve real-world problems [11]. Therefore, he believes that any learning behavior is based on knowledge, skills, and strategies, and that without proper guidance and adjustment, it is impossible to achieve the goals and implementation of learning and to develop the ability to learn. In other words, he sees basic knowledge, skills, and strategies as the foundation of learning competencies [12]. Moreover, basic knowledge and skills are the raw materials for processing, while processing methods are the most fundamental strategies. The former is internalized, structured, and networked under the guidance of the latter, which leads to a more solid cognitive structure for the learner.

According to Lee and Ho, it is important to incorporate the intellectual, nonintellectual, and strategic elements of learning in the context of the child's development [13]. The essence of learning is the enhancement of meta-learning ability, that is, whether the learner consciously changes and regulates his or her cognition and self so that he or she becomes an active organism in the learning process and can plan and effectively control his or her learning process. Dong Qi and Zhou Yong divided meta-learning competence into three levels and eight dimensions, namely, self-monitoring before the learning activity, including planning and preparation [14]; self-monitoring during the learning process (including awareness, method, and implementation); and self-monitoring, correction and summarization after the learning. According to Zhang Qinglin, Guan Peng, Hu, and others, meta-learning ability consists of the ability to motivate oneself to study hard, to determine learning goals, to choose the most suitable learning methods and approaches to achieve the goals, to be good at testing the goals, to take corrective measures when needed, to be good at summarizing successes and failures, and to adjust learning methods and approaches at the right time.

Learning activities and learning abilities are closely linked, and learning activities are their carriers. Any learning activities are carried out under the directional regulation of students' existing knowledge, skills, and strategies. Therefore, basic knowledge, basic skills, and basic strategies are the basic elements of learning ability.

3. Methodology

3.1. Technical Framework of Blockchain + University English Course. Blockchain was first proposed by Nakamoto in 2008, who pointed out in his article "Peer-to-Peer Electronic Cash Systems" that blockchain technology is a cryptographic transmission technology that addresses the inherent weaknesses of traditional transactions.

On this basis, the concept of "MU English Course Blockchain" is proposed, which is based on the Blockchain 2.0 architecture (Table 1) and provides blockchain technology for MU credit certification and personalized teaching based on teaching records and evaluation [15]. The MUEnglish blockchain provides a blockchain architecture for developing English courses, including an assignment layer, a policy layer, a service layer, a management layer, and a network layer. In the assignment layer, teaching resources, learning records, and learning evaluations can be generated according to the learning needs of students; in the strategy layer, based on the characteristics of users (teachers and students) and tasks, intelligent computations are performed and requests for blockchain services are classified under the monitoring and supervision of the system; in the business layer, task requests are completed and grouped by the business layer according to different strategies, managers encrypted, verified and signed data blocks; on the basis of P2P, data mining technology is used to implement blockchain business [16]. p2p network, which means mining to reach an agreement or reach an agreement to connect between data blocks.

Table 2 shows the data block structure of the MU English course blockchain. While each block contains information about bitcoin transactions, each block in the MU English course blockchain contains a record and evaluation of teaching and learning activities. Instructional activity refers to the node's input time, knowledge state, and educational resources, and is analyzed using an "input and output" model. In this data, the nodes are the people on the blockchain, both students and teachers. The "learning coin" is a measure of student identity; the "teaching coin" is an important measure of teacher identity; "relationships" and "comments" can be used to measure teaching resources. "Comments" can be used to measure teaching resources, referring to IEEE (Electronics and Electrical Electronics) LOM (Electrical Electrical Electrical Electronics). The characteristics of "relationship," "comment," "classification," and "ownership" can be used to classify the status of teaching resources. The status of teaching resources can be classified by features such as "relationship," "comment," "classification" and "ownership."

The teaching activity blocks are organized in MPT (merkle-patricia), which are wrapped into blocks using techniques such as hashing operations and time stamping. The hashing algorithm is transforming the data into a fixed hash value, which cannot be recovered with a known hash value. In addition, it is difficult to get the same hash value in different input messages and it is also very resistant to interference [17]. The timestamp tag seals each segment of the packet to ensure that the data will not be corrupted.

The schematic diagram of MPT is shown in Figure 1. The data generated from teaching activities can be divided into L1, L2, L3, L4, etc. To facilitate quick confirmation later, all the data (teaching behaviors or node status) are grouped and hashed. In this way, the hash value Hash0-0 is obtained from the L1 block. Since the L1 block is only a whole in the classroom (e.g., students in the classroom having an oral discussion), its hash is also hashed with the hashes of the other L2 blocks, Hash0-1. Similarly, Hash0 and Hash1 are concatenated into a string, which is then hash transformed to obtain a hash table of root hashes. Using this mechanism, the next node can confirm the hash list against the root hash from a trusted data source when the data are transmitted through the P2P network, and the block is verified by the verified hash list. The most common binomial Merkle tree is used in the "MU English Blockchain" [18].

3.2. Principle of DHNN Algorithm. Hopfield Neural Network HNN is a neural network that combines a storage system and a binary system. It is guaranteed to converge to a local minimum, but may also converge to the wrong local minimum. Hopfield Neural Network also provides models that simulate human memory.

Hopfield networks are a class of nonlinear networks in which the output of any one of its nodes is fed back to other nodes without self-feedback. Continuous Hopfield networks are often used in solving optimal problems. Since the ability assessment problem discussed in this thesis is essentially based on a model to classify and assess students' abilities using a DHNN [19], the DHNN uses 1 and −1 to indicate that the corresponding neurons are in activation and inhibition, and its associative memory process is divided into two stages: memory and association. The algorithm of the DHNN is as follows:

Let$X = (x_1, x_2, \ldots, x_n) T \in \{-1, 1\}$n be the input sample matrix of DHNN, v_i $(i = 1, 2, \ldots, n)$ be be the input value of the ith neuron, and $oi(t)$ be the output value of the hth neuron at some moment t. Then the formula to calculate the input weighted sum of the i-th neural is shown in equation (1). Where wij is the connection weight between the i-th neuron and the j-th neuron, vj is the output value of any neuron different from the i-th neuron, and δi is the threshold value of the i-th neuron. The input value of the i th neuron at a particular moment t is calculated as shown in equation (2).

$$h_i(t) = \sum_{i=1}^{n} w_{ij} \cdot v_j - \delta_i, j = (1, 2, \ldots, n), \tag{1}$$

$$V_i(t) = h_i(t). \tag{2}$$

Starting from the output layer, the weights are adjusted in the reverse direction, and the adjustment consensus is as follows:

Table 1: Blockchain architecture for MU English courses.

Architecture	MOOC university English course regional chain system
Task layer	Teaching resources, learning records, learning evaluations, clients
Policy layer	Identity services, referral policies, access control, audit monitoring, etc.
Service tier	Regional chain services
Management	Encryption algorithms, rule verification, digital signatures, consensus mechanisms, mining modules
Network layer	Distributed P2P network

Table 2: Data block structure.

Block header	Block body
The address of the previous block, the timestamp, and other teaching activities root Hash value and the node status root hash value	Recording and evaluation of teaching activities

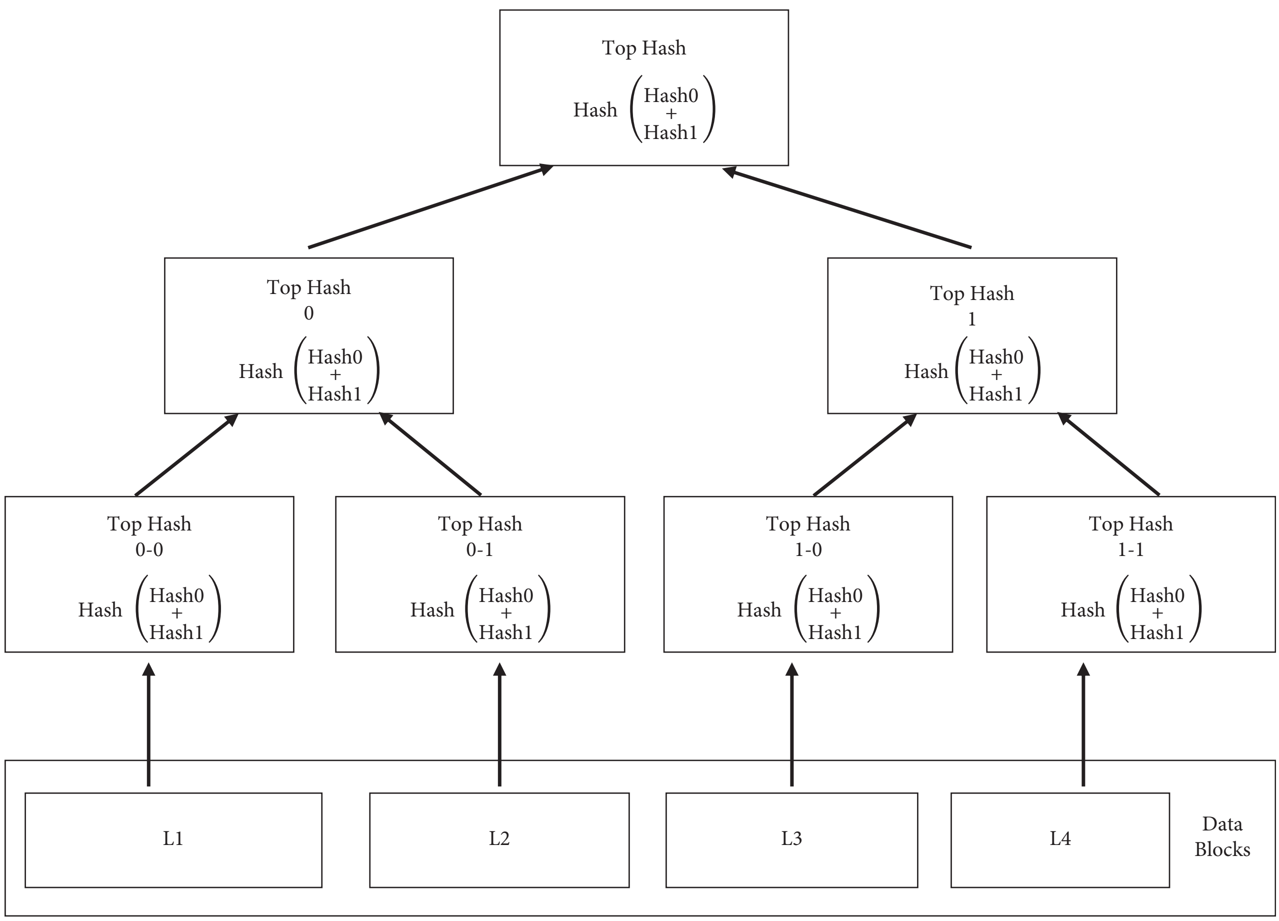

Figure 1: Merkle tree schematic.

$$W_{jk+1} = W_{jk} + \eta\delta_k V_j,$$
$$W_{ij+1} = w_{ij} + \eta\delta_j X_i, \tag{3}$$

where

$$\delta_k = \left(Z_k - \widehat{Z}_k\right)\widehat{Z}_k\left(1 - \widehat{Z}_k\right),$$
$$\delta_j = y_j\left(1 - y_j\right) \cdot \sum_{k=0}^{L-1} \delta_k \cdot W_{jk}. \tag{4}$$

The network is trained to determine its connection power matrix *wij*, and the DHNN output at time t is determined by the current input sampling matrix X. The network output value for the next moment $(t + 1)$ is then obtained by the feedback action of the network. As shown in equation (7), the output value of the ith neuron at the next t+1 moment is calculated, and then the output value $oi(t + 1)$ is fed back to the input. When the output value of the network satisfies equation (10), the network can finally reach a steady state after several iterations as shown in equation (8).

$$O_i(t+1) = f\left[v_i(t)\right] = f\left[h_i(t)\right], \tag{5}$$

$$O_i(t+1) = \operatorname{sgn}\left[\sum_{i=1}^{n} w_{ij} \cdot v_j(t) - \delta_i\right], \tag{6}$$

$$\operatorname{sgn}\left[v_i(t)\right] = \begin{cases} v_i(t) \geq 0, \\ v_i(t) < 0, \end{cases} \tag{7}$$

$$\begin{cases} o_i(t+1) = \operatorname{sgn}\left[\sum_{i=1}^{n} w_{ij} \cdot v_j(t) - \delta_i\right], \\ o_i(0) = x_i. \end{cases} \tag{8}$$

3.3. Construction of DHNN Evaluation Index System. Hopfield neural network is a feedback neural network, its output will be fed back to its input, and its output will undergo continuous state change. When the Hopfield neural network is a convergent and stable network, the changes caused by its feedback and iteration will gradually decrease, and when it reaches a stable equilibrium, the Hopfield neural network will output a constant constant quantity.

Based on the existing survey results, the indicators were further refined, and finally 12 evaluation indicators that can reflect English proficiency in colleges and universities were constructed: speaking ($X1$), listening ($X2$), vocabulary ($X3$), grammar ($X4$), reading ability ($X5$), translation level ($X6$), learning motivation ($X7$), interest in learning ($X8$), intercultural communication skills ($X9$), strategies ($X10$), discourse knowledge ($X11$), and knowledge of British and American culture ($X12$). The data were collected by creating a set of 10-point tests for each indicator and listing the relevant scoring criteria. 25 English teachers were asked to rate the English compositions of two natural classes of non-English majors (60 students in total) at a university by means of interviews and written tests. In order to avoid the influence of subjective factors in the evaluation process as much as possible, this paper used hierarchical analysis to calculate the weights of each evaluation index, and the linear weighted sum S of each index was used as the final score to classify the evaluation results as follows: $9 \leq S \leq 10$, category 1 (excellent); $8. \leq S < 9$, category 2 (good)); $7. \leq S < 8$, category 3 (moderate); $6. \leq S < 7$, category 4 (pass); $0 \leq S < 6$, and category 5 (failure). The raw data for the English assessment component of the students are shown in Table 3.

4. Result Analysis and Discussion

4.1. Evaluation Modeling of DHNN. Hopfield neural networks (HNN) are a class of neural networks with periodic recursive properties that combine memory with binary systems. invented by John Hopfield in 1982, the central problem of Hopfield neural networks is the determination of the weighting coefficients at steady state. Hopfield neural networks can be classified as discrete or continuous, and their biggest difference is their activation function. HNN (Hopfield NANN) provides a model for simulating human memory. It is widely used in machine learning, associative memory, pattern recognition, optimal computing, VLSI, and optical components.

Based on the five major bases proposed above, the preliminary proposed index system is presented in Table 4.

The prestored patterns are first coded so that if the corresponding neuron state is greater than or equal to the ideal assessment indicator value for a level, it is set to 1, otherwise it is set to −1. "●" is used to indicate that the sample data has reached the ideal assessment indicator value, and "○" is used to indicate that it has not [20]. The ideal assessment indicator for each level is the average of each assessment indicator sampled at each level in Table 1, and since the results of the student's ability assessment are to be divided into 5 categories and 12 indicators, the evaluation results (5 in total) its constitutes a DHNN consisting of 60 (5 × 12) neurons. vector of DHNN memory patterns The vector of DHNN storage patterns can be expressed as $Ak = (ak1, ak2, \ldots, akn)$ $k = 1, 2, 3, 4, 5$, $n = 60$, and the standard pattern of memory for the DHNN evaluation model can be represented in Figure 2.

The DHNN was constructed by calling the newhop function in MATLABR2013a, and then the DHNN was trained to obtain the memory weighting matrix w and the threshold vector b of the DHNN.

From the five evaluation samples (60 samples in total), two samples (10 in total) are randomly selected as the set of test samples, and the test samples are sorted to obtain the evaluation indices of the 10 samples, as shown in Table 2. the sample size indices in Table 2 are transformed into DHNN recognizable patterns, i.e., the raw information is encoded. The evaluation indexes of the 10 samples to be classified are coded as shown in Figure 3.

Through repeated iterations, the output state of DHNN does not change, indicating that the network has entered a stable state and the results of y can be used to determine the evaluation results of each to be classified.

4.2. Model Generalization Ability Test. Hopfield neural networks are classified into two types: (1) discrete Hopfield neural networks and (2) continuous Hopfiel neural networks. To verify the correctness of this model, we propose a classification model of BP neural network, which uses a typical single hidden layer structure that has the same number of dimensions as the sample feature vector, that is, 12; the number of output layer nodes and the number of classification results are the same in the case that the number of output layer nodes and the number of classification results are the same, that is, 5; according to the empirical formula, in the case that the number of hidden. According to the empirical formula, the best performance of the network is achieved when the number of layers is 15. The topology of BPNN 12-15-5 is defined; the method utilizes the standard gradient descent algorithm to train the network; the implicit layer transfer function is set as the tansig function; and the transfer function of the output layer is set as the purelin function. The data shown in Table 5 are normalized and used as a set of test sample sets for the BPNN. The simulated

Table 3: Evaluation raw data.

Sample serial number	X_1	X_2	X_3	X_4	...	X_9	X_{10}	X_{11}	X_{12}	Evaluation grade
1	9.35	9.56	9.67	9.22	...	9.18	8.76	9.34	9.09	1
2	9.54	9.47	9.76	9.60	...	9.10	8.88	9.15	9.23	1
3	9.30	9.65	9.81	9.58	...	9.22	8.62	9.31	8.99	1
⋮	⋮	⋮	⋮	⋮	...	⋮	⋮	⋮	⋮	⋮
48	6.91	7.55	6.44	5.99	...	6.05	6.56	6.06	7.17	5
49	6.99	6.97	6.09	5.43	...	5.68	5.32	5.97	7.15	5
50	7.08	6.61	6.84	6.09	...	6.01	6.17	6.21	6.98	5

Table 4: Table of English learning ability evaluation index system for high school students.

Evaluation targets	Indicator system
High school students' ability to learn English	Listen to the aspect Speaking of aspects Read the aspect Aspects of writing Comprehensive application

experimental results show that the BPNN model cannot accurately identify the detected samples of 3 classes (numbers 5 and 6) correctly, and the classification accuracy of BPNN reaches 80%.

The 10 sample vectors to be classified in Table 5 are input into DHNN, and the classification results of the samples to be classified are obtained by DHNN through associative learning, as shown in Figure 4. From the classification results, the method basically matches with the actual situation, indicating that the method has good application prospects in classification and promotion. At the same time, the simulation experiments also show that if the number of evaluation indices is reduced, the complexity of the model will be reduced, but the classification accuracy of the model will also be reduced, which in turn affects the model's generalization performance. In addition, in associative learning, the input value of DHNN is a comparison of linear weighted sums of individual indices, so this evaluation criterion can be either quantitative or qualitative. DHNN is able to analyze capabilities qualitatively and quantitatively. The DHNN algorithm is more intuitive than the BPNN algorithm, and after 20 iterations, the convergence time of the BPNN algorithm is 2534, and the DHNN algorithm has a great advantage in computational speed and accuracy.

4.3. Operation of the English Course Blockchain. The 10 sample vectors to be classified in Table 5 are input into DHNN, and the classification results of the samples to be classified are obtained by DHNN through associative learning, as shown in Figure 4. From the classification results, the method basically matches with the actual situation, indicating that the method has good application prospects in classification and promotion. At the same time, the simulation experiments also show that if the number of evaluation indices is reduced, the complexity of the model will be reduced, but the classification accuracy of the model will also be reduced, which in turn affects the model's generalization performance. In addition, in associative learning, the input value of DHNN is a comparison of linear weighted sums of individual indices, so this evaluation criterion can be either quantitative, qualitative, or. DHNN is able to analyze capabilities qualitatively and quantitatively. the DHNN algorithm is more intuitive than the BPNN algorithm, and after 20 iterations, the convergence time of the BPNN algorithm is 2534, and the DHNN algorithm has a great advantage in computational speed and accuracy.

On this basis, a learning resource is proposed, on which the system compares the student's current learning status with the prepared knowledge in the teaching resource and confirms the passage if the requirements have been met; through activities such as MU online courses and online tests, MU is able to keep a record of the student's learning throughout; after completing this learning, the participants are played through their personal networks and the teacher's grading panel will then grade the process (e.g., a lesson). The remaining nodes, i.e., all students, record the block, and the system adds some "coins" to the student based on the evaluation provided by the teacher. In the Achievement Blockchain, the system counts "coins" for each student according to the course progress and the final test results, and the students use the "coins" as a basis for broadcasting to everyone through their network. The student's score is announced, and other nodes confirm it through a negotiation mechanism.

In the teaching process blockchain, each learning process only needs to be evaluated by the teacher's evaluation group, while other nodes only need to record, and PBFT can be used as a consensus operation (PBFT) to ensure the consistency of information among nodes; the consensus mechanism of the achievement blockchain is similar to the Bitcoin blockchain but not based on the calculation of complex mathematical problems. However, this consistency algorithm is not based on the computation of certain difficult mathematical problems, but on the computation of student nodes on other students' achievements, which is less computationally intensive and the fastest node passes the computation and is recorded by each node after being confirmed by more than 51% of the nodes. In addition, the system could have certain reward and penalty mechanisms, such as a "grading bonus" for students, where the node (student) with the highest number of successful verifications receives a credit fee for the course returned by the system, equivalent to a student who takes the course for free. In addition, the reward and punishment mechanism can be adjusted according to the

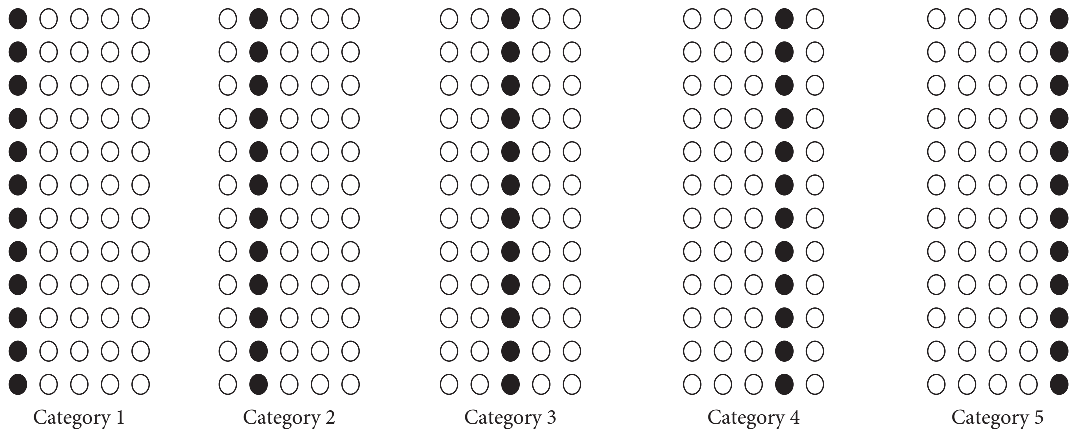

FIGURE 2: Memory standard model of DHNN evaluation model.

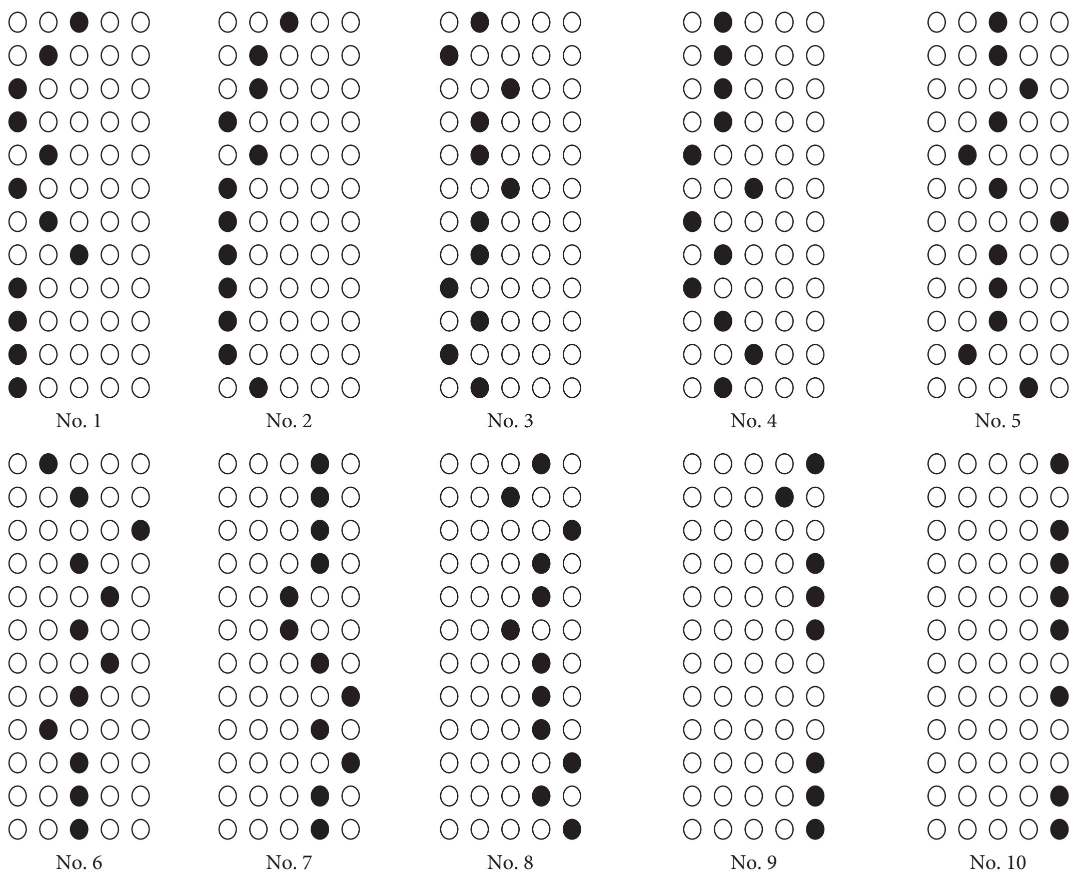

FIGURE 3: Coding of evaluation indicators for the 10 samples to be classified.

TABLE 5: Evaluation indicators for the 10 samples to be classified.

Sample serial number	X_1	X_2	X_3	X_4	⋯	X_9	X_{10}	X_{11}	X_{12}	Target evaluation level
1	8.32	9.33	9.75	9.61	⋯	9.37	9.12	9.50	9.11	1
2	8.27	9.24	9.38	9.72	⋯	9.25	9.41	9.45	8.09	1
3	9.32	9.65	9.12	9.43	⋯	9.17	8.49	9.27	8.79	2
4	9.36	9.18	9.64	9.38	⋯	9.18	8.66	7.22	8.97	2
5	8.31	8.69	8.19	8.58	⋯	8.34	8.08	8.77	7.49	3
6	9.32	8.22	7.65	8.53	⋯	9.04	8.02	7.07	8.05	3
7	7.42	8.11	7.88	7.97	⋯	7.43	7.56	6.75	7.61	4
8	7.14	8.17	6.95	8.08	⋯	7.38	7.43	6.86	7.28	4
9	7.01	7.68	6.32	6.03	⋯	6.13	6.76	6.59	7.04	5
10	7.05	6.98	6.54	6.11	⋯	5.98	6.04	6.37	7.11	5

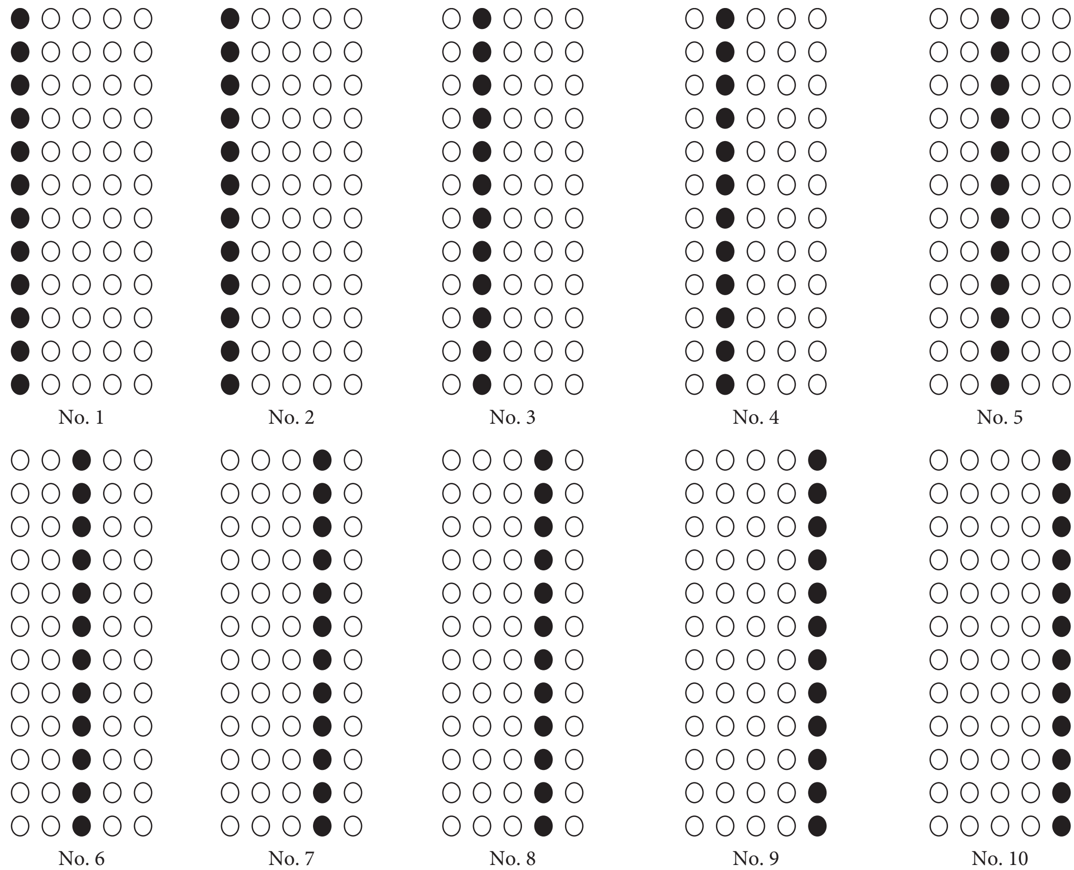

Figure 4: Simulation results of discrete DHNN model.

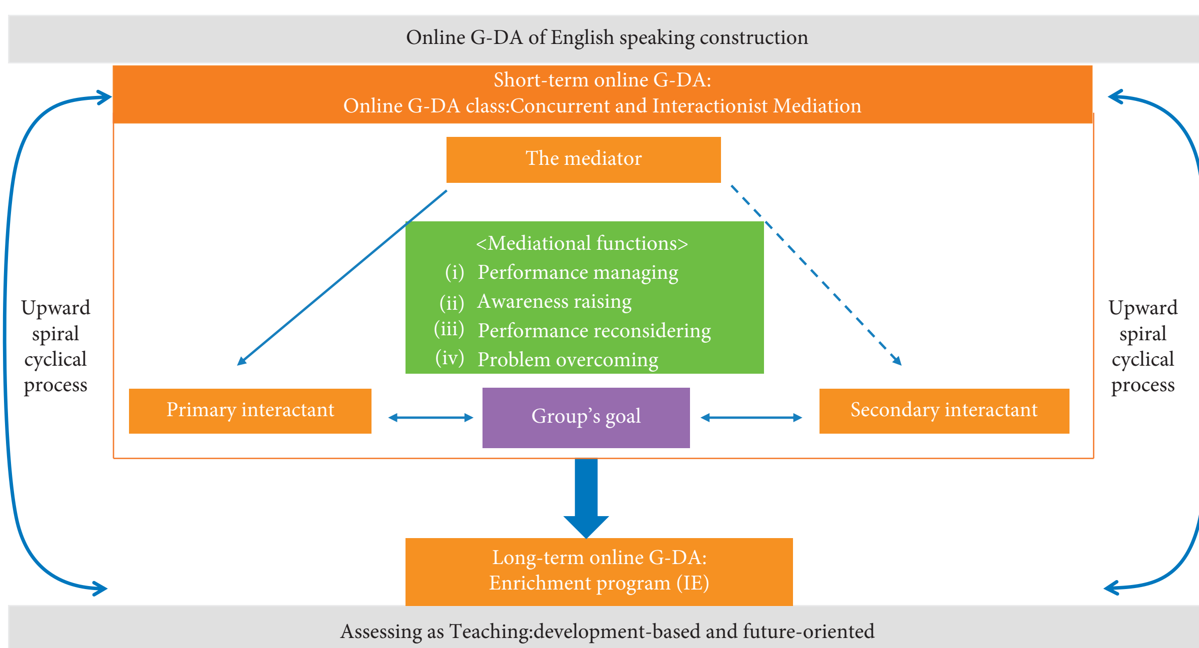

Figure 5: Online G-DA of college English speaking construction.

effectiveness of the system. In short, once the teaching teacher or student changes during the learning process, previous learning assessments may be zeroed out and cannot be accumulated, and teachers need to spend a lot of time refamiliarizing themselves with and understanding the subject, and relying on experience and intuition to reassess.

There are two ways to assess the quality of teachers' teaching: one is summative, or outcome, assessment. The second is formative assessment, or process assessment: assessing the characteristics of teachers' teaching behaviors and assessing their teaching quality according to certain guidelines. Currently, universities are actively exploring and implementing process evaluation, and the key to implementing such evaluation lies in determining the characteristics of teachers' teaching behaviors and evaluation methods. Curriculum in a broad sense is the sum of the various subjects and their purpose, content, scope, weight and process established to achieve the purpose of school education. Curriculum in a narrow sense is the variety of subjects included in the teaching program, and their location and sequence in the teaching program [21].

5. Conclusion

The advent of the big data era brings more new ideas, new directions and new thinking. The size of the university lies more in the fact that its people should face the influence and impact of new things with an open, inclusive and positive attitude. As a new thing, blockchain technology is booming and its impact and application in education is still in its infancy; English learning has always been a subject of constant innovation and progress, and blockchain technology is profoundly affecting the process of change and renewal of its educational assessment mechanism, thus triggering more ideas and possibilities. The development and application of blockchain technology has provided a new technological platform for education and learning reform. Based on this paper, we propose the concept of blockchain for MU English courses and organically integrate the teaching and learning of MU with English teaching. Through the blockchain system, students' learning process and results can be stored and recorded in a distributed manner, which provides a strong support for the credit certification of MU English courses, and is used to explore how to cultivate higher level English application talents through the MU English teaching model. At present, the application of blockchain technology in education is still in its early stage, and most of the research is focused on the storage and recording of students' learning contents and results. Therefore, the "MU English Curriculum Blockchain" established in this thesis is still in the exploratory stage, with a view to showing a new path for the development of English teaching and learning, and improving and optimizing it in practical operation.

Data Availability

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

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This work was supported by Henan University of Animal Husbandry and Economy.

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