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PAPER

Deep Learning-Driven Optimization Strategies for Teaching Decisions in Smart Classrooms

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ABSTRACT

With the rapid advancement of information technology, smart classrooms have increasingly become a vital component of modern education. By integrating technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data, smart classrooms provide a smart, efficient educational setting for teachers and students. However, the challenge of fully utilizing these technologies to enhance teaching effectiveness in smart classrooms remains unresolved. Existing research has highlighted the significant potential of deep learning in optimizing teaching decisions. However, its application faces challenges, including insufficient integration of technologies and limited effectiveness in practical implementations. The main focus of this study encompasses three parts: firstly, a biological neural network model targeted at optimizing teaching decisions, which emulates the mechanisms of biological neural networks to efficiently optimize teaching decisions; secondly, an active consciousness teaching decision model within smart classroom settings, which merges deep learning with theories of active consciousness to support dynamic, intelligent teaching decisions; and thirdly, a biologically inspired teaching process coordination network in smart classrooms, designed to optimize and coordinate educational processes based on biological principles. Through these investigations, this study provides both theoretical and practical support for optimizing teaching decisions in smart classrooms, offering significant academic value and practical application prospects.

KEYWORDS

smart classrooms, deep learning, optimization of teaching decisions, biological neural network, active consciousness, teaching process coordination network

1 INTRODUCTION

With the rapid development of information technology, smart classrooms have gradually become an integral part of modern education [1, 2]. These classrooms, through the integration of advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data, provide an intelligent and efficient teaching

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environment for educators and students [3, 4]. In particular, the application of deep learning technologies offers new possibilities for the optimization of teaching decisions. However, the full utilization of these technologies to enhance teaching outcomes within smart classroom environments remains a pressing challenge.

The study of optimization strategies for teaching decisions in smart classroom environments is of significant importance [5–8]. On one hand, it assists educators in more accurately understanding students' learning conditions and needs, thereby enabling the formulation of more personalized teaching plans. On the other hand, by optimizing teaching decisions, both teaching efficiency and student learning outcomes can be enhanced, further advancing the overall development of education [9–12]. Moreover, research on smart classrooms can also provide valuable experience and theoretical support for the development and application of other intelligent educational systems.

Numerous studies on smart classrooms and the optimization of teaching decisions still have deficiencies and shortcomings. Existing research methods often focus on the application of a single technology, lacking a systematic study of the integrated application of multiple technologies [13–15]. Additionally, many studies show limited effectiveness in practical applications, failing to adequately address the complex issues present in challenging teaching environments [16–20]. Especially, the lack of flexibility and adaptability for different teaching scenarios makes these methods difficult to generalize and apply in actual teaching.

This study primarily focuses on three aspects: First, a biological neural network model aimed at optimizing teaching decisions. This model emulates the mechanisms of biological neural networks to efficiently enhance decision-making. Secondly, an active consciousness-based teaching decision model in smart classroom settings. This model combines deep learning with theories of active consciousness to provide dynamic, intelligent support for teaching decisions. Lastly, a biologically inspired teaching process coordination network in smart classrooms is designed to optimize and coordinate educational processes based on biological principles. Through these investigations, this study offers both theoretical and practical support for optimizing teaching decisions in smart classroom environments, presenting significant academic value and practical application prospects.

2 A BIOLOGICAL NEURAL NETWORK MODEL FOR OPTIMIZING TEACHING DECISIONS

The plasticity of synaptic connections and the cooperative excitation among neurons are crucial for expressing decision-making information in the brain, directly influencing the brain's decision processes. Inspired by relevant research findings, a neural network autonomous decision-making dynamical model was employed for optimizing teaching decisions in smart classroom environments.

Smart classrooms, through the integration of the IoT, AI, and big data technologies, provide an intelligent teaching environment for educators and students. However, achieving efficient teaching decisions in such environments remains a significant research topic. The establishment of a neural network-assisted decision-making dynamical model offers a new solution for optimizing teaching decisions in smart classrooms. Initially, this model is capable of simulating the decision-making processes of teachers in various teaching scenarios. Through mechanisms such as the plasticity of synaptic connections and cooperative excitation among neurons, it assists teachers in better understanding students' needs and learning states, thereby enabling the formulation of more personalized teaching plans.

A biological neural network model was applied in this study to optimize teaching decisions in smart classroom settings, providing more intelligent and dynamic decision support for the teaching process. In smart classrooms, teaching decisions should consider multiple factors, such as students' learning states, the complexity of teaching content, and educators' teaching strategies. The neural network model in this study is composed of four types of neurons: R_M, R_E, U, and VTR. By introducing excitatory neuron clusters similar to R_E and R_M, the competitive process of different teaching decisions, such as selecting appropriate teaching methods or content for a class, can be simulated. When a decision cluster reaches a threshold under the combined effect of external inputs and internal inhibition, that decision will be executed, while other decisions are suppressed. The roles of inhibitory neuron cluster U and non-selective neuron cluster VTR ensure the stability and flexibility of the decision-making process, preventing any single decision from dominating excessively or the system from becoming deadlocked.

(a) Synaptic strength

In the biological neural network model, each neuron within a cluster can form synaptic connections to every neuron in the target cluster, characterized by synaptic efficacy denoted as g. The application of this synaptic strength mechanism within the smart classroom environment to optimize teaching decisions can significantly enhance the precision and response speed of the decision system. In smart classrooms, teaching decisions are required to process a vast amount of real-time data, such as students' learning behaviors, teachers' feedback, and the allocation of teaching resources. By simulating synaptic connection efficacy among neurons, effective competition and selection among different teaching strategies can be achieved.

Taking excitatory connections as an example, synaptic efficacy h is constant, represented by g_{AMPA} and g_{NMDA} through signals from *AMPA* and *NMDA* receptors. Additionally, each neuron in the network is also influenced by background noise input introduced by *VTR* neurons. The introduction of background noise, akin to random factors and uncontrollable variables in the teaching process, impacts teaching decisions. However, through appropriate synaptic conductance, the decision-making process can be stabilized to a certain extent, preventing excessive fluctuations and uncertainties in the decision system. The excitatory and inhibitory components of external stimuli, mediated through *AMPA* and *GABA* receptors, can respectively simulate positive and negative teaching feedback, thereby dynamically adjusting teaching decisions.

$$
\begin{aligned}
&h^{U-U} = 1.075 \\
&h^{VTR-U} = 0.04 / 0.13 \\
&h^{VTR-VTR} = 0.05 / 0.165 \\
&h^{R_E-R_E} = h^{R_M-R_M} = 0.09 / 0.297 \\
&h^{R_M-I} = h^{R_M-I} = 0.04 / 0.13 \\
&h^{R_E-VTR} = h^{R_M-VTR} = 0.05 / 0.165 \\
&h^{R_E-R_M} = h^{R_M-R_E} = 0.04294 / 0.1417 \\
&h^{VTR-R_E} = h^{VTR-RM} = 0.04294 / 0.1417 \\
&h^{U-R_E} = h^{U-R_M} = h^{U-VTR} = 1.3975
\end{aligned}
\tag{1}
$$

(b) A single neuron and a synaptic model

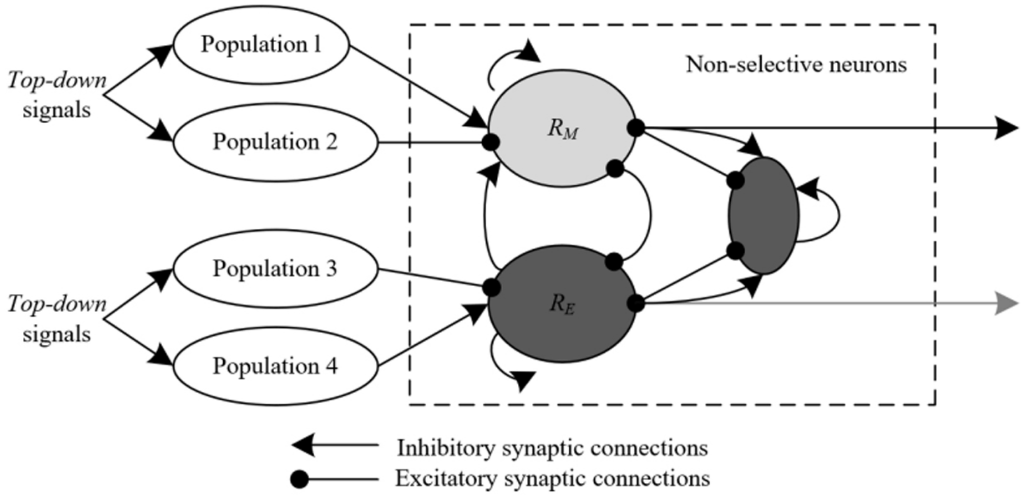

Fig. 1. A conductance-based synaptic model

In the smart classroom environment, the synaptic model of the biological neural network model is based on integrate-and-fire (IAF) model, which effectively simulates and optimizes the teaching decision process. The IAF model, a conductance-based synaptic model depicted in Figure 1, enables the dynamic adjustment of synaptic connections between different neuron clusters representing various teaching strategies in the optimization process of teaching decisions. This adjustment reflects the priorities and adaptabilities of teaching strategies. For example, excitatory neuronal activities are influenced by conductance changes mediated by *AMPA* receptors due to external input signals, such as real-time student feedback, while inhibitory neuronal activities are modulated by inhibitory factors through the action of *GABA* receptors.

Furthermore, smart classrooms require real-time processing of extensive data, including students' learning states, classroom interactions, and instructional feedback. The IAF model allows for the integration of input signals received by neurons; upon reaching a certain threshold, a decision action is triggered. This mechanism ensures the timeliness and accuracy of teaching decisions. Assuming that the membrane capacitance, membrane potential, synaptic current, conductance, and resting potential are denoted by Z_l, $N(s)$, $U_{SY}(s)$, h_l, and N_M, respectively, the following relationships are established:

$$Z_l \frac{dN(s)}{ds} = -h_M[N(s) - N_M] - U_{SY}(s) \tag{2}$$

In the research of teaching decision optimization strategies based on deep learning in smart classroom environments, synaptic currents in the biological neural network model are a key element, encompassing various components, such as visual stimuli $U_{ST}(s)$, other neuronal currents $U_{RE}(s)$ in the circuit, background noise $U_{NO}(s)$, and external input signal currents $U_{RDT}(s)$. These components collectively determine the changes in neuronal membrane potential and the triggering of decision processes. In smart classrooms, the components of synaptic currents correspond to different types of inputs and feedback. Visual stimuli can be analogized to real-time behaviors and interactions of students in the classroom, such as raising hands, answering questions, or using learning devices. These behaviors, inputted into the neural network model as visual stimuli, influence the adjustment and optimization of teaching strategies.

The currents from other neurons in the circuit represent the internal feedback mechanisms of the teaching process, such as explanations by teachers, the conduct of classroom activities, and interactions among students. These internal feedbacks are conducted and integrated repeatedly within the neural network, forming a comprehensive assessment of teaching effectiveness. Background noise in the smart classroom environment can be regarded as uncontrollable random factors and disturbances in the teaching process, such as environmental noise, network delays, or equipment malfunctions. These background noises are filtered and suppressed within the model through certain mechanisms to minimize adverse effects on the decision-making process, ensuring the stability and reliability of teaching strategies. External input signal currents refer to information and data from external sources, such as students' learning records, examination results, and feedback from parents, which play a crucial role in the teaching decision-making process. Through the processing of the neural network model, these components help optimize teaching strategies and decisions.

$$U_{SY}(s) = U_{ST}(s) + U_{RE}(s) + U_{NO}(s) + U_{RDT}(s) \tag{3}$$

The synaptic receptors in the biological neural network model play a crucial role in optimizing teaching decision strategies. These receptors include *AMPA*, *NMDA*, and *GABA* receptors. *AMPA* receptors are primarily responsible for the rapid transmission of excitatory signals. For optimizing teaching decisions in smart classrooms, *AMPA* receptors can simulate the immediate responses and behavioral feedback of students in the classroom, such as answering questions and participating in discussions. These rapid feedbacks act on neuron clusters through *AMPA* receptors, allowing real-time adjustment of teaching strategies. *NMDA* receptors regulate the transmission of slower excitatory signals and have plastic properties, facilitating the formation of long-term memory. In smart classrooms, *NMDA* receptors can simulate the longer-term effects of teaching and the accumulation of student learning outcomes. For example, by analyzing students' learning records and examination results, *NMDA* receptors can help the teaching decision system identify long-term effective teaching strategies and apply and optimize them in future teachings, thereby enhancing the continuity and stability of teaching effectiveness. *GABA* receptors are responsible for the transmission of inhibitory signals, helping to balance excitatory signals to prevent excessive excitation. In a smart classroom environment, *GABA* receptors can simulate mechanisms of classroom management and order maintenance. For instance, when students exhibit overly active or distracted behaviors, *GABA* receptors can balance and regulate through inhibitory signals, maintaining an appropriate learning state in the classroom. This is crucial for enhancing teaching efficiency and maintaining a conducive learning atmosphere. Assuming the reversal potential is represented by N_R, extracellular magnesium concentration by $[Mg^{2+}]$, synaptic efficacy by h, and the conductance's of *AMPA*, *NMDA*, and *GABA* receptors that mediate neuron signals are denoted by h_{XLOX}, h_{VLFX}, and h_{HXYX}, respectively, the formula is given as follows:

$$\begin{aligned} U_{SY}(s) = {} & h_{XLOX} t_{XLOX}(s)[N(s) - N_R] \\ & + \frac{h_{VLFX} t_{VLFX}(s)[N(s) - N_R]}{1 + [Mg^{2+}] r^{-0.062N(s)/3.57}} + h_{HXYX} t_{HXYX}(s)[N(s) - N_U] \end{aligned} \tag{4}$$

Specifically, in the smart classroom, *AMPA* receptors are responsible for the rapid transmission of excitatory signals, and their gating variable $t_{XLOX}(s)$ can be used to simulate the dynamic changes in students' immediate responses and behavioral feedback. By adjusting $t_{XLOX}(s)$, the degree of student engagement and interaction in class can be captured and reflected in real time, thus assisting the teaching decision system in rapidly adjusting teaching strategies. For instance, a high value of $t_{XLOX}(s)$ indicates active student interaction, allowing the teaching system to continue the current pedagogical approach; conversely, a strategy adjustment might be necessary to enhance student engagement. Although the mediating role of *NMDA* receptors in external inputs was initially overlooked in the model, $t_{VLDX}(s)$ still plays a crucial role in modeling long-term memory and enduring learning outcomes. The gating variable $t_{VLDX}(s)$ of the *NMDA* receptors can be used to simulate the accumulation and optimization of long-term effective strategies during the teaching process. By adjusting $t_{VLDX}(s)$, the impact of teaching activities on long-term student learning outcomes can be captured, thereby optimizing subsequent teaching decisions to ensure the continuity and stability of teaching effectiveness. *GABA* receptors are responsible for the transmission of inhibitory signals, and their gating variable $t_{HXYX}(s)$ plays a key role in maintaining classroom management and order. By adjusting $t_{HXYX}(s)$, inhibitory factors in the classroom, such as preventing excessive student activity or distraction, can be effectively simulated and controlled. A high $t_{HXYX}(s)$ value indicates a current need for more inhibitory signals to maintain classroom order, thus aiding the teaching system in maintaining balance in a dynamic environment and enhancing overall teaching efficiency. The decay constant for *AMPA* receptors is denoted by π_{XLOX}, for *NMDA* receptors by π_{VLDX}, and for *GABA* receptors by π_{HXYX}; the constant is represented by β, the Dirac function by $\sigma(s - s^j)$, and the time of presynaptic pulses by s^j, with the j-th moment indicated by superscript j. The derivatives of the gating variables for the three receptors are as follows:

$$\frac{dt_{XLOX}(s)}{ds} = \sum_j \sigma(s - s^j) - \frac{t_{XLOX}}{\pi_{XLOX}} \tag{5}$$

$$\frac{dt_{VLFX}(s)}{ds} = \beta[1 - t_{VLFX}(s)]\sum_j \sigma(s - s^j) - \frac{t_{VLFX}}{\pi_{VLFX}} \tag{6}$$

$$\frac{dt_{HXYX}(s)}{ds} = \sum_j \sigma(s - s^j) - \frac{t_{HXYX}}{\pi_{HXYX}} \tag{7}$$

3 AN ACTIVE CONSCIOUSNESS TEACHING DECISION MODEL IN SMART CLASSROOMS

According to recent biological and experimental results, interneurons control motor decisions by inhibiting decision-related neuron clusters in the superior colliculus. This discovery provides a theoretical foundation for the top-down control signals of active consciousness decision-making mechanisms in optimizing teaching decisions within smart classroom environments.

Firstly, the top-down control signals of active consciousness decisions can suppress the immediate stimulus responses of students in the classroom, thereby avoiding unnecessary distractions. Such top-down control signals are executed by higher-level neurons within the model, which are responsible for integrating external information and making comprehensive decisions. For instance, if the teaching system detects that certain students are distracted, an increase in the inhibitory signals from higher-level neurons can reduce the students' responses to irrelevant stimuli, aiding them in refocusing their attention. Secondly, the input stimulus and action response mapping mechanism based on active consciousness decision rules ensures the precision and efficiency of teaching activities. This implies that the teaching system is capable of flexibly adjusting teaching strategies to accommodate various student needs and classroom scenarios according to predefined educational goals and rules. For example, in response to the individualized learning needs of certain students, the system can adjust the teaching content and methods in real-time based on their feedback and performance, thus enhancing teaching effectiveness.

Figure 2 depicts the active consciousness teaching decision model in smart classroom environments. In this biological neural network model, the competitive mechanism between stimulus response and active consciousness decisions is modeled, enabling the teaching decision system to achieve optimization in dynamic environments. The combination of top-down control signals and rule-based mapping mechanisms not only enhances classroom management and teaching efficiency but also improves students' learning experience and participation. This comprehensive competitive mechanism ensures that the teaching system can flexibly respond to various teaching scenarios, providing personalized and intelligent teaching support.

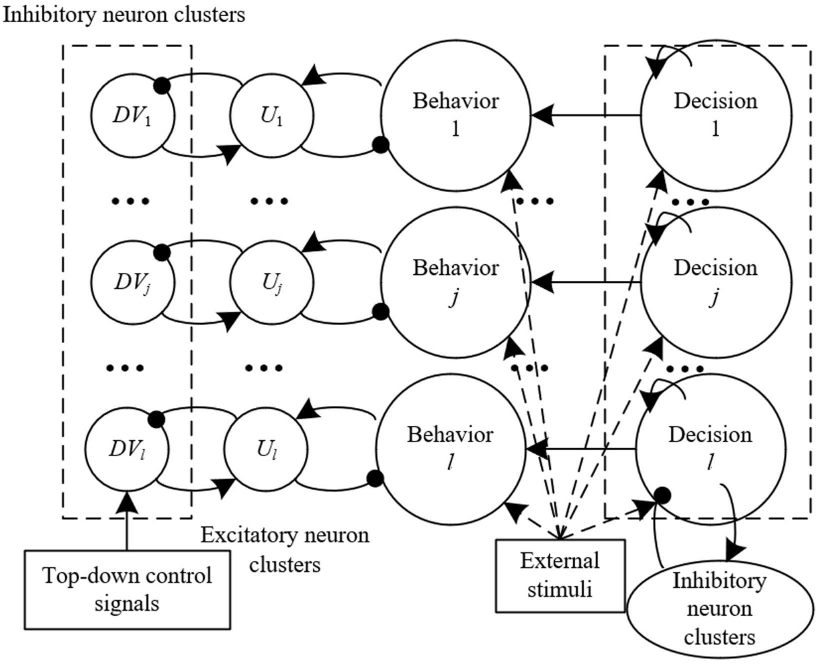

Fig. 2. An active consciousness teaching decision model in smart classrooms

Inspired by biological experimental results, a neural network model was established in this study to explore the competitive mechanism between active consciousness decisions and stimulus responses. In smart classroom environments, this competitive mechanism can be used to optimize teaching decisions. Top-down control signals can be utilized to suppress the inappropriate immediate responses of students in the classroom, aiding their concentration. For instance, when the system detects students' attention drifting, responses to irrelevant stimuli can be reduced by activating inhibitory neuron clusters, thus maintaining classroom order. The role of excitatory neuron clusters is evident in the system's response to various teaching strategies. By processing external stimulus inputs, the system can flexibly adjust teaching content and methods to suit diverse student needs and classroom situations. Additionally, by simulating the winner-take-all mechanism found in biological neural networks, the system can make optimal choices among multiple teaching options. This mechanism ensures that the most suitable teaching strategy prevails under multiple decision options, thus enhancing the overall quality of teaching.

Specifically, in the smart classroom environment, the teaching system can effectively control students' responses by adjusting the intensity of external stimuli, such as the difficulty or diversity of teaching content, and the strength of top-down control signals, such as teacher guidance or system feedback. For example, when the system detects a marked stress response in students facing complex problems, the top-down control signals can be intensified to provide more guidance and support, helping students alleviate stress and focus their attention. In the smart classroom, this mechanism can be used to optimize teaching pacing and content presentation. The slow reflective excitation gives the system more time to conduct comprehensive assessments and choose the optimal strategy when processing student feedback and adjusting teaching strategies in real time. For instance, after a teaching unit concludes, the system can adjust the teaching content and methods of the next unit based on students' overall performance and feedback to ensure the best learning outcomes.

4 A BIOLOGICALLY INSPIRED TEACHING PROCESS COORDINATION NETWORK IN SMART CLASSROOMS

During the teaching process, the system can detect the learning state and feedback of students in real time. Through the episodic memory mechanism of a biological neural network, teaching strategies and content are dynamically adjusted to ensure that each student receives the most suitable teaching resources. The emergence of characteristics of autonomous decision-making manifests as support for personalized teaching in smart classroom environments. By simulating the parallelism and coordination of biological neural networks, the system can simultaneously handle the diverse needs of multiple students and adjust teaching content based on real-time feedback. For instance, in a large classroom setting, the system can adjust personalized learning paths and resource allocation based on each student's performance and feedback in real time, thereby enhancing overall teaching efficiency and effectiveness.

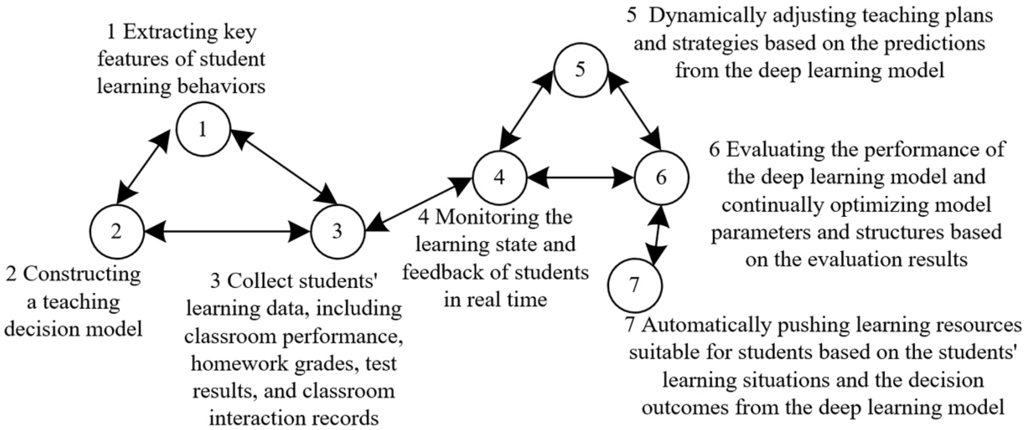

Fig. 3. A biologically inspired teaching decision diagram in smart classroom environments

a) In smart classrooms, the simplicity of agents manifests as straightforward interactions between the teaching system and individual students. Similar to the simple abilities and rules of individuals within biological groups, students in smart classrooms can interact with the teaching system through simple feedback mechanisms, such as answering questions or selecting options. Based on these simple interactions, teaching strategies are adjusted in real time to provide personalized content that meets student needs.

b) The distributed nature of organizational structures in smart classrooms is exhibited as decentralized teaching decisions. Like biological groups that alter their behavior through information exchange with nearby individuals, the teaching system in smart classrooms can adjust overall teaching strategies based on interactions and feedback among students. For example, the system can monitor all students' learning progress and feedback, dynamically adjusting course content and teaching pace by analyzing the data, thereby enabling more efficient teaching decisions.

c) The flexibility in operational modes within smart classrooms is demonstrated by the rapid adaptation to changes in the teaching environment. Similar to biological groups that can react swiftly and uniformly to environmental changes, the smart classroom system can quickly adjust teaching strategies upon detecting changes in students' learning states. For instance, if the system identifies that a subset of students is struggling with the current content, supplementary materials can be provided immediately or teaching methods adjusted to ensure effective learning outcomes.

d) The overall intelligence of the system in smart classrooms is displayed through the synergistic effects between the teaching system and students. Similarly, by leveraging interactions and feedback among students, the teaching system in smart classrooms facilitates the emergence of overall teaching intelligence. For example, by analyzing the learning data of the entire class, the system can identify common issues and individual needs, thereby adjusting teaching strategies to enhance overall teaching quality and effectiveness.

Figure 3 shows a biologically inspired teaching decision diagram in smart classroom environments. Research on optimization strategies for teaching decisions in smart classrooms, based on deep learning and inspired by biologically inspired coordination networks, has achieved a high degree of intelligent and personalized optimization of the teaching process. By emulating the simplicity, distributed structure, flexibility, and intelligence of biological neural networks, the teaching system can autonomously coordinate and optimize decisions within complex and variable teaching environments, ultimately enhancing teaching quality and student learning experiences.

5 EXPERIMENTAL RESULTS AND ANALYSIS

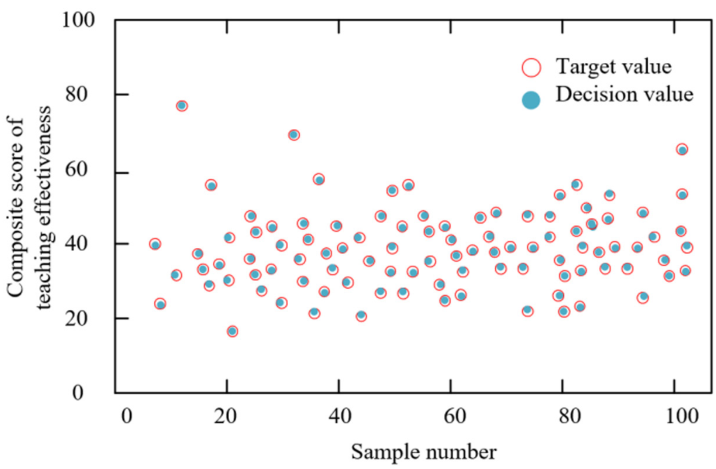

Fig. 4. Composite score decision results for test set samples

In this study, a test sample set was utilized to evaluate a biological neural network model that had been trained, assessing its capability to optimize teaching decisions within smart classroom environments. Figure 4 illustrates that the model, trained with the current parameter set, performed well in predicting the maintenance period of teaching effectiveness, with decision results generally aligning with the target values of the test samples. However, as shown in Figure 5, under the current parameters, the model exhibited a maximum decision error of 6% on the test samples. Despite this error, the system possesses a certain tolerance for errors because the teaching cycle decision values rely on the partitioning of the teaching state composite score rather than absolute values. This was further confirmed by Figure 6, which demonstrated a high degree of alignment between the model's decision results and the samples' target values, indicating that the model accurately predicted the teaching cycle decision values in most cases.

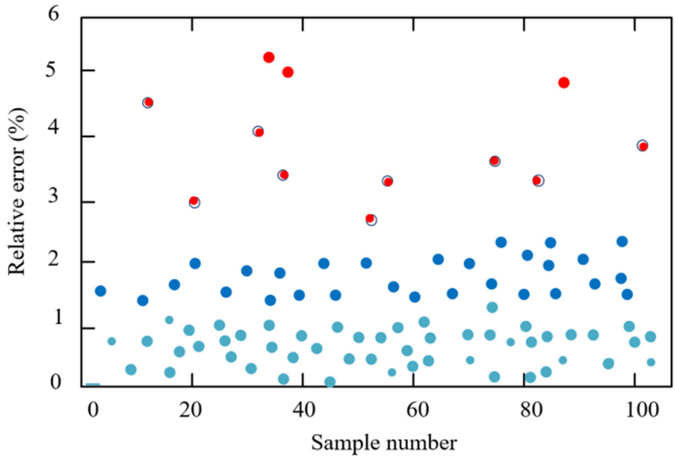

Fig. 5. Relative error between target values for test set samples and decision values of the model

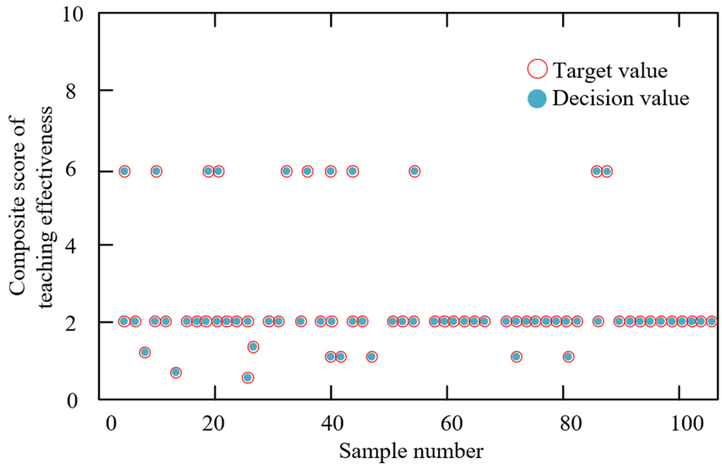

Fig. 6. Teaching cycle decision results on the test set in the smart classroom environment

Based on the experimental results, the following conclusion can be drawn: the teaching decision optimization strategy proposed in this study generally exhibits high effectiveness. Although some errors exist, the model's predictions of teaching effectiveness are accurate in most instances. Due to the system's fault tolerance, these errors do not significantly impact the effectiveness of the teaching decisions. Therefore, the biological neural network model can provide reliable support for teaching decisions in smart classroom environments. Through continuous optimization and adjustment of model parameters, further enhancement of its prediction accuracy and decision quality can be achieved, effectively improving overall teaching outcomes and the learning experiences of students.

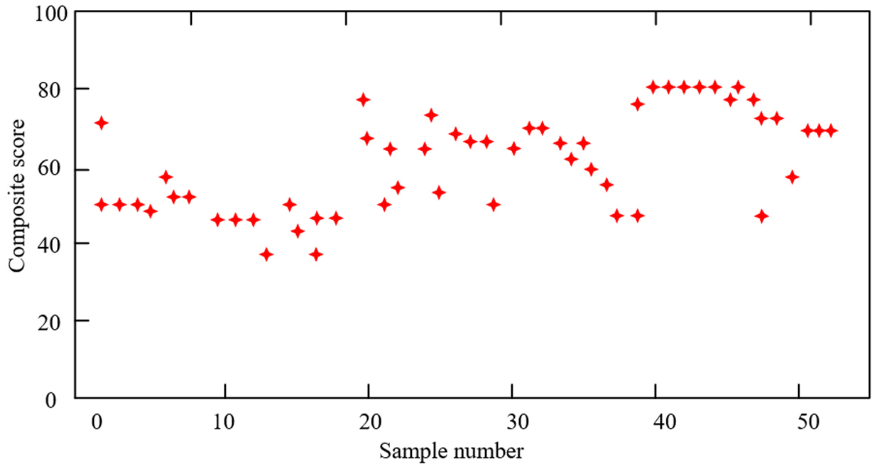

Fig. 7. Decision values of the teaching effectiveness composite score in the smart classroom environment

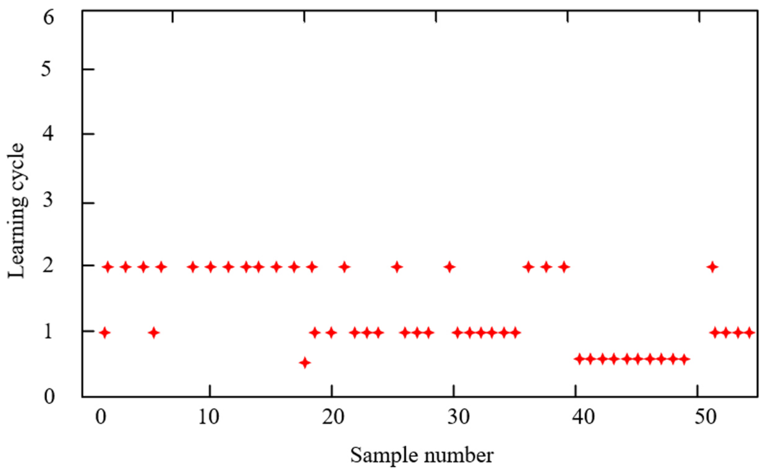

Fig. 8. Teaching cycle decision values in the smart classroom environment

In this study, the teaching effectiveness metric scores for different samples in a smart classroom environment were closely examined based on actual monitoring data of the teaching process. To facilitate comparison with decision outcomes, the same metric scores were used as the basis for decisions. The trained decision model was employed to make decisions on the teaching cycles for different samples within the smart classroom environment, with the results presented in Figures 7 and 8. Figure 7 displays a comparison of teaching cycle decision outcomes with actual metric scores for different samples. The model's predictions generally aligned with the target values, although significant discrepancies were evident in some samples. Figure 8 further illustrates the relative errors between decision outcomes and the samples' target values, with the maximum error reaching 6%.

Table 1. Training results for teaching cycle decisions in the smart classroom environment

Dataset	Sample Number	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	Target Value	Decision Value
1	1	0	1	0	1	1	1	1	0	1	1
	2	0	0.5	0	0.5	1	0.75	0.75	0	2	2
	3	0	0.5	0	0.5	1	0.75	0.75	0	2	2
	4	0	0.5	0	0.5	1	0.75	0.75	0	2	2
	5	0	0.5	0	0.5	0.25	1	62	0	2	2
2	6	0	1	0.5	0.5	0.25	0.75	0.75	0	1	1
	7	0	1	0	0.5	0.25	0.75	0.75	0	2	2
	8	0	1	0	0.5	0.25	0.75	0.75	0	2	2
3	9	0	0.5	0	1	0.5	1	0	0	2	2
	10	0	0.5	0	1	0.5	1	0	0	2	2
	11	0	0.5	0	1	0.5	1	0	0	2	2
4	12	0	0	0	1	1	1	0	0	2	2
	13	0	1	0	0.5	0.5	0.75	0	0	2	2
	14	0	0.5	0	0.5	0.5	0.75	0	0	2	2
5	15	0	0	0	1	1	1	0	0	2	2
	16	0	0.5	0	0.5	0.5	1	0	0	2	2

The experimental results demonstrate that the teaching decision optimization strategy proposed in this study exhibits high overall effectiveness. Despite certain errors, the model accurately predicted the decision values for teaching cycles in most cases. In addition, due to the system's inherent fault tolerance, these errors did not significantly impact the effectiveness of the teaching decisions. Therefore, the biological neural network model can provide reliable support for teaching decisions within smart classroom environments. By further optimizing model parameters and training methods, prediction accuracy and decision quality can be enhanced, effectively improving overall teaching outcomes and student learning experiences.

In Table 1, C_1 to C_8 correspond to eight evaluation indicators, namely, mean squared error, classroom interaction, prediction consistency, student satisfaction, effectiveness of personalized recommendations, utilization rate of teaching resources, decision response time, and accuracy. Training datasets 1 to 5 correspond to diverse course types and class sizes, teacher experiences and teaching styles, student backgrounds and learning abilities, time periods and academic stages, and the use of teaching tools and resources, respectively.

In Dataset 1, for samples 1 to 5, the decision values matched the target values, indicating good decision accuracy under conditions of diverse course types and class sizes. The evaluation metric scores were relatively uniform, particularly in classroom interaction (C_2) and student satisfaction (C_4), reflecting the model's adaptability across various course types and class sizes. In Dataset 2, samples 6 to 8 demonstrated that the decision values aligned with the target values, showing the model's adaptability to different teacher experiences and teaching styles. High scores in the effectiveness of personalized recommendations (C_5) and prediction consistency (C_3)

indicate the strong capability of the model in handling various teaching styles with strong personalized recommendation capacity and consistency. In Dataset 3, for samples 9 to 11, the decision values corresponded with the target values, showing the model performed well under conditions of different student backgrounds and learning abilities. High scores in the utilization rate of teaching resources (C_6) and classroom interaction (C_2) reflect the effectiveness of the model across different student groups. In Dataset 4, for samples 12 to 14, the decision values matched the target values, illustrating the model's good predictive capability under different time periods and academic stages. High scores in decision response time (C_7) and accuracy (C_8) indicate that the model can respond quickly and maintain high accuracy in dynamic environments. In Dataset 5, for samples 15 and 16, the decision values were consistent with the target values, showing the model's adaptability under different conditions of teaching tool and resource usage. High scores in the utilization rate of teaching resources (C_6) and the effectiveness of personalized recommendations (C_5) suggest that the model can effectively utilize teaching resources and provide personalized recommendations.

6 CONCLUSION

This study primarily explored the optimization of teaching decisions within smart classroom environments. Initially, a biological neural network model aimed at optimizing teaching decisions was introduced. This model, by simulating the mechanisms of biological neural networks, achieved effective optimization of teaching decisions. Through the self-learning and adaptive capabilities of biological neural networks, teaching decisions were rendered more accurate and intelligent. Furthermore, an active consciousness teaching decision model in smart classrooms was proposed, which integrated deep learning with active consciousness theory to provide dynamic, intelligent support for teaching decisions. Teaching strategies were adjusted by this model based on real-time data to enhance teaching outcomes. Lastly, the teaching process was coordinated and optimized by a biologically inspired teaching process coordination network based on biological principles. By mimicking the collaborative mechanisms found within biological organisms, this network improved the utilization efficiency of teaching resources and the response speed of teaching decisions.

Through the analysis of the research content and experimental results, several comprehensive conclusions can be drawn from this study. Firstly, the study has significant value. By incorporating biological neural networks and active consciousness theory, the model can make accurate decisions across a variety of teaching environments and conditions, thereby enhancing teaching effectiveness. Notably, the model excels in enhancing classroom interaction and student satisfaction, significantly improving overall teaching quality. Additionally, the model effectively utilizes teaching resources, achieving efficient optimization of teaching decisions through enhanced resource utilization efficiency.

However, the study also has certain limitations. The construction and training of the model are complex, requiring substantial computational resources and technical support. Moreover, the model necessitates a large amount of diverse data for training and validation, and data acquisition and processing present significant challenges. Although the model performs well in experimental settings, its application in real-world environments may be influenced by various unpredictable factors. Future research could further enhance the adaptability and robustness of the model by optimizing its algorithms to improve performance across different teaching environments. Furthermore, by expanding datasets and application scenarios, the model's effectiveness in more practical environments could be validated, enhancing its generalizability. Integrating other intelligent technologies with the model could further improve the optimization of teaching decisions in smart classroom environments.

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