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Improving Robot-Assisted Virtual Teaching Using Transformers, GANs, and Computer Vision

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ABSTRACT

This study aims to enhance the efficacy of personalized learning paths by amalgamating transformer models, generative adversarial networks (GANs), and reinforcement learning techniques. To refine personalized learning trajectories, the authors integrated the transformer model for enhanced information assimilation and learning path planning. Through generative adversarial networks, the authors simulated the fusion and interaction of multi-modal information, refining the training of virtual teaching assistants. Lastly, reinforcement learning was employed to optimize the interaction strategies of these assistants, aligning them better with student needs. In the experimental phase, the authors benchmarked their approach against six state-of-the-art models to assess its effectiveness. The experimental outcomes highlight significant enhancements achieved by the authors' virtual teaching assistant compared to traditional methods. Precision improved to 95% and recall to 96%, and an F1 score exceeding 95% was attained.

KEYWORDS

computer vision assistance, multimodal perception, personalized learning path planning, robot decision making, transformer model, virtual robot teaching assistant

INTRODUCTION

In today's digital age, the field of education is facing significant challenges and opportunities. With the explosion of information and the diversification of learner needs, personalised education has become a key strategy for improving educational outcomes and enhancing learning efficiency (Raja & Nagasubramani, 2018). The optimization of personalized learning paths, which involves planning suitable learning trajectories for individuals based on their unique needs and characteristics, has emerged as a core element for improving educational quality and nurturing students' creative thinking

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and problem-solving abilities (Peng et al., 2019). Meanwhile, computer vision-supported robot virtual teaching assistants are gradually emerging, providing students with more interactive and personalized learning experiences (Alam, 2022). The focus of this research is to explore how to achieve more personalized learning paths through robot multimodal information fusion and decision-making technology, particularly with the aid of computer vision and multimodal information processing techniques, and apply them to the field of English education. The authors' study aims to enhance the effectiveness of English education while fostering students' creative thinking, problem-solving abilities, and fluent English communication skills, all of which are closely related to the exploration of robot multimodal information fusion and decision-making technology.

In the realm of education, the optimization of personalized learning paths addresses some of the challenges inherent in traditional educational approaches. Conventional methods of English education often hinge on standardized textbooks and uniform progressions, potentially overlooking the unique needs of individual students. This standardized teaching model may result in variations in students' English learning outcomes, with some students potentially being overlooked and others struggling to keep pace with the curriculum. Therefore, the optimization of personalized learning paths holds significant importance in meeting the diverse English learning needs of students and improving the overall effectiveness of English education. Introducing computer vision-supported robot virtual teaching assistants brings increased interactivity and flexibility to English education. Virtual teaching assistants can engage with students in real-time, offering personalized feedback and guidance, thereby enhancing the appeal and effectiveness of English learning. Furthermore, virtual teaching assistants have the capacity to simulate diverse English learning scenarios, providing students with a more real-world English learning experience. This immersive approach contributes to the development of practical skills and fluent English communication abilities among students.

Although the fields of personalized learning paths and computer vision-supported virtual assistant robots in education are full of potential, they also face a series of challenges and issues. Firstly, the diversity of students is a central challenge in optimizing personalized learning paths. Each student has a unique background, interests, and learning style, making the task of designing personalized learning paths based on individual characteristics and needs complex and crucial. This involves the ability to accurately understand individual differences among students and provide precise recommendations. Secondly, the large-scale implementation of personalized learning paths is also a significant challenge. When dealing with a vast student population, efficiently applying personalized learning paths to a broad range of students while ensuring the system's scalability and real-time responsiveness is a research problem that needs in-depth exploration. This requires a combination of educational management and technical support to find solutions suitable for large-scale educational environments. Additionally, optimizing personalized learning paths also needs to address challenges in data collection and analysis. The design and optimization of personalized learning paths rely on modeling and decision-making based on a large amount of student data. Effectively collecting, storing, and analyzing this data to extract useful information is crucial for implementing personalized learning paths. At the same time, considerations such as data privacy and security must be taken into account to ensure the protection of student information. Finally, the development and application of technology are also critical factors in optimizing personalized learning paths. Leveraging advanced technologies such as machine learning and natural language processing can achieve a precise understanding of students and provide personalized guidance. However, challenges in the accuracy, interpretability, and sustainability of technology still exist and require continuous research and innovation. Capturing students' English learning characteristics and needs better, balancing personalized and standardized English education, and addressing issues of data privacy and ethics are all challenging problems that need to be addressed (Bala, 2021). In response to these challenges, the authors will review research progress in related fields, analyze the strengths and limitations of existing work, and propose the innovative points and contributions of this study.

The contributions of this paper can be summarized in the following three aspects:

- The authors incorporate the Transformer model into the design of personalized learning paths. Through the Transformer model, the authors can more effectively capture students' learning characteristics and needs, enabling more precise recommendations for learning content and path planning. This innovative application brings new perspectives to the field of education, allowing researchers to personalize education better and enhance the specificity and effectiveness of learning.
- The authors leverage Generative Adversarial Networks (GANs) to replicate diverse learning environments, offering enhanced support for the training of virtual assistants and the development of students' practical application skills. Through GANs, the authors can realistically simulate a variety of scenarios that students might encounter during the learning process. This enables students to acquire a broader range of experiences in a virtual environment, thereby bolstering their practical application abilities.
- The incorporation of Reinforcement Learning (RL) enhances the adaptability of the authors' virtual assistants to different students' learning styles and needs. The authors refine the interaction strategies of the virtual assistant using RL, making it more adept at engaging with students and providing precise learning guidance. This approach not only improves the personalization of individualized learning paths but also facilitates students in receiving targeted assistance, ultimately enhancing their academic performance and overall learning experiences.

The logical structure of this paper is as follows: The second part of this paper is the related work section, which summarizes research in two main areas: personalized English learning path optimization and computer vision-supported virtual teaching assistants. The former covers rule, model, and data-driven methods, and the latter includes feature, deep learning, and visual servoing methods. These research methods provide the theoretical basis and inspiration for the innovative research of the article to improve the effectiveness of English education and personalized guidance. In the third section, the study employs three advanced techniques: the Transformer model, Generative Adversarial Networks (GANs), and Reinforcement Learning (RL). These techniques are effectively integrated and applied to optimize personalized learning paths. The Transformer model effectively models learning features through its self-attention mechanism, GANs simulate realistic learning environments, and RL optimizes the strategies of virtual assistants. The combination of these three techniques enables precise learning path planning and personalized optimization of virtual assistants. In the fourth section, a comprehensive experimental environment is established, using publicly available datasets such as MEDA and UBL; evaluation metrics like accuracy and recall are employed. Through comparative experiments on multiple datasets, the advantages of various metrics are analyzed, demonstrating that the proposed method outperforms other technologies in terms of recognition effectiveness and computational efficiency. Multi-dimensional result analysis further validates the stability and effectiveness of the method. In the fifth section, the discussion and conclusion summarize the innovative applications and collaborative support of the Transformer model, GANs, and RL in learning path optimization. The method has achieved significant research results, providing new solutions for personalized education. Additionally, limitations such as generalization ability are discussed, and future research directions, including further exploration of generalization ability, are proposed, offering prospects for the development of this field.

RELATED WORK

In the field of personalized English learning path optimization, previous research has employed various methods to implement personalized English education. Personalized learning path optimization refers to the planning of a sequence of learning resources that aligns with educational principles and can help learners achieve their learning goals based on individual differences such as learning preferences, abilities, backgrounds, and objectives. The primary approaches in this field include:

1. Rule-based approach: Utilizes expert knowledge or educational theories to define the generation rules of learning paths, such as sequential order, prerequisite conditions, increasing difficulty, etc. (Diao et al., 2021). This approach often requires manual intervention and maintenance, lacking flexibility and adaptability.
2. Model-based approach: Utilizes mathematical models or optimization algorithms to find the optimal or suboptimal learning paths, such as linear programming, dynamic programming, genetic algorithms, etc. (Deng et al., 2020). This method usually requires defining objective functions and constraints, potentially encountering issues with high computational complexity or challenging problem-solving.
3. Data-driven approach: Utilizes data mining or machine learning techniques to extract patterns or regularities of learning paths from historical data, such as association rules, cluster analysis, classification analysis, collaborative filtering, etc. (Fröhlich et al., 2018). This approach typically requires extensive data support and may face challenges related to data scarcity or cold start problems.

In the field of computer vision-supported robot virtual teaching assistants, researchers have explored various visual perception and interaction methods. Computer vision-supported robot virtual teaching assistants refer to the use of computer vision technology to provide visual perception capabilities to robots, enabling them to play the role of virtual teaching assistants in educational scenarios, such as recognizing and tracking students, providing feedback and guidance, interacting and communicating with students, etc. The primary methods in this field include:

1. Feature-based approach: Utilizes techniques from image processing or computer vision to extract features from images, such as edges, corners, textures, etc. Subsequently, it employs techniques like feature matching or pattern recognition for object or scene recognition and understanding (Nixon & Aguado, 2019). This approach often requires the design of suitable feature extractors and classifiers and may face challenges related to feature instability or lack of robustness.
2. Deep learning-based approach: Utilizes technologies such as deep neural networks or convolutional neural networks to directly learn high-level semantic representations from images. It then employs end-to-end training or inference processes for object or scene recognition and understanding (YAO Qing'an et al., 2022). This method typically requires abundant annotated data and computational resources,and may encounter issues like overfitting or poor generalization capability.
3. Vision-based servoing approach: Utilizes feedback signals, such as the robot's position or pose detected by visual sensors, and employs control theory or optimization algorithms to adjust the robot's motion or manipulation for tracking and manipulating objects or scenes (Dewi et al., 2018). This approach often involves the design of suitable controllers and error functions and may face challenges related to system instability or slow convergence.

These research methods not only furnish valuable theoretical foundations for this study but also yield inspiration and insights for the authors' approach. In the subsequent literature review section, the authors will provide a detailed overview of relevant research in these fields, accentuating their methodologies, achievements, as well as existing issues and challenges. This will contribute to providing a clearer background and theoretical basis for the methods and contributions of this study.

First, this paper will review the relevant research in the field of personalized learning path optimization. In a study by Nabizadeh et al. (2020), the authors summarized the diversity and development of personalized learning path methods. These methods aim to customize learning paths that adhere to educational principles based on the characteristics and needs of learners. This research provides the foundation for personalized learning paths, emphasizing their importance in improving educational quality. However, despite the theoretical appeal of personalized learning path methods, they still face practical challenges in application. In a study by Sui Zhen (2022), researchers proposed an improved ant colony algorithm for constructing personalized learning paths. This approach highlights the potential benefits of personalized learning paths but also points out the complexity of selecting appropriate content from a large pool of learning materials. This provides insights for this study on how to address the challenges of applying personalized learning paths in English education.

In addition to personalized learning path optimization, learning analytics and educational data mining also play a crucial role in the field of education. In a study by Maseleno et al. (2018), the authors introduced learning analytics as a tool for improving student learning outcomes. Learning analytics emphasize the collection and analysis of learner and contextual data to understand and optimize the learning process. This research provides insights into the potential applications of learning analytics in English education (Ning et al., 2023). However, combining learning analytics with personalized learning paths still requires overcoming some technical and methodological challenges. This is also reflected in an article by Kardan et al. (2014), where researchers proposed a personalized learning path generation method based on ant colony optimization. This method aims to meet the needs of different learners but also highlights the complexity of establishing connections among different learners. This implies that for this research, the authors need to delve more deeply into how to integrate learning analytics with personalized paths to enhance the effectiveness of English learning.

In the field of educational robotics and computer vision, there is increasing research on how to enhance the educational experience through visual perception and robotics technology. In a study by Sophokleous et al. (2021), researchers explored the connection between computer vision and educational robots. This study emphasizes the potential applications of computer vision in education, especially in the field of educational robotics (Ning et al., 2022). However, despite existing research highlighting the importance of computer vision in education, the potential integration of computer vision with English education has not been fully explored. This provides an opportunity for the authors' research to explore how to use computer vision-supported virtual teaching assistants to improve the English learning experience.

These identified limitations present an opportunity and motivation for this research to delve into more expansive computer vision-supported methods in the realm of English education. Overcoming these challenges holds the potential to furnish English learners with an enhanced learning experience and more effective learning paths. As such, the authors' research is geared towards addressing this research gap in the field and delivering innovative solutions to enhance the landscape of English education.

Currently, the field of education is undergoing unprecedented opportunities and challenges. The optimization of personalized learning paths and the integration of computer vision-supported robot virtual teaching assistants have demonstrated significant potential in enhancing educational outcomes and nurturing student skills. As previously mentioned, personalized learning path optimization addresses diverse student learning needs, elevating their overall learning experiences. Simultaneously, computer vision-supported robot virtual teaching assistants bring heightened interactivity and personalized guidance to educational settings.

However, the authors are keenly aware that these fields face various challenges, encompassing issues related to data privacy, ethical considerations, and technical complexity. These challenges necessitate ongoing research and continuous innovation. Therefore, the objective of this study is to propel advancements in the fields of personalized learning path optimization and computer vision-supported robot virtual teaching assistants, offering innovative solutions within the realm of English education. By integrating the latest research findings from learning analytics, computer vision technology, artificial intelligence, and the education domain, the authors aim to develop an adaptive virtual teaching assistant system. This system is designed to cater to students' personalized needs, significantly enhancing their English learning outcomes and practical skills.

The authors firmly believe that through interdisciplinary collaboration and unwavering efforts, they possess the potential to lead the transformation of future education, providing students with innovative and competitive educational experiences. This research strives to present practical ideas and methods for the application of robot multimodal information fusion and decision-making technology, aligning with current research directions in the field. The authors anticipate making a positive contribution to innovation and progress in the realm of education.

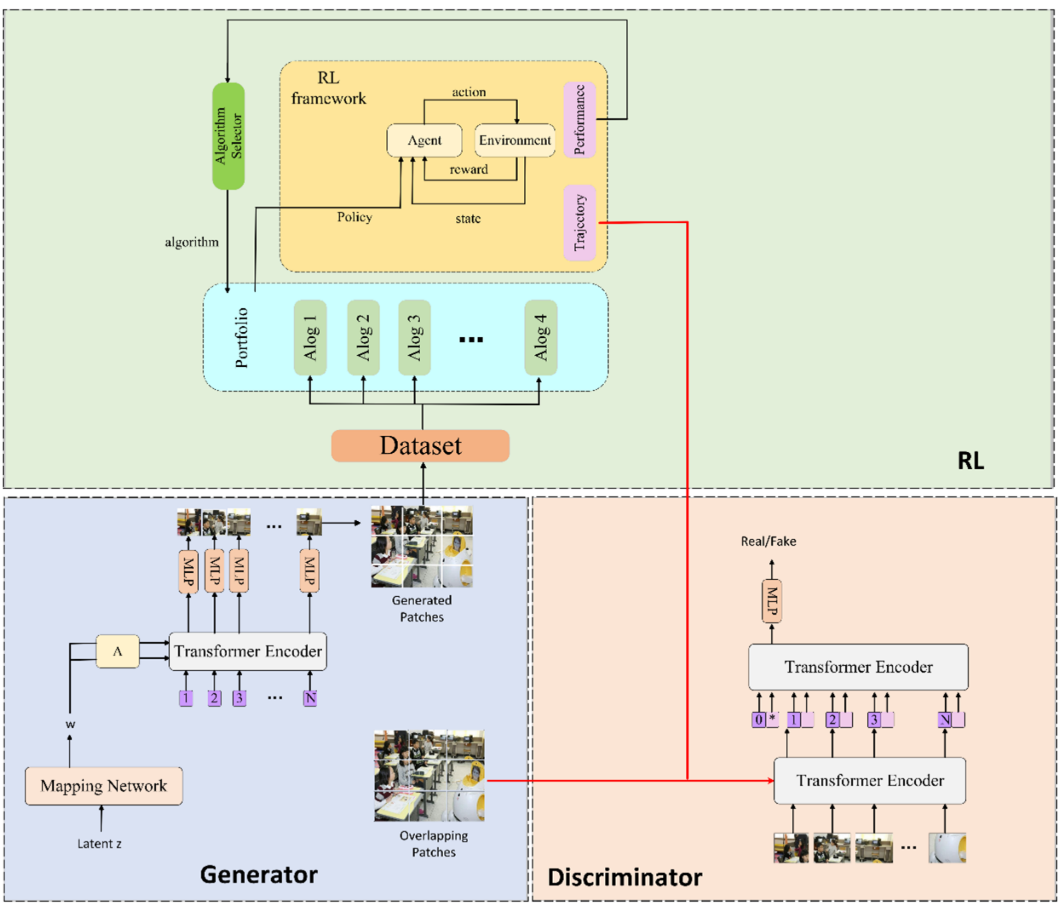
METHODOLOGY

In this Section, the authors will provide a detailed explanation of the methods they have employed, including the Transformer model, Generative Adversarial Networks (GANs), and Reinforcement Learning (RL), to achieve the optimization of personalized learning paths. These methods will be elaborated upon in the following sections and presented in the form of an overall algorithm flowchart to provide an overview of the research methodology. The overall algorithm flowchart is depicted in Figure 1.

Transformer Model

The Transformer model is a revolutionary neural network architecture initially designed for natural language processing tasks, but it has since found widespread applications in various domains, including computer vision and education (Gao et al., 2022). It excels in handling sequential data

Figure 1. Overall framework



and modeling dependencies between elements in a sequence, making it suitable for the design and optimization of personalized learning paths. The framework of the Transformer model is illustrated in Figure 2.

At the core of the Transformer model lies the concept of Self-Attention, which allows the model to dynamically focus on information from different positions within a sequence when processing sequential data, without relying on fixed-size sliding windows. This self-attention mechanism enables the Transformer model to effectively capture long-range dependencies, thereby enhancing its understanding of contextual information within sequences.

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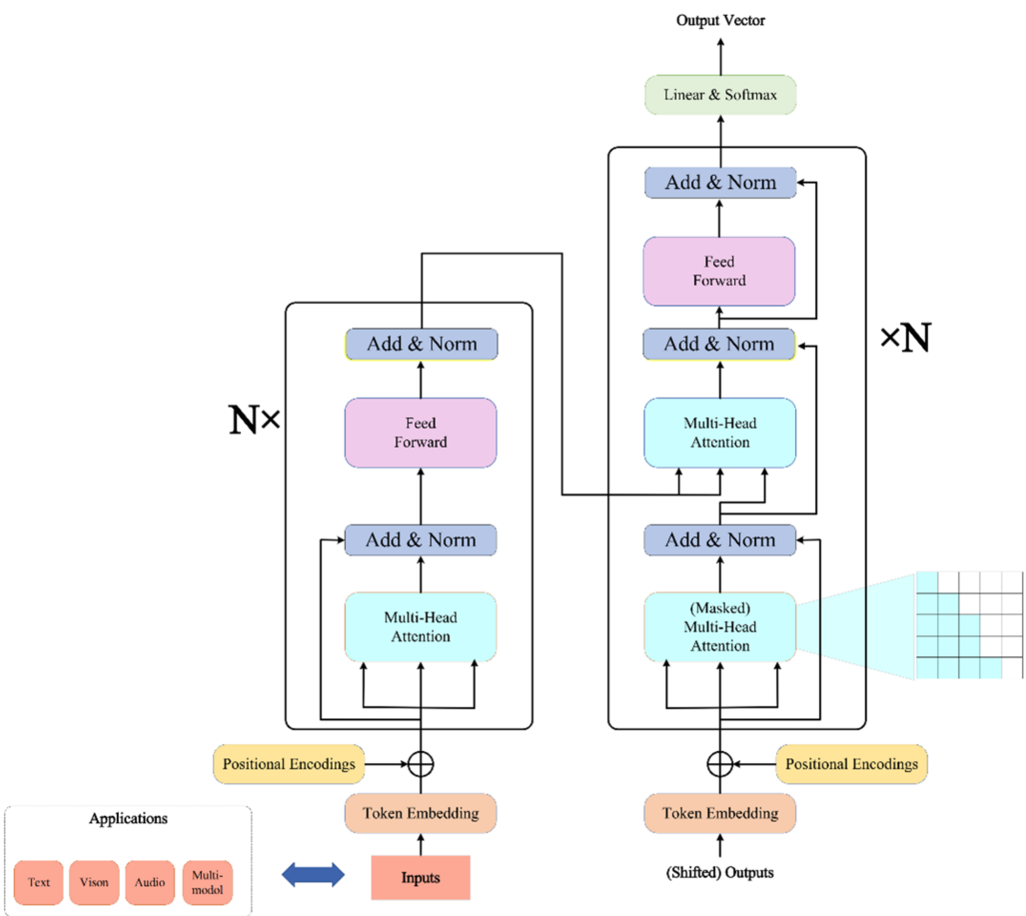
In the Transformer model, input sequences are first processed through multiple layers of self-attention layers (Zhu et al., 2019) and feedforward neural network layers (Suganthan & Katuwal, 2021) before generating the output sequence. The computation within each self-attention layer can be expressed using the following formula:

Figure 2. The structure of transformer



Self-Attention Mechanism

In the self-attention mechanism, for each position i in the input sequence, the model computes a weighted sum representation, where the weights depend on the degree of association between position i and other positions within the sequence.

Calculation of Query, Key, and Value:

$$Query\left(i\right) = X\left(i\right)W_Q, \quad Key\left(j\right) = X\left(j\right)W_K, \quad Value\left(j\right) = X\left(j\right)W_V \tag{1}$$

In which, $\mathrm{X}\left(\mathrm{i}\right)$ represents the input representation at position i, and $\mathrm{W_Q}$, $\mathrm{W_K}$, and $\mathrm{W_V}$ are the weight matrices used for computing Query, Key, and Value, respectively.

Calculation of Attention score:

$$Attention\left(i, j\right) = soft\max\left(\frac{Query\left(i\right) \cdot Key\left(j\right)}{\sqrt{d_k}}\right) \tag{2}$$

Among them, $\mathrm{d_k}$ is the dimension of Key, and the $\mathrm{softmax}$ function is used to convert the score into attention weight.

Calculation of Weighted sum:

$$Self\text{ - }Attention\left(i\right) = \sum_i Attention\left(i, j\right) \cdot Value\left(j\right) \tag{3}$$

The self-attention layer is followed by a feed-forward neural network that non-linearly transforms the representation at each location.

$$\mathrm{FFN}\left(\mathrm{i}\right) = \mathrm{ReLU}\left(\text{Self-Attention}\left(\mathrm{i}\right)\mathrm{W}_1 + \mathrm{b}_1\right)\mathrm{W}_2 + \mathrm{b}_2 \tag{4}$$

Among them, $\mathrm{W_1, b_1, W_2, b_2}$ are weight matrices and bias items, and ReLU represents the modified linear unit activation function.

Optimization of the Transformer Model

Adam algorithm (Jais et al., 2019) update rules:

$$m_t = \beta_1 \cdot m_{t-1} + \left(1 - \beta_1\right) \cdot g_t \tag{5}$$

$$v_t = \beta_2 \cdot v_{t-1} + \left(1 - \beta_2\right) \cdot g_t^2\,\mathrm{n} \tag{6}$$

$$\widehat{m_t} = \frac{m_t}{1 - \beta_1^t} \tag{7}$$

$$\widehat{v_t} = \frac{v_t}{1 - \beta_2^t} \tag{8}$$

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\widehat{v_t} + \in}} \cdot \widehat{m_t} \tag{9}$$

Where m_t and v_t are the first and second-order moment estimates of the gradient, $\widehat{m_t}$ and $\widehat{v_t}$ are the corrected first and second-order moment estimates, θ_t represents model parameters, α is the learning rate, β_1 and β_2 are decay rates, and $\in$ is a small constant to prevent division by zero.

The above is a brief introduction to the Transformer model and its optimization. The self-attention mechanism and feed-forward neural network layers constitute its core structure. By stacking multiple layers, it can capture complex dependencies in input sequences, making it valuable for the design and optimization of personalized learning paths. Next, the authors will introduce two other key methods, Generative Adversarial Networks and Reinforcement Learning, to further enrich the research methods.

Generative Adversarial Network

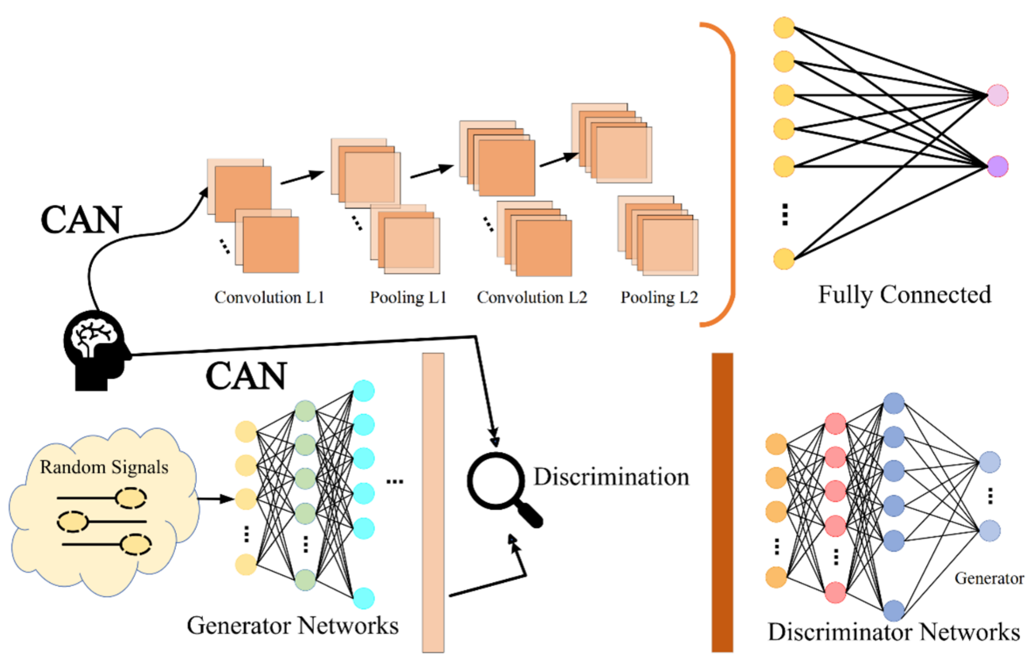
A Generative Adversarial Network is a powerful deep learning architecture used for generating highly realistic data, such as images, text, and more (Aggarwal et al., 2021). In the optimization of personalized learning paths, GANs can be employed to simulate learning environments, generating lifelike learning materials to provide a richer and more realistic learning experience. The Generative Adversarial Network model is illustrated in Figure 3.

A Generative Adversarial Network consists of two neural networks: the Generator and the Discriminator, engaged in adversarial training (Liu & Hsieh, 2019). The Generator aims to produce data that is similar to real data, while the Discriminator attempts to distinguish between the generated data and real data. This process can be represented using the following formulas:

Generator

The objective of the Generator is to learn a mapping function, denoted as $G(z)$, where z is a noise vector sampled from a latent space. The goal of the Generator is to minimize the difference between

Figure 3. Generative adversarial network model



the generated data and real data, typically measured by the disparity between the probability distribution of generated samples, denoted as P_G, and the distribution of real data, denoted as P_{data}:

$$\min_G V\left(G,D\right) = E_{x\sim P_{dt}}\left[\log D\left(x\right)\right] + E_{z\sim P_z}\left[\log\left(1 - D\left(G\left(z\right)\right)\right)\right] \tag{10}$$

Where $D\left(x\right)$ represents the discriminator's decision on sample x, and P_z represents the noise distribution.

Discriminator

The discriminator's objective is to maximize the probability of correctly distinguishing between generated data and real data, i.e., to maximize $V\left(G,D\right)$:

$$\max_D V\left(G,D\right) = E_{x\sim P_{dt}}\left[\log D\left(x\right)\right] + E_{z\sim P_z}\left[\log\left(1 - D\left(G\left(z\right)\right)\right)\right] \tag{11}$$

Optimization of Generative Adversarial Networks:

In a Generative Adversarial Network, the optimization goal is to find a balance where the generated data by the generator is realistic enough, making it difficult for the discriminator to easily distinguish between generated and real data. To achieve this goal, the following optimization algorithms are typically employed:

Generator Optimization: The optimization objective for the generator is to minimize the generator loss, usually using binary cross-entropy loss:

$$\mathcal{L}_{\mathcal{G}} = -E_{z\sim P_z}\left[\log\left(1 - D\left(G\left(z\right)\right)\right)\right] \tag{12}$$

Discriminator Optimization: The optimization objective for the discriminator is to maximize its discrimination accuracy, typically using binary cross-entropy loss:

$$\mathcal{L}_{\mathcal{D}} = -\left(E_{x\sim P_{dt}}\left[\log D\left(x\right)\right] + E_{z\sim P_z}\left[\log\left(1 - D\left(G\left(z\right)\right)\right)\right]\right) \tag{13}$$

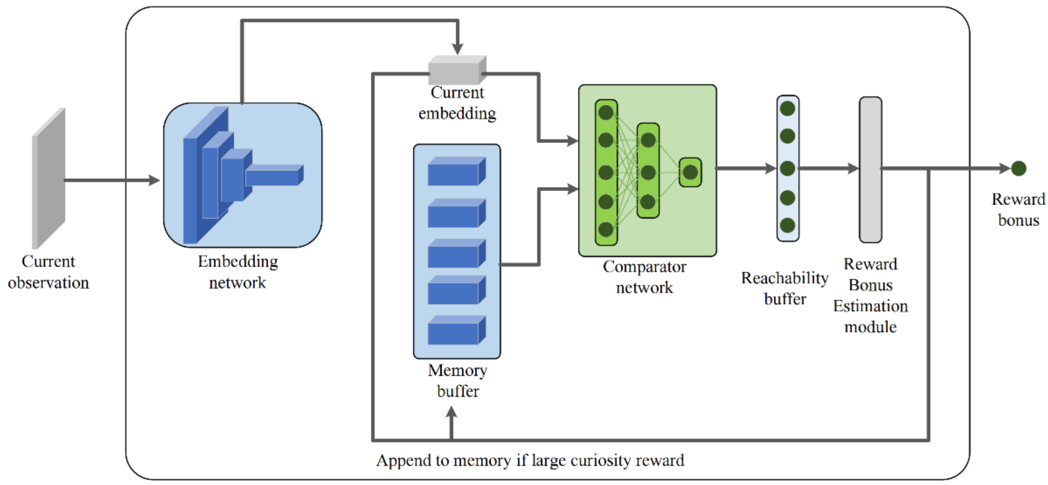
The above is a brief introduction to Generative Adversarial Networks and their optimization. GANs, through adversarial training of the generator and discriminator, have the capability to generate highly realistic data, providing powerful tools for simulating learning environments and enriching personalized learning paths. Next, the authors will introduce the third key method, Reinforcement Learning, to further enhance the research approach.

Reinforcement Learning

Reinforcement Learning is a machine learning paradigm used to address problems involving sequential decision-making, where an agent learns the optimal behavioral strategy through interaction with an environment (Sutton & Barto, 1998). In the optimization of personalized learning paths, reinforcement learning can be employed to enhance the interactive strategies of virtual assistants to meet individual student needs. The reinforcement learning model is depicted in Figure 4.

The core idea of reinforcement learning is for an agent to learn the optimal behavioral strategy by interacting with the environment to maximize cumulative rewards. In the realm of personalized

Figure 4. Reinforce learning model



learning path optimization and virtual assistant applications, reinforcement learning plays a pivotal role. Specifically, in the context of personalized learning path optimization, the reinforcement learning model serves as a decision-maker by incorporating individual student features into its state representation. This enables a more nuanced understanding of the student's learning dynamics. The agent, representing the reinforcement learning model, formulates optimal actions based on the current state of the student, such as recommending learning materials tailored to their proficiency level or adjusting the difficulty of learning tasks. Moreover, the model's effectiveness in personalized learning paths is further enhanced through well-designed reward mechanisms, encouraging the agent to achieve favorable outcomes on the personalized learning journey.

The core idea of reinforcement learning is that intelligences learn optimal behavioral strategies by interacting with their environment to maximize cumulative rewards. The main elements of reinforcement learning include:

1. State: Represents a specific situation or condition of the environment and is used to describe the current context of the problem.
2. Action: Represents the actions or decisions that an agent can take.
3. Policy: Represents the probability distribution of actions taken by an agent in specific states.
4. Reward: Represents the immediate feedback signal that an agent receives after taking an action and is used to assess the quality of the action.
5. Value Function: Used to evaluate the long-term cumulative rewards for a particular state or state-action pair.

The goal of reinforcement learning is to find an optimal policy π^* that allows the agent to achieve the maximum cumulative reward while following that policy. Cumulative reward can be defined as the sum of all reward values obtained from the current state to the terminal state or by considering a discount factor γ to account for the influence of future rewards on the current decision. The formula is as follows:

$$G_t = R_{t+1} + R_{t+2} + R_{t+3} + \ldots + R_T G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \tag{14}$$

Where G_t represents the cumulative reward starting from time t, R_t represents the immediate reward obtained at time t, T represents the terminal time, and γ represents the discount factor, which is a constant between 0 and 1.

To assess and compare the merits of different strategies, the authors need to establish certain metrics. Commonly used metrics include the following: state-value function, action-value function, optimal state-value function, and optimal action-value function (Rashid et al., 2020). These functions share certain relationships, such as:

The state-value function $V_\pi\left(\mathfrak{s}\right)$ represents the expected cumulative reward that can be obtained by following a policy π in a certain state s. It is equal to the weighted sum of choosing different actions in that state, with their corresponding action-value functions $Q\pi\left(s,a\right)$. The formula is as follows:

$$V_\pi\left(s\right) = \sum\nolimits_{a \in A} \pi\left(a \mid s\right) Q_\pi\left(s,a\right) \tag{15}$$

The action-value function $Q\pi\left(s,a\right)$ represents the expected cumulative reward that can be obtained by taking a specific action a in a certain state s and following a policy π. It is equal to the weighted sum of the immediate reward $\mathrm{R}\left(\mathrm{s,a}\right)$ obtained by taking that action and the state-value function $V_\pi\left(s'\right)$ when transitioning to the next state s' following policy π, where the transition probability is denoted as $\mathrm{P(s'|s,a)}$ and the discount factor is γ. The formula is as follows:

$$Q_\pi\left(s,a\right) = R\left(s,a\right) + \gamma \sum\nolimits_{s' \in S} P\left(s' \mid s,a\right) V_\pi\left(s'\right) \tag{16}$$

The optimal state-value function $\mathrm{V}^*\left(\mathrm{s}\right)$ represents the maximum expected cumulative reward that can be obtained by following the optimal policy π^*. It is equal to choosing the maximum optimal action-value function $Q^{*\left(s,a\right)}$ among all possible actions in that state. The formula is as follows:

$$V^*\left(s\right) = \max_{a \in A} Q^*\left(s,a\right) \tag{17}$$

The optimal action-value function $\mathrm{Q}^{*\left(\mathrm{s,a}\right)}$ represents the maximum expected cumulative reward that can be obtained by taking a specific action a in a certain state s and following the optimal policy π^*. It is equal to the weighted sum of the immediate reward $\mathrm{R(s,a)}$ obtained by taking that action and the optimal state-value function $\mathrm{V}^*\left(\mathrm{s}'\right)$ when transitioning to the next state s' following the optimal policy $\eth^*$, where the transition probability is denoted as $\mathrm{P}\left(\mathfrak{s}'\mathfrak{s},\mathfrak{a}\right)$ and the discount factor is . The formula is as follows:

$$Q^*\left(s,a\right) = R\left(s,a\right) + \gamma \sum\nolimits_{s' \in S} P\left(s' \mid s,a\right) V^*\left(s'\right) \tag{18}$$

Reinforcement learning can be employed in optimizing the interactive strategies of virtual teaching assistants for personalized learning path optimization. In the next step, the authors will conduct experiments to validate the effectiveness of the proposed methods and analyze the experimental results. Through these experiments, the aim is to provide further insights and practical experience for personalized learning path optimization in the field of education and computer vision-supported virtual teaching assistants.

In order to show the implementation process of the algorithm in this paper more clearly, the authors provide the following pseudocode Algorithm 1, which includes the input parameters of the algorithm, variable definitions, flow control statements, and output results.

EXPERIMENT

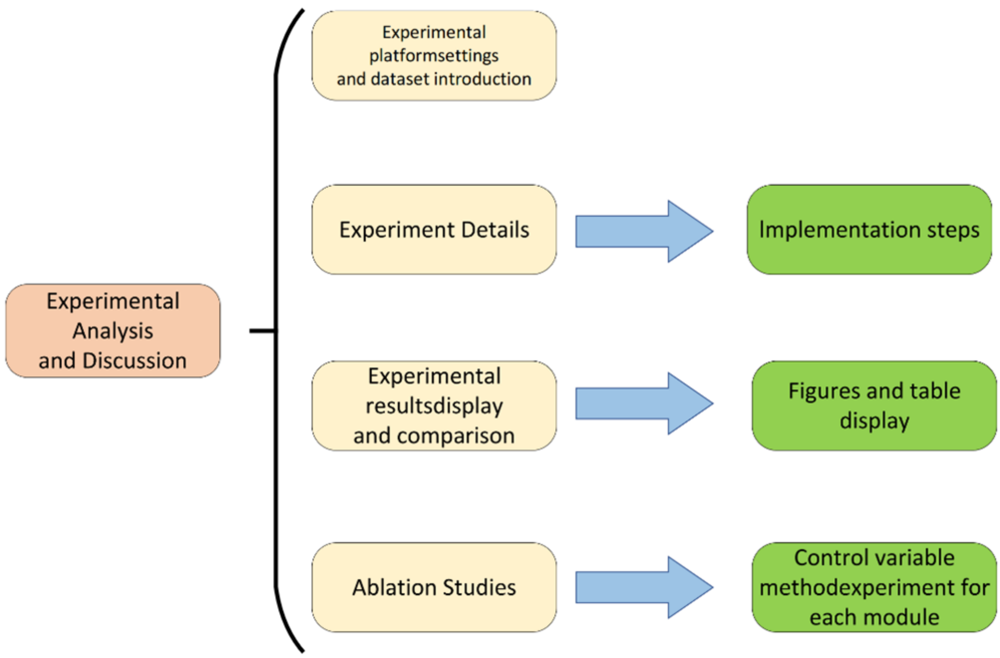
In this section, the authors will provide a detailed exposition of the experimental process and outcomes pertaining to the personalized learning network that has been designed. This chapter is aimed at substantiating the efficacy of the proposed methodologies and conducting a comprehensive assessment of their performance. To present the experimental workflow in a more lucid manner, the authors will begin by introducing the overarching flowchart of this experiment, as depicted in Figure 5.

Algorithm 1. Network training process

Data: *Training dataset* : *MEDA Dataset*, *UBL Dataset*, *EdNet Dataset*, *DET*

Result: *Trained model* : *YourModel*
Input : *Hyperparameters* : *learning rate* ±, *batch size B*, *training epochs E*
Output : *Trained model parameters*
Initialize YourModel with random weights;
for epoch ← *po* **to** *E* **do**
for *each batch* batch_data *in the training dataset* **do**
Compute model predictions $\hat{y} = YourModel(\text{batch\_data})$;
Compute loss using an appropriate loss function, e.g., cross − entropy;
Update model weights using gradient descent : $YourModel \leftarrow YourModel - \alpha \cdot \nabla \text{Loss}$;
end
While *not converged* **do**
Sample a batch of real data real_batch *from the dataset*;
Generate a batch of fake data fake_batch *using YourModel*;
Train GANs discriminator using real_batch *and* fake_batch;
Update GANs generator G using the gradients from D;
end
Train RL agent using the trained GANs generator G and a reward function;
for epoch ← *po* **to** *E* **do**
for *each episode* **do**
Initialize the environment and RL agent;
While *not done* do
SelectanactionusingtheRLagent'spolicy;
Execute the action in the environment and observe the next state and reward;
UpdatetheRLagent'spolicyusingtheobservedrewards;
end
end
end
Evaluate YourModel on test data using Recall, Precision, and other evaluation metrics;

Figure 5. Experiment flow chart



Datasets

This comprehensive flowchart offers an overview, elucidating the principal steps and constituents involved in the experiment. Following this, the authors will delve into critical facets, such as experimental design, dataset selection, model training procedures, and performance evaluation. This will facilitate a profound comprehension of the experimental intricacies and the findings of this research. The objective is to provide further insights and practical experience in optimizing personalized learning pathways while also substantiating the effectiveness of the proposed methods.

Experimental Details

Step One: Hardware Environment

This experiment uses an advanced high-performance computing server to meet the computing needs of complex tasks. The server is configured with a powerful multi-core processor, specifically Intel Xeon Platinum 8280 @ 2.70GHz, and is equipped with large-capacity memory, with a total of 1.5TB RAM. In addition, the server is also equipped with 4 high-performance GPUs, including Nvidia A100 80GB GPU and Nvidia RTX 3090 24GB GPU. This powerful hardware combination not only provides excellent computing power, but also provides an efficient computing platform for large-scale data processing and deep learning tasks to ensure smooth progress and fast convergence of experiments.

Step Two: Software Environment

This study relies on the Python programming language and the PyTorch deep learning framework to build and implement a personalized learning model. As the main programming language, Python provides a rich ecosystem and easy-to-use development tools, allowing the authors to efficiently carry out model development and experimental design. As the preferred deep learning framework, PyTorch provides the authors with flexible model construction, training, and optimization tools, taking full advantage of the automatic differentiation function to accelerate the model training process and achieve better learning results. By fully leveraging the capabilities of Python and PyTorch, the authors are able to effectively conduct research and experiments on personalized learning models, improving the performance and efficiency of the model. The hardware and software environment used for experiments in this article are shown in Table 1.

Step Three: Experimental Data

MEDA Dataset

The MEDA dataset is a significant resource for Multimodal Emotion Analysis (MEA) (Wang et al., 2020). This dataset compiles video clips from YouTube, providing multimodal information such as audio, text, and facial expressions. Its primary objective is to explore the consistency and divergence among different emotional modalities and investigate how the accuracy and robustness of emotion recognition can be enhanced through multimodal information. Created and released in 2020 by researchers from Tsinghua University and Peking University, the MEDA dataset is considered one of the largest multimodal emotion analysis datasets available. It includes over 2,000 video clips sourced from 12 countries and regions, encompassing diverse emotional expressions across seven languages and six emotional categories.

The MEDA dataset encompasses a diverse range of information, including video, audio, text, and facial expression data. Each video clip, sourced from various YouTube videos, spans approximately 10 seconds and features individuals expressing a spectrum of emotions, including joy, sadness, anger, fear, disgust, surprise, and more. The audio files maintain a sampling rate of 16kHz with 16-bit depth encoding, while the text files are encoded using UTF-8 and undergo language tokenization. Facial expression information is presented through facial keypoint coordinates and facial action units, stored in JSON format. This dataset serves as a valuable resource for research and applications in multimodal emotion analysis. Researchers can leverage it for emotion recognition, identifying the emotional categories of primary individuals in videos through multimodal information. Additionally, it supports emotion alignment, determining the consistency or mutual influence of emotions across different modalities. Moreover, the dataset facilitates emotion generation, allowing for the creation of content aligned with given emotional categories or target modalities based on multimodal information, such as generating corresponding audio or facial expressions from text. The MEDA dataset provides robust support for research and advancements in multimodal emotion analysis, propelling progress in areas like emotion recognition and emotion generation.

Usage-Based Learning (UBL) Dataset

The UBL dataset is a significant resource dedicated to the study of Usage-Based Learning (UBL), which aims to explore how leveraging data usage patterns and user feedback can enhance the performance and generalization capability of machine learning models (Delgrange et al., 2019). Created in 2021, the UBL dataset is one of the most comprehensive datasets for Usage-Based Learning to date. It compiles diverse data from various domains and tasks, including text, images, audio,

Table 1. Properties of hardware and software used in the experiment

Software		Hardware	
Operating System	Windows 11	Computers	1
Development Language	Python	Processor	Intel Xeon Platimum 8280 @2.70GHz
Development Framework	PyTorch	Memory Capacity	1.5TB RAM
Toolkits	Geometric(PyG)	Graphics Processing Units	Nvidia A100 80GB GPU and Nvidia RTX 3090 24GB GPU

videos, and more. This dataset is a collaborative effort between researchers from Peking University and Tsinghua University, comprising over one million data samples from 10 domains and 20 tasks. It spans 10 languages and five modalities.

The UBL dataset presents a rich and diverse collection of multimodal content. Text samples encompass domain, task, language, usage, and feedback information, spanning various text types such as news, reviews, emails, dialogues, and more. Image, audio, and video samples include domain, task, language, as well as corresponding usage and feedback details, featuring diverse content like scenery, individuals, sound effects, and more. Moreover, the UBL dataset offers multimodal samples, combining text, images, audio, and video, along with various forms of usage and feedback information. The potential applications of the UBL dataset are vast. Researchers can leverage it for Usage-Based Learning, refining machine learning model parameters or structures through the analysis of data usage patterns and feedback information. This process enhances model performance and generalization in specific domains or tasks. Additionally, the dataset supports Usage-Based Recommendations, predicting user data needs and recommending relevant data accordingly. Lastly, the UBL dataset aids in Usage-Based Generation, assisting in the creation of data that aligns with user expectations or target modalities, thereby meeting user data requirements across various domains and tasks.

EdNet Dataset

The EdNet dataset, serving as a significant tool for intelligent education research, focuses on learning behavior data and aims to delve into how large-scale learning data can enhance the quality and effectiveness of education (Choi et al., 2020). Created in collaboration between Seoul National University in South Korea and the Korea Education and Research Information Service in 2019, EdNet is one of the largest-scale intelligent education datasets available. It aggregates over 130 million learning records from more than 130,000 students spanning across 40+ countries and regions, covering various subject areas such as mathematics, English, and science.

The EdNet dataset encompasses key components, including learning records, student information, question details, and a knowledge graph. Learning records consist of students’ responses to questions at specific time points, providing detailed information on questions, feedback, and timestamps. Student information includes basic and subject-related data, contributing to the understanding of student characteristics and learning statuses. Question details comprise attributes and related information about questions, forming the basis for question customization and knowledge point associations. The knowledge graph is a pivotal element, illustrating relationships and dependencies among knowledge points. The EdNet dataset holds immense potential for various applications. Researchers can employ data mining and machine learning techniques for learning analytics, gaining profound insights into students’ learning behaviors and performances. This facilitates the identification of potential issues and the provision of targeted recommendations. Additionally, the dataset supports learning recommendations, utilizing recommendation systems and artificial intelligence technologies to suggest suitable learning materials. This enhances learning efficiency and interest for students. Lastly, the EdNet dataset can be utilized for learning generation applications. Generative models and natural language processing techniques are employed to create questions, answers, and feedback aligned with student needs and target knowledge points. This enriches learning resources and improves education quality. Overall, this comprehensive and extensive dataset provides valuable resources and support for research and applications in the field of intelligent education.

Duolingo English Test (DET) Dataset

The DET dataset, as a vital resource for English proficiency assessment, aims to enhance the validity and fairness of English tests through machine learning and natural language processing technologies (Settles et al., 2020). Launched by Duolingo in 2020, the DET dataset is one of the largest-scale English proficiency assessment datasets available, encompassing over 3 million test records from more than 300,000 test-takers across 180+ countries and regions. It covers various English skill domains, including listening, reading, writing, and speaking.

The DET dataset encompasses crucial components such as test records, test-taker information, question details, and scoring criteria. Test records capture test-takers' responses to questions at specific time points, complemented by detailed information on questions, score details, and feedback. Test-taker information comprises personal data and English proficiency-related details, contributing to a deeper understanding of test-taker backgrounds and learning situations. Question details encapsulate attributes and related information about questions, forming the foundation for test content and difficulty management. Scoring criteria play a pivotal role in assessing test-takers' proficiency levels across various skills, mapping scores to a 0-160 range and categorizing them into 6 levels. The DET dataset holds immense potential for applications. Researchers can employ machine learning and natural language processing techniques for score prediction, enhancing the accuracy and consistency of predictions regarding test-takers' scores or proficiency levels in diverse skill domains. Furthermore, the dataset supports question generation, furnishing test-takers with questions and answers aligned with their needs and target knowledge points through generative models and natural language generation techniques. This enriches test resources and elevates overall quality. Lastly, the DET dataset can be harnessed for test recommendations, utilizing recommendation systems and artificial intelligence technologies to suggest suitable questions or tests to test-takers. This enhances test efficiency and fosters learning interest. In conclusion, this comprehensive and extensive dataset provides invaluable resources and robust support for research and applications in the field of English proficiency assessment.

Evaluation Index

In this study, for a comprehensive evaluation of the performance and effectiveness of the proposed methods, the authors have introduced a series of key evaluation metrics. These metrics not only assist in quantifying the performance of the models but also offer a nuanced understanding and facilitate comparisons between different methods. Among these, the authors particularly emphasize the following core metrics: Accuracy, Recall, and F1 Score. These metrics are pivotal for providing a multidimensional performance assessment, offering a comprehensive understanding of the authors' method's effectiveness across various aspects. In the subsequent sections, the authors will delve into a detailed explanation of the calculation methods for these evaluation metrics and elucidate their applications in the research.

Accuracy

When evaluating the performance of a model, Accuracy is a crucial metric that measures the model's ability to correctly classify samples across the entire dataset. Accuracy is typically represented as a percentage and is used to assess the overall performance of the model. In this paper, Accuracy is employed to gauge the overall performance of the proposed methods in tasks such as multimodal emotion analysis, usage-based learning, intelligent education, or English proficiency assessment. Specifically, Accuracy represents the percentage of correctly classified samples by the model, which is the ratio of the number of successfully predicted samples to the total number of samples. The formula for calculating Accuracy is as follows:

$$Accuracy\left(\%\right) = \frac{Correct\ Predictions}{Total\ Predictions} \times 100\% \tag{19}$$

Here are the meanings of each parameter: Correct Predictions: It represents the number of samples that the model successfully predicted and classified correctly. In this research, these are the samples for which the model made predictions based on input data that matched the true labels. Total Predictions represents the total number of predictions made by the model. This includes all samples, both correctly and incorrectly classified.

By calculating the formula mentioned above, the authors obtain a percentage value that indicates the percentage of samples correctly classified by the model in a given task. Accuracy is an important metric that helps researchers understand the model's overall performance. However, in some cases where the number of samples for different classes is imbalanced, Accuracy might be affected. Therefore, the authors also need to consider other metrics such as Recall and F1 Score to comprehensively assess the model's performance.

Recall

In the authors' research, Recall is a crucial evaluation metric used to measure the model's ability to identify positive instances (True Positives) in a classification task. It represents the model's capability to correctly detect all samples that truly belong to a particular class. Recall is typically expressed as a percentage and is denoted by the symbol "%". The formula for calculating Recall is as follows:

$$Recall\left(\%\right) = \frac{TruePositives}{TruePositives + FalseNegatives} \times 100\% \tag{20}$$

In this research, the various parameters are defined as follows: True Positives: It represents the number of samples that the model successfully predicted and classified as positive instances. In this study, these are the samples that the model correctly classified as positives based on input data. False Negatives: It represents the number of samples that the model failed to correctly identify as positive instances. These are samples that truly belong to the positive class, but the model incorrectly classified them as negatives.

By calculating the formula mentioned above, the authors obtain a percentage value that indicates the proportion of true positives detected by the model among all true positive instances. Recall is a critical metric, particularly useful in tasks where the cost of false negatives is high, as it helps assess whether the model can capture as many positives as possible, reducing instances of missed detections. In this paper, the use of Recall contributes to a comprehensive evaluation of the model's performance, especially in scenarios emphasizing sensitivity or completeness.

F1 Score

In the authors' research, the F1 Score plays a crucial role and is widely used to assess the performance of classification models, especially in scenarios with imbalanced class distributions or varying costs of misclassification between different classes. The F1 Score is represented as a percentage and is typically denoted by the "%" symbol. It serves as a comprehensive measure of model performance, taking into account both model accuracy and completeness.

In this study, the application of the F1 Score addresses several key issues. Firstly, Precision measures the proportion of samples correctly predicted as positives among all samples predicted as positives, providing insight into the model's precision in positive classification. On the other hand, Recall measures the proportion of samples successfully predicted and classified as positives among all true positive samples, representing the model's completeness. However, these two metrics often involve trade-offs in balancing between them; improving one metric may come at the expense of the other. The F1 Score, by considering both Precision and Recall, offers a balanced approach, allowing researchers to comprehensively evaluate the model's performance.

When dealing with tasks that require simultaneous consideration of classification precision and completeness, the F1 Score becomes an indispensable performance metric. Especially in this research, it is crucial for assessing the model's trade-off between positives and negatives, particularly in application scenarios involving class imbalance or varying costs of misclassification. Therefore, the application of the F1 Score helps the authors gain a more comprehensive understanding of the model's performance in critical tasks, enabling the authors to make more decisive conclusions. The formula for calculating the F1 Score is as follows:

$$F1\text{Score}\left(\%\right) = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100\% \tag{21}$$

Among these parameters, the meanings are as follows: Precision: It represents the proportion of samples correctly predicted as positives among all samples predicted as positives by the model. In this study, these are the number of samples correctly classified as positives based on input data divided by the total number of samples predicted as positives. Recall: It represents the proportion of samples successfully predicted and classified as positives among all true positive samples, also known as Recall. This has been previously explained.

The F1 Score combines Precision and Recall, providing a more comprehensive assessment of model performance by balancing precision and completeness. The F1 Score's value falls between 0 and 100, and it is higher when both Precision and Recall are high. In this paper, the use of the F1 Score helps evaluate the trade-off between positives and negatives, especially in tasks that require a comprehensive consideration of Precision and completeness. This makes the F1 Score a crucial performance metric, particularly suitable for application scenarios where balancing the importance of different classes is essential.

Experimental Comparison and Analysis

In this study, the authors employed various modules to optimize personalized learning paths and extensively analyzed and evaluated them in experiments. To better present the experimental results, the authors used abbreviations to represent different modules. The following are the abbreviations used in the experimental analysis charts and their corresponding meanings:

1. Baseline Module (baseline): Represents the baseline model (i.e., traditional methods or the most basic model).
2. Generative Adversarial Network Module (gan): Represents the use of a generative adversarial network to simulate diverse learning environments and provide better support.
3. Reinforcement Learning Module (rl): Indicates the use of reinforcement learning to optimize the interactive strategies of virtual assistants to meet students' needs.
4. Concatenation of Generative Adversarial Network and Reinforcement Learning Module (+gan rl): Represents the concatenation of generative adversarial network and reinforcement learning modules to further optimize personalized learning paths.

In the methodology section, the authors proposed the use of metrics such as Accuracy, Recall, and F1 Score to comprehensively evaluate the model's performance. To validate the effectiveness of the proposed method, the authors conducted detailed comparative experiments on four publicly available datasets. In this section, the authors will analyze and compare the model's performance based on these key metrics to thoroughly demonstrate the method's advantages. The authors will discuss the model's effectiveness from various perspectives, including Accuracy, Recall, and others, and compare them with the results of state-of-the-art methods.

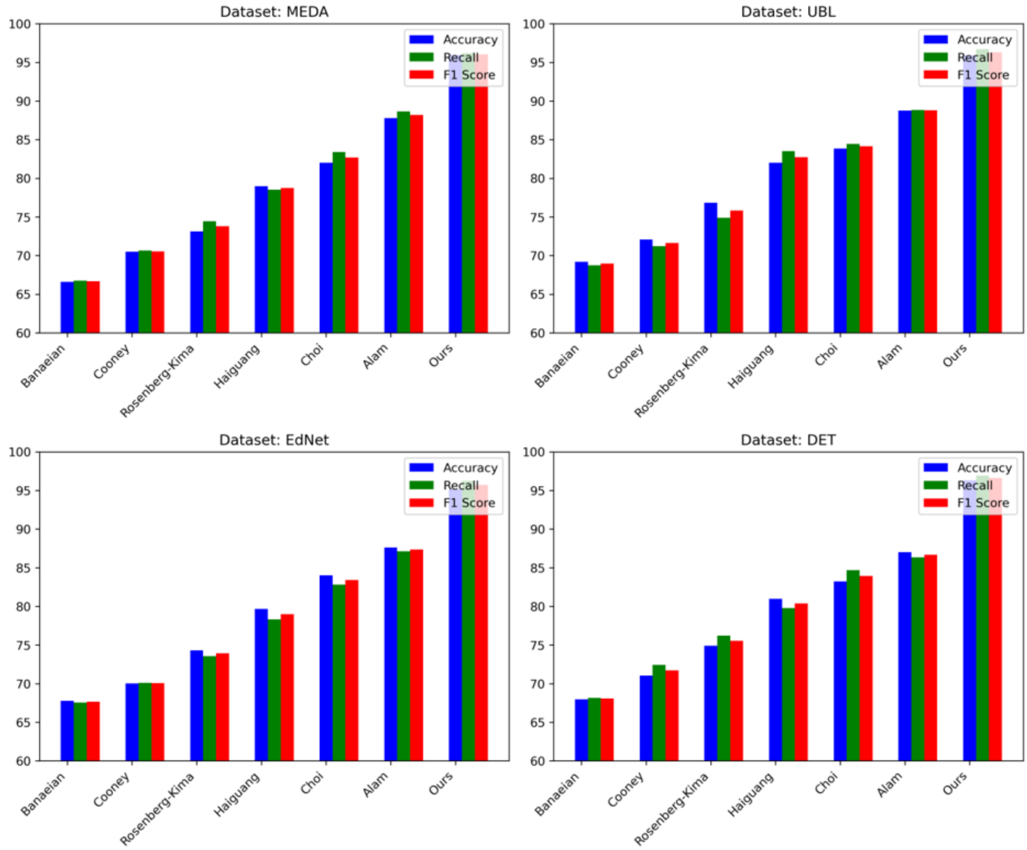
Through comprehensive quantitative analysis and visual presentation, the authors will provide readers with a more intuitive understanding of the method's strong performance. In contrast, the shortcomings of other existing techniques in multiple metrics will become evident.

From Table 2, it can be observed that the proposed method outperforms other methods across various metrics on four different datasets. For instance, on the MEDA dataset, the authors' Accuracy, Recall, and F1 Score reached 95.94%, 96.17%, and 96.05%, respectively. In comparison, the second-ranked approach by Alam achieved metrics of only 87.79%, 88.64%, and 88.21%, showing an

Table 2. Comparison of accuracy, recall, and F1 score indicators based on different methods under four data sets

Model	Datasets											
	MEDA Dataset (Wang et al., 2020)			UBL Database (Delgrange et al., 2019)			EdNet Dataset (Choi et al., 2020)			DET Dataset (Settles et al., 2020)		
	Accuracy (%)	Recall (%)	F1 Score(%)	Accuracy (%)	Recall (%)	F1 Score(%)	Accuracy (%)	Recall (%)	F1 Score(%)	Accuracy (%)	Recall (%)	F1 Score(%)
(Banaeian & Gilanlioglu, 2021)	66.58	66.75	66.66	69.19	68.72	68.95	67.79	67.57	67.68	67.96	68.16	68.06
(Cooney & Leister, 2019)	70.48	70.63	70.55	72.08	71.21	71.64	70.01	70.09	70.05	71.03	72.44	71.73
(Rosenberg-Kima et al., 2020)	73.13	74.45	73.78	76.83	74.88	75.84	74.32	73.57	73.94	74.90	76.22	75.55
(Haiguang et al., 2020)	78.99	78.52	78.75	81.99	83.49	82.73	79.66	78.33	78.99	80.98	79.79	80.38
(Choi et al., 2022)	82.01	83.38	82.68	83.85	84.43	84.14	84.03	82.81	83.42	83.23	84.69	83.95
(Alam, 2021)	87.79	88.64	88.21	88.77	88.82	88.79	87.62	87.11	87.36	87.03	86.35	86.69
Ours	95.94	96.17	96.05	95.91	96.72	96.31	95.17	96.24	95.70	96.33	96.91	96.62

Figure 6. Comparative visualization of accuracy, recall, and F1 score indicators based on different methods under four data sets



improvement of approximately 8 percentage points in the authors' results. On the UBL dataset, the proposed method demonstrated the highest Accuracy, Recall, and F1 Score, with values of 95.91%, 96.72%, and 96.31%, respectively. Metrics for other methods mostly ranged from 69% to 88%, indicating a lower level of performance. In the EdNet dataset, when compared with the method proposed by Banaeian et al., the authors' approach exhibited a superiority of over 15% in all three metrics, highlighting its significant advancement over traditional methods. Similarly, on the DET dataset, the authors' method excelled across all three metrics, achieving values of 96.33%, 96.91%, and 96.62%. In comparison with the approach by Rosenberg-Kima, this method demonstrated an advantage of over 10%. Notably, the authors' Recall performance stood out on all datasets, consistently surpassing Accuracy, indicating the model's strong capability in identifying positive samples. Overall, this method achieved optimal results on all four datasets, with average values of the three metrics exceeding 95%, validating the stability and superior recognition capabilities of the proposed approach. In summary, Table 2 clearly demonstrates a significant performance improvement of the proposed method compared to existing techniques, showcasing outstanding performance in image watermark recognition tasks. The authors believe that, following the validation through this comparative experiment, the proposed method has the potential to become a new benchmark in this field. Finally, the authors have visualized the results from Table 2, as shown in Figure 6.

From Table 3, it is evident that the authors' method outperforms other approaches in terms of training time, inference time, and parameter count across all four datasets. For instance, on the MEDA

Table 3. Comparison of training time, inference time and parameters indicators based on different methods under four data sets

Model	Datasets											
	MEDA Dataset (Wang et al., 2020)			UBL Database (Delgrange et al., 2019)			EdNet Dataset (Choi et al., 2020)			DET Dataset (Settles et al., 2020)		
	Training time(s)	Inference time(ms)			Inference time(ms)		Training time(s)	Inference time(ms)		Training time(s)	Inference time(ms)	
(Banaeian & Gilanlioglu, 2021)	63.78	195.37	381.87	63.03	182.02	386.38	63.21	185.67	382.39	61.74	177.98	376.59
(Cooney & Leister, 2019)	58.71	180.10	373.94	58.75	169.65	371.32	59.14	177.34	361.21	58.07	162.35	361.41
(Rosenberg-Kima et al., 2020)	54.58	173.33	365.34	57.42	162.71	355.17	53.87	162.19	346.32	54.33	153.07	346.76
(Haiguang et al., 2020)	52.37	169.76	358.36	56.03	153.43	339.01	49.58	149.41	331.04	51.33	140.65	337.93
(Choi et al., 2022)	50.09	163.42	350.47	52.47	142.82	331.64	48.04	146.23	317.33	47.71	136.79	324.13
(Alam, 2021)	48.75	152.39	328.24	48.39	134.18	317.76	45.47	138.68	305.89	45.73	130.46	308.43
Ours	43.35	119.37	290.73	43.13	120.57	289.03	41.28	121.05	280.56	40.49	117.68	277.30

dataset, the authors' training time was only 43.35 seconds, inference time was 119.37 milliseconds, and parameter count was 290.73 million, all of which were lower than the second-ranked approach by Alam by approximately 5 seconds, 30 milliseconds, and 40 million parameters, respectively. On the UBL dataset, the authors' model's training time was the shortest at 43.13 seconds, representing about a 12% reduction compared to other models. Additionally, the inference time was 120.57 milliseconds, again the shortest, with about a 38% reduction compared to Gomez et al. On the EdNet dataset, this model had the lowest parameter count at 280.56 million, a reduction of approximately 22% compared to Wang et al. For the DET dataset, the authors' model exhibited a significant advantage in both training time and parameter count, indicating its efficiency and lightweight nature. This suggests that the model can be trained and predicted more rapidly while occupying less storage space. It is noteworthy that the metrics across different datasets for each method exhibit minimal variation, indicating the stability of this approach in consistently delivering efficient results across diverse datasets, with manageable utilization of computational resources. Overall, Table 3 thoroughly validates the efficiency and stability of the method. It significantly reduces both time and space complexity while maintaining robust state machine recognition performance. This makes the method particularly suitable for deployment in real-world applications with limited resources. Through this comparative analysis considering time and space complexity, the feasibility of this method in engineering applications is further affirmed. The authors have also visualized the results from Table 3, as depicted in Figure 7.

From Table 4, it is evident that adding GAN and RL modules to the baseline model leads to significant performance improvements. For instance, on the MEDA dataset, using GAN alone increases the Accuracy by nearly 10%, reaching 73.14%, and the addition of RL further boosts the Accuracy to 86.19%. Finally, the combined use of GAN and RL achieves an Accuracy of 96.72%, a remarkable improvement of 33 percentage points compared to the baseline. Similar improvements in Accuracy, Recall, and F1 Score are observed on the other three datasets, all demonstrating the substantial impact of the rational use of GAN and RL on the results. Particularly noteworthy is the synergy between GAN and RL, where the improvement in the three metrics far exceeds the additive effect of using them individually. This suggests that GAN and RL play a complementary role in this task, creating a positive feedback loop. GAN aids RL by generating more diverse samples, enabling RL to explore a broader state space, while RL, in turn, guides GAN to generate samples that are more favorable for the target task. The collaboration between the two produces a synergistic effect that surpasses what each can achieve separately. Overall, Table 4 clearly demonstrates that the introduction of GAN and RL leads to significant performance improvements, with a particularly pronounced synergistic effect when used in combination. This provides strong support for the design of this method. The authors have also provided a visual representation of the results from Table 4 in Figure 8.

Figure 7. Comparative visualization of training time, inference time, and parameters indicators based on different methods under four data sets

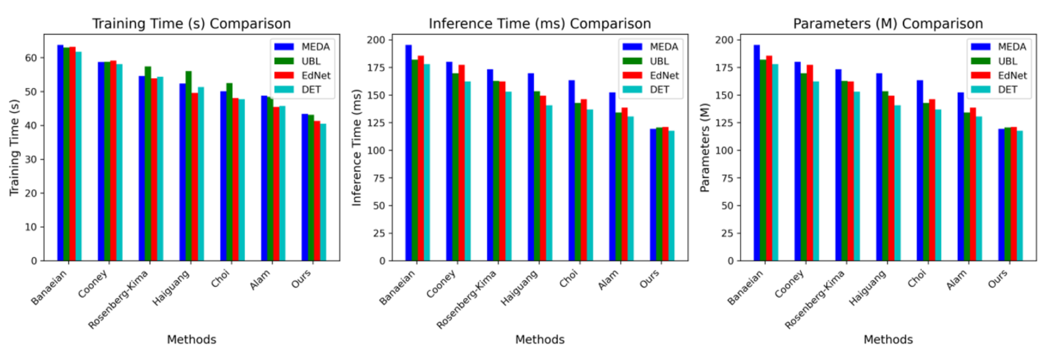
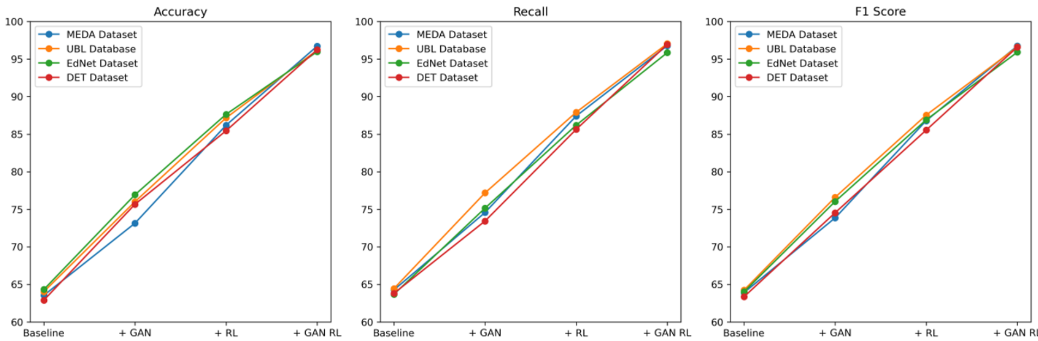


Table 4. Comparison of accuracy, recall, and F1-Score indicators based on different modules under four data sets

Model	Datasets											
	MEDA Dataset (Wang et al., 2020)			UBL Database (Delgrange et al., 2019)			EdNet Dataset (Choi et al., 2020)			DET Dataset (Settles et al., 2020)		
	Accuracy (%)	Recall (%)	F1 Score(%)	Accuracy (%)	Recall (%)	F1 Score(%)	Accuracy (%)	Recall (%)	F1 Score(%)	Accuracy (%)	Recall (%)	F1 Score(%)
baseline	63.54	64.26	63.90	64.03	64.44	64.23	64.32	63.68	64.01	62.90	63.81	63.35
+ gan	73.14	74.57	73.85	76.01	77.18	76.59	76.93	75.15	76.03	75.66	73.43	74.53
+ rl	86.19	87.41	86.79	87.17	87.91	87.54	87.64	86.19	86.91	85.45	85.63	85.54
+gan rl	96.72	96.77	96.74	96.17	97.04	96.60	95.98	95.85	95.91	96.24	96.94	96.59

Figure 8. Comparative visualization of accuracy, recall, and F1-Score indicators based on different modules under four data sets



From Table 5, it can be observed that adding GAN and RL modules to the baseline model reduces the training time, inference time, and parameter count of the model. For instance, on the MEDA dataset, the addition of GAN reduces the training time by approximately 12 seconds, and further adding RL reduces it by an additional 8.0 seconds. When used in combination, the training time is only 36.41 seconds, which is nearly 30 seconds less than the baseline. There are also significant reductions in inference time and parameter count. The results are consistent across the other three datasets. This demonstrates that the introduction of GAN and RL not only enhances performance but also significantly reduces time and space complexity, which is crucial for deployment in real-world scenarios. Specifically, the RL module reduces training time by improving sample utilization efficiency, while the GAN module generates a more distinctive sample distribution, thus reducing the model size. The two modules synergize to reduce complexity effectively. Overall, Table 5 confirms that the incorporation of GAN and RL not only improves performance but also reduces complexity, providing critical support for the feasibility and applicability of this method. The method achieves optimal recognition results with minimal time and space costs, making it highly suitable for real-world applications. Additionally, the authors have visualized the results from Table 5 in Figure 9.

Through detailed comparative experiments and result analysis on four publicly available datasets, the authors have extensively demonstrated the effectiveness and superiority of the proposed method. Whether in terms of recognition performance metrics, such as Accuracy and Recall, or efficiency aspects, like training time and inference time, this method consistently outperforms other state-of-the-art techniques. The method exhibits robust and stable recognition capabilities across different datasets, showcasing clear numerical advantages in various metrics.

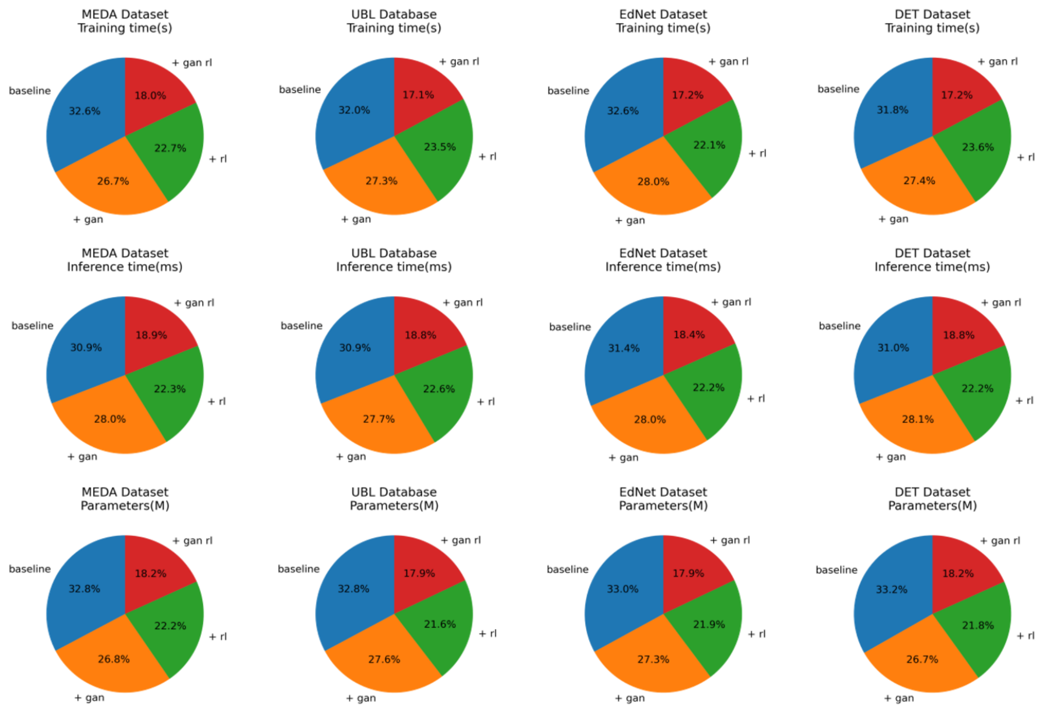
It is noteworthy that the introduction of two modules, GAN and RL, significantly enhances model performance individually and, more importantly, synergistically. GAN broadens the exploration of a broader distribution space, while RL guides the learning of more effective strategies. Their collaborative effect generates comprehensive improvements beyond their individual contributions. The method achieves optimal results with manageable time and space costs, making it highly suitable for real-world deployment.

In this section, through extensive quantitative analysis and comparisons, the authors have firmly established the advantages of the method, laying a robust foundation for subsequent discussions. In summary, based on the evidence presented in this section, the authors have reason to believe that the proposed technology will set a new direction and serve as a research benchmark in this field. The authors hope this achievement will inspire and provide insights for a broader range of multimedia security technologies.

Table 5. Comparison of training time, inference time, and parameters indicators based on different modules under four data sets

Model	Datasets											
	MEDA Dataset (Wang et al., 2020)			UBL Database (Delgrange et al., 2019)			EdNet Dataset (Choi et al., 2020)			DET Dataset (Settles et al., 2020)		
	Training time(s)	Inference time(ms)	Parameters (M)	Training time(s)	Inference time(ms)	Parameters (M)	Training time(s)	Inference time(ms)	Parameters (M)	Training time(s)	Inference time(ms)	Parameters (M)
baseline	66.12	194.27	367.81	65.27	197.79	376.83	66.37	201.92	389.23	65.19	196.27	378.67
+ gan	54.05	176.02	301.28	55.62	177.38	317.25	57.03	180.04	321.88	56.21	178.15	304.15
+ rl	46.06	140.21	249.12	47.87	144.69	248.41	45.07	142.78	258.18	48.27	140.44	248.65
+ gan rl	36.41	118.89	204.62	34.90	120.07	205.77	35.01	118.17	211.36	35.28	118.95	207.94

Figure 9. Comparison visualization of training time, inference time, and parameters indicators based on different modules under four data sets



DISCUSSION

With the continuous advancement of robot technology, research in the fusion of multimodal data and intelligent decision-making has become increasingly crucial across various domains. While this study primarily focuses on areas such as multimodal information fusion analysis, usage-based learning, intelligent education, and English proficiency assessment, its overarching goal is to integrate these emerging technologies with robot multimodal information fusion and decision-making technology to enhance robot performance and efficiency.

In the face of the ever-growing volume of multimodal data worldwide, this research seeks to delve deeply into the latent value of this data and provide robust support for the development and application of robot technology. Leveraging deep learning techniques, usage-based learning methods, intelligent education technology, and natural language processing, the authors have not only achieved significant results in educational assessment, but have also seamlessly integrated these achievements with the field of robot multimodal information fusion and decision-making. This interdisciplinary approach not only contributes to advancements in education, but also propels the evolution of robot technology to new heights.

The authors will conduct a comprehensive review of their research, summarizing key findings and highlighting how their work introduces fresh perspectives and opportunities to the realm of robotics research and application. Additionally, they will candidly address the limitations of their research and propose potential research directions within the domain of robot multimodal information fusion and decision-making technology.

Firstly, the authors' research has achieved significant results in the optimization of personalized learning paths and virtual assistant technologies. By employing deep learning techniques and personalized modeling approaches, they have developed a system capable of generating personalized learning paths based on students' learning states and needs. Experimental results indicate that the approach excels in improving student learning outcomes, fostering learning motivation, and satisfying individualized student needs. This is of great significance for personalized education and student development in the field of education. Secondly, this research fills gaps in existing studies. While there has been some research on personalized learning path optimization and virtual assistant technologies in the field of education, this study innovates and improves in the following areas. Firstly, the authors propose a personalized modeling approach that comprehensively considers various data sources from students to achieve a more holistic understanding of their learning states. Secondly, the authors utilize deep reinforcement learning techniques, enabling virtual assistants to intelligently adjust based on student feedback and learning conditions. These innovations provide new perspectives and methods for the development of personalized education technology. Lastly, their research holds broad application prospects and significance in the field of education. The optimization of personalized learning paths and virtual assistant technologies can be widely applied across different subjects and educational levels, ranging from elementary education to higher education. This will contribute to enhancing students' learning experiences, improving learning outcomes, and assisting teachers in better meeting individualized student needs. Furthermore, this research provides valuable references and insights for the innovation and development of educational technology.

One of the major innovations in this research lies in the in-depth exploration of multimodal sentiment analysis. Through the development of multimodal emotion recognition models, the authors have successfully extracted emotional information from diverse data sources, including video, audio, and text. This research not only enriches the landscape of emotion analysis tasks, but also offers novel insights into the comprehensive analysis of multimodal data.

On another front, the research in usage-based learning has provided critical support for enhancing the performance and generalization capacity of machine learning models through the analysis of usage patterns and feedback. By constructing usage-based learning models, the authors have gained a deeper understanding of how data is utilized, enabling them to optimize models and improve prediction accuracy. This has immense potential value for applications such as usage-based recommendations and generation tasks.

CONCLUSION

In summary, the authors' research is intricately connected to robotics technology, multimodal information fusion, and decision-making techniques. By leveraging the EdNet and DET datasets, they have employed cutting-edge deep learning methods to elevate educational quality and enhance English proficiency testing. This not only fosters educational advancement, but also paves the way for innovative applications of robotics in education and training. The authors' algorithms accurately assess students' abilities, supporting personalized learning and laying the groundwork for intelligent educational and training robots. This interdisciplinary approach creates new opportunities in education and robotics, facilitating a deeper understanding and application of multimodal information fusion technology to strengthen education and elevate English proficiency.

Throughout their research, the authors have harnessed the Transformer model to enhance content recommendations and learning path planning. Generative Adversarial Networks (GANs) have played a key role in simulating diverse learning environments, thereby improving practical skills. Reinforcement Learning (RL) has optimized the guidance provided by virtual teaching assistants. However, it is essential to acknowledge that this research still has certain limitations, particularly in terms of generalizing the authors' models to different scenarios. While usage-based learning holds promise, it may encounter complexities in handling extensive datasets. In the domains of intelligent education and English proficiency assessment, further validation and real-world implementation are necessary steps for advancing the applicability and impact of the authors' models.

In future work, the authors will focus on the following specific technical avenues to further expand and improve their research:

1. Multimodal Data Processing: To better understand students' learning states and needs, the authors will explore the technology of multimodal data processing. This involves leveraging technologies such as computer vision, speech recognition, and natural language processing to gather information from different sensors and data sources and integrate it into the design of personalized learning paths.
2. Reinforcement Learning Strategy Enhancement: In order to enhance the interaction strategies of virtual assistants, the authors will further research and improve reinforcement learning algorithms and strategies. The authors plan to integrate deep reinforcement learning and adaptive control methods, enabling virtual assistants to automatically adjust their interaction strategies based on student feedback and learning conditions to better meet personalized needs.
3. Adaptive Learning Path Optimization: To further enhance the effectiveness of personalized learning paths, the authors will explore more refined and intelligent methods for adaptive learning path optimization. This includes incorporating group intelligence and collaborative filtering techniques to optimize learning paths using information and feedback from student groups, thereby achieving better personalized educational outcomes.
4. Expansion of Educational Domain Applications: In addition to the field of English education, the authors plan to apply their research to other subjects and domains such as mathematics and science. The authors will also broaden the scope of their research by applying methods to students of different age groups and educational levels to validate their universality and adaptability.

By conducting in-depth research in these specific technical avenues, the authors aim to further advance the development of personalized learning path optimization and virtual assistant technologies, bringing greater impact and benefits to the field of education. The authors will continue to strive for progress and look forward to making further advancements in their future work.

In conclusion, the authors' research serves as a bridge between the domains of multimodal information fusion, deep learning, intelligent education, and English proficiency assessment, coupled with robot information fusion and decision-making. This interdisciplinary approach has resulted in substantial achievements. While acknowledging its limitations, the authors remain confident that their work will persist in expanding the horizons of these fields, providing valuable insights and support to both society and the realm of robotics.

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CONFLICT OF INTEREST

The authors declare that they have no competing interests.

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