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Computer-Aided Design AND APPLICATIONS

Implementing Personalized Recommendation in Digital Media Art Design Using Machine Learning

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Abstract. Digital Media Art (DMA) not only drives innovation in the field of art but also opens up broader imaginative spaces for creators. This study focuses on utilizing big data-driven machine learning techniques to achieve precise, personalized recommendations in the computer-aided design (CAD) process of DMA. In response to the uniqueness of this field, we have customized and optimized the recommendation system to ensure that it better adapts to the designer's workflow. By capturing multidimensional data from designers during the creative process, this system can gain a deeper understanding of their creative intentions and provide more appropriate recommendations for design elements. Compared with traditional recommendation methods, the system pays more attention to the diversity of recommended content while maintaining recommendation relevance. The results show that the personalized recommendation system constructed based on this method performs well in user assessment, fully verifying its effectiveness in improving user satisfaction. By delving into the core technologies and methods of recommendation systems, not only has it brought accurate and efficient recommendation experiences to the field of CAD design, but it has also provided valuable practical experience and research ideas for the future development of recommendation systems.

Keywords: Big Data; Machine Learning; Digital Media Art; CAD; Personalized Recommendation
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1 INTRODUCTION

As digital technology and the Internet continue to advance rapidly, DMA has emerged as a novel art form that has seamlessly integrated into various facets of people's lives. This innovative art form not only pushes the envelope of artistic expression but also offers a more extensive platform for creativity among artists and designers. Among them, using machine learning algorithms to create computational artworks has become a popular research direction. Artut [1] explores the use of machine learning algorithms to create computational artworks with humanistic and artistic value.

Data-driven creative generation and interactive art. Interactive art is a technology that enhances the interactive experience between users and artworks, allowing artworks to dynamically adjust based on user input and feedback. This work takes the history, culture, and art of Athens, Greece, as its background and processes and analyzes relevant data through machine learning algorithms to generate visual and auditory representations with humanistic and artistic value. In terms of vision, the work utilizes deep learning algorithms to transfer the style of artworks from the history of Athens, generating textures and patterns with Greek characteristics. At the same time, the work also simulates the development and changes of the city of Athens through the analysis of geographical data, presenting a dynamic and multidimensional scene of Athens to the audience.

CAD technology plays a pivotal role in this evolution, enabling designers to translate their creative visions into reality with precision and efficiency. Machine vision and new media art have gradually become important components of our daily lives and work. The intersection between these two, especially in the field of "label aesthetics," provides a unique platform for artists and social scientists to explore and express social and technological themes in innovative ways. The concept of "label aesthetics" originates from the observation of the information society. In the era of information explosion, a large amount of information is received every day. Bozzi [2] often uses various labels to classify and organize this information. This process of labelling affects not only how we understand and process information but also our way of thinking and social behaviour. By combining new media art and machine vision, we can delve deeper into and explore social and technological themes. For example, We can analyze visual tags on social media to reveal changes in social hotspots and public emotions. We can also stimulate people's reflection on the phenomenon of labelling and re-examine the role of technology in social development by creating artworks with label aesthetics. Therefore, how to realize personalized recommendations in DMA CAD design has become an urgent problem. A personalized recommendation system can select the content that best meets the user's interests from the massive amount of information by analyzing the user's historical behaviour, preferences, and needs. Calilhanna [3] explored how to visualize and vocalize rhythm theory through ski hill. The theory of rhythm is an important concept in music theory, which describes the organizational structure of rhythm and movement in music. To better understand and analyze the theory of rhythm, we can use visualization tools such as Ski Hill. Ski Hill is a visualization tool that can be used to represent the organizational structure of rhythm and movement in music. Through Ski Hill, we can present the rhythm of music in a graphical way, thereby better understanding and analyzing the theory of rhythm in music. In addition to visualization, we can also analyze and understand the theory of rhythm through vocalization.

Personalized recommendation systems have been widely used in e-commerce, social networks, online education, and other fields and have achieved remarkable results. Especially in the highly interdisciplinary field of media, machine-assisted learning has brought unprecedented opportunities and challenges to modern art multimedia. Chatzara et al. [4] explored the current situation, development trends, and key role of machine-assisted learning in this field, aiming to provide a comprehensive guide to modern art multimedia for relevant practitioners. These fields are intertwined with each other, forming a complex interdisciplinary network. With the continuous progress of digital technology, the production and consumption methods of media content are also undergoing profound changes. Artists and creators face the challenge of adapting to this change and utilizing new technologies for innovation. This automated and intelligent creative approach greatly reduces the threshold for artistic creation, allowing more people to have the opportunity to participate in artistic creation. In the field of DMA CAD design, the application of a personalized recommendation system is still in its infancy. This is mainly due to the diversity and complexity of the elements involved in the design process, which makes it difficult for the system to accurately capture the designer's intentions and needs. Emerging fields such as digital media art have brought unprecedented convenience and experience to our lives. In this context, collaborative filtering personalized recommendation systems based on digital media art scenes of the Internet of Things have emerged, aiming to enhance the personalized experience of users through the power of technology. The Internet of Things digital media art scene is a comprehensive platform that combines the sensing technology of the Internet of Things and the artistic expression forms of digital media.

Through this platform, users can more intuitively obtain information, perceive the world, and enjoy the perfect combination of art and technology. The collaborative filtering personalized recommendation system based on this scenario further optimizes the user experience and meets personalized needs. Collaborative filtering is an important technology in recommendation systems, whose basic idea is to utilize user behaviour data [5]. In addition, the creative process of designers is often nonlinear, and they may need to try to modify and adjust constantly in the design process, which also brings great challenges to the recommendation system.

Machine learning algorithms have been widely applied in the representation techniques of sculpture art space. By combining digital media technology and machine learning algorithms, sculpture art can achieve richer and more dynamic forms of expression, bringing a brand-new visual experience to the audience. Guo and Wang [6] discussed the application and value of machine learning algorithms in digital media art sculpture design. Firstly, digital media art provides new expressive techniques and creative methods for sculpture art. Traditional sculpture art is often limited by materials, craftsmanship, and production costs, making it difficult to achieve complex and dynamic forms of expression. The introduction of digital media technology has enabled sculpture art to break through traditional limitations and achieve more free and innovative expression. Through digital modelling, 3D printing, and other technologies, sculpture works can be accurately created, presenting more realistic and vivid visual effects. By combining big data and machine learning algorithms, designers can apply and innovate colours more efficiently and accurately, bringing more possibilities to artworks. He and Sun [7] explored the application and value of big data machine learning algorithms in computer-aided art colour image design. Firstly, big data technology provides massive data resources for computer-aided art colour image design. These data can not only guide the practice of colour design but also establish a theoretical system for colour design. Secondly, machine learning algorithms play a crucial role in computer-aided art colour image design.

In art courses, this intelligent teaching method provides teachers and students with a more intuitive and vivid teaching experience. He [8] discussed how to use diagrams to improve teaching quality and student learning outcomes. In such an environment, teachers can use smart devices for efficient teaching management, and students can also have a more personalized learning experience. For art courses, the intelligent classroom environment not only provides rich digital teaching resources but also provides strong technical support for schematic interactive visual teaching. Schema interactive visual teaching is a new teaching method that combines schema theory, interactive design, and visual presentation. Through multimedia, digital art, and other means, abstract art theory knowledge is concretized, enabling students to understand and master it more intuitively. In an intelligent classroom environment, schematic interactive visual teaching can better leverage its advantages and improve the teaching quality of art courses. The research of the above scholars not only provides a rich theoretical basis for DMA design but also provides strong guidance for design practice through empirical research. However, some studies are too theoretical and lack validation in practical application scenarios, making it difficult to translate their theoretical results into practical design tools or methods. Some studies have not fully considered the needs and experiences of users during the design process, resulting in design results that do not meet their actual expectations. Big data technology can process and analyze massive, diverse, and rapidly changing data to uncover hidden values and patterns. In the field of CAD design in DMA, by collecting and analyzing various data generated by designers during the design process, such as operation records, material selection, design results, etc., Machine learning algorithms as a core component of big data technology, play a crucial role in personalized recommendation systems. This type of algorithm can automatically learn useful knowledge and patterns from data without the need to artificially set too many rules and conditions. In terms of theory, this article will comprehensively apply methods from multiple disciplines. In terms of application, research results will directly serve the creative process of designers and improve their design level. Specifically, this study has the following innovations:

(1) This article systematically introduces big data technology and machine learning algorithms into the CAD design field of DMA, achieving the cross-integration of multiple disciplines such as

computer science, art design, and cognitive psychology. This interdisciplinary approach provides a new perspective and solution for solving personalized recommendation problems in DMA design.

(2) Based on the characteristics and requirements of CAD design for DMA, this article has made adaptive improvements to the personalized recommendation system. By capturing the multidimensional data generated by designers during the creative process, the constructed recommendation system can more accurately understand the designer's intentions.

(3) Through comparative experiments and user feedback analysis, the practicality of using big data-based machine learning algorithms to achieve personalized recommendations in DMA CAD design has been demonstrated.

This article aims to use big data-based machine learning algorithms to achieve personalized recommendations in DMA CAD design. Firstly, this article will systematically review and analyze the characteristics and requirements of CAD design for DMA and clarify the application scenarios of personalized recommendation systems in this field. Then, explore how to use big data technology to collect and process various data generated during the design process, as well as how to use machine learning algorithms to mine valuable information and patterns from these data. Finally, this study will construct a prototype system and validate the effectiveness and feasibility of this method through experiments.

2 THE CHARACTERISTICS AND REQUIREMENTS OF CAD DESIGN FOR DMA

Big data provides abundant data resources for environmental art and design. By analyzing market demand, user feedback, and other data, Jin and Yang [9] gain a deeper understanding of the trends and changes. These data can not only help students understand the latest trends in the industry but also provide valuable teaching references for teachers and a basis for personalized teaching. Machine learning algorithms have significant advantages in processing big data. By performing pattern recognition, correlation analysis, prediction, and other operations on a large amount of data, machine learning can help us discover the patterns and trends behind the data, providing strong support for environmental art and design teaching. Digital media design is an indispensable component. Digital media design technology provides more forms of expression and creative tools for environmental art design. Through digital media design, students can present design solutions more intuitively, collaborate better with teams, and improve the feasibility and implementation efficiency of designs. In art and design majors in universities, graphic design skills are one of the important foundational courses. Kimani et al. [10] explored how to use big data-based machine learning algorithms to investigate teacher evaluations and market demand. It is possible to gain a deeper understanding of students' performance and existing problems in graphic design skills. At the same time, big data can help us discover the potential strengths and weaknesses of students in terms of skills, providing a basis for personalized teaching. Machine learning algorithms have significant advantages in processing big data by performing pattern recognition, correlation analysis, and prediction, providing strong support for the teaching of graphic design skills. Big data provides abundant resources for contemporary art. Liu and Yang [11] have gained a deep understanding of the dynamics and trends in the art field and explored potential innovative points. Performing pattern recognition, correlation analysis, prediction, and other operations help us discover patterns and trends behind the data, providing strong support for artistic innovation. It utilizes machine learning algorithms to classify and recommend artworks, providing viewers with a more personalized artistic experience based on their interests and preferences. By performing pattern recognition, correlation analysis, prediction and other operations on data, it can discover the patterns and trends behind the data, providing inspiration and a basis for artistic innovation. At the same time, using machine learning algorithms to classify and recommend artworks can provide audiences with a more personalized artistic experience based on their interests and preferences. This design provides users with a more personalized and rich music experience, making music no longer limited to traditional listening methods. Liu [12] discussed in detail the current situation, challenges, and future development directions in this field. Context-aware technology refers to a technology that provides personalized services to users by collecting and analyzing environmental information. In music and art systems, context-aware technology can help the system understand the user's environment, context, and preferences, thereby providing users with music content that better meets their needs. When the user is exercising, the system can automatically adjust the rhythm and volume of the music based on the user's exercise data and environmental noise level so that the music matches the user's exercise state. Machine learning technology provides powerful data analysis and pattern recognition capabilities for music and art systems, which is gradually being welcomed by teachers and students as a new type of teaching tool [13]. In hardware design, high-quality pianos are selected as the main performers, high-precision sensors are installed to detect the movements of the piano keyboard, and cameras are used to capture the performer's hand movements and expressions. The core of the software part is artificial intelligence algorithms, including music style recognition, performance action analysis, intelligent scoring, etc. Through deep learning techniques, the system can automatically identify and analyze the performer's performance style and techniques and provide personalized teaching suggestions. The experimental results show that students who use this system have improved performance skills, music perception, and understanding. At the same time, students have shown strong interest and enthusiasm for this new teaching method.

Online resources provide rich materials for music appreciation courses, such as music works from different periods and styles, biographies of musicians, music reviews, etc. In addition, students can also engage in communication and cooperation to jointly explore music issues and improve learning outcomes [14]. Among them, the development of the music field is particularly remarkable. The relationship between machine learning and music is no longer simply a relationship between tools and content but a relationship of mutual influence and shaping. Sterne and Razlogova [15] explored this relationship, particularly how platformed artificial intelligence technology can achieve broader possibilities for music mastery. Machine learning has been widely applied in the field of music. Through training, machine learning models can understand and imitate specific music styles and even create brand-new music works. Platformized artificial intelligence technology provides new possibilities for music mastery. By establishing a unified platform, artificial intelligence can process large-scale music data and provide users with more personalized and high-quality music services. This platform-based artificial intelligence technology not only changes the way we acquire and appreciate music but also provides us with more tools for creating and expressing music [16].

After setting goals, it established a theoretical framework to guide the evaluation process. This can include principles of art and design, theoretical foundations of artificial intelligence and machine learning, and knowledge in related fields. Comprehensively applying these theories can provide a solid theoretical foundation for evaluation, and we can combine specific cases for analysis. For example, some art and design projects that have been successfully applied can be selected and evaluated using the GTMA framework. Through case analysis, it can summarize successful experiences, identify existing problems and improvement directions, and provide useful references for future art and design. Due to differences in cultural background, aesthetic concepts, and values, people's reactions to machine-generated artworks may also vary. Therefore, conducting cross-cultural research is crucial for gaining a deeper understanding of the acceptance and cognitive approaches of machine-generated art on a global scale. Xu et al. [17] compared user feedback from different cultural backgrounds and found commonalities and differences, providing useful references for the further development of machine-generated art. Through cross-cultural research, users in certain cultural backgrounds may pay more attention to the creativity and uniqueness of machine-generated artworks, while users in other cultural backgrounds may pay more attention to their aesthetic value and artistry. In addition, we may also find that the attitudes and acceptance levels of users towards machine-generated artworks gradually change in different cultural backgrounds. These findings will provide important references for us to gain a deeper understanding of the global development trends and influencing factors of machine-generated art.

Digital media art landscape computer-aided design, as an emerging interdisciplinary field, is of great significance in fields such as landscape design and planning [18]. By using machine learning algorithms to process and analyze these data, we can deeply explore the patterns and trends behind the data, providing useful references for designers. By utilizing big data and machine learning technologies, teachers can analyze students' learning behaviour and grades, providing them with personalized teaching advice and feedback. At the same time, students can also use machine learning algorithms for self-evaluation and reflection, improving their self-learning abilities. Computer graphics provides rich visual expression forms for art and design teaching. Zhang and Rui [19] create more three-dimensional and realistic works through techniques such as 3D modelling and rendering. The application of this technology not only improves students' modelling ability but also cultivates their perception of space, light and shadow. Secondly, image-assisted design provides students with convenient editing and processing tools. By using image processing software, students can make detailed adjustments and optimizations to their design works, filter processing, etc. This enables students to focus more on creative expression rather than tedious techniques during the creative process. In addition, computer graphics and image-assisted design have brought diverse teaching methods to art and design teaching. Teachers can combine theory with practice through multimedia courseware, online tutorials, and other means to guide students to master advanced design concepts and technologies. At the same time, students can also showcase and exchange their works through online platforms, broaden their horizons, and improve their creative skills.

3 PERSONALIZED RECOMMENDATION ALGORITHMS ARE DRIVEN BY BIG DATA

3.1 Data Collection and Processing

The CAD design of DMA is a comprehensive discipline that integrates knowledge and skills in graphics, art design, and multimedia technology. In order to succeed in this field, designers not only need to possess traditional artistic literacy and aesthetic ability but also need to proficiently master the operating skills of various CAD software and have a deep understanding of the presentation forms of digital media. Compared to traditional art and design, DMA CAD design places more emphasis on the dynamic effects and interactivity of the work. Designers need to cleverly use CAD software to create artwork that can respond to user operations and display dynamic changes. This unique dynamism and interactivity add appeal and fun to the work while also requiring designers to pay more attention to user experience and feedback in the design process, ensuring that the work can generate good interaction with users.

Designers can use more advanced and diverse tools and techniques to create more diverse and ingenious works of art. These works are not only pleasing to the eye but also find a perfect balance between technology and art in the process of DMA CAD design. These data cover multiple aspects, such as the attributes of design elements, user behaviour records, and assessment feedback of design results. Through in-depth mining and analysis of these data, designers can obtain more comprehensive and accurate information, providing strong data support for creativity. At the same time, the application of intelligent algorithms also provides designers with powerful auxiliary tools to help them complete design tasks more efficiently.

In DMA CAD design, the designer's reliance on efficient design tools and smooth design processes is self-evident. These tools and processes provide designers with strong support, helping them improve design efficiency, reduce design time, and more accurately meet customer needs. Faced with a vast array of design elements, designers need to rely on their own aesthetic judgment, and customers need to screen out the most distinctive elements and cleverly combine them to create unique works. This personalized design not only enhances the uniqueness and attractiveness of the work but also showcases the designer's infinite creativity and outstanding talent.

Through immediate feedback and continuous iterative optimization, designers can quickly identify and solve potential problems in their designs, ensuring the continuous improvement of design quality. Meanwhile, this real-time interaction greatly enhances customer engagement and satisfaction, enabling the final design results to perfectly align with customer expectations and vision.

The uniqueness and diversity of requirements in CAD design based on DMA have shown great potential for personalized recommendation systems in this field. This system can accurately push relevant design elements to designers based on their past behaviour and preferences, thereby significantly improving their work efficiency. Not only that, but personalized recommendation systems can also recommend matching design tools and plugins for designers based on their work habits and needs. At the same time, the system can recommend similar design cases or innovative inspirations to designers through in-depth analysis of their design styles and preferences, thereby helping designers break through their thinking limitations and create more distinctive works of art.

In addition, the system can provide designers with customized optimization suggestions and improvement plans through in-depth comparative analysis of a large number of excellent design works and user feedback, promoting the continuous improvement of their design skills. With the in-depth application of big data technology and machine learning algorithms, personalized recommendation systems are expected to become indispensable auxiliary tools and innovative engines in the CAD design field of DMA. In the field of DMA CAD design, data mainly comes from various operation records, material selection, and design results of designers during the design process.

The data collection stage mainly focuses on the operation logs of designers in the design software, metadata of design materials, and storage information of design results. These data exist in structured or unstructured forms and need to be collected through appropriate data scraping techniques.

In the data processing stage, the collected raw data is transformed and integrated to facilitate subsequent feature detection. This includes operations such as data format conversion, filling in missing values, handling outliers, and data normalization. In addition, data visualization technology will be used for preliminary exploratory analysis of the data to understand its distribution and potential patterns.

3.2 Feature Detection and Selection

The behaviour and preferences of designers can be described through various characteristics, such as operating frequency, material type preferences, colour matching habits, etc. The effective extraction and selection of these features are crucial for improving the performance of recommendation systems. In the feature detection stage, features reflecting the designer's preferences and needs will be extracted based on various operations and behaviours of the designer during the design process. These features can be based on statistical data such as number of operations, duration of operations, etc. It can also be based on content, such as the colour, shape, texture, etc. of the material. It can also be context-based, such as the requirements of the design task, the configuration of the design environment, etc. By comprehensively considering these characteristics, the behaviour and preferences of designers can be described more comprehensively. The basic model of personalized recommendation based on big data is shown in Figure 1.

The relationship between designers' preferences and needs, design elements, and tools may be complicated to describe with a simple linear model. Deep learning (DL) can build complex nonlinear models, better capture these relationships, and provide more accurate recommendations. Set the DL model with five hidden layers, resulting in the following terminal output:

$$y_b = f\left(\sum_{b=a}^{n} \mu_{bj} z_j\right) \qquad b = a,\cdots,b,\cdots,c \tag{1}$$

Next comes the error's backward propagation process, utilizing the defined error function:

$$E = \frac{1}{2}\sum_{q=1}^{Q}\sum_{b=a}^{c} \; t_{bq} - y_{bq} \;^{2} = \sum_{q=1}^{Q} E_Q \tag{2}$$

Using the error's reverse propagation, the margin of error consistently diminishes, drawing nearer to the prescribed value until the preset criteria for algorithmic cessation are fulfilled. Subsequently, the weights about the input-hidden layer, inter-hidden layers, and hidden layer output are fine-tuned by the ensuing formula:

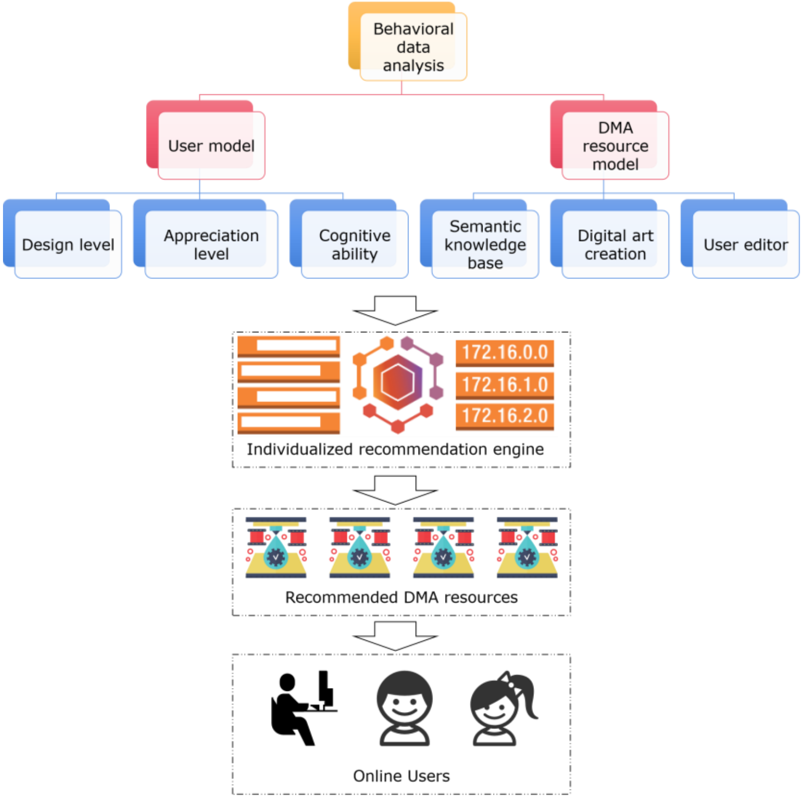

Figure 1: Personalized recommendation model.

$$\Delta\omega_{jm} = -\eta\frac{\partial E}{\partial\omega_{jm}} = -\eta\frac{\partial}{\partial\omega_{jm}}\left(\sum_{q=1}^{Q} q\right) = \sum_{q=1}^{Q}\left(\eta\frac{E_q}{\partial\omega_{jm}}\right) \tag{3}$$

Where $0 < \eta < 1$.

In the feature selection stage, the extracted features are screened and reduced in dimension by using the technology and method in the field of machine learning so as to remove redundant features, reduce computational complexity, and improve the performance of the recommendation system.

3.3 Construction and Optimization of Recommendation Models

In order to achieve accurate and personalized recommendations in the CAD design of DMA, this paper adopts a hybrid recommendation algorithm. A hybrid recommendation algorithm refers to the fusion of multiple recommendation techniques to overcome the limitations of a single recommendation technique and improve the overall performance of a recommendation system. In the field of CAD design in DMA, the preferences and behaviour patterns of designers are often influenced by various factors, including personal interests, design task requirements, fashion trends, etc. Therefore, adopting a hybrid recommendation algorithm can better adapt to this complexity. Collaborative filtering algorithms recommend similar design elements or tools by analyzing the similarity between designers, while content recommendation algorithms recommend results that meet designer preferences by analyzing the content characteristics of design elements or tools. Integrating these two algorithms can fully utilize their respective advantages and improve the accuracy and satisfaction of recommendations. This framework is based on the data layer and ensures the quality and availability of data by collecting, preprocessing, and storing multi-source data from CAD design software, user behaviour logs, and design material libraries. Furthermore, in the feature layer, we carefully extracted and selected key features that reflect the designer's intentions and needs and adapted them to different machine-learning models through feature transformation. At the model level, appropriate machine learning algorithms were selected for model training based on the characteristics of the problem and data. At the recommendation layer, we utilize trained models to provide designers with real-time and personalized recommendations and ensure the richness and novelty of recommendation results through diverse techniques. At the same time, the setting of the feedback layer allows us to continuously collect feedback data from designers, optimize and adjust recommendation results, and form a closed-loop recommendation system, continuously improving recommendation performance and user experience. The overall framework of the recommendation algorithm is shown in Figure 2.

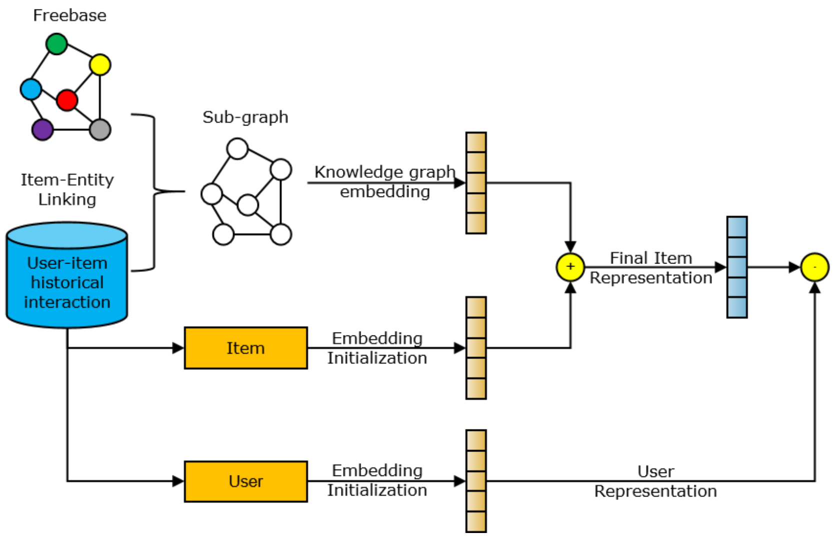

Figure 2: Overall framework of the algorithm.

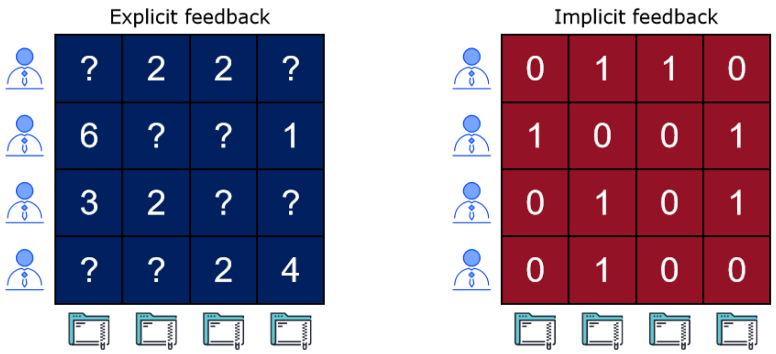

Figure 3: Explicit feedback and implicit feedback between users and projects.

Figure 3 shows the explicit and implicit feedback between users and items in the personalized recommendation. In the field of CAD design in DMA, explicit feedback usually refers to the designer's direct assessment and selection of design elements, tools, or results. This feedback can be obtained through rating systems, survey questionnaires, user feedback forms, and other means. By collecting and analyzing explicit feedback data from designers, the system can more accurately understand their preferences and needs and recommend design elements, tools, or inspirations that are more in line with their personal preferences. Implicit feedback usually refers to the behavioural data of designers during the design process, such as operational records, frequency of use of design elements, design duration, etc. These data can indirectly reflect the preferences and needs of designers without the need for designers to actively provide assessment information. By analyzing the implicit feedback data of designers, the system can automatically learn their behaviour patterns and preference patterns, thereby recommending more personalized design elements, tools, or design inspiration to them.

In the personalized recommendation system of CAD design in DMA, explicit feedback and implicit feedback usually do not exist in isolation but complement and work together. Explicit feedback provides designers with direct assessment information on design elements, tools, or results with high accuracy and credibility. Implicit feedback provides behavioural data for designers during the design process, which can more comprehensively reflect their preferences and needs. Attribute reduction is founded on the utilization of matrices. Consider the following as the decision table:

$$S = U,C,D,V,f \tag{4}$$

$M_D = m_{ij}$ is described as:

$$m_{ij} = \begin{cases} a \in C : f\ x_i,a \neq f\ x_j,a\ ,f\ x_i,D \neq f\ x_j,D \\ \varnothing \end{cases} \tag{5}$$

The algorithm's reduction foundation relies on the measure of influence, which is delineated as follows:

$$IM\ x,P,D = \left|POS_{P\cup X}\ D\right| / \left|U\right| - \left|POSP\ D\right| / \left|U\right| \tag{6}$$

Wherein P represents a conditional attribute subset, given that any attribute $x \in C - P$. Relevance embodies the significance of conditional attributes in decision-making, reflecting the magnitude of alterations in decision outcomes triggered by attribute variations within the decision table. The correlation increment is delineated as follows:

$$CONT\ P\cup\ x\ ;D - CONT\ P;D = ENT\ D\middle|P - ENT\ D\middle|P\cup\ x \tag{7}$$

In this context, P it represents a subset comprising conditional attributes while an arbitrary attribute $x \in C - P$.

The weight of each intermediate node word in the interest-spanning tree is:

$$Node\ p_j \cdot w_j = \sum_{i=1}^{k} w_i \tag{8}$$

The degree of novelty or originality associated with every intermediary node term can be described as its freshness:

$$Node\ p_j \cdot x_j = \sum_{i=1}^{k} \left(\frac{w_i x_i}{w_j} \right) \tag{9}$$

In this scenario, w_j it denotes the weight assigned to the intermediate node while representing the freshness of the entry corresponding to the intermediate node p_j. k It is used to indicate the count of child nodes associated with the node p_j. w_i It signifies the weight of the interesting entry for the child node and reflects the freshness of the interesting entry about the child node p_i.

4 ALGORITHM TESTING AND ANALYSIS

The operating system was Windows 10 Professional Edition, and Python 3.8 programming language and TensorFlow 2.5 deep learning framework were used to implement recommendation algorithms and user tag generation methods. In addition, multiple open-source datasets were used to train and test the recommendation system experimental results. Figure 4 shows the relationship between prediction accuracy and the number of iterations. The recommendation accuracy gradually improves. After approximately 60 iterations, the recommendation accuracy reached a high level, and further changes tended to flatten out. This result reflects the impact of iteration times on the performance of recommendation systems and provides a reference for selecting iteration times in practical applications.

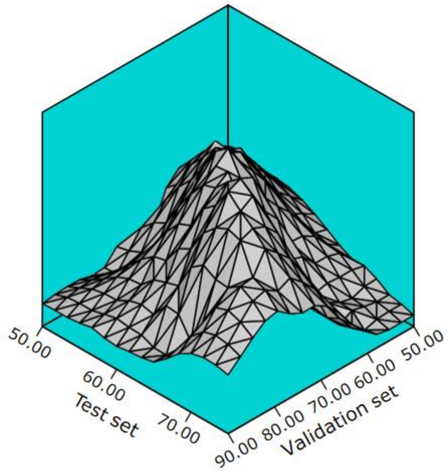

Figure 4: Relationship between iteration times and prediction accuracy.

An increase in the number of iterations helps improve the accuracy of recommendations. During the iteration process, the recommendation system gradually adapts to the designer's preferences and behaviour patterns through continuous learning and optimization. After a certain number of iterations (approximately 60 in this case), the change in recommendation accuracy tends to flatten out. This indicates that the system is approaching the optimal solution, and further increasing the number of iterations has a limited effect on improving recommendation accuracy.

When designing a recommendation system, it is not enough to simply recommend similar design solutions to users. It is also crucial to provide diverse recommendations for users to experience different content. This study uses the DL algorithm to explore the correlation between art and design information while improving recommendation accuracy and solving the problem of lack of diversity in recommendation results. Figure 5 shows the comparison of different recommendation methods in terms of similarity of recommended content. The other two methods exhibit high similarity in recommending content, which means they tend to recommend the same or similar items to users. In contrast, the method used in this article focuses more on the diversity of recommendations when recommending content with similar interests; that is, the recommended items have lower similarity between them.

A recommendation method with high similarity may lead to the homogenization of recommendation results, as well as a lack of diversity and novelty. This may reduce the attractiveness and effectiveness of the recommendation system for users. By providing different and diverse recommendation results, the system can meet the needs of users for a wide range of interests and potential favourite projects.

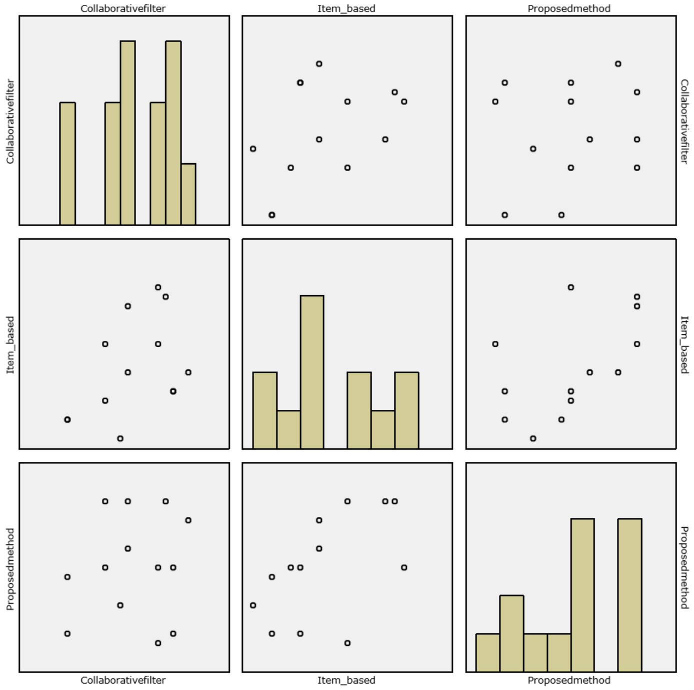

Figure 5: Similarity of recommended content.

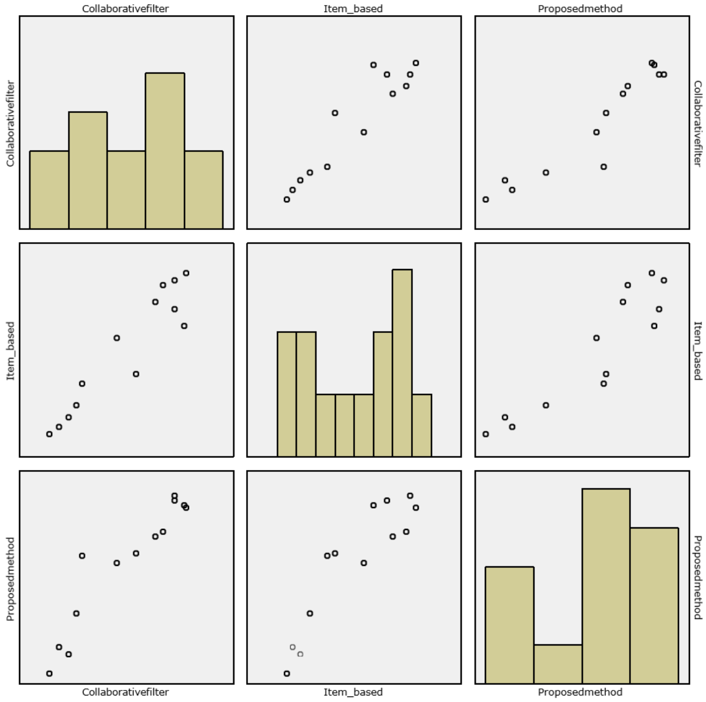

Figure 6: Changes of recall of different models on data sets.

Figures 6 and 7 show the changes in recall and accuracy of different models on data sets, respectively. The model proposed in this paper is superior to the other two models in recall and accuracy. This shows that the model in this paper can not only predict users' tags more accurately but also identify users with specific tags in a wider user group.

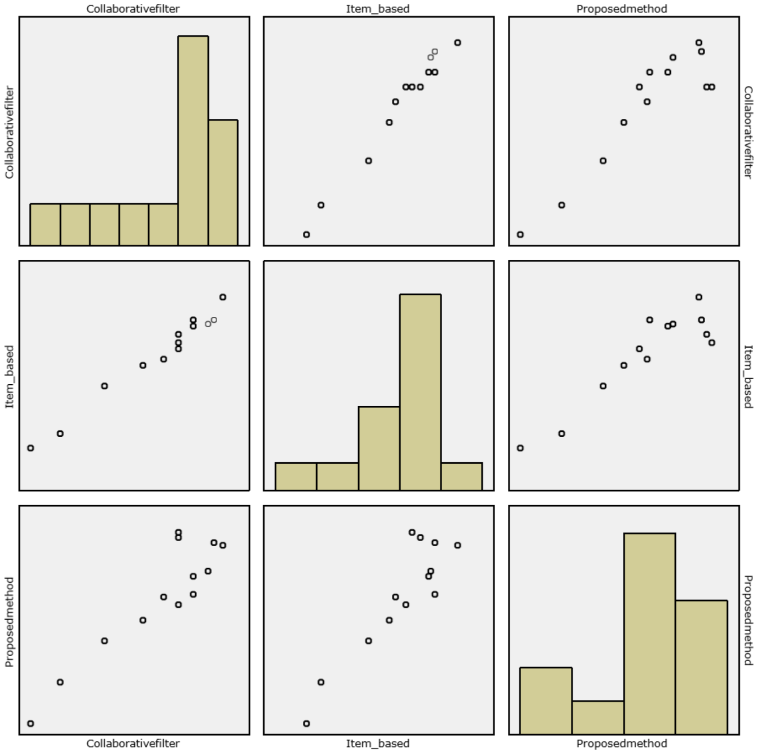

Figure 7: Accuracy changes of different models on data sets.

By adopting supervised learning methods combined with effective model design and training strategies, this paper achieved significant performance improvement in user label generation tasks. This not only improves the accuracy of user tags but also provides strong support for user profile construction and personalized recommendations in practical applications.

When users first visit the homepage of a personalized recommendation system, a series of carefully designed algorithms and strategies operate behind the system. These algorithms will deeply analyze the user's historical behaviour, preferences, points of interest, and other possible implicit and explicit feedback, thereby generating a series of resource recommendations that the user may be interested in. In order to more accurately evaluate the performance of the recommendation system and understand whether it truly meets the needs of users, we collected user assessment data on the system and visualized it in Figure 8. These assessment data include multiple aspects, such as user satisfaction with recommended content, accuracy of recommendation results, and ease of use of the system.

The user assessment results in Figure 8 show that the personalized recommendation system based on this method has achieved better user assessment. This not only verifies the practicability of this method but also shows that the system can truly understand and meet the personalized needs of users.

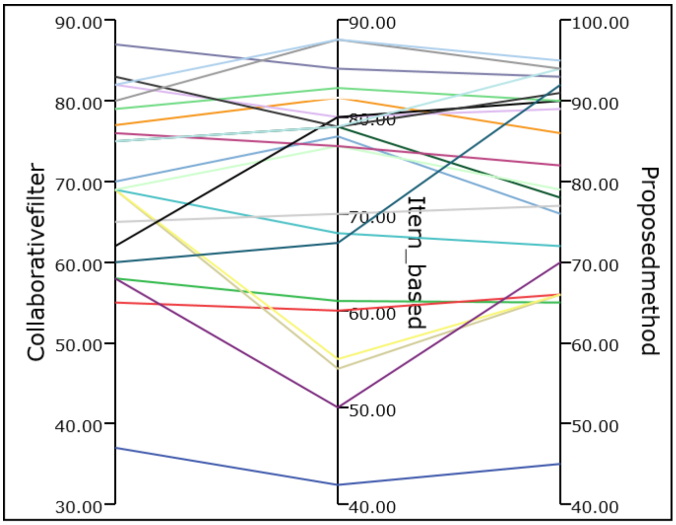

Figure 8: User's subjective assessment score.

5 CONCLUSION

Personalized recommendation systems play a crucial role in today's digital media era. Especially in the field of CAD design, an efficient and accurate recommendation system can greatly improve the work efficiency of designers while meeting their growing personalized needs. To achieve this goal, this study investigated the application of DL in DMA design recommendation systems and validated its unique advantages in feature detection, processing large-scale data, and constructing complex models. By comparing with other methods, it has been proven that emphasizing diversity can significantly improve user satisfaction when recommending content with similar interests. By collecting and analyzing user assessment data, the system's excellent performance in improving user satisfaction has been verified. These conclusions and findings have important theoretical and practical significance for promoting the further development of recommendation systems.

Ensuring that user privacy is not compromised is an important issue in the process of collecting and using user data. Research will be conducted on how to strengthen the privacy protection of user data while ensuring recommendation accuracy in order to achieve more secure and reliable personalized recommendations.

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