# The Application of CAD Combined Deep Learning Algorithms in Advertising Creative Design

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**Abstract.** In the era of digitization and informatization, advertising creative design has become a key link in product promotion, brand promotion, and marketing. Creative advertising design often involves the integration and processing of various media information, such as images, text, and audio. Computer-aided design (CAD) tools can help designers complete design tasks more efficiently and accurately. The DL algorithm can accurately infer user interests and consumption habits by analyzing user data. This article proposes a user feature identification and interest mining algorithm based on deep learning (DL) and combines it with CAD tools to achieve advertising creative design. Compared with other algorithms, it was found that the Graph Convolutional Neural Network (GCN) model has higher accuracy in user feature identification tasks. Meanwhile, the user feature identification model constructed using the GCN method received higher user evaluations in optimizing advertising creative design. The GCN method can accurately capture user interests and behavioral habits, providing more targeted guidance for creative advertising design.

**Keywords:** Computer-Aided Design; Deep Learning; Graph Convolutional Neural Network; Advertising Creative Design
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## 1 INTRODUCTION

Creative advertising design has become a key link in commodity promotion, brand promotion, and marketing. In this context, exploring a new method that can combine modern science and technology to improve the effect of advertising creative design has become the focus of attention inside and outside the industry. In the past decades, machinery, electronics, clothing, etc. The field of advertising image reconstruction is undergoing unprecedented changes. However, there are also some issues with the application. Antun et al. [1] delved into these issues and their impact on the application. The application of deep learning technology in advertising image reconstruction is becoming increasingly widespread. For example, through deep learning techniques, high-quality reconstructed images can be generated from the original images, or automatic classification and recognition of specific advertising images can be achieved. The application of these technologies improves advertising effectiveness and enhances user experience. The complexity and number of parameters of deep learning models are usually large, which makes the model prone to getting stuck in local optima, leading to unstable results. In addition, overfitting of the model may also lead to a decrease in its ability to generalize new data. However, due to various reasons such as hardware failures, software errors, etc., the training process may be interrupted or failed, resulting in unstable results. CAD tools can help designers complete design tasks more efficiently and accurately. By providing rich design resources and tools, designers can get rid of tedious manual drawing and design innovation and creativity. The position of digital advertising in smart cities is increasingly prominent. In order to better meet people's demand for digital advertising, Austin et al. [2] explored how to combine deep learning algorithms with the construction of smart city digital advertising semantic models and machine learning to achieve more efficient and accurate digital advertising placement. The smart city refers to the use of various advanced technologies and means to achieve the intelligence, networking, and informatization of various services in a city, thereby providing citizens with a better and more convenient living and working environment. Digital advertising, as an important component of smart cities, has advantages such as large information content, fast dissemination speed, and strong interactivity, which can better meet people's needs. A semantic model is a model used to describe the meaning and structure of language, which can be used for semantic analysis and understanding of digital advertising. Combining deep learning algorithms with semantic models can better achieve automated placement and personalized recommendations of digital advertising. By analyzing and learning historical advertising data through deep learning algorithms, the relationship between advertising effectiveness and advertising features can be automatically discovered, thereby achieving automated evaluation and recommendation of new advertisements.

However, although CAD tools have significantly improved design efficiency, their application in the field of advertising creative design is still limited. Traditional CAD tools lack an in-depth understanding of users' needs and interests and can't provide creative advertising design that really meets users' needs. Location-based mobile advertising has become an important trend in the advertising industry. However, maximizing the effectiveness of location-based mobile advertising and improving the accuracy and effectiveness of advertising are important issues faced by advertisers and advertising practitioners. Cheng et al. [3] explore the deep learning algorithms in location-based mobile advertising and how to maximize their effectiveness. Deep learning algorithms can predict the future behaviour and needs of users by analyzing their historical behaviour data. For example, deep learning algorithms can predict where users may go during a certain period of time and, based on this information, make corresponding advertising placements. Deep learning algorithms can evaluate the effectiveness and revenue of different advertisements by analyzing a large amount of advertising placement data. To analyze the advertising effectiveness at different times, locations, and audiences, thereby optimizing advertising strategies and improving advertising effectiveness. DL can automatically learn and identify complex patterns and laws. In user feature identification and interest mining, the DL algorithm can accurately infer users' hobbies and consumption habits by analyzing users' network behaviour, purchase records, search history, and other data, and it can provide a valuable reference for advertising creative design. The placement of traffic advertisements has become an important means of promotion. How to accurately predict the effectiveness of traffic advertising and optimize its placement strategy is an urgent problem that needs to be solved. Guo et al. [4] proposed a dynamic graph convolutional network for traffic advertising prediction based on the Laplace matrix estimation of latent networks. The Laplace matrix is a matrix that describes the connection relationships between nodes in the graph and can reflect the topological structure of the graph. By estimating the Laplace matrix, potential network relationships can be discovered, thereby optimizing the placement of traffic advertisements. In traffic advertising prediction, potential networks can be represented as the connections between advertising audiences, the associations between advertising and products, and so on. By estimating the potential network connections, it is possible to better understand the behaviour and preferences of advertising audiences, thereby optimizing advertising placement strategies. It can capture the dynamic changes of graph data and the complex relationships between nodes and is suitable for dynamic scenarios such as traffic advertising placement. DGCN can better process graph data with temporal characteristics by independently updating node features and network structure at each time step.

Deep learning algorithms have become indispensable tools in advertising creative design. Especially in the innovative design of art advertising panels, the combination of these two technologies can unleash greater potential. He and Sun [5] discussed deep learning algorithms in the innovative design of art advertising panels. In the design of art advertising panels, deep learning algorithms provide designers with more design inspiration. By utilizing deep learning algorithms to automatically recognize and understand images, we can extract useful design elements, such as lines, shapes, colours, etc., from a large amount of image data. These design elements can be automatically combined and optimized to form new art advertising panel design schemes. By using computer-aided design software, we can free designers from the tedious design process. For example, the software can automatically complete the layout, layout, colour matching, and other tasks of art advertising panels based on the design requirements and parameters provided by designers.

With the rapid development of the advertising industry, accurately classifying and creatively designing advertising images has become an important task. Traditional image classification methods are usually based on pixel or regional features, which cannot fully explore the global and local information of advertising images. In recent years, the combination of hyperspectral convolutional networks (HS-GCN) and deep learning algorithms has provided new solutions for the creative design of advertising images. Hong et al. [6] explored the classification application of combining hyperspectral convolutional networks with deep learning algorithms in creative advertising image design. Hyperspectral Graph Convolutional Network (HS-GCN) is a convolutional neural network specifically designed for hyperspectral images. Combining hyperspectral convolutional networks with deep learning algorithms can fully leverage their advantages. Firstly, HS-GCN is used to extract features from hyperspectral advertising images and obtain global and local information about the images. Creative designs are made based on the content and semantic information of the images. In addition, HS-GCN and deep learning algorithms advertise image classification and creative design. With the acceleration of urbanization and the rapid development of intelligent transportation systems, the design and placement of traffic advertisements have become an important means of promotion. How to accurately capture the spatiotemporal behaviour of users and design attractive and effective advertisements based on this is an urgent problem that needs to be solved. Hu et al. [7] proposed a traffic advertising design. Spatiotemporal Graph Convolutional Neural Network (STGCN) is a neural network designed specifically for spatiotemporal data, which can effectively process data with spatiotemporal correlations. STGCN can convert spatiotemporal data into graph data and use Graph Convolutional Neural Network (GCN) for feature extraction and classification. In traffic advertising design, STGCN can capture the spatiotemporal behaviour of users and use it as a basis for precise advertising placement. The Graph Learning Spatiotemporal Graph Convolutional Neural Network (G-STGCN) is a method that introduces graph learning on the basis of STGCN. G-STGCN can utilize existing graph data for learning and use it as a basis for predicting and classifying new graph data. In traffic advertising design, G-STGCN can use user spatiotemporal behaviour data and learned knowledge graphs to accurately determine user interests and needs and, based on this, design attractive and effective advertisements.

The advertising industry is facing unprecedented challenges and opportunities. In this process, deep learning algorithms. Especially in the field of environmental advertising art design, CAD-assisted design software combined with deep learning algorithms can unleash greater potential. Jin and Yang [8] create and edit various advertising works such as billboards, logos, posters, etc. By combining deep learning technology, CAD-assisted design software can achieve a more intelligent and automated design process. Environmental advertising art design refers to the combination of advertising information and environmental scenes, conveying advertising information through various means, such as visual and auditory. In the traditional teaching process, students usually need to master various design software and manual production skills in order to complete the design and production of environmental advertising works. However, this method is inefficient. Through CAD-assisted design software under deep learning, students can more efficiently design and produce environmental advertising works. With the rapid development of technology and digital transformation, the advertising industry is facing unprecedented challenges and opportunities. As an important part of the advertising market, the creative design and effectiveness of online advertising directly affect a company's brand image and marketing effectiveness. In recent years, the combination of computer-aided design and deep learning algorithms has provided new solutions for the creative design of online advertising. Kim et al. [9] explored how to utilize this combination to optimize the contract design of online advertising and enhance the effectiveness of advertising placement. By using deep learning algorithms to learn from a large number of advertising samples, innovative and attractive advertising ideas can be automatically generated. The analysis of user behaviour data using deep learning algorithms can accurately identify the accuracy of advertising placement. By using deep learning algorithms to monitor and provide real-time feedback on advertising effectiveness, it is possible to adjust advertising creativity in real time to improve advertising effectiveness. The contract design of online advertising refers to the agreement between advertisers and advertisers, including the advertising placement time, location, target audience, and evaluation of placement effectiveness. In traditional contract design, a large amount of manual research and negotiation is often required.

With digital transformation, the advertising industry is facing unprecedented challenges and opportunities. In this process, although these technologies can improve the design quality and effectiveness of advertising, their poor application skills are still a concern. Kimani et al. [10] investigated the application skill gap of CADA design and deep learning algorithms in advertising creative design for art and design majors in universities. Deep learning algorithms are a type that can automatically form large amounts of data and perform autonomous learning. The analysis of user behaviour data using deep learning algorithms can accurately identify the audience and improve the accuracy of advertising placement. By using deep learning algorithms to monitor and provide real-time feedback on advertising effectiveness, it is possible to adjust advertising creativity in real time to improve advertising effectiveness. Through this survey, we found certain skill gaps when applying CADA design and deep learning algorithms for advertising creative design. To solve this problem, we need to strengthen software operation training, increase basic courses in mathematics and programming, and increase practical experience. Through the DL algorithm, users' network behaviour, purchase records, search history and other data are deeply mined and analyzed to identify users' characteristics and interests. Then, take these user characteristics and interests as input and use CAD tools to carry out creative advertising design. Compared with traditional research, this article has the following innovations:

⊖ This article develops a DL-based user feature identification and interest mining algorithm. By analyzing user network behaviour, purchase records, search history, and other data, this algorithm can accurately identify user characteristics and interests.

⊜ By combining DL and CAD tools, the method proposed in this article can achieve individualized advertising design. Based on the characteristics and interests of users, generate advertising creative design solutions that meet their needs and make real-time adjustments through DL algorithms.

⊛ The traditional advertising design process often relies on the experience and creativity of designers, requiring a lot of manual intervention. This method can achieve intelligence in advertising design and reduce the complexity of manual operations. Designers only need to input relevant user data and design requirements, and the system can automatically complete the process of user feature identification, interest mining, and advertising creative design.

The goal is to advertise creative design based on DL and CAD tools to meet the diverse needs of modern markets. The research content includes 1) studying the application of the DL algorithm in user feature identification and interest mining; 2) Research how to combine the results of DL with CAD tools to achieve efficient advertising creative design; 3) Research the implementation and application of DL based advertising creative optimization algorithms.

## 2 THEORETICAL BASIS

In this process, deep learning algorithms and computer-aided design (CAD) software have become indispensable tools in advertising creative design. 3D Convolutional Neural Networks (3D CNNs) especially have significant advantages in processing complex 3D data. Lee et al. [11] explored how to use 3D CNN combined with 3D CAD models and gradient visual interpretation to achieve automatic recognition and understanding of advertising creative design features. 3D CAD models are a method of using computer technology to assist designers in creative design. It can help designers achieve more precise and flexible control in the creative design process. By combining 3D CAD models with 3D CNN, we can fully utilize the advantages of these two technologies to achieve more efficient and accurate advertising creative design. Gradient visual interpretation is a machine learning technique that interprets the decision-making process of convolutional neural networks by calculating gradient directions. By combining gradient visual interpretation with 3D CNN, we can better understand the feature recognition process of advertising creative design. Specifically, gradient visual interpretation can help us understand the key features and design elements that 3D CNN focuses on when processing 3D CAD models, thereby providing designers with more references and insights. With the rapid development of technology and digital transformation, the advertising industry is facing unprecedented challenges and opportunities. Especially when we combine computer-aided design with deep learning algorithms, this technology can unleash greater potential and bring more innovation and value to advertising creative design. Rahman et al. [12] design with deep learning algorithms in advertising creative design. Computer-aided design using designers in creative design. Deep learning algorithms are a type that can automatically extract large amounts of data and perform autonomous learning. When we combine computer-aided design with deep learning algorithms, we can unleash greater advantages. Specifically, computer-aided design can provide fast and efficient design tools and methods, helping designers achieve more precise and flexible control in the creative design process and providing designers with more design inspiration and references. By combining the two, we can achieve a more intelligent and automated advertising creative design process.

Through CAD software, Ruediger et al. [13] can conveniently perform a series of operations such as modelling, rendering, and modification, improving the efficiency and accuracy of the design. However, relying solely on CAD software cannot meet the growing design needs. To better address this challenge, we can combine transfer learning algorithms to expand and reuse CAD data, thereby achieving more efficient and accurate advertising design classification. CAD data is a crucial resource in architectural and advertising creative design. These data include information on building models, as well as images, text, videos, and other content involved in advertising design. In advertising design classification, transfer learning algorithms can help us apply knowledge obtained from one advertising design to another, thereby achieving faster and more accurate classification. By using deep learning algorithms to monitor and provide real-time feedback on advertising effectiveness, we can adjust advertising design plans in real time to improve advertising effectiveness. Deep learning algorithms can be used to analyze user feedback and understand the audience's focus on advertising creative design, providing more reference and optimization directions for future advertising creative design. The application of computer technology has become increasingly common. Especially in advertising creative design, how to use massive data to help artists better create is a hot research topic. Salimbeni et al. [14] explored a machine learning application based on Giorgio Morandi's still life advertisement, which utilizes a three-dimensional convolutional neural network (3D CNN) to analyze and predict the three-dimensional composition in advertisements, helping artists make better decisions during the creative process. Machine learning is an artificial intelligence technology that automatically recognizes patterns and makes predictions by learning large amounts of data. In the field of artistic creation, machine learning can play an important role. For example, by analyzing the works of master painters, we can automatically extract their features in composition, colour, brushstrokes, and other aspects, thereby providing valuable references for artists. In addition, machine learning can extract information related to artistic creation from a large amount of user feedback, such as the audience's preference for a certain style or element, thereby providing artists with real-time and personalized feedback. By using 3D CNN, we can automatically extract features related to 3D composition from preprocessed images. Next, we need to train a classifier or regressor to predict the composition style that artists may adopt based on these features, which can use transfer learning methods to apply models that have already been trained on other datasets to this problem.

The advertising industry is facing unprecedented challenges and opportunities. In this process, CAD-assisted design and deep learning algorithms have become important tools and means. Shivegowda et al. [15] explore how to combine CAD-assisted design with deep learning algorithms to achieve more efficient and accurate advertising manufacturing processes in architectural design. CAD assists designers in creative design. In architectural design advertising, CAD-assisted design can help designers achieve more precise and flexible control in the creative design process. Thereby improving the efficiency and quality of design. Deep learning algorithms are machine learning techniques that use images and text in advertisements. By analyzing this information, deep learning algorithms can automatically generate ideas and suggestions related to advertising, providing designers with more inspiration and references. By using deep learning algorithms to monitor and provide real-time feedback on the effectiveness of advertising placement, we can adjust the creative design scheme of architectural design advertisements in real-time to improve the effectiveness of advertising placement. In advertising creative design, the accuracy of image detection is crucial for product promotion and promotion. Srivastava et al. [16] explore the fast rendering in advertising creative design. A deep learning image detection algorithm is a machine learning algorithm that learns and recognizes image data through deep neural networks. Classify and recognize them, thereby improving the accuracy and efficiency of image detection. In advertising creative design, fast rendering is very important. Fast rendering refers to the use of computer graphics technology to present three-dimensional models, animations, and other visual effects of advertising design in the form of images. By quickly rendering, designers can better evaluate the visual effects and interactivity of advertising design, thereby better-adjusting design parameters. Deep learning image detection algorithms can automatically extract image features and classify and recognize them by learning from a large amount of image data. This enables deep learning image detection algorithms to better handle complex advertising design scenes and details, thereby improving rendering quality.

Online advertising has become an indispensable part of marketing strategies. However, how to effectively embed product or service information into advertisements to attract the attention of target audiences and improve conversion rates has always been a core challenge in advertising design. In recent years, deep reinforcement learning algorithms have achieved significant results in many fields, but their application in advertising design is not yet mature. Yan et al. [17] converted graph data into matrix form and extracted features using convolution operations. In advertising design, GCN can convert advertising elements (such as text, images, videos, etc.) into graph data and use its powerful feature extraction ability to extract features related to the target audience, thereby achieving precise delivery. It enables intelligent agents to interact in the environment and learn optimal strategies to achieve complex tasks. In advertising design, deep reinforcement learning can be used to adjust advertising elements automatically to maximize the attention and conversion rate of the target audience. How to effectively recommend product advertisements to users has become an important issue. Traditional recommendation methods are usually based on rules or statistical models and cannot handle large-scale, high-dimensional, and complex data well. In recent years, the application of deep learning and distributed representation in recommendation systems have gradually received widespread attention and application. Zhou [18] discussed the user behaviour model and product feature extraction results; a recommendation model is constructed using deep learning algorithms to recommend suitable product advertisements to users based on their interests and needs. Using distributed expression technology to transform user behaviour data into low-dimensional feature vectors for better user behaviour modelling and recommendation. Transform product images, descriptions, and other information into distributed expression vectors for better product feature extraction and classification. Train a deep learning model using preprocessed data, including tasks such as user behaviour modelling and product feature extraction, and apply the training results to advertising recommendations. Train a distributed expression model using features extracted from deep learning models, including tasks such as user feature representation and product information compression, and apply the training results to advertising matching.

## 3 USER FEATURE IDENTIFICATION AND INTEREST MINING BASED ON GCN

"Depth" usually refers to the number of layers in a neural network. Through deep structure, the DL model can learn representation from a large number of unlabeled or semi-labeled data and automatically extract complex features. In recent years, DL has made remarkable achievements and a recommendation system. In the field of advertising, DL technology can be applied to user portrait construction, click rate prediction, advertising recommendation, and other tasks. CAD tools can provide rich design resources and tools to help designers complete design tasks more efficiently.

CAD tools can be used to make advertising images, animations, and videos. Through CAD tools, designers can quickly complete the design tasks of advertisement layout, colour matching, and font selection. The DL algorithm can deeply mine and analyze the needs and interests of users and obtain their features and interests; then, the designer uses CAD tools to design advertisements creatively based on these user characteristics and interests. This combination approach combines the data analysis capabilities of DL with the design capabilities of CAD tools, providing a new solution for advertising creative design. For example, designers can use DL algorithms to generate design schemes for advertising layout, colour matching, and font selection based on user interests and characteristics. Then, these design schemes are used as input parameters for CAD tools for rapid production. By analyzing user network behaviour, purchase records, search history, and other data, the DL algorithm can accurately identify user characteristics and interests. These features and interests can be used to guide the creative design of advertisements, making them more in line with user needs.

At present, various DL algorithms have been applied in user feature identification and interest mining. For example, CNN can be used for image identification and analysis of user visual preferences; RNN can be used for sequence data modelling and analyzing user behaviour habits; Autoencoder can be used for data dimensionality reduction and extracting hidden features of users. User behaviour on the Internet is becoming increasingly diverse, and the generated data is also becoming increasingly massive. How to accurately identify user characteristics and interests from these data is an important issue facing the field of advertising creative design. Traditional user feature identification and interest mining methods are mainly based on statistical analysis and machine learning algorithms. Although they have achieved certain results, there are still some problems, such as low utilization of data and limited processing ability for complex relationships. To address these issues, this article proposes a user feature identification and interest mining method based on GCN.

GCN is a DL model based on graph-structured data. Unlike traditional CNN, GCN can handle irregular graph-structured data and effectively capture complex relationships between nodes. The basic idea of GCN is to aggregate the features of nodes and the information of neighbouring nodes by performing convolution operations on the nodes of the graph in order to obtain a new representation of the nodes. This new representation can capture the local structure and global information of nodes, thereby improving the performance of tasks such as node classification and link prediction. The basic principle of GCN is shown in Figure 1.

By identifying and analyzing the characteristics of users, advertising designers can understand their needs and interests and thus design advertisements that better meet their needs. This article proposes a user feature identification method based on GCN. This method includes the following steps:

⊖ Building a user relationship graph: Construct a graph structure based on user attributes and behaviour data, where each node represents a user, and the edges between nodes represent the relationships between users. This graph structure can be an undirected or directed graph, and the weights of edges can be set based on the strength of the relationship.

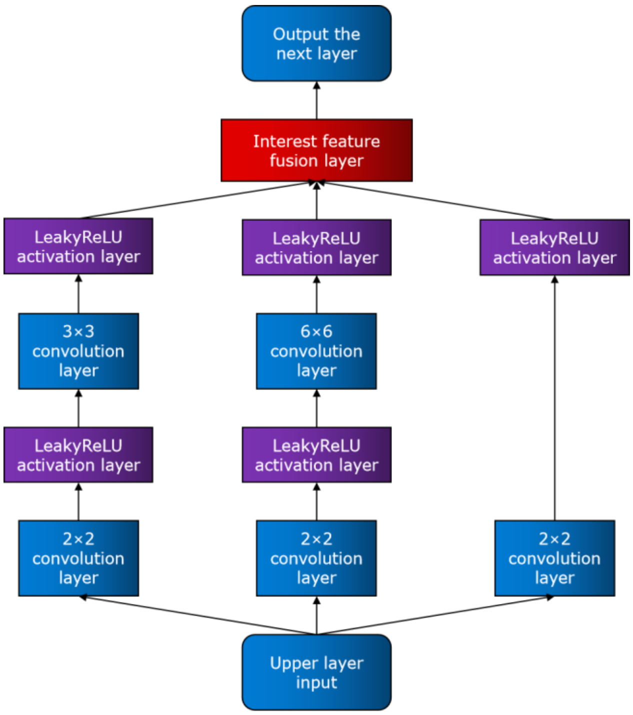


**Figure 1**: Basic principle of GCN.

㊂ Graph convolution operation: Using GCN to perform convolution operation on the constructed user relationship graph. When performing convolution operations on each node, the features of that node and the information of neighbouring nodes are aggregated to obtain a new representation of that node. This process can be iteratively optimized through multi-layer GCN to capture deeper node relationships.

㊃ User feature detection: Extracting feature vectors for each user by performing node classification or link prediction tasks on the convolved user relationship graph. This feature vector contains both local and global information of the user, which is used in subsequent advertising creative design tasks.

Based on the predefined initialization strategy and parameters, the weights in the GCN model are set to their initial values. Typically, this entails going through each layer of the model and assigning suitable starting values to each weight based on the chosen strategy. By pre-training specific network layers on a related task, a more optimal weight initialization can be achieved for those layers. Subsequently, this hierarchical weight structure is transferred to the GCN model as an integral component of intelligent initialization. The process of initialization involves the following steps:

$$W \sim U\left[-\frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}}, \frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}}\right] \tag{1}$$

Where $n_{in}, n_{out}$ is the number of input and output neurons at the convolution kernel weight.

The layer represents a novel aspect of GCN, distinguishing it from conventional fully connected neural networks. Its primary purpose is to extract features related to users' interests. By incorporating two groundbreaking theories, namely local perception and parameter sharing, it effectively accomplishes the task of automatic feature detection:

$$X^L = f(Z^L) = f(X * K^L + b^L) \tag{2}$$

Optimizing network parameters through network training to reduce losses:

$$L = \sum_{i=1}^{N} L(W,(y,x_1,x_2)^i) \tag{3}$$

In addition to user feature identification, user interest mining is also an important part of advertising creative design. The process of extracting user interest features based on GCN is shown in Figure 2.

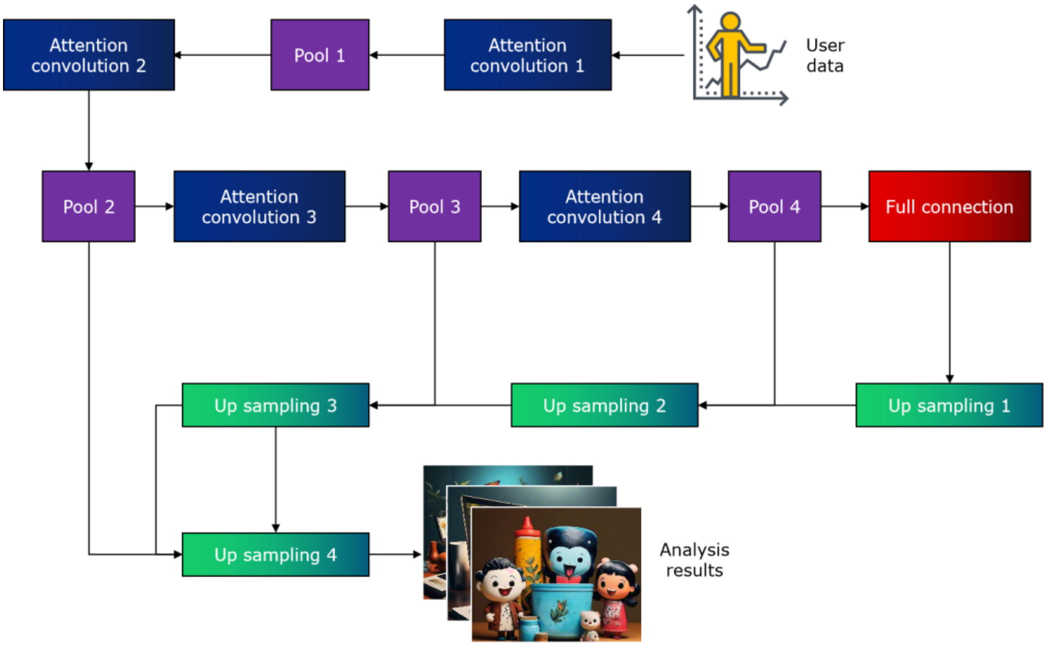


**Figure 2**: User interest feature detection.

Construct a graph structure based on user browsing history and click behaviour data, where each node represents a user or advertisement, and the edges between nodes represent user interaction behaviour with advertisements. This graph structure can be a bipartite graph, where users and advertisements are located in different sets of nodes. When performing convolution operations on each node, the features of that node and the information of neighbouring nodes are aggregated to obtain a new representation of that node. This process can be iteratively optimized through multi-layer GCN to capture deeper node relationships and semantic information of advertisements. By performing tasks such as node classification or link prediction on the convolutional user advertisement interaction graph, information such as interest preferences and satisfaction of each user towards different types of advertisements can be extracted. This information can be used for subsequent advertising creative design tasks.

## 4 CAD OPTIMIZATION OF ADVERTISING DESIGN BASED ON USER PREFERENCE ANALYSIS

After understanding user preferences and behaviour patterns, this information can be used to guide the optimization of advertising design. Specifically, this method can transform user preferences and behaviour patterns into requirements and constraints for advertising design and then use CAD tools for automated or semi-automated optimization of advertising design. The fusion diagram of advertising creative design features is shown in Figure 3.

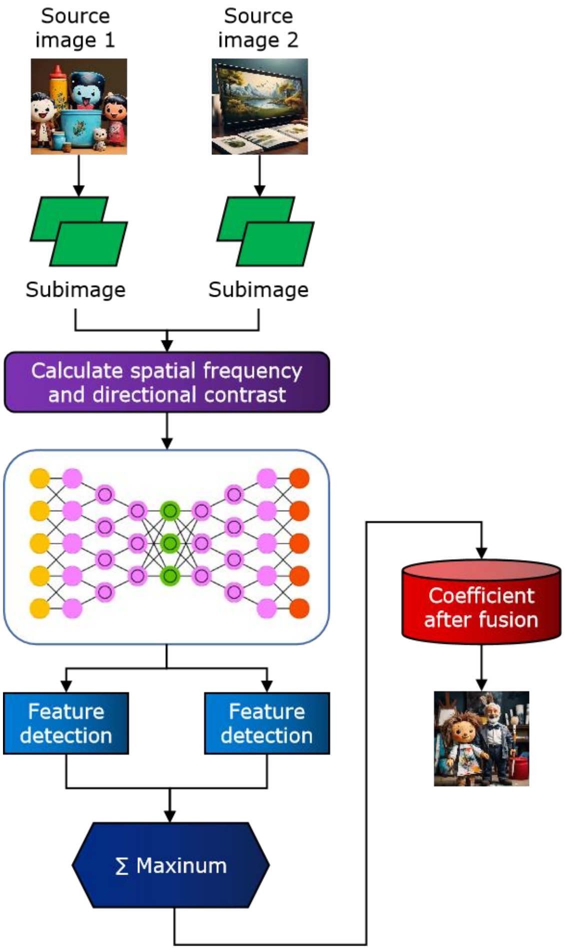


**Figure 3**: Feature fusion framework of advertising creative design.

$$P(W)=P(w_1)P(w_2|w_1)P(w_3|w_1w_2)\cdots P(w_n|w_1w_2\cdots w_{n-1}) \tag{4}$$

The Naive Bayes (NB) model represents a paradigm based on probability and statistics, with its mathematical foundation rooted in Bayes' theorem. The fundamental concept of classification involves an initial learning phase using a set of training samples. During this phase, statistical techniques are employed to ascertain the conditional probabilities of various categories. These probabilities, along with prior probabilities derived from statistical data, facilitate the classification process. Specifically, within the NB classification framework, the assumption of conditional independence among characteristic attribute variables within data samples underlies the subsequent deductions:

$$P(C_i|A)=\frac{P(A|C_i)P(C_i)}{P(A)} \tag{5}$$

$$P(a_k|C_i)=\frac{s_{ik}}{s_i} \tag{6}$$

Where $S_{ik}$ is the number of samples with the attribute value of $a_k$ and class $C_i$.

Optimize the layout of advertisements based on user visual habits and browsing paths, making important information more prominent and easily accessible. For example, for mobile users, a concise design style can be adapted to meet the needs of small screens and fast browsing. Based on user colour preferences and emotional reactions, the colour matching and contrast of advertisements can be optimized to make them more attractive and easy to remember. For example, for young users, bright colours and contrasting combinations can be used. Optimize the font selection and layout of advertisements based on user reading habits and font preferences, making the text easier to read and understand. For example, elderly users, use large fonts and clear layouts to facilitate their understanding of advertising content. Based on user interaction habits and feedback data, optimize the dynamic effects of advertisements to make them more vivid and interesting. For example, incorporating interactive elements and gamified design to increase user engagement and stickiness. Establish a historical preference similarity set according to the similarity criterion of interest points;

$$sim(i,j)=\frac{\sum_{u\in U}(R_{ui}-\bar{R}_i)(R_{uj}-\bar{R}_j)}{\sqrt{\sum_{u\in U}(R_{ui}-\bar{R}_i)}^{2}\sqrt{\sum_{u\in U}((R_{uj}-\bar{R}_j)^2}} \tag{7}$$

The above formula $U$ represents the set of all users, $R_{ui},R_{uj}$ the historical preference data of users for advertising graphic in a certain time period, and the average value of historical preference score data of advertising graphic.

After the sorted list is obtained, the user interest characteristic value to be used is finally calculated:

$$pref_{HOT}(u,i)=1-\frac{R_i}{N} \tag{8}$$

## 5 RESULT ANALYSIS AND DISCUSSION

A series of experimental tests were conducted in this section. Firstly, a large amount of user and advertising data was collected, including user browsing history, click behaviour, purchase records, and advertisements. Then, divide these data into training and testing sets and use the DL algorithm to train user interest models, behaviour models, and ad click-through rate prediction models. Then, based on different optimization strategies, use CAD tools to design advertisements and generate multiple advertising design schemes. The advertising creative design rendering in Figure 4 displays multiple advertising works, which not only fully showcase product features but also consider the user's aesthetic experience.

These advertising works all showcase the main features and advantages of the product very well. Through clear images and attractive colour combinations, users can quickly understand the appearance, functionality, and usage scenarios of the product. These advertising works are very in line with the user's aesthetic experience in terms of design style and colour matching. They adopt a simple and atmospheric design style, avoiding overly cumbersome and complex visual elements, allowing users to quickly grasp the key points.

From the network convergence trend chart (Figure 5), it can be seen that the algorithm has converged to a certain extent after 36 iterations. This indicates that the optimization method based on the model proposed in this article is effective and can effectively complete user feature identification and interest mining.

The convergence speed of the algorithm in the first few iterations is relatively fast, indicating that the model already has good feature identification and interest mining capabilities during initialization. As the number of iterations increases, the convergence speed gradually slows down, indicating that the model is gradually approaching the optimal solution. After 36 iterations, the algorithm has converged to a certain extent. That is, the loss function value has stabilized. This indicates that the model has learned the user's features and interest preferences and can effectively recognize them.

Figure 4: Advertising creative design renderings.

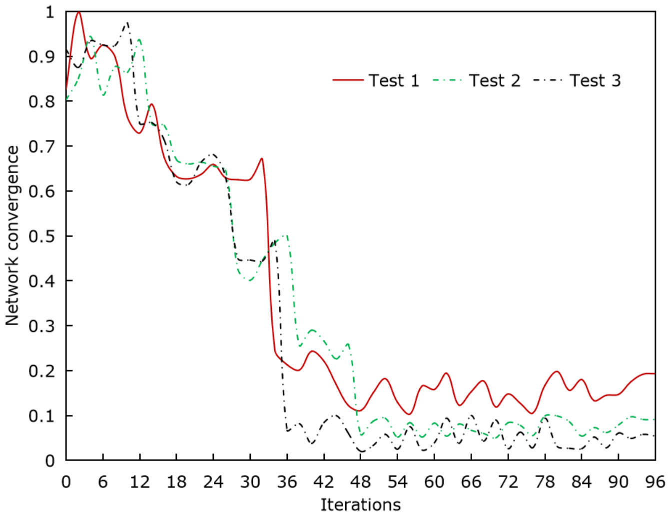


Figure 5: Network convergence trend diagram.

In addition, there was no obvious overfitting or underfitting phenomenon in the model. This indicates that the model and optimization methods have good generalization ability in handling user feature identification and interest-mining tasks. Through the application of this method, we can interest users and provide targeted guidance for advertising creative design.

Figure 6 shows the comparison of accuracy between the GCN model and other algorithms in user feature identification tasks. The accuracy of the GCN model is higher than that of the RNN and CNN models.

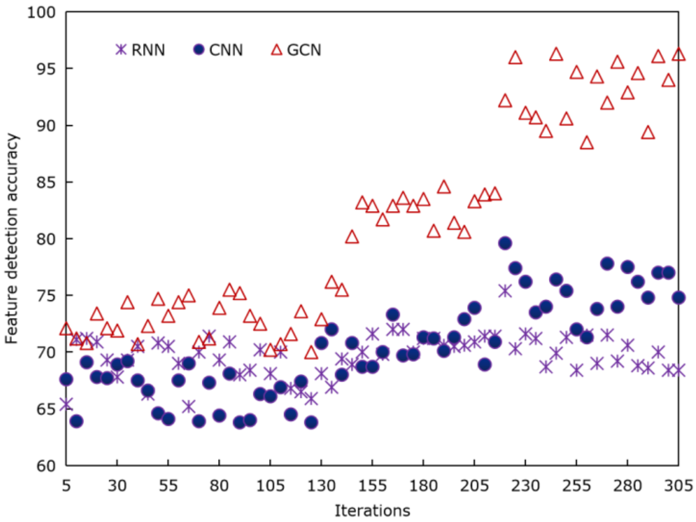


**Figure 6**: Accuracy of user feature identification.

GCN is a neural network specifically designed for processing graph data. In user feature identification tasks, the relationships and interactions between users can be represented as a graph structure, so GCN can fully utilize the topological information and node features in graph data for learning and identification. In contrast, RNN and CNN have better performance in processing sequence data and image data but may not fully utilize structural information in processing image data, leading to a decrease in identification accuracy. GCN can effectively extract features and correlation information between nodes through graph convolution operations and can propagate and update information based on the topological structure of the graph. This enables GCN to better capture the complex relationships and potential features between users.

Figure 7 shows the subjective rating results of advertising design works created using different methods. From the subjective rating results, the user feature identification model constructed using the GCN method achieved higher user evaluations in advertising creative design optimization, reaching over 85.

The high accuracy of the GCN method in user feature identification enables advertising creative design to grasp user needs more accurately. By accurately identifying the interests, preferences, and behavioural habits of users, advertising creative design can be more closely aligned with their psychological expectations. Preferences and behavioural patterns in advertising creative design can be more flexible in creative conception and design adjustments, meeting the individualized needs of users. By balancing creativity and practicality, advertising creative design can attract users' attention while conveying clear and effective information.

Advertising creative design plays an important role in modern marketing, and its success largely depends on the accurate grasp of user needs and preferences. By comparing with other algorithms (RNN, CNN), it was found that the GCN model has a higher accuracy in user feature identification tasks. This is mainly attributed to the structural advantage of the GCN model in processing graph data, which can fully utilize the topological information and node features in the user relationship graph for learning and identification. The user feature identification model constructed using the GCN method received higher user evaluations in optimizing advertising creative design. The GCN method can accurately capture user interests, preferences, and behavioural habits, providing more targeted guidance for advertising creative design.

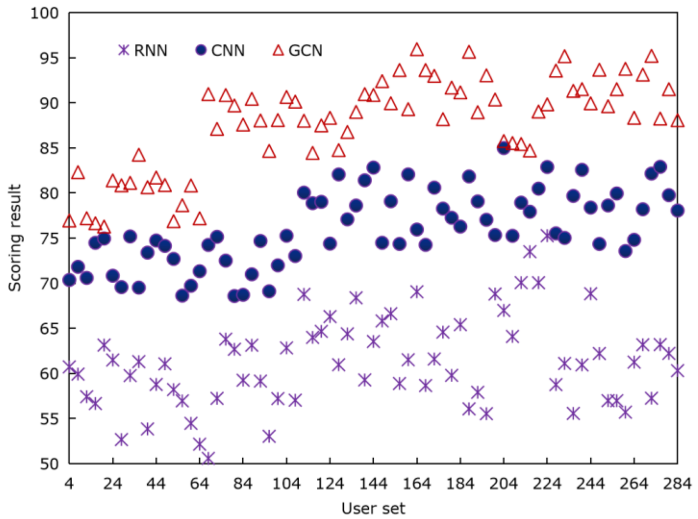


**Figure 7**: Subjective scoring results.

With the continuous growth of big data technology, data-driven creative design will become a trend in the advertising industry. Through deep mining and analysis of massive amounts of user data, advertising creative design can more accurately grasp the needs of users. With the integration and growth of different industries and fields, cross-border integration and innovation will become important directions in advertising creative design. Through cooperation and communication with other industries and fields, advertising creative design can draw more inspiration and resources. In future advertising, creative design, social responsibility, and sustainable development will become important considerations. Advertising content needs to focus on social hot topics, convey positive values, and promote sustainable growth of the industry.

## 6 CONCLUSION

Traditional CAD tools lack a deep understanding of user needs and interests and cannot provide advertising creative design that truly meets user needs. This article develops a DL-based user feature identification and interest mining algorithm. By combining DL and CAD tools, this method can achieve individualized advertising design. Based on the characteristics and interests of users, designers can use CAD tools to quickly generate advertising creative design solutions that meet their needs and make real-time adjustments through DL algorithms. The GCN method has significant advantages in user feature identification, as its structural characteristics enable it to fully utilize the topological information and node features in the user relationship graph for learning and identification. Compared to other algorithms, such as RNN and CNN, the GCN model exhibits higher accuracy. Applying the GCN method to advertising creative design optimization can effectively improve user satisfaction and evaluation of advertising works.

In summary, the integration of CAD and DL provides a new approach and technical support for advertising creative design, which helps to improve the quality and user experience of advertising works. In the future, with the continuous progress and innovation of technology, we look forward to seeing more advanced user feature identification methods applied in advertising creative design, promoting the sustainable growth of the advertising industry.

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