Optimal Measurement of Visual Transmission Design Based on CAD and Data Mining

Wenchao Wu[1,2], Irwan Syah Md Yusoff[3], Hassan bin Hj Alli[4] and Qi Wang[5]

[1]Faculty of Arts, North University of China, Taiyuan 030051, China, 20130020@nuc.edu.cn
[2]Department of Industrial Design, Faculty of Design and Architecture, University Putra Malaysia, 43400 UPM Serdang, Malaysia, 20130020@nuc.edu.cn
[3]Department of Resource Management & Consumer Studies, Faculty of Human Ecology, University Putra Malaysia, 43400 UPM Serdang, Malaysia, irwansyah@upm.edu.my
[4]Department of Industrial Design, Faculty of Design and Architecture, University Putra Malaysia,43400 UPM Serdang, Malaysia, halli@upm.edu.my
[5]Modern Languages and Communication Faculty, University Putra Malaysia,43400 UPM, Serdang, Selangor Malaysia, gs63372@student.upm.edu.my

Corresponding author: Wenchao Wu, 20130020@nuc.edu.cn

Abstract. This study aims to build a complete visual transmission design optimization measurement system by integrating CAD (Computer-aided design) and DM (Data mining) technologies. Specifically, this article first uses CAD technology to model and quantitatively analyze the visual design elements accurately and then extracts the key factors and laws that affect the design effect from a large quantity of design data through DM. Finally, combining the results of CAD and DM, a scientific and effective optimization scheme is proposed, and experiments verify its feasibility and effectiveness. Experiments show that users often show higher stay time and more frequent interaction behavior when facing attractive design elements. Moreover, users have a positive attitude toward innovative and personalized design elements; Bright colors and dynamic visual effects are outstanding in attracting users' attention. This study is expected to provide more accurate and efficient optimization measurement methods for visual transmission design and promote innovation and development in this field.

Keywords: Computer-Aided Design; Data Mining; Visual Transmission Design; Optimized Measurement
DOI: https://doi.org/10.14733/cadaps.2024.S19.226-244

1 INTRODUCTION

In today's society, with the rapid growth of science and technology, the progress of digitalization and intelligence has brought unprecedented opportunities and challenges to the field of visual transmission design. Traditional image compression methods are usually based on transformation encoding, prediction encoding, etc., but these methods may lose important feature information during the compression process, affecting the accuracy of classification. In recent years, deep learning has achieved significant results in the field of image processing. By automatically learning the feature representation of images, the accuracy of classification can be effectively improved. However, deep learning models often require a large amount of computing resources and storage space, which limits their application in compressed image classification. With the rapid development of information technology, a large amount of image data is constantly being generated, and how to effectively store, transmit, and process these image data has become an important issue. Compressed image classification technology aims to improve storage and transmission efficiency while maintaining classification accuracy by reducing redundant information in image data. Bacca et al. proposed a coupled deep learning coding aperture design method for compressed image classification based on CAD (computer-aided design) and data mining to achieve efficient image compression and accurate classification [1]. With the popularization and development of fiber optic networks, optical coherent transmission technology has become an important pillar in the field of modern communication. However, with the continuous increase of transmission baud rate, signal distortion becomes increasingly serious, which has a serious impact on the performance of communication systems. To address this issue, digital pre-distortion technology has been widely applied in optical coherent transmission systems. Bajaj et al. [2] investigated the digital pre-distortion technique for high Bode optical coherent transmission based on deep neural networks. A deep neural network (DNN) is a machine learning model that simulates human brain neural networks and has strong feature learning and classification capabilities. In digital pre-distortion technology, deep neural networks can learn the mapping relationship between the original signal and the distorted signal through training and then perform the inverse transformation on the distorted signal to restore the original signal. Compared with traditional linear pre-distortion methods, digital pre-distortion methods based on deep neural networks have better nonlinear compensation ability and higher adaptability.

In traditional image matching, manually designed feature detection and description operators are widely used to extract local features from images. These operators generate feature descriptors with scale, direction, and rotation invariance by detecting local features such as corners, edges, and spots in the image. These descriptors can be used in subsequent image-matching processes, such as nearest neighbor search or feature point matching. Although handmade design features have shown good performance in many cases, they also have some limitations. Firstly, these operators typically require adjusting parameters to adapt to different image conditions, which increases the difficulty of use. Secondly, manually designed features are more sensitive to interference factors such as lighting changes, noise, and occlusion. The image-matching methods of deep learning can be divided into two categories: regression-based methods and similarity comparison-based methods. Regression-based methods typically use CNN to regress the entire image or image block to predict the position and pose of the target image. These methods typically have high computational efficiency and real-time performance but may be limited by model training and data annotation. The method based on similarity comparison uses CNN to extract image features and matches them by comparing the similarity between features. These methods perform well in terms of accuracy but have high computational complexity [3]. On the Android platform, achieving dynamic 3D graphic stereoscopic display has become an important research direction. Chen and Jiu [4] introduce a method of implementing dynamic 3D graphic stereoscopic displays on the Android platform aimed at improving the visual experience of mobile devices. Dynamic 3D graphic stereoscopic display technology is a technique that can generate three-dimensional images with depth. This technology renders images from both left and right perspectives on mobile devices and then utilizes the visual characteristics of the human eye to allow users to experience a three-dimensional effect. Compared to traditional 2D graphic displays, dynamic 3D graphic stereoscopic display technology can provide a more realistic and vivid visual experience. After configuring the projection matrix, it is necessary to render images from both left and right perspectives separately. This can be achieved by setting different viewpoint positions in the shader. After rendering, combine the two images together to generate a stereo effect. The dynamic 3D graphic stereoscopic display technology has broad application prospects in fields such as mobile games, virtual reality, and augmented reality. This technology can provide a more immersive visual experience and improve user engagement and satisfaction.

The complexity of hyperspectral images poses many challenges to their classification tasks. Fang et al. [5] explored a hyperspectral visual transmission image classification method based on dense convolutional networks and spectral attention mechanisms. The hyperspectral visual transmission image classification method based on dense convolutional networks and spectral attention mechanism can effectively combine the advantages of both to improve classification performance. Firstly, use DenseNet to extract features from hyperspectral images. Then, the extracted features are adaptively screened and emphasized through the spectral attention mechanism. Finally, use a classifier to classify the processed features. This method can fully explore useful information in hyperspectral images to improve classification accuracy and stability. The hyperspectral visual transmission image classification method based on dense convolutional networks and spectral attention mechanism is an effective solution to the problem of hyperspectral image classification. By combining the feature extraction ability of DenseNet and the adaptive filtering ability of the spectral attention mechanism, useful information in hyperspectral images can be fully explored, improving the accuracy and stability of classification. Simple realism does not always bring the best user experience. In order to improve the expressiveness and attractiveness of 3D visualization, not only technological progress but also innovative visual design concepts are needed. Johnson et al. [6] explored how to utilize natural and traditional visual media to achieve more expressive and attractive 3D visualization through artificial product-based rendering. Natural and traditional visual media, such as painting, sculpture, photography, etc., have unique visual language and expressive power. They can capture and convey emotions, atmosphere, and stories, which is what 3D technology pursues. By drawing on the characteristics of these traditional visual media, more expressive and attractive 3D visualizations can be created. Artifact-based rendering is a technique that emphasizes the importance of artificial elements in 3D visualization. It not only focuses on the surface details and lighting effects of objects but also emphasizes the texture, material, construction, and design elements of objects. By carefully designing and rendering artificial products, 3D visualization can be endowed with more emotions and storytelling. Existing design methods often fail to meet the growing demand for multifunctionality. Therefore, Kim et al. [7] proposed a pixelated dual functional element surface-driven visual transmission design method for CAD and data mining platforms. Pixelated dual-functional element surface is a new design concept that combines the advantages of pixelization and functional design, aiming to create a design scheme that is both artistic and practical. This design method treats the surface as discrete units at the pixel level, each with independent functional characteristics. By adjusting the arrangement and combination of pixel units, various visual effects, and functional expressions can be achieved. In the visual transmission design driven by pixelated dual functional element surface, CAD and data mining technology are key to achieving efficient and accurate design. By integrating CAD technology, designers can create precise 3D models and perform detailed parametric design and optimization on them. Data mining techniques can be used to analyze user behavior and market trends, providing valuable design reference information for designers.

The core problem of this study is how to use CAD and DM to optimize the measurement of visual transmission design more accurately and efficiently. Based on this problem, this article puts forward the following assumptions:

A. Through CAD technology, accurate modeling and quantitative analysis of visual design elements can be realized.

B. Using DM technology, we can extract the key factors and laws that affect the design effect from a large quantity of design data.

C. Combining CAD and DM, a complete set of optimization measurement systems of visual transmission design can be constructed, and the quality of design can be improved.

This study will adopt the methods of literature review, experimental research, and case analysis and comprehensively use CAD modeling, DM algorithm, and statistical analysis. The specific research steps include collecting and sorting out relevant literature and constructing a theoretical framework; Designing and implementing experiments and collecting data; and Using CAD and DM tools to process and analyze data. Finally, the experimental results are discussed and explained. Its innovations are as follows:

A. In this study, CAD and DM technology are combined and applied to the field of visual transmission design. This comprehensive application not only improves the accuracy of design but also reveals the potential relationship and law between design elements and user behavior through deep mining of a large quantity of data.

B. This study adopts the method of user testing, invites the target users to participate in the experiment, and collects their behavior data. This user-centered experimental design can more truly reflect the user's reaction and demand for design and provide valuable feedback and guidance for designers.

C. Through in-depth excavation and analysis of experimental data, this study found some new relationships and laws between design elements and user behavior. These findings not only enrich the theoretical system of visual transmission design but also provide designers with a deeper understanding of user needs and market dynamics.

D. This study focuses on the different preferences and demands of different user groups for design elements and explores the strategies and methods of personalized design for different user groups. This concept and method of personalized design are helpful in meeting the diverse needs of users and improving the pertinence and effectiveness of design.

Structure and main contents of the paper:

This article is structured into six distinct sections. The introductory section outlines the research background, significance, challenges, and assumptions. The second section reviews the research status and development trend in related fields and introduces the theoretical framework and methodological basis of the research. The third section describes the research methods and experimental design in detail. The fourth section reports the experimental process and result analysis. The fifth section discusses and explains the experimental results and verifies the research hypothesis. The last section is conclusions and suggestions, summarizing the research results and looking forward to the future research direction.

2 RELATED WORK

Computer-aided design (CAD) and data mining techniques have been widely applied in many fields. These technologies provide powerful tools for interpretation and prediction, especially in the field of visual transmission. Kim and Panda [8] explore how to combine CAD and data mining techniques to explain visual transmission using spike neural networks (SNNs). CAD technology provides precise models and design tools for visual transmission. Designers can create detailed 3D models of complex mechanical systems and transmission devices through CAD software. This model can accurately represent the relationships and motion trajectories between various visual transmission components, providing a foundation for subsequent analysis and optimization. A spike neural network is a new type of neural network model that simulates the spike-firing mechanism of biological neural systems. Compared with traditional neural networks, SNN has stronger robustness and dynamism and can better handle complex nonlinear problems. In visual transmission, SNN can be used to explain and predict the behavior and performance of transmission. By training the SNN model, we can learn the inherent mechanisms and patterns of transmission, thereby better understanding and optimizing the visual transmission system. Edge-driven artificial intelligence is a new type of artificial intelligence technology that emphasizes computation and processing at the source of data generation, thereby reducing the cost and delay of data transmission. In landscape visual design, edge-driven artificial intelligence can be applied to real-time data collection, analysis, and processing, providing designers with more accurate and real-time data support. By utilizing edge-driven artificial intelligence technology, designers can obtain and analyze environmental information more quickly, improving design efficiency and accuracy. Ma et al. [9] explored how to utilize environmental analysis and edge-driven artificial intelligence technology, combined with soft multimedia assistance, to achieve more efficient and innovative visual landscape design. The soft multimedia-assisted landscape visual design based on environmental analysis and edge-driven artificial intelligence is an innovative design method. By comprehensively utilizing various technological means, this method can help designers carry out design work more efficiently and improve the expressiveness and feasibility of the design. Data mining techniques can extract useful information and patterns from a large amount of data. In visual transmission image classification, data mining can be applied to feature selection, classifier optimization, and other aspects. Through data mining, we can discover patterns and patterns hidden in the data, thereby improving the accuracy and efficiency of classification. In addition, data mining can also be used to evaluate the performance of classifier optimization and improve models. Ma et al. [10] explored the application of a dual-branch multi-attention mechanism network based on CAD and data mining techniques in visual transmission image classification. The dual-branch multi-attention mechanism network is a new type of deep learning model that combines the advantages of attention mechanism and multi-branch network. The network consists of two branches: one is the feature extraction branch, which is used to extract features from images; Another is the classification branch, which is used to classify the extracted features. In each branch, a multi-attention mechanism is adopted to better focus on important regions and detailed information in the image. Through this structure, the dual branch multi-attention mechanism network can effectively capture complex features in images and improve classification accuracy and robustness.

The application of visual communication design in various fields is becoming increasingly widespread. Especially in multi-source information virtual art painting and interactive 3D dynamic scenes, visual transmission design plays a crucial role. Pan and Deng [11] discussed how to combine multi-source information virtual art painting with interactive 3D dynamic scenes to achieve a realistic visual transmission design. Multi-source information virtual art painting is a technology that integrates multiple information sources into virtual art creation. This technology can create unique virtual artworks by digitizing, analyzing, reorganizing, and reproducing various media information. Realistic visual transmission design is a design method that combines virtual and reality. Through this design method, virtual elements, information, and scenes can be integrated with the real world to create a unique visual experience. The application scope of realistic visual transmission design includes augmented reality, mixed reality, and smart home. Holographic technology can display objects in three-dimensional form, giving people a more realistic and three-dimensional visual experience. Pi et al. [12] explored the computer-generated holographic visual transmission design for color dynamic holographic 3D displays based on CAD and data mining and analyzed its potential and application prospects in modern display technology. CAD (Computer Aided Design) plays a crucial role in holographic visual transmission design. Through CAD, designers can create 3D models and convert them into holographic images. The precision and flexibility of CAD enable designers to create complex and detailed holographic images, providing viewers with a stunning visual experience. Color dynamic holographic 3D display technology is the key to achieving computer-generated holographic visual transmission design. This technology can display dynamic holographic images at high resolution and frame rate, providing viewers with a realistic and vivid visual experience. In addition, color dynamic holographic 3D display technology can also display different content according to changes in the audience's perspective, further improving visual effects. Convolutional neural networks (CNNs) have achieved significant success in the field of image processing. However, for nonimage data, directly applying CNN faces many challenges. Sharma et al. [13] proposed a visual transmission image optimization method that converts nonimage data into a convolutional neural network architecture, aiming to address this issue. Necessary preprocessing operations are carried out for the characteristics of nonimage data, such as word embedding in text, spectral conversion of audio, and normalization of temporal data. The purpose is to convert the raw data into a format suitable for CNN processing. It designs a feature converter that converts preprocessed nonimage data into convolutional features compatible with CNN. The key to this step is to find an effective convolution operation that can extract meaningful feature representations from nonimage data. To verify the effectiveness of the proposed method, we conducted experiments on multiple nonimage datasets, including text classification, audio recognition, and time series prediction. The experimental results show that after processing with the method proposed in this paper, the performance of CNN on nonimage data is significantly improved. Compared with traditional nonimage processing methods, the proposed method has significant advantages in accuracy, recall, and F1 score.

Big data technology also plays an increasingly important role in the development and optimization of visual transmission design in CAD systems. Yang et al. [14] explored how to use big data technology for the development and optimization of visual transmission design in CAD systems. CAD systems are indispensable tools in modern industrial design and manufacturing. In CAD systems, visual transmission design refers to the process of improving design effectiveness and user experience through visual elements and information communication. The application of big data technology makes CAD systems more efficient and accurate in visual transmission design. Through big data technology, we can collect, store, analyze, and process massive design data to better understand user needs and market trends. These data can provide valuable reference information for designers to better carry out visual transmission design. Meanwhile, big data technology can also automate the analysis and prediction of user behavior and market changes through techniques such as data mining and machine learning, providing designers with more intelligent support. With the rapid development of technology, the intelligent visual Internet of Things has become a hot research field. Through IoT technology, we can connect various sensors, cameras, and other devices to achieve real-time data transmission and processing. In the intelligent visual Internet of Things, the 3D visualization technology for achieving autonomous crowd management in visual transmission design is particularly crucial. Yu et al. [15] explored how to use intelligent visual IoT technology to achieve 3D visualization of visual transmission design for autonomous crowd management. Visual transmission design 3D visualization is a technique that transforms design concepts into 3D models. Through 3D modeling software and visualization technology, we can create realistic 3D scenes and models and perform dynamic demonstrations and interactions. In autonomous crowd management, visual transmission design 3D visualization technology can help us better understand and display the behavior and movement trajectory of the crowd, improve management efficiency and safety. Using visual transmission design 3D visualization technology to visualize and display data and information related to crowd management, helping managers better understand and grasp the dynamic changes of the crowd. By creating a virtual 3D environment, VR technology provides users with an immersive experience, allowing them to experience various scenes firsthand. Zhang and Kou [16] discussed the research and implementation of digital 3D panoramic visual transmission design based on virtual reality and analyzed its potential and application prospects in the field of design. In the design of digital 3D panoramic visual transmission, the first step is to study the visual perception characteristics of the human eye in virtual reality environments. This includes research on color, lighting, spatial sense, and other aspects to ensure that the design can meet the visual habits and needs of users. In the design of digital 3D panoramic visual transmission, scene construction and optimization are key steps. Designers need to use 3D modeling techniques, texture mapping techniques, and other means to create realistic virtual scenes and improve the rendering efficiency and visual effects of the scenes through optimization algorithms. In order to achieve a smooth virtual reality experience, real-time rendering and optimization are required. By adopting efficient rendering algorithms and optimization techniques, the operational efficiency of the system can be improved while ensuring visual effects.

Zhang and Kim [17] explored how to apply chromaticity to sustainable color visual transmission design in ocean cities and integrated interactive genetic algorithm optimization design process. Chromaticity is the science that studies color measurement, color reproduction, and color mixing. In urban landscape design, chromaticity mainly focuses on the visual effects, psychological feelings, and cultural significance of colors. Especially in ocean cities, the selection and use of colors are crucial for creating a unique urban atmosphere and image. When the algorithm reaches the preset number of iterations or finds a solution that meets the requirements, the evolution process is terminated. The optimal color scheme obtained at this time should meet the requirements of sustainable development, have good visual effects, and be culturally adaptable. Taking a certain ocean city as an example, this article introduces how to apply interactive genetic algorithms to sustainable color visual transmission design. Firstly, collect information on the history, culture, geographical environment, climate, and other aspects of the city to determine the constraints and goals of the design. Then, apply the principles of chromaticity to conduct color analysis and planning of urban landscapes. Next, the interactive genetic algorithm is integrated into the design process to find the optimal color combination scheme through simulation and optimization. Finally, based on algorithm suggestions and designer adjustments, complete the urban landscape color design that meets the requirements of sustainable development. Zhang et al. [18] explored the application of CAD and data mining in the development of a visual transmission information management system. And analyze its contribution to improving design efficiency and optimizing product performance. CAD technology can help designers create accurate 3D models and achieve product visualization. This enables designers to have a more intuitive understanding of the appearance and structure of the product, thereby enabling better design and optimization. CAD technology supports parametric design, and designers can change the shape and performance of products by adjusting parameters. This flexibility allows designers to quickly respond to market demands and make product improvements based on user feedback. CAD technology can be used for simulation and validation, helping designers predict the performance and behavior of products. By simulating the operating environment and working conditions of the product, designers can identify and solve potential problems before actual manufacturing. The development of a visual transmission information management system based on CAD and data mining has brought significant advantages in improving design efficiency and optimizing product performance. By fully utilizing CAD technology and data mining techniques, enterprises can respond to market demand more quickly and improve product quality and user satisfaction. Graphic language is a visual communication method based on elements such as graphics, symbols, and colors. It can express complex concepts and information in a concise and clear manner, enabling people from different cultural backgrounds and languages to quickly understand. In an intelligent environment, graphic language has greater significance as it can help users quickly understand the functions and operating methods of devices and systems. In intelligent environments, devices and systems often have a high degree of complexity and integration. When using these devices and systems, users need to quickly understand their functions, operating methods, and interaction methods. The animation visual guidance system provides users with intuitive and vivid guidance information through dynamic graphics, images, and text elements, helping them quickly grasp the use of devices and systems. Through graphical language, the operation process can be presented in the form of graphics, allowing users to intuitively understand the operation steps and sequence. Through graphical language, an intuitive and user-friendly interactive interface can be designed, allowing users to operate and interact easily [19].

3 USE CAD AND DM TOOLS FOR DATA PROCESSING AND ANALYSIS

3.1 Research Design

CAD covers a wide range of design tools and methods and provides a comprehensive platform for designers to create, modify, analyze, and optimize designs. The basic theories of CAD include geometric modeling, graphic rendering, animation simulation, etc. Through these theories, designers can accurately represent and manipulate design elements on computers. Technically, CAD software usually provides a complete toolset, including drawing, modeling, rendering, animation, and other functions. Designers can use these tools to create complex 3D models, apply materials and textures, and simulate light. In addition, CAD software also provides accurate measurement and analysis functions to help designers understand and optimize all aspects of design.

DM is a process of extracting useful information and patterns from a large quantity of data. It combines knowledge from many fields, such as statistics, machine learning, and database technology, aiming to help users better understand and utilize data. Technically, DM usually involves a series of complex algorithms and technologies, such as decision trees, neural networks, support vector machines, and so on. These technologies can help users extract hidden patterns and laws from data, predict future trends, and discover the correlation between data. In addition, DM also includes data visualization and result interpretation so that users can better understand and use the mining results. In recent years, with the growth and integration of technology, the combined use of CAD and DM has attracted more and more attention.

In visual transmission design, the combination of CAD and DM can provide strong support for the optimization measurement of design. First of all, using CAD technology, designers can accurately model and represent design elements, including shapes, colors, materials, and other aspects. This provides accurate basic data for subsequent data analysis and optimization. Secondly, through DM technology, a large quantity of design data can be deeply analyzed and mined. These mining results can provide targeted guidance and suggestions for design optimization.

Although CAD and DM technology has achieved some application results in visual transmission design, there are still some problems and challenges to be solved. Currently, research efforts are primarily concentrated on the utilization of individual technologies, neglecting the comprehensive exploration of integrating CAD and DM technologies. Secondly, the existing optimization methods are mostly based on experience or intuition, lacking systematic theoretical guidance and experimental verification. Finally, there is no unified understanding and standard for the optimal measurement methods and standards in different design fields. Therefore, based on the above theory and technology, this study puts forward an optimized visual transmission design measurement framework that integrates CAD and DM. Through this theoretical framework, this study aims to achieve a comprehensive optimization measurement of visual transmission design and improve the quality of design. The framework includes the following main steps:

A. Accurate modeling and quantitative analysis of visual design elements by using CAD technology to obtain basic data.

B. Through DM technology, a large quantity of design data is deeply excavated and analyzed, and the key factors and laws affecting the design effect are extracted.

C. Combining the results of CAD and DM, the design optimization model is constructed, and the optimization scheme and suggestions are put forward.

D. Verify the effectiveness of the optimization scheme through experiments and constantly improve and perfect the optimization model.

Quantitative methods are mainly used for data collection and analysis, while qualitative methods are used for in-depth understanding and interpretation of research results. The specific research design is as follows:

Experimental design: Design and implement a series of experiments to collect data about visual transmission design elements. Experiments include user testing, market feedback collection, and so on.

Questionnaire survey: Collect users' views and feedback on the design through a questionnaire survey to understand users' needs and market trends.

Case study: Select representative design cases for in-depth analysis to extract the key factors and laws that affect the design effect.

3.2 Data Collection

Data collection is one of the key links in this study. This article will use a variety of data sources, including experimental data, questionnaire survey data, market data, and so on. Specific data collection methods and analysis purposes are shown in Table 1:

Data type	*Data source*	*Method of data capture*	*Data analysis purpose*
Experimental data	Interaction between users and design elements	Record click-through rate, stay time, etc.	Analyze the effectiveness and attractiveness of design elements.
Questionnaire survey data	Users' views and feedback on the design	Online or paper questionnaires, including closed and open questions.	Fully understand user needs and market dynamics.

Market data	Visual transmission design related to the market	Collect trends, competitor analysis, etc.	Provide market background and support for design optimization.

Table 1: Data collection methods and analysis purposes.

After data collection is completed, data will be cleaned and preprocessed to eliminate noise and abnormal values and ensure the accuracy and reliability of data.

3.3 Data Processing and Analysis

This study will make full use of CAD and DM tools for data processing and analysis. Among them is the application of CAD tools: using CAD software to model and quantitatively analyze visual design elements accurately. Through CAD tools, detailed information such as geometric features, colors, and materials of design elements can be obtained, which provides accurate basic data for subsequent data analysis and optimization. Application of DM algorithm: DM is used to analyze and mine the collected data deeply. In this article, the association rule mining algorithm is used to discover the relationships and laws between design elements. Use classification and prediction algorithms to predict users' preferences and trends in design; Cluster analysis algorithm is used to group and classify design elements. The DM and clustering process is shown in Figure 1.

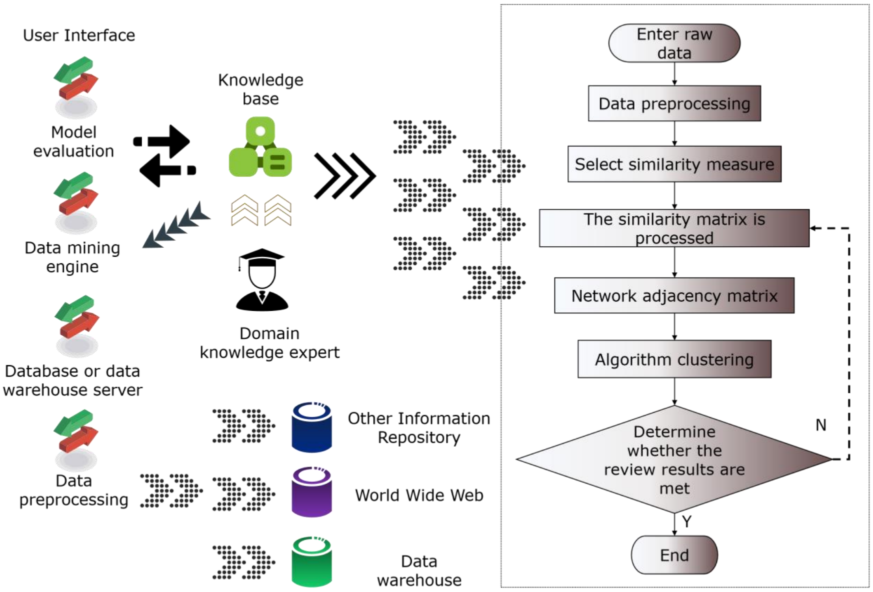


Figure 1: DM and clustering process.

The implicit form of association rules is $X \Rightarrow Y$, and it exists:

$$X \subset I \quad Y \subset I \quad X \cap Y = \varnothing \tag{1}$$

In the algorithm, the support degree is probability $P(X \cup Y)$. Where $X \cup Y$ represents a transaction that contains both X and Y. Another objective measure of association rules is confidence. Confidence is conditional probability $P(Y|X)$. Support and confidence are defined as:

$$Support(X \Rightarrow Y) = P(X \cup Y) \tag{2}$$

$$Confidence\left(X \Rightarrow Y\right) = P\left(Y \middle| X\right) \tag{3}$$

Let $P' \subseteq P$ then P''s support for user interaction T is:

$$\sup\left(P'\right) = \left|\left\{t \middle| P' \subseteq P \cap P' \subseteq t.p \cap t \in T\right\}\right| / \left|T\right| \tag{4}$$

P' Its support count for user interaction T is:

$$\sup\_count\left(P'\right) = \left|\left\{t \middle| P' \subseteq P \cap P' \subseteq t.p \cap t \in T\right\}\right| \tag{5}$$

Suppose the entropy of the random variable X is set to:

$$H\left(X\right) = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{6}$$

Suppose the sample set D. The random variable X is the category of the sample. The sample has K categories, $\left|C_k\right|$ which represent the quantity of samples of each category and the total quantity of samples. Then, the probability of each category is $\frac{\left|C_k\right|}{\left|D\right|}$, and the entropy of the sample set D is:

$$H\left(D\right) = -\sum_{k=1}^{K} \frac{\left|C_k\right|}{\left|D\right|} \log_2 \frac{\left|C_k\right|}{\left|D\right|} \tag{7}$$

The entropy of the sample set D before division is certain. A certain feature A is used to divide the data set D, and the entropy of the divided data subset is calculated. The information gain is equal to the entropy $H\left(D\right)$ of the sample set before division minus the entropy $H_A\left(D\right)$ of the data subset after division. The formula for calculating the information gain $g\left(D,A\right)$ is:

$$g\left(D,A\right) = H\left(D\right) - H_A\left(D\right) \tag{8}$$

Visualization and interpretation of results: Visualize the results of CAD modeling and DM to understand better and explain the analysis results. Show the relationship and trend between data through charts, images, and other forms to help designers intuitively understand the optimization direction and improvement measures of design. Moreover, combined with the qualitative analysis method, the results are discussed and explained in depth, and specific optimization schemes and suggestions are put forward.

4 EXPERIMENTAL DESIGN AND IMPLEMENTATION

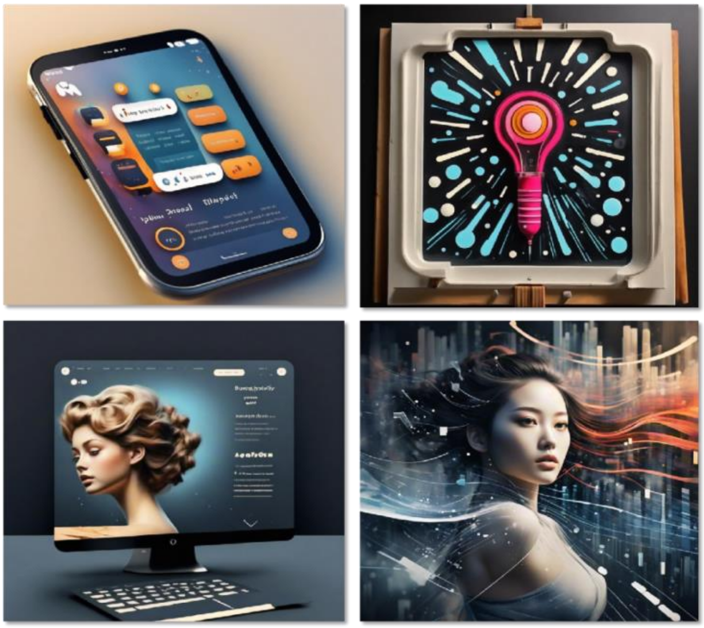
4.1 Experimental Design

The optimization effect of design can be evaluated by controlling the experimental conditions, collecting the interaction data between users and design elements, and analyzing the influence of design elements on users' behavior.

The experimental subjects are two groups of samples with different visual transmission design elements. These samples may include different graphics, colors, layouts, and other design elements to comprehensively evaluate the influence of each design element on user behavior. As shown in Figure 2 and Figure 3.

Sample 1

Figure 2: Visual transmission design elements (Sample 1).



Sample 2

Figure 3: Visual transmission design elements (Sample 2).

This experiment adopts the method of user testing and invites a certain number of target users to participate in the experiment. During the experiment, users will interact with design elements and record relevant data. Specific experimental steps are shown in Table 2.

Serial number	Experimental procedure	Specific content
1	Experimental preparation	Prepare CAD and DM tools for the experiment and set relevant parameters and configurations.
2	User invitation	Invite people who meet the characteristics of the target users to participate in the experiment to ensure the representativeness of the experimental results.
3	Experimental explanation	Explain the purpose and process of the experiment to users to ensure that they have a full understanding of it.
4	Experimental operation	Users interact with design elements in the experimental environment and record relevant data.
5	Data collection	Collect user behavior data during the experiment, such as click-through rate, residence time, etc.
6	Data reduction	Clean and sort out the collected data to eliminate abnormal values and noise.

Table 2: Experimental procedure.

4.2 Settings and Parameters of CAD Tools and DM Tools

During the experiment, professional CAD software is used to model and quantitatively analyze the visual design elements accurately. After the experimental data collection is completed, DM tools are used to analyze and mine the data deeply. Specific settings and parameters are shown in Table 3 and Table 4:

Project	*Set up*
Modeling tool	Select CAD modeling tools suitable for visual transmission design -AutoCAD and SketchUp.
Modeling accuracy	According to the complexity of design elements and experimental requirements, appropriate modeling accuracy is set to ensure the accuracy and reliability of the model.
Color and material settings	Set corresponding color and material parameters for design elements to simulate real visual effects.
Measuring tool	Use the measuring tools in CAD software to accurately measure the dimensions and angles of design elements.

Table 3: Settings and parameters of CAD tools.

Data processing steps	*Specific settings and parameters*	*Method*
Data preprocessing	Cleaning, conversion, and normalization treatment.	Data cleaning technology, data conversion method, normalization algorithm
Association rule mining	Discover the relationships and laws between design elements. Set appropriate support and confidence thresholds.	Apriori algorithm According to the experimental requirements and data characteristics.
Classification and prediction	Predict and classify user behavior. Select the appropriate algorithm	Decision tree algorithm Cross-validation and selection are carried

	and parameter settings.	out according to experimental data.
Cluster analysis	Group and classify design elements.	K-means algorithm
	Set an appropriate quantity of clusters and iterations.	According to the experimental requirements and data characteristics.

Table 4: Settings and parameters of DM tool.

4.3 Data Processing and Visual Display of Results

During the experiment, this article attaches great importance to the interaction behavior data between users and design elements. By using professional recording tools or software, the user's various operation behaviors during the experiment are recorded in detail, including clicking, sliding, dragging, and other actions, and the user's stay time on each design element is accurately calculated. These behavioral data are very important for understanding users' preferences and behavior patterns. After the data collection is completed, the data is cleaned. This step is very critical, aiming at eliminating outliers and noise data and ensuring the accuracy and reliability of the data. In this article, a variety of cleaning techniques, screening, abnormal value detection and processing, missing value filling, etc., are comprehensively adopted to ensure the quality and consistency of data. Figure 4 shows the data cleaning results.

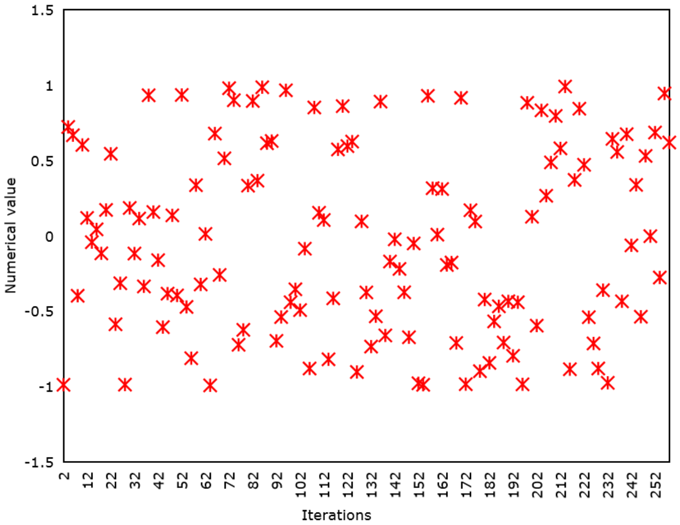


Figure 4: Data cleaning results.

The cleaned data then enters the stage of statistics and collation. In this article, the data are described and analyzed comprehensively by statistical methods, and the statistics, such as the average value and standard deviation of each index, are calculated. These statistics help us to understand the overall characteristics and distribution of user behavior and provide a basis for subsequent DM and analysis. Finally, the DM algorithm is used to deeply analyze and mine the sorted data. Figure 5 shows the classification accuracy of the algorithm.

The relatively stable classification accuracy is one of the important indexes to evaluate the performance of classification algorithms. Judging from the data in Figure 5, the classification accuracy of this algorithm is quite good, ranging from 85% to 95%, which means that the algorithm can accurately classify the data into the correct categories in most cases. Figure 6 shows the prediction accuracy of the algorithm.

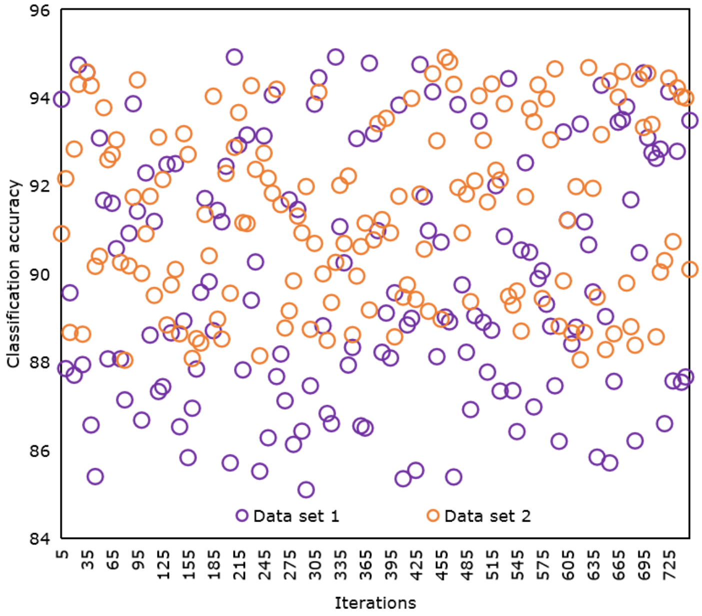


Figure 5: Classification accuracy of the algorithm.

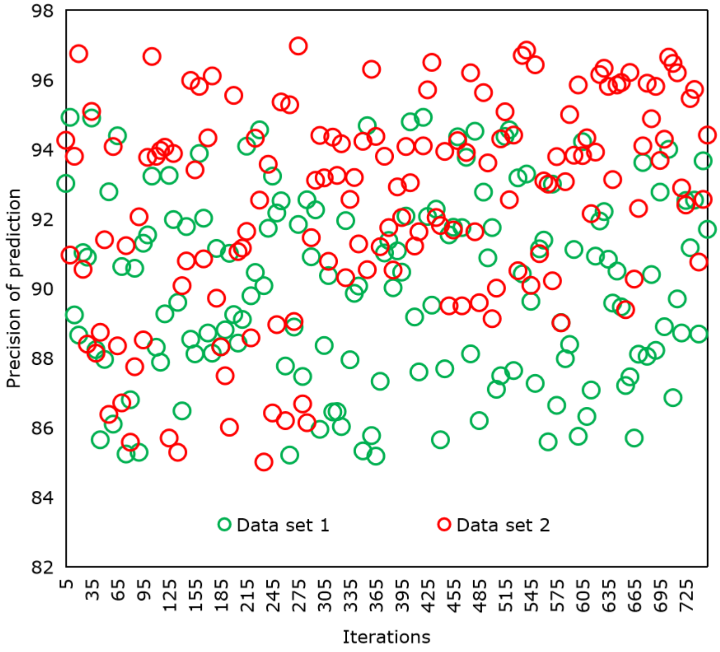


Figure 6: Prediction accuracy of the algorithm.

The algorithm's ability to predict future or unknown data is measured by its high prediction accuracy. As indicated in Figure 6, the algorithm exhibits exceptional prediction accuracy, achieving over 96%. This demonstrates the algorithm's robust performance in forecasting tasks, demonstrating its capability to effectively learn, comprehend underlying data patterns, and make precise predictions. Additionally, Figure 7 illustrates the algorithm's RMSE.

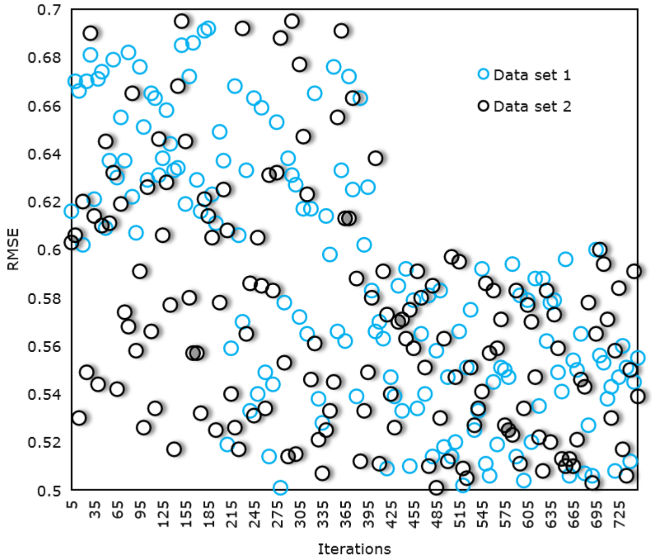


Figure 7: RMSE of the algorithm.

The RMSE is a crucial metric for assessing the performance of regression algorithms, as it quantifies the discrepancy between predicted and actual values. Referring to the data presented in Figure 7, the algorithm's RMSE values are low, falling within the range of 0.5 to 0.7. A smaller RMSE value signifies that the algorithm's predictions closely align with actual outcomes, indicating minimal error. This serves as further evidence of the algorithm's outstanding performance in forecasting tasks.

5 RESULT ANALYSIS

5.1 Analysis of Experimental Results

After a series of experiments and data collection, this article gets a lot of data about the interaction between users and design elements. User behavior data are shown in Table 5:

Design element	*Residence time (seconds)*	*Number of interactions*	*User feedback score*
Bright colors	12.5	8	8.2
Dynamic visual effect	15.3	12	8.7
Innovative design	18.6	15	9.0
Personalized design elements	20.4	18	9.3

Table 5: User behavior data.

Through the analysis of user behavior data, we can draw the following conclusions:

When faced with attractive design elements, users tend to show higher stay time and more frequent interaction behavior. For example, bright colors and dynamic visual effects attract users' attention, which makes them stay on these design elements for a longer time and conduct more interactive operations.

Some design elements stand out in attracting users' attention. Bright colors and dynamic visual effects are such examples. Users have a strong interest in these elements, actively participate in the interaction, and show their preference and recognition for these elements.

Users' feedback data shows that they have a positive attitude towards innovative and personalized design elements. Innovative design and personalized design elements have obtained high user feedback scores, indicating that users appreciate and love these elements.

To sum up, through the analysis of user behavior data, we can find that users show higher interest and participation in attractive design elements. These conclusions provide valuable reference and guidance for designers and help to optimize the design scheme and enhance the user experience.

By utilizing DM technology, the correlation between design elements and user behavior is further investigated. The detailed experimental findings are presented in Table 6.

Analytical method	*Design elements and user settings*	*Experimental values or examples*	*Findings and conclusions*
Association rule mining	{Bright colors, dynamic visual effects}	User support is 0.6, and confidence is 0.8.	When this combination appears, the probability that users will like it is high.
Classification and prediction algorithm	Young users (18-30 years old); Middle-aged users (31-50 years old)	Young users: bright colors and dynamic scores are 9.31; Middle-aged users: concise and clear design score is 9.46.	Young users prefer bright colors and dynamic visual effects; Middle-aged users prefer simple and clear designs.
Cluster analysis	User group 1; User group 2; User group 3	Group 1: Innovative and dynamic design scores are higher; Group 2: Practicality and simplicity scores are high; Group 3: Traditional and classic design elements score higher.	Different user groups have different preferences and needs for design elements.

Table 6: The relationship between design elements and user behavior.

Mining association rules: Using this DM technology, interesting relationships between design elements can be found. Some combinations of design elements frequently appear together and are loved by users. This means that these combinations represent a "best practice" or "successful model" of a certain design. The specific experimental values are shown in the example, which gives the support and confidence of a popular design element combination.

Classification and prediction algorithms: These algorithms are used to explore how users' demographic characteristics affect their preferences for design elements. The experimental results show that different user groups have obviously different preferences for design elements. For example, young users may prefer bright and dynamic designs, while middle-aged users may prefer simple and clear designs.

Cluster analysis: This analysis method allows users to be grouped according to their preferences for design elements. Through cluster analysis, it is found that there are different user groups, and each group has its own unique design preferences and needs. This provides designers with valuable information so that they can carry out more personalized designs for different user groups.

5.2 Verification and Discussion of Research Hypothesis

According to the experimental results, the hypothesis put forward in this study can be verified; that is, CAD and DM technology can be effectively applied to the optimization measurement of visual transmission design. The experimental results not only verify the correctness of the research hypothesis but also reveal some new findings and laws. Compared with the expected results, the experimental results exceed expectations in some aspects, such as the depth and complexity of the relationship between design elements and user behavior. These differences provide us with a deeper research perspective and thinking space.

5.3 The Influence and Significance of the Results on the Field of Visual Transmission Design

Through the DM algorithm, the relationship and law between design elements are explored, and the key factors affecting the design effect are identified. These findings provide valuable insight and guidance for designers and help to optimize the design scheme and enhance the user experience.

The results of this study have an important influence and significance on the field of visual transmission design. First of all, it confirms the effectiveness of CAD and DM technology in design optimization and provides designers with new tools and methods to improve their design work. Secondly, by revealing the relationship and law between design elements and user behavior, this study provides designers with a deeper understanding of user needs and market dynamics, which helps them create designs that are more in line with user needs and market trends. Finally, the results of this study also provide new research perspectives and teaching materials for researchers and educators in the field of visual transmission design, which is helpful in promoting academic progress and personnel training in this field.

6 CONCLUSIONS AND SUGGESTIONS

6.1 Main Findings and Contributions of the Study

In this study, the field of visual transmission design was deeply explored through mixed research methods and quantitative and qualitative analysis. The following are the main findings and contributions of the study:

Verified the effectiveness of CAD and DM technology: Through experimental design and implementation, this study confirmed the effectiveness of CAD and DM technology in visual transmission design optimization. These technologies provide designers with accurate data analysis and optimization suggestions, which are helpful in improving the attractiveness of design and user satisfaction.

Reveals the relationship between design elements and user behavior: This study reveals the potential relationship and law between design elements and user behavior by using DM technology. These findings provide designers with a deeper understanding of user needs and market dynamics and help guide designers in creating design works that better meet user needs and market trends.

It has promoted academic progress in the field of visual transmission design: the results of this study provide new research perspectives and teaching materials for researchers and educators in the field of visual transmission design. These findings are helpful in promoting academic progress and personnel training in this field and provide valuable reference for future research and practice.

6.2 Future Research Direction

Based on the results and findings of this study, this article puts forward the following suggestions for future research directions and possible improvements:

Further exploration of the relationship between design elements and user behavior is warranted. While this study has uncovered certain associations between design elements and user behavior, numerous unexplored areas remain ripe for deeper investigation. Future research can focus on more design elements and user behavior indicators so as to fully understand their relationships and laws.

Expand the research methods and tools: This study mainly adopts CAD and DM technology for design optimization analysis. Future research can try to introduce more methods and tools, such as virtual reality and artificial intelligence, to evaluate the optimization effect and user satisfaction of the design more comprehensively.

Pay attention to the needs and preferences of different user groups: This study found that different user groups have different preferences and needs for design elements. Future research can pay more attention to these differences and explore strategies and methods of personalized design for different user groups.

7 ACKNOWLEDGEMENT

This work was supported by Shanxi Provincial Department of Education, Research on Results-Oriented Practical Teaching System Reform of Visual Communication Design Professional Talent Training, Project number: J20230725.

Wenchao Wu, https://orcid.org/0009-0000-7220-2902
Irwan Syah Md Yusoff, https://orcid.org/0000-0002-9803-0421
Hassan bin Hj Alli, https://orcid.org/0000-0003-1727-4561
Qi Wang, https://orcid.org/0009-0006-5864-7319

REFERENCES

[1] Bacca, J.; Galvis, L.; Arguello, H.: Coupled deep learning coded aperture design for compressive image classification, Optics Express, 28(6), 2020, 8528-8540. https://doi.org/10.1364/OE.381479
[2] Bajaj, V.; Buchali, F.; Chagnon, M.; Wahls, S.; Aref, V.: Deep neural network-based digital pre-distortion for high baud-rate optical coherent transmission, Journal of Lightwave Technology, 40(3), 2021, 597-606. http://dx.doi.org/10.1109/JLT.2021.3122161
[3] Chen, L.; Rottensteiner, F.; Heipke, C.: Feature detection and description for image matching: from hand-crafted design to deep learning, Geo-Spatial Information Science, 24(1), 2021, 58-74. https://doi.org/10.1080/10095020.2020.1843376
[4] Chen, S.; Jiu, Z.: A method of stereoscopic display for dynamic 3D graphics on Android platform, Journal of Web Engineering, 19(5-6), 2020, 849-863. https://doi.org/10.13052/jwe1540-9589.195612
[5] Fang, B.; Li, Y.; Zhang, H.; Chan, J.-C.-W.: Hyperspectral images classification based on dense convolutional networks with spectral-wise attention mechanism, Remote Sensing, 11(2), 2019, 159. https://doi.org/10.3390/rs11020159
[6] Johnson, S.; Samsel, F.; Abram, G.; Olson, D.; Solis, A.-J.; Herman, B.; Keefe, D.-F.: Artifact-based rendering: harnessing natural and traditional visual media for more expressive and engaging 3D visualizations, IEEE Transactions on Visualization and Computer Graphics, 26(1), 2019, 492-502. https://doi.org/10.1109/TVCG.2019.2934260
[7] Kim, I.; Jang, J.; Kim, G.; Lee, J.; Badloe, T.; Mun, J.; Rho, J.: Pixelated bifunctional metasurface-driven dynamic vectorial holographic color prints for photonic security platform, Nature Communications, 12(1), 2021, 3614. https://doi.org/10.1038/s41467-021-23814-5
[8] Kim, Y.; Panda, P.: Visual explanations from spiking neural networks using inter-spike intervals, Scientific Reports, 11(1), 2021, 19037. https://doi.org/10.1038/s41598-021-98448-0
[9] Ma, B.; Dong, Y.; Liu, H.; Cao, Z.: Soft multimedia assisted new energy productive landscape design based on environmental analysis and edge-driven artificial intelligence, Soft Computing, 26(23), 2022, 12957-12967. https://doi.org/10.1007/s00500-021-06155-9
[10] Ma, W.; Yang, Q.; Wu, Y.; Zhao, W.; Zhang, X.: Double-branch multi-attention mechanism network for hyperspectral image classification, Remote Sensing, 11(11), 2019, 1307. https://doi.org/10.3390/rs11111307
[11] Pan, J.; Deng, X.: Multi-source information art painting fusion interactive 3D dynamic scene virtual reality technology application research, International Journal of Communication Systems, 35(5), 2022, e4705. https://doi.org/10.1002/dac.4705

[12] Pi, D.; Liu, J.; Wang, Y.: Review of computer-generated hologram algorithms for color dynamic holographic three-dimensional display, Light: Science & Applications, 11(1), 2022, 231. https://doi.org/10.1038/s41377-022-00916-3

[13] Sharma, A.; Vans, E.; Shigemizu, D.; Boroevich, K.-A.; Tsunoda, T.: DeepInsight: A methodology to transform a nonimage data to an image for convolution neural network architecture, Scientific Reports, 9(1), 2019, 11399. https://doi.org/10.1038/s41598-019-47765-6

[14] Yang, C.; Weng, Y.; Huang, B.; Ikbal, M.: Development and optimization of CAD system based on big data technology, Computer-Aided Design and Applications, 19(S2), 2021, 112-123. https://doi.org/10.14733/cadaps.2022.S2.112-123

[15] Yu, Q.; Hu, L.; Alzahrani, B.; Baranawi, A.; Alhindi, A.; Chen, M.: Intelligent visual-IoT-enabled real-time 3D visualization for autonomous crowd management, IEEE Wireless Communications, 28(4), 2021, 34-41. https://doi.org/10.1109/MWC.021.2000497

[16] Zhang, G.; Kou, X.: Research and implementation of digital 3D panoramic visual communication technology based on virtual reality, International Journal of Communication Systems, 35(5), 2021, e4802. https://doi.org/10.1002/dac.4802

[17] Zhang, L.; Kim, C.: Chromatics in urban landscapes: Integrating interactive genetic algorithms for sustainable color design in marine cities, Applied Sciences, 13(18), 2023, 10306. https://doi.org/10.3390/app131810306

[18] Zhang, M.; Fan, J.; Sharma, A.; Kukkar, A.: Data mining applications in university information management system development, Journal of Intelligent Systems, 31(1), 2022, 207-220. https://doi.org/10.1515/jisys-2022-0006

[19] Zhao, L.: The application of graphic language in animation visual guidance system under intelligent environment, Journal of Intelligent Systems, 31(1), 2022, 1037-1054. https://doi.org/10.1515/jisys-2022-0074