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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 19 No. 10 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijim.v19i10.54081

PAPER

Interactive Visual Communication Design of Mobile App Interface Based on Artificial Intelligence Technology

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ABSTRACT

Mobile app interface design is a crucial aspect of human-computer interaction. Interactive mobile app interface design becomes even more important. However, the traditional design system based on convolutional neural networks (CNN) has low accuracy and poor effect. It is important to improve the system to enhance user experience. To address these issues, the study utilizes the K-means clustering (KMC) algorithm and principal component analysis to analyze the collected user data for demand analysis. Then, a deep adversarial CNN is employed to generate a design scheme for the interactive mobile cell phone application. After evaluation by several mobile front-end engineers, the system designed products with an average rating of 85 for aesthetics, 89 for ease of use, and 83 for information intuitiveness. These excellent results highlight the method's supremacy in interface design aesthetics and user experience, as well as its effectiveness and clarity in information organization and presentation.

KEYWORDS

K-clustering, principal component analysis, deep adversarial convolutional neural network (CNN), mobile app, artificial intelligence (AI)

1 INTRODUCTION

As artificial intelligence (AI) technology continues to advance and gain popularity, more scholars are focusing on its potential applications in mobile application program (M-APP) interface visual communication design (VCD). At present, the M-APP interface VCD based on AI technology has become a popular research field, and its research results and application practices are continuously enriched and deepened [1]. In terms of application practice, some enterprises and research organizations have successfully applied AI technology to M-APP interface VCDs [2–3]. For example, how to improve the accuracy and stability of the algorithm, protect the privacy and data security of users, and reduce the design cost while improving the design efficiency. In addition, related research is difficult to better adapt to and process complex user data and generate new design solutions according to the needs

Shan, L., Li, B. (2025). Interactive Visual Communication Design of Mobile App Interface Based on Artificial Intelligence Technology. *International Journal of Interactive Mobile Technologies (iJIM)*, 19(10), pp. 182–198. https://doi.org/10.3991/ijim.v19i10.54081

Article submitted 2024-12-25. Revision uploaded 2025-02-02. Final acceptance 2025-02-06.

of the user group. Some social apps use AI technology to intelligently categorize and recommend the content published by users to improve their experience and activity. Even while the AI-based M-APP interface VCD has shown some promise, there are still certain issues that need to be resolved. For instance, how to increase the algorithm's precision and stability, safeguard user privacy and data security, and lower design costs while boosting design effectiveness. In view of this, the study adopts the K-means clustering (KMC) algorithm in conjunction with data envelopment analysis (DEA) and makes a series of improvements to the KMC algorithm and then utilizes deep convolutional generative adversarial networks (DCGAN) for generating a new design solution based on the needs of user groups. It is expected that this technique will strengthen the technology development and application practice in order to promote the further development of the M-APP interface VCD based on AI technology. The study mainly consists of four parts, and the first part specifically reviews the current research status on generative adversarial networks (GAN) and image formation, which provides a theoretical basis for further technical applications. The second part describes in detail how to combine the improved KMC algorithm with the deep GAN algorithm to design a brand-new IDCGAN-based M-APP interface VCD system. In the third part, the algorithm's performance is compared, tested, and analyzed. The fourth part is a summary of this paper and its prospects for the future.

The main contributions of this study are reflected in the following aspects: Firstly, by constructing a comprehensive M-APP interface design platform, the entire process from user input to design solution output has been automated, greatly improving design efficiency. Secondly, the study innovatively proposed the IK-Means clustering algorithm, effectively solving the problem of sensitivity of traditional K-means algorithms to initial clustering centers and improving the accuracy and stability of clustering. Furthermore, by introducing Principal Component Analysis (PCA) technology, the dimensionality reduction of high-dimensional data has been successfully achieved, simplifying the data structure and providing convenience for subsequent design element analysis and user behavior prediction. Finally, the study also improved the DCGAN by optimizing the network structure and loss function, enhancing the quality and diversity of generative design solutions.

2 RELATED WORKS

As AI technology continues to advance and gain popularity, an increasing number of academics are focusing on its potential applications in M-APP interface VCD. Aiming at the current problem that a single recognition function cannot meet the demand, Fang et al. proposed a prediction model combining LSTM and DCGAN and used a stacking cascade strategy to control the convergence of parameters. Experimental results revealed that the model is more efficient and robust than 3DCNN and ConvLSTM in temporal prediction with stronger generalization ability [4]. Li et al. addressed the issue of shape and intensity similarity on mobile app imaging (MRI) by introducing a novel feature learning technique called DC-AL GAN, which is based on DCGAN and AlexNet. The results showed that the accuracy and AUC of DC-AL GAN in distinguishing PsP and TTP were 0.920 and 0.947, respectively [5]. Dewi and other scholars proposed the use of DCGAN for image data enhancement in order to address the impact of unbalanced plant disease image data on the performance of CNN classification models. Experimental results showed that image data enhancement by DCGAN can improve the accuracy of CNN classifiers by up to 30% [6]. In order to address the complexity of traffic sign detection and traffic picture identification, Park et al. suggested using DCGAN to create high-quality images of forbidden signs. CNN models with various feature extractors and backbone networks are used in the study. The models' maximum average accuracy, as determined by evaluation, was 92% (DenseNet DCGAN), with 91% (ResNet 50 DCGAN), 88% (DenseNet), and 63% (ResNet 50) following [7]. Cho et al. proposed a system for generating new images using DCGAN to address the problem of low accuracy of image generation for smart educational devices. The results of the study showed that by using this system, new images related to text can be generated, thus providing more resources for children's education [8].

In addition, clustering algorithms and neural networks play an increasingly important role in demand analysis. A three-stage, multi-stage, unsupervised, DCGAN-based technique for detecting textile surface defects of various types in the absence of defect samples was proposed by Wei, C., and colleagues. Based on the f-score metric, the experimental findings showed that the strategy performs better than other methods that have been developed recently [9]. To address the problem of diversified customer demands and supply chain management challenges, Bandyopadhyay et al. proposed an analytical algorithm based on KMC and principal component analysis (PCA). The method was used to effectively group customers buying apparel through a clustering algorithm, and PCA was used to reduce the dimensionality of product and customer characteristics. The results showed that the clustering results based on PCA and K-Means were similar and satisfied the customers within their budget [10]. Cinaroglu et al. explored the issue of technical efficiency assessment of public hospitals by combining KMC and DEA, and this integrated approach helped to identify the technical efficiency of public hospitals in provinces with similar welfare states [11]. Nainggolan et al. addressed the issue of advantages and disadvantages of online shopping by mining e-commerce website review data and using the KMC algorithm to generate clusters to help potential customers make purchase decisions. The results showed that cluster analysis can help consumers identify online shopping risks such as product and service quality, payment security, and fraud [12]. Hasanah et al. addressed the problem of product expiration and inventory backlog in Rizki Barokah Store by proposing to use the KMC algorithm for data mining, which classifies the products into interested and uninterested categories through cluster analysis and gives inventory suggestions based on the clustering results to understand the demand of the products. The results indicated that the method can effectively solve the product expiration problem, reduce the inventory backlog, and improve the sales efficiency [13]. El Khattabi et al. for the problem of K-means cluster, k, comparing four cluster evaluation index, and considering the influence of data normalization, the results show that data distribution, normalization form, and evaluation index have a significant impact on the clustering accuracy. Clustering Gaussian distribution data normalization is more accurate, advanced analysis data shape, and normalized [14]. Yang and other researchers have proposed an improved K-means algorithm and designed a comprehensive energy data system for the problem of big data collection, storage, and data errors. The method is applied to the monitoring of power equipment. The results show that the improved algorithm significantly improves the accuracy and reduces the classification error rate to less than 1%, and the designed system effectively meets the actual requirements and improves the storage and processing efficiency [15].

The DCGAN algorithm provides a wide range of potential applications in the field of image production, providing an important theoretical basis for the continuous development of the M-APP design department. However, few studies have combined the KMC algorithm with DCGAN for M-APP visual communication. Therefore, this study focuses on a method combining improved K-means clustering (IK-Means) and DCGAN to design the M-APP interface visual communication system based on AI so as to improve the design efficiency and meet the personalized needs of users.

3 VISUAL COMMUNICATION DESIGN SYSTEM BASED ON AI TECHNOLOGY

This section is broken down into two subsections. The first one discusses a number of KMC enhancements as well as the general scheme design for M-APP's VCD system. The second subsection focuses on training the features and user data using DCGAN to generate a new design scheme.

3.1 System data processing and overall system design for visual communication design

The system is a comprehensive M-APP interface design platform that starts from a user input layer where users can upload their design samples through an intuitive user interface. At the same time, the platform will collect user interaction data, such as click-through rate, dwell time, and user ratings, in order to better understand user needs. In the data processing layer, these data will be cleaned and transformed. The feature engineering layer extracts key features from design samples, such as color, shape, and layout. Next, in the analysis and model training layer, user behavior and design preferences are analyzed using the KMC model in order to perform fine-grained segmentation of users. At the same time, PCA is used to reduce the dimensionality of the design elements and find the key visual factors. In addition, features and user data are trained using DCGAN to generate new design solutions. The generation and optimization layer uses these trained models to automate the generation of design sketches and prototypes and adjusts these designs based on user feedback and clustering results to better meet the preferences of different user groups. In the user output layer, the generated design solutions will be presented in a user-friendly way. Figure 1 depicts the system architecture.

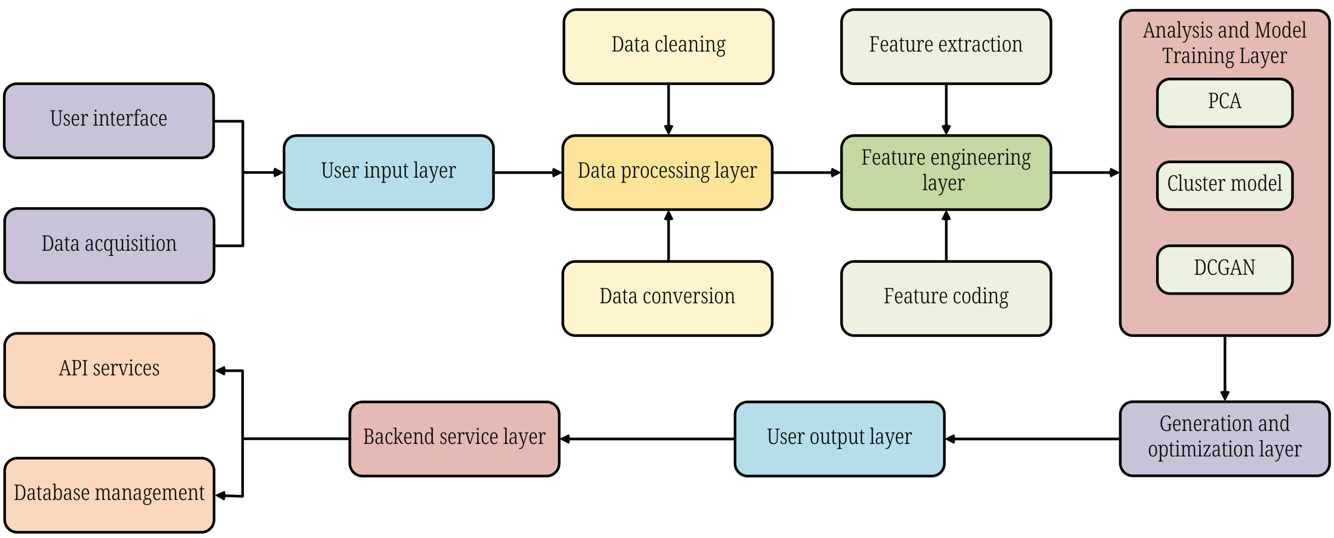


Fig. 1. Architecture of VCD system based on AI technology

One popular unsupervised learning technique for classifying data points into a fixed number of clusters is the KMC algorithm. The terms "mean" and "K" denote the number of clusters and the centroid, or center of mass, of each cluster, respectively [16–17]. This helps the system to understand different groups of users and customize the design for each group. The KMC algorithm is an iterative procedure that generates the clustering result by first selecting K samples at random to serve as the initial cluster centers. Next, the algorithm determines the distance between each sample and the class center and assigns each sample to the class that is located in the center that is closest to it. Next, for the obtained clustering results, calculate the mean of the samples in each class as the new clustering center. Finally, it is judged that if the iteration converges or meets the stopping conditions, the results are output; otherwise, it returns to continue the iteration. The K mean clustering algorithm is simple and easy to understand, but for choice of data type and initial value has a certain degree of sensitivity to the clustering process shown in Figure 2.

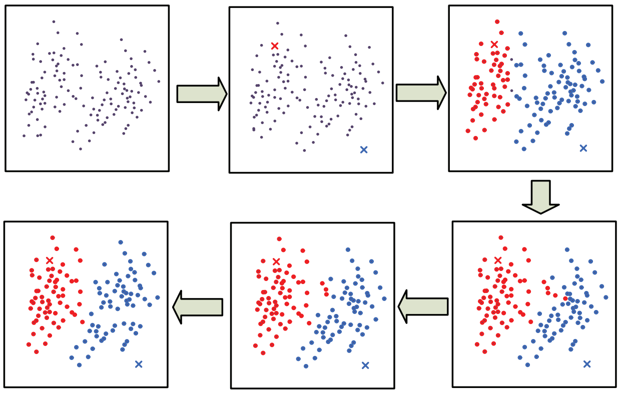


Fig. 2. Schematic diagram of K-clustering algorithm clustering process

The initial clustering centers have an impact on the clustering outcomes of the classical K-means algorithm, and various initial centers may produce various clustering outcomes. Furthermore, noise and outliers might alter the clustering results of the K-means algorithm by interfering with the calculation of the clustering center. In order to overcome these shortcomings, the study draws on the idea of minimum variance to design a clustering center selection method (IK-Means) that maximizes the minimum distance, assuming that the dataset to be clustered is X. The Euclidean distance between samples x_i, x_j is calculated as shown in equation (1).

$$d(x_i, x_j) = \sqrt{(x_i - x_j)^T (x_i - x_j)} \tag{1}$$

It is also important to compute the average distance from sample x_i, x_j to the other samples, as given in equation (2), in order to determine which known data point is most similar to the new data point by comparing the average distance between the new and the known data points.

$$E(x_i) = \frac{1}{n}\sum_{j=1}^{n} d(x_i, x_j) \tag{2}$$

In equation (2), n represents the data samples, and in the process of selecting KMCs, the points that are farther away from each other are more representative relative to the near neighbors. Therefore, in the selection of the initial clustering center, the maximization of the minimum distance method can be referred to. Assuming that there are two C_1, C_2 clustering centers, the new clustering center is selected as shown in equation (3).

$$C_1 = x_1, C_2 = x_2 \tag{3}$$

First, a sample is randomly selected as the first clustering center, and the sample x_2 with the farthest distance is selected as the new clustering center among the remaining data samples. Figure 3 depicts the algorithm's flow.

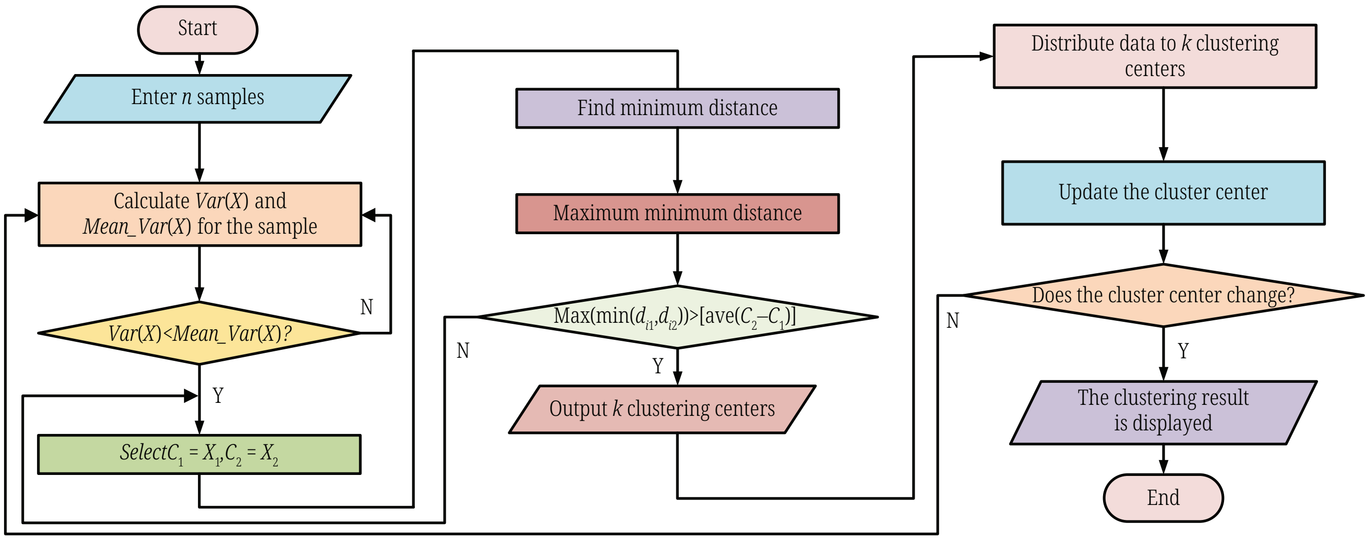


Fig. 3. Calculation process of the IK Means method

After the computation of the new clustering centers is completed, the distance of each remaining sample in the dataset to these existing clustering centers is computed. This step is a critical part of the clustering algorithm because it involves correctly categorizing each sample into the cluster to which it belongs. Assuming that d_{i1}, d_{i2}, ..., d_{iy} denotes the distance of different samples to the existing clustering centers, then the maximum value of the minimum value of the distance of all samples to the clustering centers is calculated as shown in equation (4).

$$\text{max\_min} = \max\begin{pmatrix}\min(d_{11}, d_{12}, \ldots, d_{1y}), \min(d_{21}, d_{22}, \ldots, d_{2y}), \ldots, \\ \min(d_{h1}, d_{h2}, \ldots, d_{hy})\end{pmatrix} \tag{4}$$

In equation (4), $\min(d_{i1}, d_{i2}, ..., d_{iy})$ denotes the minimum distance among them. By combining the principle of minimum variance, the IK-Means algorithm can better handle non-spherical clusters and noisy data while avoiding the sensitivity to the initial clustering center. As a result, the classic K-means method's drawbacks can be effectively addressed by using the IK-Means algorithm as a substitute.

3.2 IDCGAN-based visual communication design system

In practical applications, datasets often contain a large number of features, which increase the complexity and data processing of computational cost. Moreover, due to the high dimensionality of the data involved in the M-APP interface VCD, this leads to increased computational complexity and processing difficulty [18–19]. In order to process this data effectively and extract meaningful information from it, it needs to be downscaled using PCA before using the K-clustering algorithm. First, multidimensional data related to user behavior and design preferences, such as click-through rates and purchase records, are collected and preprocessed with necessary cleaning and coding. Next, numerical features must be normalized as shown by equation (5) in order to guarantee the algorithm's stability and accuracy.

$$z = (x - \mu)/\sigma \tag{5}$$

In equation (5), x is the original eigenvalue, μ is the mean of the feature, and σ is the standard deviation of the feature. The standardized eigenvalue z will have zero mean and unit variance, which is standardized to eliminate the effects of magnitude and order of magnitude to make it have a uniform scale. Then, the linear relationship between different features is revealed by calculating the covariance matrix of the standardized data, which is shown in equation (6) for the dataset X containing n samples and p features.

$$\sum = \left(\frac{1}{(n\ -\ 1)}\right) * (X - \mu)' * (X - \mu) \tag{6}$$

Then the eigenvalues and eigenvectors of the covariance matrix are extracted using the eigen decomposition technique, and these eigenvectors represent the main direction of change of the data. The projection matrix is created by selecting the first k eigenvectors with the biggest eigenvalues as principal components in order to minimize the dimensionality of the data. The projection matrix P composed of some principal components is shown in equation (7).

$$P = [v1, v2, \ldots, vk] \tag{7}$$

In equation (7), vk is the eigenvector corresponding to the first k largest eigenvalues, and through this projection matrix, the original data can be mapped to a new low-dimensional space, thus realizing the dimensionality reduction of the data. Finally, the KMC algorithm is applied on the dimensionality-reduced data to finely classify users into different groups based on their behavior and design preferences. By choosing the appropriate number of clusters, k, and going through the iterative process of the algorithm, it is possible to determine the center of each cluster and accurately assign the data points to the corresponding clusters, and the flow of the PCA algorithm is shown in Figure 4.

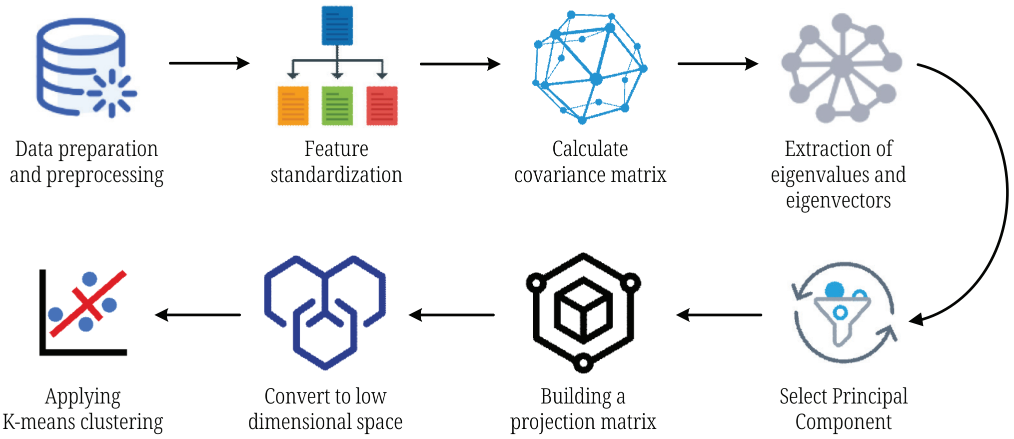


Fig. 4. Principal component analysis module algorithm process

In the algorithm process of principal component analysis, data preparation and preprocessing are the first steps, which involve data cleaning, filling in missing values, and handling outliers to ensure the quality and reliability of the data. The next step is featuring standardization, which eliminates the influence of dimensionality by subtracting the mean and dividing it by the standard deviation so that each feature has the same scale. Then calculate the covariance matrix to reveal the correlation between features. By extracting the eigenvalues and eigenvectors of the covariance matrix, the main direction of data change can be identified. Selecting principal components involves selecting the eigenvector corresponding to the largest eigenvalue and constructing a projection matrix. By using projection matrices, the original high-dimensional data is transformed into data in a low-dimensional space, achieving dimensionality reduction. Finally, the KMC algorithm is applied to cluster the dimensionality-reduced data, dividing the data points into different groups. Each group represents a set of data points with similar features, thus completing the fine classification of user behavior and design preferences. This approach combines the dimensionality reduction benefits of PCA and the grouping capabilities of KMC to provide a powerful tool to deeply understand and analyze user behavior and design preferences, to specify the characteristics of each group, and to extract key design elements and user behavioral characteristics of each cluster for use in generating design solutions. Next, the DCGAN module will utilize the results of the clustering to select the design elements associated with each user group as training data. Using this data to train the DCGAN, the generative network will learn how to generate design patterns that satisfy the preferences of a specific user group. The generator will produce fresh design samples throughout the training phase, and the discriminator will attempt to differentiate the created samples from the real samples. This adversarial process, which has a schematic representation in Figure 5, will optimize the generator.

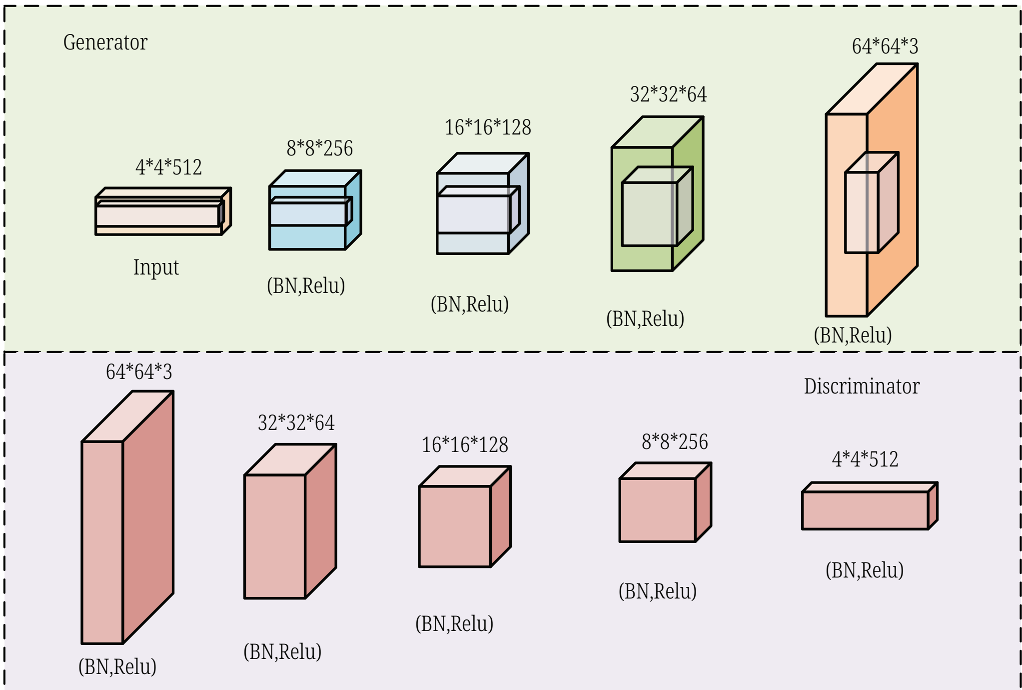


Fig. 5. Schematic diagram of DCGAN structure

The primary novelty of DCGAN, an improved version of GAN, is the use of convolutional neural network (CNN) techniques to maximize the effectiveness of the discriminator and generator. Structurally, the generator (G-network) utilizes the inverse convolutional technique to reconstruct the original image, while the discriminator (D-network) applies the convolutional technique to recognize the features of the image in order to make an accurate discrimination. Specifically, the generator network (G-net) uses ReLU as the activation function and the Tanh activation function in the last layer and removes the fully connected layer to realize the design of a fully convolutional network. In contrast, the discriminator network (D-network) removes all pooling layers, utilizes the transposed convolution with a step size greater than or equal to 2 for up-sampling, and introduces the convolution of stride instead of the pooling operation, while employing LeakyReLU as the activation function. These improvements allow DCGAN to exhibit higher quality and stability on image generation tasks. In order to be able to better scale the resolution of the image, the study uses an SRGAN-like discriminator structure to improve DCGAN. The network structure of the SRGAN discriminator usually contains a convolutional layer, a batch normalization layer, and a LeakyReLU activation function, but unlike DCGAN, the SRGAN discriminator may have a deeper network structure and smaller convolution kernels in order to better capture the details of high-resolution images, and its structure is shown in Figure 6.

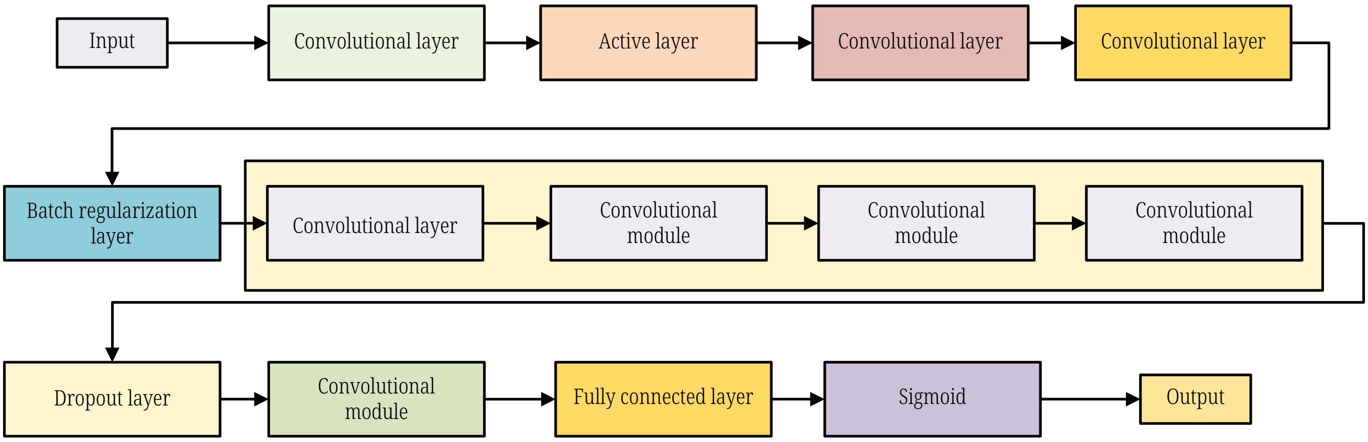


Fig. 6. Schematic diagram of IDCGAN discriminator structure

In the IDCGAN discriminator structure, the input data first passes through a convolutional layer, which is responsible for extracting local features of the image. Then, an activation layer is added to enhance the model's non-linear expression ability. Subsequently, the data passes through multiple consecutive convolutional layers, each layer further refining features, gradually transitioning from low-level edge information to high-level abstract features. Between these convolutional layers, batch regularization standardization is introduced to standardize the output of each layer, which helps to solve the problem of internal covariate shift, thereby accelerating training and improving the model's generalization ability. In addition, to prevent overfitting, the discriminator adds a dropout layer, which randomly discards some neural connections during training to enhance the model's generalization ability. The robustness of the model is improved. Finally, the discriminator maps high-dimensional features to a one-dimensional space through a fully connected layer, facilitating final classification and judgment. The output layer uses a sigmoid activation function to compress the discriminator's output to between 0 and 1, representing the probability that the input data is judged as a real sample. The entire structure is compact and efficient and can effectively distinguish between real samples and generated samples. In addition, the discriminator also uses adversarial loss (AL) and perceptual loss (PL) to optimize the training of the model. Assuming that $D(x)$ is the discriminator output probability for real data and $G(z)$ is the fake data generated by the generator, then its AL formula is shown in equation (8).

$$L\_adv = E[Log^{(D(x))} + E[Log^{(1-D(G(z)))}]] \tag{8}$$

In equation (8), $D(G(z))$ represents the output probability of the discriminator on the generated data. The PL function expression is shown in equation (9).

$$L\_perceptual = \Sigma\_i \left\| \phi\_i(I\_gen) - \phi\_i(I\_real) \right\|^2 \tag{9}$$

In equation (9), $L\_perceptual$ denotes the PL, ϕ_i denotes the feature extraction function of layer i in the pre-trained neural network, I_gen denotes the generated image, and I_real denotes the real high-resolution image. $\left\| \bullet \right\|^2$ denotes the square of the Euclidean distance. Equation (10) displays the expression of the conditional contrast loss, which is the loss function utilized during the training phase.

$$\delta(a_i, a_j, t) = -\log\left(\frac{\exp(l(a_i)^T l(a_j)/t)}{\sum_{k=1}^{2m} \exp(l(a_i)^T l(a_j)/t)}\right) \tag{10}$$

In equation (10), t is the temperature that controls the push and pull forces. Then the introduction of dense connections can help to solve the gradient vanishing problem and speed up the training process, the expression of which is shown in equation (11).

$$H(x) = [F1(x), F2(x), \ldots, Fn(x)] \tag{11}$$

In equation (11), $H(x)$ denotes the output of the network layer, $Fn(x)$ denotes the nonlinear transformation function, and x denotes the input. In order to improve the stability and generation quality of IDCGAN, spectral normalization is used in the discriminator to constrain the spectral paradigm of the weight matrix, thus stabilizing the training process as shown in equation (12).

$$W\_SN = W/\sigma(W) \tag{12}$$

In equation (12), W denotes the weight matrix and $\sigma(W)$ denotes the spectral paradigm of W.

4 CORRELATION ALGORITHM PERFORMANCE TESTING AND APPLICABILITY ANALYSIS

This chapter is primarily divided into two subsections. The first subsection focuses mostly on a set of algorithmic comparative analyses and performance tests of the IK clustering algorithm and IDCGAN that were proposed in the study.

The second subsection mainly focuses on the applicability analysis of the proposed VCD system by applying it to the actual M-APP practice.

4.1 IK clustering algorithm and IDCGAN performance test

In designing IDCGAN, the study used AL and PL respectively to optimize the model. In order to test the effect of AL and PL on the model training, the experiment used the ImageNet dataset to test the change of the two loss function values during the training process, as shown in Figure 7.

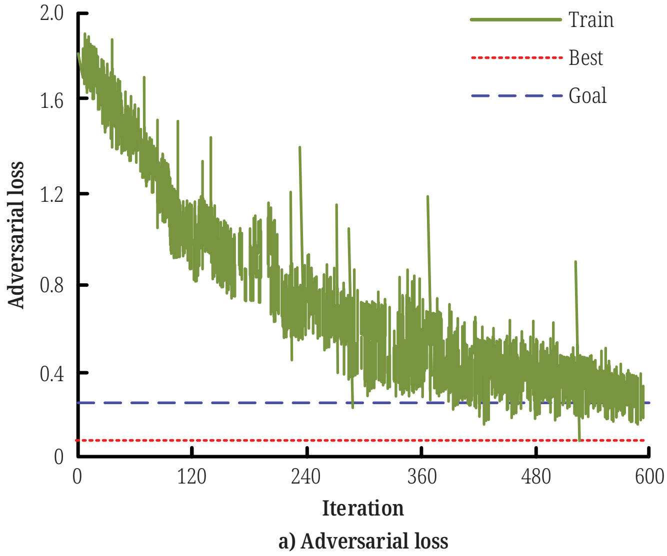


Fig. 7. Comparative loss function values of IDCGAN model on two datasets

Figure 7 shows the training process of the IDCGAN model on two different datasets, comparing the two loss functions with the number of training rounds. In Figure 7a, in the ImageNet dataset, the AL function value undergoes a gradual decrease as the number of iterations increases. After about 380 iterations, this value gradually stabilizes and converges to 0.25, a result that not only meets the expectation but even outperforms the originally set target value of 0.35. This observation suggests that the IDCGAN model on the ImageNet dataset successfully learns the ability to generate forged images that are similar to the real ones through effective adversarial training. In Figure 7b, similar to the AL, the PL also experienced a significant decline. After about 280 iterations, the value of the PL function converges to 0.05, an achievement that is significantly better than the expected target set at 0.25. This result indicates that the IDCGAN model performs better at the perceptual level, indicating that it can produce fake images that are remarkably close to the actual ones in terms of visual perception. For the comparative experiments, which were conducted on an Ubuntu 64-bit system platform using PyTorch 1.4 software with 600 iterations of the three algorithms using the CV-PTON dataset, respectively, the experiments introduced the DLE-TEC-IC method proposed in the literature [20] as well as the standard DCGAN algorithm to verify the superior performance of the IDCGAN algorithm proposed in the study. Additionally, the PR curve served as a standard, and Figure 8 displays the outcomes of the experiment.

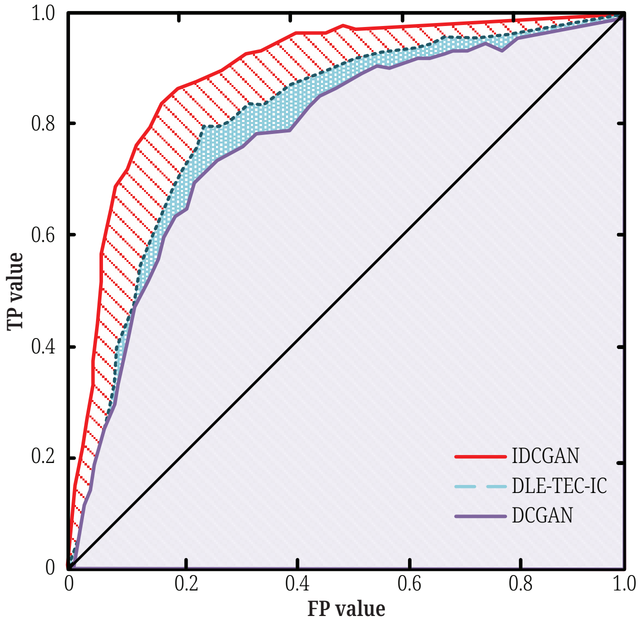


Fig. 8. PR curves during the training process of each algorithm

In Figure 8, among the three algorithms, the PR curve of the IDCGAN algorithm proposed in the study is located at the top, while the algorithm proposed in the literature [18] is the second best, and the standard DCGAN performs the worst, and the AUC areas of the three algorithms are 0.913, 0.852, and 0.826, respectively. By comparing the DCGAN before and after the improvement, it can be found that the IDCGAN maintains the DCGAN;s original advantages while significantly improving the performance of the model by introducing new optimization strategies or improvement methods. The study uses the KMC model to analyze user behavior and design preferences. And a series of improvements are made to it, and the IK-Means algorithm is designed. To confirm the superiority of this algorithm, simulation tests are performed on the two algorithms using the scikit-learn package, and the experiment presents the RIS-SSL-GA approach suggested in the literature [21] for comparison. The experimental results are shown in Figure 9.

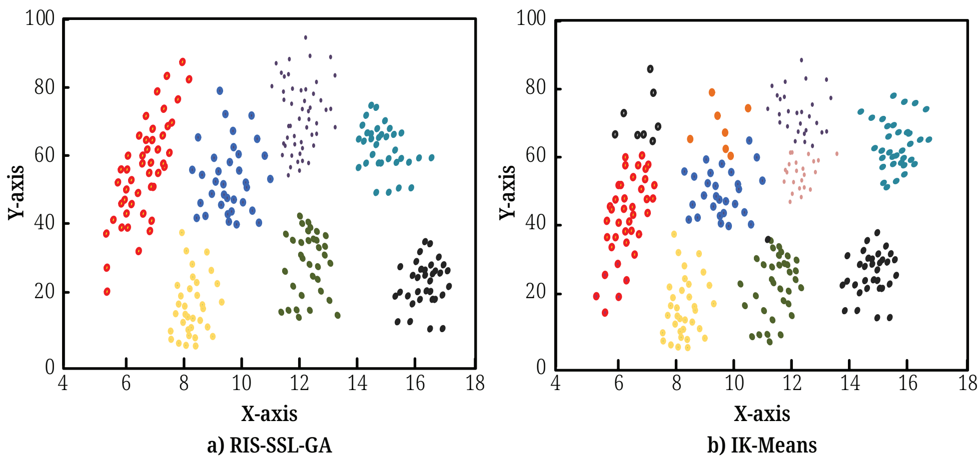


Fig. 9. Clustering effect of K-clustering algorithm

Figure 9a makes it clear that the algorithm suggested in the literature [21] processes the input into seven distinct groups. These categories are clearly delineated in the figure, showing that the algorithm is effective and accurate in processing this type of data. However, it can also be observed that the clustering results of the algorithm have some overlapping and fuzzy boundaries in some regions, which may imply that the algorithm may have some limitations when dealing with complex or high-dimensional data. On the other hand, Figure 9b illustrates that the IK-Means algorithm suggested in the research generates 12 categories when working with identical data. These categories are not only more numerous but also more uniform and detailed in spatial distribution.

4.2 Applicability analysis of M-APP's VCD system

The experiments have fully demonstrated the significant advantages of the proposed algorithm of the study in various performance indicators through a rigorous validation process. However, the study team specifically created a number of applied and practical experiments in order to more thoroughly assess the scheme's performance in real-world applications and guarantee its stability and reliability. And using advanced visualization techniques, the similarity heat map of IDCGAN in processing different data samples was drawn to visualize the similarity distribution between data, as shown in Figure 10.

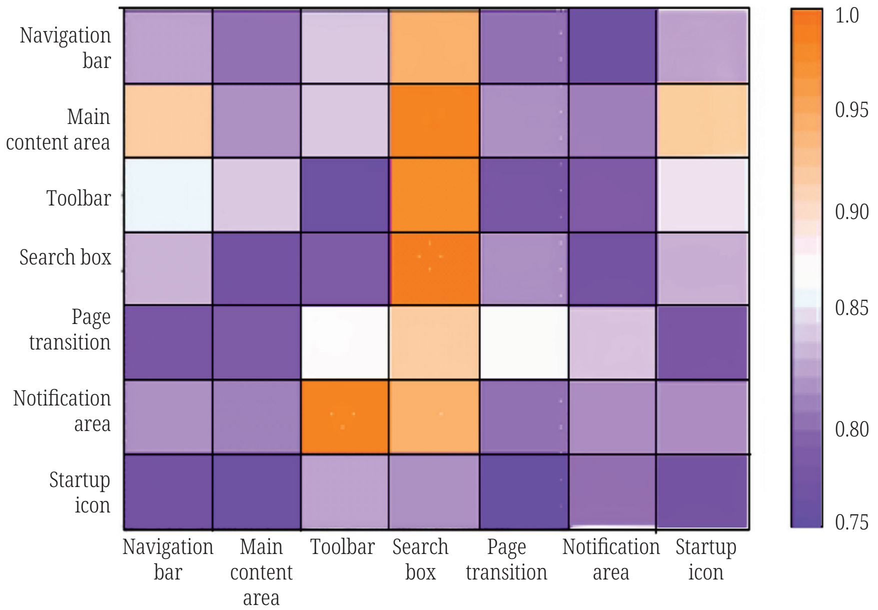
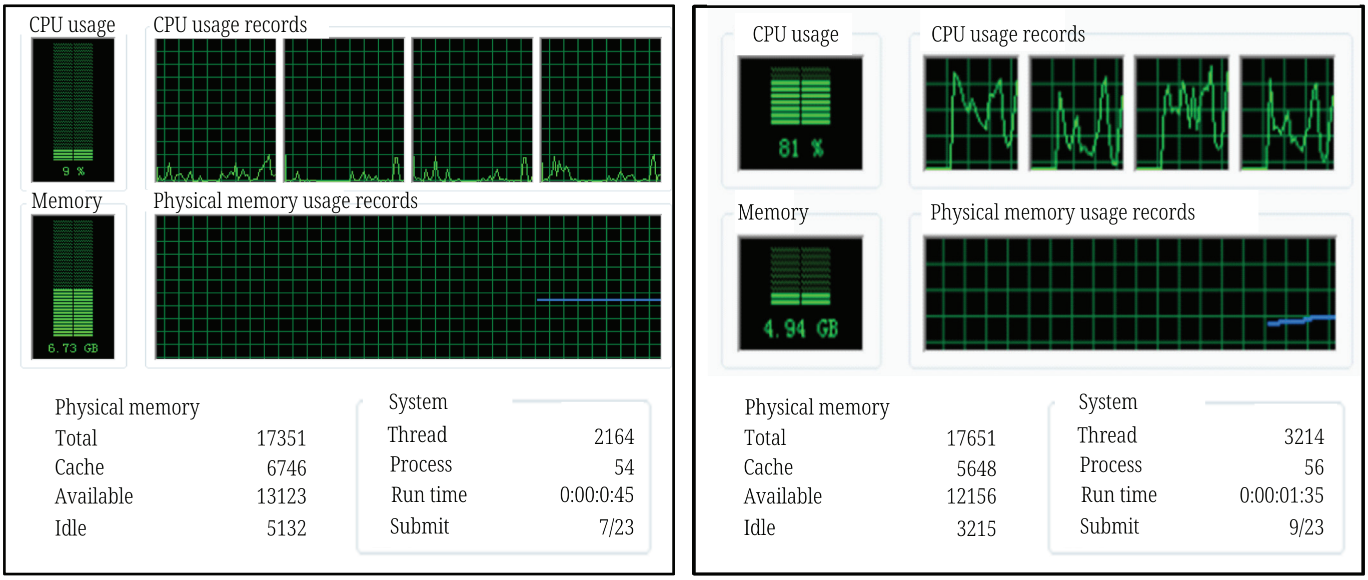


Fig. 10. Improving IDCGAN similarity thermal map

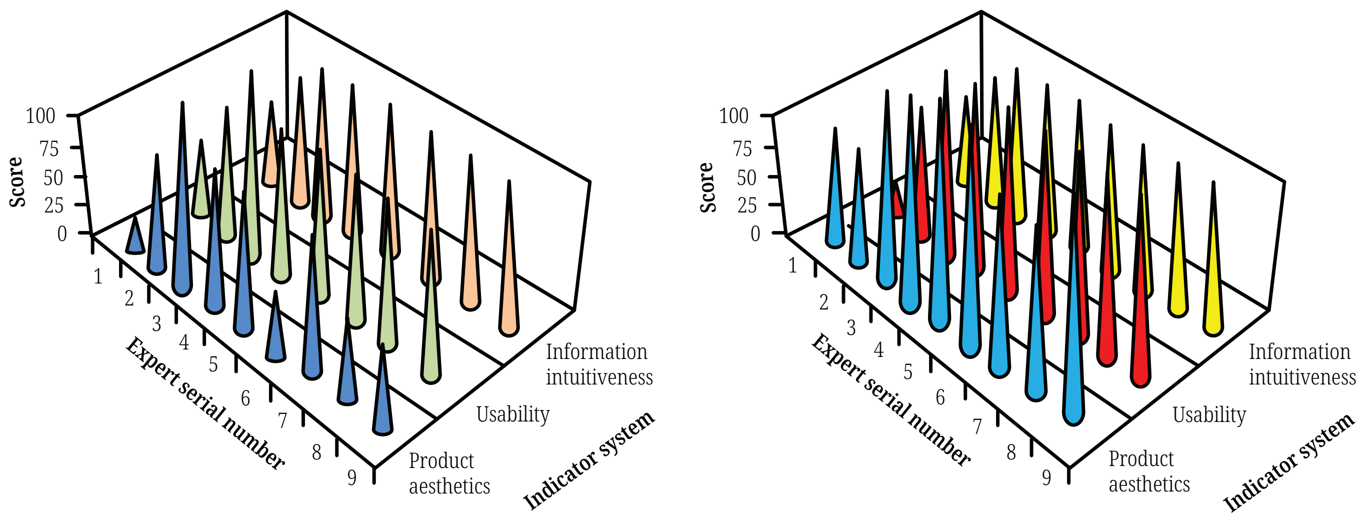
Figure 10 illustrates the IDCGAN similarity heatmap, and the results show that IDCGAN has high accuracy in simulating and learning APP elements, which stably stays above 0.80. This proves that IDCGAN can reliably capture core attributes with consistency across different experimental scenarios and datasets. The high similarity shows that the generative capability of IDCGAN reaches high standards in real-world applications and is important for the application domain of fine-grained feature reproduction. To validate the scheme, experiments were conducted to apply the system in real APP automation design, and the DCGAN-RTA system proposed in the literature [22] was introduced for comparison. The experiment counts the system resource consumption of the two systems during operation, and the results are shown in Figure 11.



a) IDCGAN b) DCGAN-RTA

Fig. 11. Comparison of resource consumption between two systems

In terms of resource use, Figure 11 compares the system suggested in the study with the system suggested in the literature [22]. The former has a low CPU usage (9%), small memory usage (341 MB), short running time (45 seconds), and high efficiency. The latter has a high CPU utilization (81%), high memory usage (846 MB), long running time (1 minute 35 seconds), high consumption, and low efficiency. In conclusion, the PCA system performs well in resource utilization efficiency, operation speed, and user experience. At the end of the experiment, nine M-APP front-end designers were recruited to rate the product aesthetics, ease of use, and information intuition of the two systems on a percentage scale as an evaluation system, and the results of the survey are shown in Figure 12.



a) DCGAN-RTA b) IDCGAN

Fig. 12. Comprehensive evaluation of two systems by front-end designers of mobile apps

Figure 12a demonstrates the experts' evaluation of the method proposed in the literature [22], in which the average rating of product aesthetics is 53, ease of use is 73, and information intuition is 84. These ratings indicate that the method has certain deficiencies in the aesthetics of interface design, the ease of user operation, and the clarity of information presentation, which need to be further optimized and improved. In contrast, Figure 12b presents the experts' positive evaluation of the proposed method of the study. Among them, the average rating of product aesthetics is 85, ease of use is 89, and information intuition is 83. These high scores not only prove the superiority of the method in terms of aesthetics and user experience of interface design, but also show the efficiency and clarity of the method in organizing and presenting information. These significant advantages make the proposed method of the study have higher value and potential in practical application.

5 CONCLUSION

In order to improve the automation of M-APP design, the study combines the KMC algorithm with improved DCGAN to design a new VCD system for M-APP. In the algorithm comparison experiments, the AL function value gradually stabilized and converged to 0.25 after about 380 iterations, and similar to the AL, the PL also experienced a significant decrease. After about 280 iterations, the value of the PL function converged to 0.05, which is significantly better than the expected target set at 0.25. In addition, the proposed system of the institute performed very well in terms of CPU usage, which was only 9%, which means that the system occupies a very low amount of CPU during the operation and is able to utilize the processor resources more efficiently. In addition, the physical memory usage of the system was quite low at 341 MB, which indicates that the system is highly efficient in memory management and is able to fully utilize the limited memory resources. Meanwhile, the running time of the system was very short, which was only 45 seconds, which further proved the high efficiency of the system. It can be seen that the system using principal component analysis (PCA) shows significant advantages in terms of resource use. In summary, the system shows significant advantages in terms of algorithm performance, resource consumption, and user experience and is capable of generating high-quality APP interface design solutions that meet users' needs. The system's information intuitiveness is only 83 points, which is marginally less than the literature-proposed algorithm [22–24]. This is another area that requires improvement in the next study.

6 FINDINGS

The study is supported by: Scientific Research Project of the Education Department of Hunan Province (project number: 24B0972).

7 REFERENCES

[1] H. Mokayed, T. Z. Quan, L. Alkhaled, and V. Sivakumar, "Real-time human detection and counting system using deep learning computer vision techniques," *Artificial Intelligence and Applications*, vol. 1, no. 4, pp. 205–213, 2023. https://doi.org/10.47852/bonviewAIA2202391

[2] S. Pal, A. Roy, Palaiahnakote, and U. Pal, "Adapting a swin transformer for license plate number and text detection in drone images," *Artificial Intelligence and Applications*, vol. 1, no. 3, pp. 129–138, 2023. https://doi.org/10.47852/bonviewAIA3202549

[3] P. P. Groumpos, "A critical historic overview of artificial intelligence: Issues, challenges, opportunities, and threats," *Artificial Intelligence and Applications*. vol. 1, no. 4, pp. 181–197, 2023. https://doi.org/10.47852/bonviewAIA3202689

[4] W. Fang, F. Zhang, Y. Ding, and J. Sheng, "A new sequential image prediction method based on LSTM and DCGAN," *Computers, Materials & Continua*, vol. 64, no. 1, pp. 217–231, 2020. https://doi.org/10.32604/cmc.2020.06395

[5] M. Li, H. Tang, M. D. Chan, X. Zhou, and X. Qian, "DC-AL GAN: Pseudoprogression and true tumor progression of glioblastoma multiform image classification based on DCGAN and AlexNet," *Medical Physics*, vol. 47, no. 3, pp. 1139–1150, 2020. https://doi.org/10.1002/mp.14003

[6] C. Dewi, R. C. Chen, Y. T. Liu, and S. K. Tai, "Synthetic data generation using DCGAN for improved traffic sign recognition," *Neural Computing and Applications*, vol. 34, no. 24, pp. 21465–21480, 2022. https://doi.org/10.1007/s00521-021-05982-z

[7] J. Park, H. Kim, and K. Kim, "Accessing impact of DCGAN image data augmentation for CNN based tomato disease classification," *Digital Content Society (JDCS)*, vol. 21, no. 5, pp. 959–967, 2020. https://doi.org/10.9728/dcs.2020.21.5.959

[8] J. Cho and N. Moon, "Design of image generation system for DCGAN-based kids' book text," *Journal of Information Processing Systems,* vol. 16, no. 6, pp. 1437–1446, 2020.

[9] C. Wei *et al.*, "Multi-stage unsupervised fabric defect detection based on DCGAN," *The Visual Computer*, vol. 39, no. 12, pp. 6655–6671, 2023. https://doi.org/10.1007/s00371-022-02754-1

[10] S. Bandyopadhyay, S. S. Thakur, and, J. K. Mandal, "Product recommendation for e-commerce business by applying principal component analysis (PCA) and K-means clustering: Benefit for the society," *Innovations in Systems and Software Engineering*, vol. 17, no. 1, pp. 45–52, 2021. https://doi.org/10.1007/s11334-020-00372-5

[11] S. Cinaroglu, "Integrated k-means clustering with data envelopment analysis of public hospital efficiency," *Health Care Management Science*, vol. 23, no. 3, pp. 325–338, 2020. https://doi.org/10.1007/s10729-019-09491-3

[12] R. Nainggolan and E. Purba, "The cluster analysis of online shop product reviews using K-means clustering," *Data Science: Journal of Computing and Applied Informatics,* vol. 4, no. 2, pp. 111–121, 2020. https://doi.org/10.32734/jocai.v4.i2-2855

[13] M. Imron, U. Hasanah, and B. Humaidi, "Analysis of data mining using k-means clustering algorithm for product grouping," *International Journal of Informatics and Information Systems*, vol. 3, no. 1, pp. 12–22, 2020. https://doi.org/10.47738/ijiis.v3i1.3

[14] M. Z. El Khattabi *et al.*, "Understanding the interplay between metrics, normalization forms, and data distribution in K-means clustering: A comparative simulation study," *Arabian Journal for Science and Engineering*, vol. 49, no. 3, pp. 2987–3007, 2024. https://doi.org/10.1007/s13369-023-07741-9

[15] W. Yang, "Analysis and application of big data feature extraction based on improved k-means algorithm," *Scalable Computing: Practice and Experience,* vol. 25, no. 1, 2024. https://doi.org/10.12694/scpe.v25i1.2281

[16] A. Hussein, F. K. Ahmad, and S. S. Kamaruddin, "Cluster analysis on Covid-19 outbreak sentiments from twitter data using K-means algorithm," *Journal of System and Management Sciences*, vol. 11, no. 4, pp. 167–189, 2021.

[17] D. D. Atsa'am, S. S. Balogun, O. S. Oyelere, R. Wario, and N. V. Blamah, "K-means cluster analysis of the West African species of cereals based on nutritional value composition," *African Journal of Food, Agriculture, Nutrition and Development (AJFAND)*, vol. 21, no. 1, pp. 17195–17212, 2021. https://doi.org/10.18697/ajfand.96.19775

[18] M. A. Ahmed, H. Baharin, and P. N. E. Nohuddin, "Analysis of K-means, DBSCAN and OPTICS Cluster algorithms on Al-Quran verses," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 8, pp. 248–254, 2020. https://doi.org/10.14569/IJACSA.2020.0110832

[19] Y. Jang, J. Yoo, and H. Hong, "Assessment and analysis of fidelity and diversity for GAN-based medical image generative model," *Journal of the Korea Computer Graphics Society*, vol. 28, no. 2, pp. 11–19, 2022. https://doi.org/10.15701/kcgs.2022.28.2.11

[20] Z. Chen *et al.*, "Improvement of a deep learning algorithm for total electron content maps: Image completion," *Journal of Geophysical Research: Space Physics*, vol. 124, no. 1, pp. 790–800, 2019. https://doi.org/10.1029/2018JA026167

[21] A. Diaz-Pinto, A. Colomer, V. Naranjo, S. Morales, Y. Xu, and A. F. Frangi, "Retinal image synthesis and semi-supervised learning for glaucoma assessment," *IEEE Transactions on Medical Imaging*, vol. 38, no. 9, pp. 2211–2218, 2019. https://doi.org/10.1109/TMI.2019.2903434

[22] V. V. Kaveri *et al.*, "Image generation for real time application using DCGAN (Deep Convolutional Generative Adversarial Neural Network)," *Turkish Journal of Computer and Mathematics Education (TURCOMAT),* vol. 12, no. 11, pp. 617–621, 2021. https://doi.org/10.17762/turcomat.v12i11.5936

[23] N. Phumeechanya, "Flipped classroom mobile learning model and its application to enhance digital intelligence quotient among secondary students," *International Journal of Interactive Mobile Technologies*, vol. 18, no. 24, pp. 19–37, 2024. https://doi.org/10.3991/ijim.v18i24.50077

[24] Q. Li, "Adaptive recommendation of teaching content in higher education using mobile interaction technology," *International Journal of Interactive Mobile Technologies,* vol. 18, no. 24, pp. 115–129, 2024. https://doi.org/10.3991/ijim.v18i24.53091

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