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ORIGINAL RESEARCH ARTICLE

The role of iconography in shaping Chinese national identity: Analyzing its representation in visual media and political propaganda

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ABSTRACT

The creation of cultural iconography that may reflect national culture and encourage individuals to identify with Chinese culture has always been a difficult issue. In this study, we present a symbolic creation framework for Chinese national cultural identity constructed from visual pictures using generative adversarial networks (GAN). To enhance the structure collapse phenomena of generative adversarial systems, form search regular procedure and generator cross-loss factors on the basis of GAN should be combined. To enhance the real-time efficiency of the model by lowering the parameters in the model, the conventional convolutional component of the generator in the system's architecture is substituted with a significant recoverable convolution. The notions of iconography and character as they relate to symbols are discussed in this essay. It also advises using iconography as a technique of symbolic imagery to give emergent symbols identity. The design in this study may create significant performance ethnic cultural symbols while preserving superior temporal performance, according to the findings of rigorous testing on real datasets, which may have practical application value. The accuracy, precision, recall, and F1 of the system in this study are 91.54%, 89.02%, 90.96%, and 87.48%.

Keywords: generative adversarial networks; accuracy; iconography; precision

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1. Introduction

Cultures are the result of traditions that have evolved over time. They create circumstances for the formation of individualities. On the one hand, character is made up of cultural constructions and develops over time. It is associated with rituals, meanings, and conventions, as well as habits, events like social activities. Inclined by people's life stories and value systems over time. Culture, on the different hand, has an impact on People's overall grasp of their physical surroundings and how to interact with them. As a result, landscape characteristics offer a conduit in the link between humans and nature. These characteristics carry significant meaning and connotations that influence the formation of a unique landscape identity rooted in local culture people. As a result, the formation of landscape classification serves as a foundation for the establishment of national identity. Landscape identity represents the image of individual people and may serve as a vision for the creation of societal identity. Meanwhile, gardens play an important part in landscape photography. It is a type of landscape that displays both the aesthetic ideals and the physicality of that environment. As a result, garden identity is seen as a component of social identity and has the potential to contribute to the establishment of national landscape identity.

Garden design, as a fine art area, has a long history of interrelationship with painting[1]. Ross regards this craft as equally honourable as the professions of sculpture and poetry in 18th-century England. Both Europe and Oriental gardening have historically been linked to various forms of art like poetry, writing, and painting. It was said, for example, that Persian plants were integrating with Persian arts such as painting, poetry, and carpet creation[2]. Similarly, painting, poetry, and calligraphy have all played a significant role in Chinese gardens. As a result, the features of such a piece of art may be used to identify a garden. Furthermore, through history, renowned garden styles have been identified by distinct pictures or emblems[3]. As a result, gardens may be studied and recognised as a fine art form by their intricate imagery or iconography. Although well-known gardens across the world, such as English, Persian, Japanese, and Chinese gardens, may be identified and recognised by distinct pictures or iconography, this does not appear to be the case with freshly developing gardens.

Nonetheless, they need the production of some essential pictures that contribute to the establishment of their symbology and identities. This chosen iconography should represent the requirements, opinions, historical context, and lifestyle of the people involved with the gardens in shape, quality, and appearance.

National identity and symbols

National symbols are things that signify a country. A song, a flag, or a ritual are all examples of national symbols. While the national emblem serves numerous purposes[4], its primary role is to develop, sustain, and consolidate national identity[5]. National identification is the attribute or state of thinking oneself to be a member of a nation. Despite significant discrepancies, the most major schools of thought, notably structuralism[6] and endosymbiosis[7], agree on the importance of national identity for contemporary states.

Identity has several definitions based on context or point of view, and it is also a term with ambiguous restrictions. The method of shaping identity operates on various cultural concepts[8]. For example, identity may be a representation of legacy that honours both people's nature and culture[9]. As a result, it must be mirrored in a location where others may learn and experience it. Meanwhile, a place's identity is a unique characteristic that separates it from other areas while expressing its ethnic roots and legacy[10]. Thus, location identity (in this case, garden identity) is described as a location's personality, which comprises its appeal, representation, image, and icon, all of which have origins in popular culture. The hostility among China and different powers in the last 100 years gave rise to the Chinese state as a self-sensible national organisation in terms of both national growth and national social thinking, but being an independent country phase is the result of numerous times of historical procedures. The varied structure of the Chinese people is both a historical byproduct and an actual reality. Due to this, individuals inherit preexisting cultural legacy that is objectively real, including traditional colours and visual symbols with regional qualities.

These conventional pictures have come to represent Chinese culture. Traditional culture and visual symbolism are linked. They represent the knowledge and ideology of the Chinese people and reflect the people's view on life, morals, ethics, traditions, society, and education. Home décor items, such as designs on windows, doors, tiles, etc., interior furnishings and designs with allegorical significance, including auspicious symbolism and patterns that convey people's desires for a better life, are examples of traditional cultural symbols that are used in everyday life. For instance, there are established notions and meanings associated with the door deity of the Spring Festival, the phoenix boat and rice dumplings of the Festival of Dragons, the rabbit and mooncakes of the Autumn Festival, etc. National aesthetic customs are consistent with conventional symbols of culture that were passed down for thousands of years. In regards to pattern expression, colour, and meaning, ancient cultural signs with Chinese features represent the genetics of traditional Chinese culture.

Explicit symbols and covert symbols are two categories of traditional cultural symbols. Conventional pattern symbols, traditional colour signs, and traditional material symbols are the three parts of the explicit use of traditional cultural symbols in modern design. These three symbols may be taken apart and put back together to form a contemporary design with Chinese traditional overtones[11]. China's rich both material and intangible cultural heritage, which includes flying murals, creating, and dyeing, pottery, silk, and New Year pictures, all of which together reflect the unique features of Chinese culture, is a very important source of creative inspiration for designers. Inherently implicit and metaphorical, invisible signals have an impact. Suzhou gardens, for instance, might represent the conventional values of "the harmony amongst man and environment" and Zen architecture. The emphasis on the unity and harmony of man and nature, the way in which the subject's feelings are expressed is permeated by external natural phenomena, and the way in which the matter and I, the topic and the object, are perfectly integrated, is what distinguishes traditional cultural expressions from other forms.

2. Literature review

Although Chinese iconography gone through years of growth and change and has collected a wealth of figurative physical resources, some of our visual image strategy has always had issues like imitativeness in employing limited culture, favouring form, and weakening to clearly express the significant knowledge. Art developers[12] must have a broad and clear understanding of various symbols in order to bridge contemporary design for visual association and symbols of culture, and they must be skilled at investigating, extending, and reassembling them, illustrating the local features and national personality they include, while producing design work that has solid vitality that meets the aesthetics.

2.1. Image generation framework

It comprises primarily of an encoded system for interacting statistical data from the input picture and an interpreting system for recreating the initial symbol. This form of propagative model has several compensations, including steady exercise and quick convergence. Though, because the VAE typical optimization's goal function is the minimal likelihood operation, the resulting image seems blurry inclusively. Another family of GAN-based image creation representations[13] apprehensions the probability pattern of real pictures implicitly through competition among generators and discriminators. GANs-like models can create crisper and more realistic pictures with adversarial training. However, the initial GANs models had several serious flaws, including feature breakdown and training variability.

Researchers have developed several useful approaches for stabilising the learning process and improving image quality. Furthermore, the researchers suggest using provisional GANs to limit the produced pictures in order to achieve certain desirable features. For example, additional details like labels in class that might be used to direct the development of digital pictures. CGANs related methodology have previously been widely employed in super-determination picture production, image style transformation, image renovation, and other domains. Because of the adversarial network's exceptional performance in creating pictures, we also utilise it to finish the production of target symbols.

2.2. Symbol formation framework

The study on symbol creation using deep neural systems may be divided into two areas. The first category includes researchers who employ discrete symbol attributes for symbol production. To build an expression production model with different looks, research[14] advocated encoding variables such as gender, reaction classification, and hair colour into the bottleneck part of the probabilistic VAE model. Literature[15] separated distinct expression states like furious and glad into various areas and presented StarGAN to realise interconversion amongst numerous common terminologies. Literature[16] separated distinct expression states like furious and glad into various domains and presented StarGAN to realise interconversion between numerous common expressions. StarGAN's discriminator must assess not only the legitimacy of the produced picture, but also the source from which it originated.

Even though these approaches may produce significant expression of symbols pictures, the decrypted symbolic qualities are insufficient to depict the rich philosophy. To address this issue, the scholars looked at ways to include ongoing additional data into the creative model. Literature[17] has suggested a direct linear regression of two distinct shapes by utilizing representation feature ideas, followed by the compression of these shapes into a limited coding vector-based using associated grid, and finally the feeding of the vector into the conflicting system to produce the ongoing signs.

The research focuses on the role of iconography in shaping Chinese national identity, with a particular emphasis on analyzing its representation in visual media and political propaganda. The study uses a symbolic creation framework for Chinese national cultural identity constructed from visual pictures using GAN. The paper also discusses the concepts of iconography and character as they relate to symbols and advises using iconography as a technique of symbolic imagery to give emergent symbols identity. This study will provide background information on the concepts of culture, identity, and landscape identity, and how they are interconnected. It also discusses the historical interrelationship between garden design, painting, poetry, and calligraphy in both European and Oriental gardening traditions, and how these features can be used to identify a garden.

3. Methodology

3.1. Generative Adversarial Network (GAN)

A generative network and a discriminatory network make up a GAN. The discriminatory network is used to discriminate between actual samples and bogus samples produced by the generator. The creative and exclusive connections are proficient instantaneously during the training method, creating an evolving game using min and max. In divergence, propagative grids are utilised to trick the discriminator by creating bogus examples.

The GAN process of training is depicted as

$$minmaxM\ (A, E) = G_{d-fdata(d)}[\log A\ (d)] + G_{d-f_E}[\log(1 - A(d))] \tag{1}$$

Here d is the sample size, $fdata$ is the significant distribution, f_E is the formation distribution size, A is the discriminator, and E is depicting the generator. In this procedure, when the $A\ (d)$ range enhances, the formed example is hugely close to the unique model; when the $A\ (d)$ range is huge and the formed sample are significantly distinguished from real values. During the constant process against the formation. The discriminator needs to lower the scatter when $fdata$ is the optimal global search.

3.2. Star GAN

Associated to various GAN methods, this model finds the solutions for the problem of the interconnections amongst the multiple cultural categories of the symbols. This framework structure of StarGAN[18] is significantly efficient and simple and it's formed from the initial domains k and the initial sample d. The system structure of starGAN is illustrated in **Figure 1**. The issue of interconversion between several symbol classes may be resolved using StarGAN, and the structure of the model is both straightforward and effective. As a result, the properties of the StarGAN and MSGAN systems are combined to create the pattern search StarGAN proposed in this research. The pattern collapse condition is further resolved by MS-StarGAN's addition of a pattern identification standard term to the engine objective role, which raises the reserve ratio to prevent vectors of contribution with comparable features from repeatedly showing at the same connecting site. This improves the standard and complexity of symbolic images.

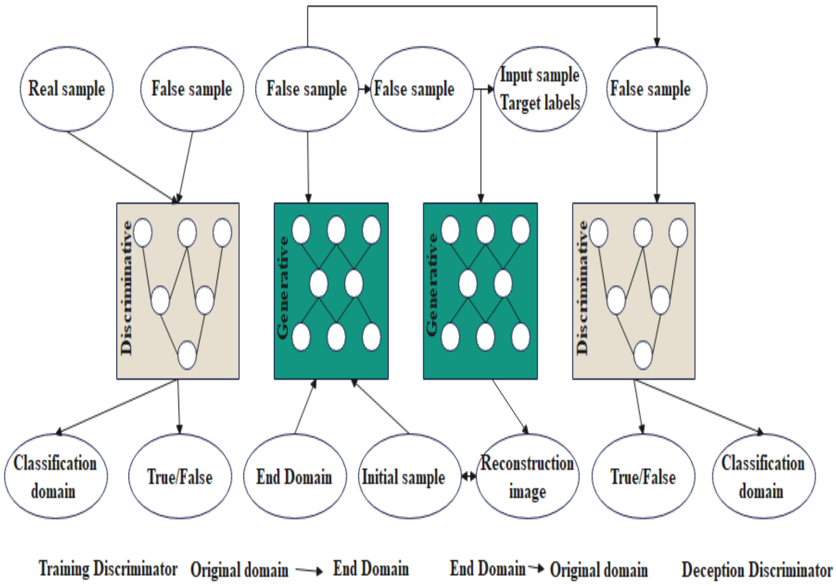

Figure 1. Structure of StarGAN network.

Instead of using convolutional layers, the generator structure employs spatially separable convolution, which lowers the model's training parameters and significantly boosts the reliability of the model training. The duplicate sample E (d, h) is communicated to the discriminator. In order to complicate the resultant example with the initial input illustration and increase the feature comparison amongst them, this fake phase E (d, c) with the desired domain label c ′ of the input instance is now being utilised as input. The pattern collapse phenomena are further improved and the generated culturally represented symbol sample is made to appear more natural and smoother by interjecting a structure search periodic term among the input sample and the created sample.

The first section adds the example normalisation level and ReLu as the stimulation unit after receiving observations and labels as involvement and convolution kernel parameters of 7 × 7, 1, 3, and a fill size of 3. The secondary and third stages are down filtered using a gaussian kernel size of 4 × 4, a step length of 2, and a fill value of 4 to generate a 4 × 4 256 feature map. The incentive role speeds up training and increases stability. Second, to decrease parameters required for training the network, a spatially separated combination is employed to divide 3 by 3 into 3 by 1 and 3 by 3.) Transposed convolution is used to achieve the final up sampling, and the output is produced using the inverse function, Tanh. Depth-separable convolution is employed in place of typical convolutional layers in this case to decrease the time overhead and enhance the model's real-time performance by lowering the amount of model parameters. Point-wise convolution (PC) and depth-wise convolution (DW) make up depth-separable convolution[19]. The estimation of model is lowered while keeping the precision of recognising targets or recognition by breaking down the traditional convolution procedure into several comparable depth-wise transformations and point based convolutions.

The depth combination DW and step-by-step convolution PC may be combined into a normal convolution with a gaussian size with kernel L × L and frequency M. The step-by-step convolutional PC utilises M neural modules of size 1 × 1 for multivariate filtering in every operation. They include the variety of limits used in the typical convolutional CNN computation method, which is displayed in Equation (2) below.

$$\Delta_{CNN} = F \times F \times X \times Y \tag{2}$$

The number of components included in the estimation of the depth convolution along with association of the PC is shown in Equation (3) below.

$$\Delta_{EV,PC} = F \times F \times L \times X + L \times L \times X \times Y \tag{3}$$

$$S = \frac{\Delta_{EV,PC}}{\Delta_{CNN}} = \frac{F \times F \times L \times X + L \times L \times X \times Y}{F \times F \times X \times Y} = \frac{1}{F^2} + \frac{1}{Y} \tag{4}$$

From Equation (4), using the convolution kernel F ≥ 2, the total components included in the estimation process is effectively minimal than the total parameters involved in the constant convolution estimation procedure. This utilizes the convolution instead of constant kernel that can be minimized the overhead during the estimation of convolution. Only one convolution kernel, which is approximately the number of channels, convolves each channel of the feature map throughout the deep convolution process. The calculation for the depth combination is illustrated in Equation (5).

$$G_{f,w,x} = \sum_{f,w,x}^{F,W,X} F_{f,w,x} \times N_{f+t,w+w,x+k} \tag{5}$$

whereas G depicts the initial feature map; F is the length of the filter and w illustrates the width and initial matrix is shown using X.

3.3. Loss in crossover

The loss of cross-entropy purpose is utilised to determine the difference between the goal rate and the real result value in order to accomplish end-to-end optimisation of the algorithm in this study. The ideal value ranges for the two types of samples were found after considerable experimentation. The neural system produces an output in a form of probability as a result of this function. Cross-entropy may therefore determine how far apart the actual output distribution of probability is from the projected probability distribution. The estimation is depicted in Equation (6).

$$M_t = vj_t + y_t \tag{6}$$

Here j_t is the hidden decoder utilised, M_t is the fully associated outcome.

$$Q(a|b) = \frac{f^{j(b,a)}}{\sum_{i=1}^{m} f^{j(b,a)}} \tag{7}$$

Here *b* is the fully associated outcome, *a* is the true association, and *Q* is the function which illustrates the SoftMax which is shown (8)

$$M(\emptyset) = -\sum_{t=1}^{R} logg(b^t|b^*) \tag{8}$$

Here the $\emptyset$ depicts the cross-entropy method loss parameter.

Algorithm 1 Accomplish end-to-end optimisation algorithm

1: Define: Feature function (δ) of the SoftMax
2: **Input:** program association (P), p = $\{p_1, p_2, p_3, \dots\dots., p_m\}$
3: **Output:** Tokenized kernel (δ, F) for every P
4: for each function used $p_i \in P$ do
5: filter function RP_i ← eradicate kernel (p_i)
6: examine Rp_i and identify kernel in RP_i where $\forall kernel \in P$
7: gather identified feature (ϵP_i) ← identify the feature selected
8: for every feature identified pϵ ϵP_i do
9: R$P_i \epsilon P_i$ ← $KernelID$

Algorithm 1 (*Continued*)	
10:	End
11:	Return R$P_i \epsilon P_i$

This study has been approved by the Ethical Committee of the Department of Art, International College, Krirk University with the approval number of ICANO/211/1811.

4. Results and discussions

This paper's data collection is mostly split into two sections. The training data set primarily consists of the in-build evaluation data group and the current opensource network information set. The initial component is the in-build test data set (**Algorithm 1**). It mostly consists of 13 different national cultural emblems, such as Chinese national heroes, cultural ambassadors, and mascot copywriting. The model has a momentum of 0.8, several batches of 42, an overall loss rate of 0.0003, and a starting rate of learning of 0.0001. Dropout is also adjusted at 0.5 to avoid the model being overfit. The learning and testing stages' loss and accuracy curves as shown in **Figures 2** and **3**. As can be observed, the model obtains stable convergence after the amount of iteration approaches 250 and the precision and Loss curve areas of the phases of testing and training are smooth.

Precision, accuracy, Recall, the F1 value, and Time Overhead (TO) in act comprehension for a unique image are the main metrics used to assess the model performance in this paper to confirm the efficacy of the algorithm. The calculated phrases are shown in equations. The Accuracy Recall curve is utilised for comparability in this study since computations for the accuracy and recall metrics are incoherent. The region contained beneath the curve should be as large as possible to maximise classification performance.

$$\text{Accuracy} = \frac{True\ negative + True\ positive}{False\ negative + True\ negative + False\ positive + True\ positive} \tag{9}$$

$$\text{Precision} = \frac{True\ positive}{False\ positive + True\ positive} \tag{10}$$

$$Recall = \frac{True\ Positive}{False\ negative + True\ positive} \tag{11}$$

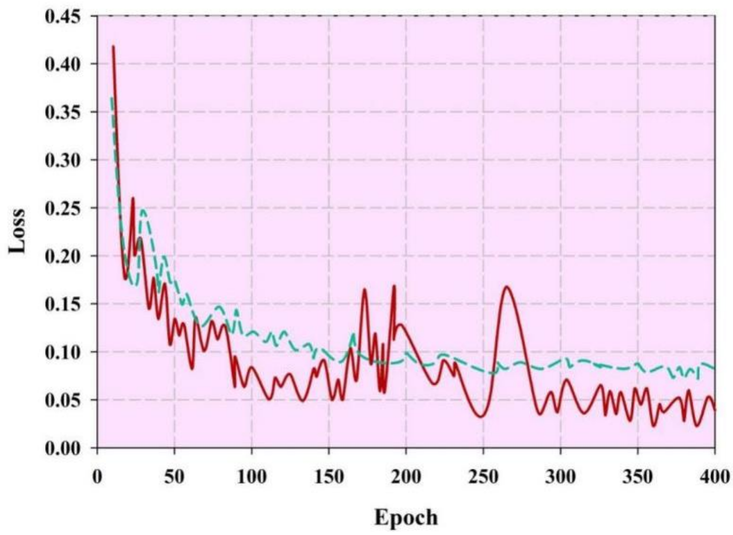

Figure 2. Loss curve during Training and testing phase.

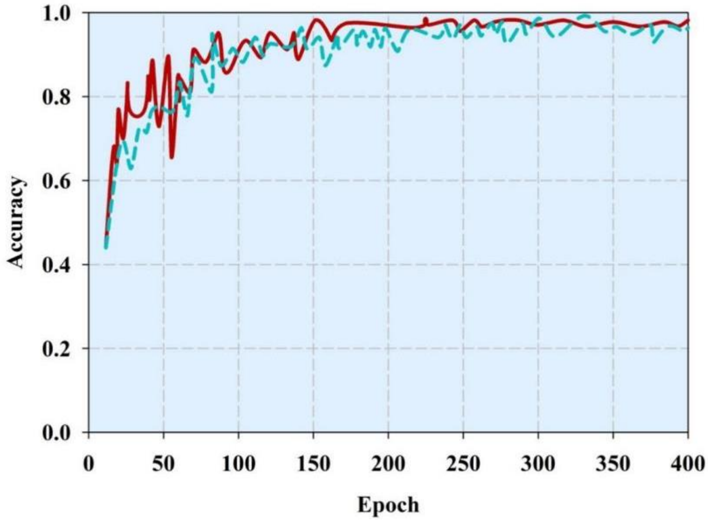

Figure 3. Accuracy curve during Training and testing phase.

The confusion matrix is the result of six sets of trials using the methodology described in this work, where each row of the matrix reflects actual symbol values and the columns the algorithm-generated symbol labels as shown in **Figure 4**. According to the confusion matrix, the six symbols in the six sets of trials have undergone 205, 205, 211, 206, 203, and 208 consecutive generations, with a corresponding accuracy of 92.61%, 94.51%, 91.36%, 95.79%, 93.51%, and 94.98% (**Figure 4**). The algorithm used in this research can also generate pictures at a pace of 8 ms each image. The aforementioned information demonstrates that the framework used in this work has strong resilience since it inclines to accomplish consistently on the outcomes of several trials and has high significant performance.

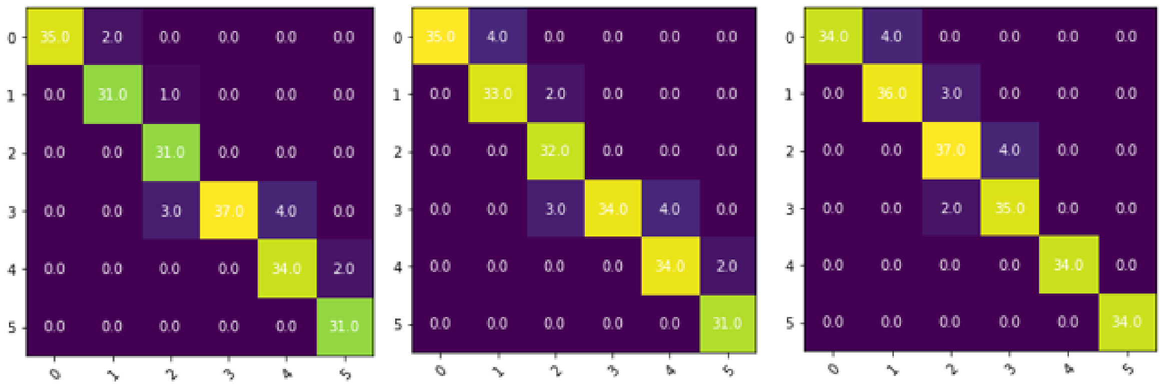

Figure 4. Confusion Matrix.

Comparative experiments are carried out with the most prevalent systems A[20], B[21], C[22], and D[23], as well as analysed using the same data and environment in order to confirm the precision of method in this article. The computed overhead of the various models is shown in **Figure 5**.

The accuracy, precision, recall, and F1 of the system in this study are 91.54%, 89.02%, 90.96%, and 87.48%, individually. In terms of Precision, the model in this study improves (82.36% ← 89.68%) and (91.32% ← 89.48%), respectively, over the two significant categories C and D between all the representations tested (**Figure 5**). The models used in this study increased in terms of Quality (90.68 % ← 91.22%) and (89.46% ← 89.58%). Each of the models in this study enhanced (92.05%← 91.89%) and (92.45% ← 83.98%) in recall. The model in this study enhanced (87.81% ← 90.88%) and (90.94% ← 91.58%) in terms of F1. The aforementioned information further demonstrates the model's superior performance for producing Chinese national cultural symbols. This considerably advances the dissemination of Chinese culture and strengthens feelings of cultural identification and national belonging.

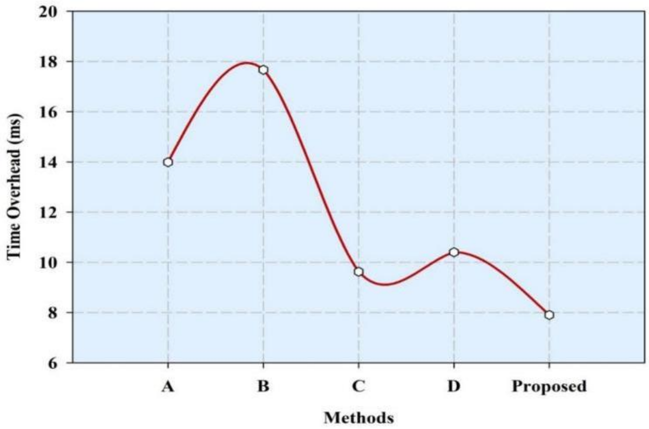

Figure 5. Association of overhead of time amongst various methods.

The study heavily relies on cultural iconography and symbols, which can be interpreted differently by various cultures or communities. The training data used in the study may also be biased towards certain cultural perspectives, limiting the accuracy and effectiveness of the model in representing the diverse range of cultural identities in China. Furthermore, the use of GANs in creating cultural identity frameworks may have unintended cultural implications. GANs, based on machine learning algorithms, may not accurately represent the nuances of cultural identity, and could perpetuate existing biases and stereotypes. It is important to approach the use of GANs in cultural identity frameworks with caution and ensure that the training data is diverse and representative of the range of cultural identities in the community.

One of the main limitations of this study is the use of GAN to construct the symbolic creation framework for Chinese national cultural identity. While GANs have proven to be effective in generating realistic images, they can suffer from mode collapse, where the generator produces limited variations of the same image. To address this, we incorporated a form search regular procedure and generator cross-loss factors based on GAN. However, this may not completely solve the problem of mode collapse, which can limit the diversity of the generated images. Another challenge we faced was the need to balance the real-time efficiency of the model with its accuracy and precision. To achieve this, we substituted the conventional convolutional component of the generator in the system's architecture with a significant recoverable convolution, which reduced the number of parameters in the model. However, this may have also affected the accuracy and precision of the model, which are crucial for its practical application.

Additionally, while the accuracy, precision, recall, and F1 of the system in this study are high, at 91.54%, 89.02%, 90.96%, and 87.48%, respectively, it is important to note that these results were obtained through rigorous testing on real datasets. The performance of the model may vary when applied to different datasets or in different contexts, which may limit its practical application. These limitations and challenges highlight the need for further research and development in this area, and we hope that our study will contribute to this ongoing effort.

5. Conclusion

In this study, we present a novel national culture symbol generating system based on the GAN network, which may considerably increase human feeling of identification and national culture belonging and quickly propagate national culture. In particular, this paper first suggests an efficient pattern search system, MS-StartGAN, depending on the GAN productive network by modelling using the explained data, and the structure collapse condition is further solved by adding structure search typical terms to the generator function in order to boost the distance proportion and reduce vectors of data with comparable characteristics from constantly showing at the same connecting positions, which enhances the quality and depth of the generated network. The model presented in this study offers strong real-time performance yet preserves high generation accuracy, according to results on a large number of tests.

Author contributions

Conceptualization, HXZ and BH; methodology, HXZ and BH; validation, HXZ and BH; formal analysis, HXZ and BG; investigation, BH and HXZ; resources, HXZ and BH; data curation, HXZ and BH; writing—original draft preparation, HXZ and BH; writing—review and editing, HXZ and BH; visualization, HXZ and BH; supervision, HXZ and BH. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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