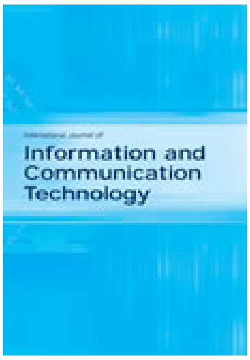

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Rule engine and neural network: reproduction and analysis of traditional festival celebration elements in animation

Guiming Tian

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Rule engine and neural network: reproduction and analysis of traditional festival celebration elements in animation

Guiming Tian

School of Visual Arts,
Hunan Mass Media Vocational and Technical College,
Changsha 410000, China
Email: mitchiet@163.com

Abstract: In this work, a framework based on the combination of generative adversarial network (GAN) and Drools rule engine, Drools-GAN, is suggested to increase the quality of reproduction and generating of traditional festival celebration elements in animation. Combining a generative adversarial network with a rule engine guarantees that the produced images not only meet particular festival aspects and rule criteria but also of great quality. We confirm the advantages of the Drools-GAN framework in terms of image quality, rule compliance, and synergy of its modules by means of a sequence of studies comprising comparison and ablation experiments. The testing results reveal that the framework can guarantee that the produced results fit the preset themes of holiday celebrations and efficiently increase the quality of image generating. The framework shows the possibility for application in animation production and offers a fresh solution for the mix of rule-based image generating.

Keywords: generative adversarial network; GAN; Drools rule engine; festive elements; image generation; animation creation.

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Biographical notes: Guiming Tian received her Doctoral degree from Hanseo University in 2023. She is currently a Lecturer in the School of Visual Arts at Hunan Mass Media Vocational and Technical College. Her research interests include machine learning, and animation production.

1 Introduction

Image generating methods have been used in various disciplines, particularly in animation, film, television and game production, with the ongoing development of computer graphics, artificial intelligence and deep learning technology (Wang, 2021). In these disciplines, traditional generation techniques can find it challenging to guarantee that produced images satisfy particular criteria when they reflect particular cultures, festival features (Del Barrio et al., 2012), or traditional symbols. Deep learning models – including generative adversarial networks (GANs) – have been extensively applied for image synthesis and their outstanding generative capacity helps to produce high-quality photos (Shamsolmoali et al., 2021). GANs are limited in some domain-specific applications, meanwhile, since they generally lack restrictions on cultural symbols and standards when creating images.

Rule engine technology is developing as one of the answers to this dilemma. By specifying unambiguous business rules, rule engines may guarantee that every stage of the generating process meets a particular specification (Ortega-Cabezas et al., 2020). Combining deep learning technology with rule engine helps image generation to guarantee image quality and to precisely replicate particular cultural components.

With computer graphics constantly developing and cultural heritage preservation and digital media art helping to shape the field of animation reproduction and analysis of traditional festival celebration elements, how best to effectively reproduce and analyse traditional festival culture using animation technology has become a progressively important research topic (Kolay, 2016). Traditional celebrations are a vital component of society and hold rich historical and social values. Therefore, how to present these festival cultural components to the public using animation – especially with the aid of contemporary digital technology – has become a great difficulty in artistic production (Knobel and Lankshear, 2008).

New discoveries in the reproduction and analysis of classic festival celebratory elements have come about with the advent of artificial intelligence and deep learning technologies, particularly with regard to GAN and rule engines. Particularly in the visual arts, where it has been extensively applied in image style migration, art creation, and other areas, GAN has shown great powers in tasks including image generation and restoration via the adversarial training of generators and discriminators (Cao et al., 2018). Researchers have made great progress in manipulating image style, content, and details and created quite realistic images or animations using GAN. By creating different images of festival scenes in the development of traditional festival elements, GAN can replicate the creation process of several traditional symbols and images, therefore offering a fresh viewpoint and approach for the reproduction of festival festivities (Alqahtani et al., 2021).

As a rule-based reasoning system, Drools rule engine has been extensively applied in several fields (Luo et al., 2021), including data processing, automation control and decision support. Drools rule engine can be quite helpful in image generating activities, particularly in cases when the generating process must adhere to particular guidelines or unique limitations. Combining the rule engine with GAN allows researchers to integrate more rule control in the generating process to guarantee that the produced images of festival celebrations not only satisfy particular cultural symbolic limitations but also meet the criteria of creative creation. Defining and controlling these rules helps the Drools rule engine to constantly intervene in the GAN generating process to guarantee that produced images not only satisfy the aesthetics but also reflect the cultural meanings of traditional events.

This work intends to integrate GAN with Drools rule engine to attain efficient replication and analysis of traditional festival celebration features. We present a new Drools-GAN framework that guarantees that the produced festival images can represent traditional cultural symbols while following certain artistic styles and rule criteria by integrating the logical control of the rule engine with the generating capacity of GAN.

This work presents original points of view as follows:

1 Drop rule engine combined with GAN. This work presents a new framework called Drools-GAN, which aggregates GAN with Drools rule engine. By means of the rule engine, this combination not only improves the diversity and quality of picture generation but also ensures that the produced images comply to particular cultural symbols and artistic styles, thereby providing an efficient reproduction of traditional festival celebration aspects.

2 Rule engine application in image generation. This work solves the lack of rule limitations in the conventional GAN generating process by creatively using the Drools rule engine to the image generating challenge. The produced festival elements not only have artistic and creative qualities but also can precisely follow the standards of cultural symbols to guarantee that they satisfy the cultural needs of traditional celebrations by means of the Drools rule engine.

The presentation of these creative ideas not only advances the development of approaches for the integration and use of GANs and rule engines, but also helps to promote the reproduction of traditional festival aspects in animation creation.

2 Relevant technologies

2.1 Rule engine

Rule engine is a computer application designed for handling intricate logic and decision guidelines (Qu et al., 2020). Usually comprises of the following basic components: rule base, inference engine and working memory: rule engine every rule comprises a conditional side (LHS, Left-hand Side) and a Conclusion Side (RHS, Right-hand Side), and the Rule Base keeps the collection of all rules (Punnoose, 2020). Drawing on the rule base and the incoming data, the reasoner chooses which rules to apply. The working memory offers background for the thinking process and stores facts or data on the current condition.

Generally speaking, rules in a rule engine are shown in the following form:

$$\text{IF } A_1 \wedge A_2 \wedge \cdots \wedge A_n \text{ THEN } B \tag{1}$$

where A_1, A_2, …, A_n is the condition section and B is the concluding component. Given the data A_1, A_2, …, A_n, a rule engine's job is to derive B – that is, to execute specific operations or decisions – using a logical process.

Forward and backward chaining are two fundamental ways to approach rule engine reasoning. Forward thinking is founded in the methodical derivation of facts (Berka, 2020). One could depict the forward thinking process as follows:

$$\text{IF } F_1 \wedge F_2 \text{ THEN } R_1 \tag{2}$$

$$\text{IF } F_3 \wedge F_4 \text{ THEN } R_2 \tag{3}$$

$$\ldots$$

$$\text{IF } F_m \text{ THEN } R_n \tag{4}$$

where F_1, F_2, …, F_m represent the present set of facts and R_1, R_2, …, R_n are the results of rule-based analysis.

As the rules are followed, the working memory is changed during the thinking process. Assume at first that the working memory is WM_0; every time the rule engine runs a rule based on the reasoner, the working memory will change to WM_1, WM_2, …, WM_n. One may represent the working memory's updating as:

$$WM_{i+1} = WM_i \cup \{R_i\} \text{ for each executed rule} \tag{5}$$

That is, the conclusion component R_i is included to the working memory whenever a rule R_i is triggered and carried out.

Many rules may be matched and triggered simultaneously in the rule engine. The rule engine requires conflict resolving systems to manage this state (Paschke and Bichler, 2008). Finding the triggering sequence depending on the rules' priority is among the most often used techniques. Every rule has a priority P_i; so, the rule with more priority is followed first. One may show the priority sequence for conflict resolution by means of the following equation:

$$P_1 > P_2 > \cdots > P_n \tag{6}$$

A decision tree model can help to streamline the thinking process in sophisticated rule engine systems (Sun et al., 2021). Assume we have a rule engine decision tree whereby every node stands for a rule and the branches of the tree indicate the conditions of the rule. One can depict the decision tree's rational process as:

$$\text{Decision Tree}: D = \{R_1, R_2, ..., R_m\} \tag{7}$$

The reasoner moves down the branches of the decision tree until it reaches a leaf node and performs the matching conclusion every new fact F is provided.

The rule engine of dynamic animation can react to outside changes via an event triggering mechanism. For instance, the rule engine activates the matching rule depending on the present situation when an element of a holiday celebration changes. Assuming that the set of rules set off upon event E, $R(E)$ the triggering of rules may be stated as:

$$R(E) = \{R_1, R_2, ..., R_k\} \text{ if } E \text{ occurs} \tag{8}$$

The rule engine runs the matching set of guidelines depending on the event E to modify the elements and scenes in the animation.

Usually modular in nature, complex animation systems need several subsystems to manage various kinds of rules. Assume the rule engine system comprises of several modules, each addressing various kinds of rules (e.g., scene generating, character behaviour, item interaction, etc.). One can show it as:

$$RE = \bigcup_{i=1}^{n} M_i \tag{9}$$

where M_1, M_2, …, M_n represent several rule engine modules. Every module handles its own rule type alone and then compiles the data to create the animated scene.

2.2 Neural networks

Using neural networks – especially convolutional neural networks (CNN) and GAN in deep learning – animation creators can automatically create more realistic and imaginative animation content, hence improving the expressiveness and viewability of animation (Zhang and Meng, 2023).

Neural networks are increasingly used in animation production for picture and video generation, image style migration, and dynamic character behaviour modelling. Using picture generation as an example, GAN is quite crucial for the creation of traditional animation. Comprising a generator and a discriminator, the generator creates images or video frames while the discriminator assesses if the produced information is authentic or not (Vougioukas et al., 2020). The generator and discriminator play with each other during the training process until the generator can create virtually perfect real images.

Usually, one may depict the generating process of a GAN as the following optimisation issue:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}} \left[\log D(x)\right] + \mathbb{E}_{z \sim p_z} \left[\log\left(1 - D\left(G(z)\right)\right)\right] \tag{10}$$

where p_z is the noise distribution; G is the generator; D is the discriminator; p_{data} is the genuine data distribution. By means of ongoing optimisation, the generator learns to create graphics or video content from noise corresponding to the festival celebration's style.

GAN may be used automatically to create all sorts of aspects of the holiday celebration, including lighting, character movement, scene layout, etc., so improving the creation efficiency and automation in the development of holiday celebration animation. For instance, assume we wish to create a new holiday scenario using neural network from a picture dataset D of a holiday party. By learning the style and structure of the dataset, the GAN generator now creates the new holiday scene on demand. One may represent the created holiday celebration image $G(z)$ as:

$$G(z) = Generator(z) \text{ } where \text{ } z \sim p_z \tag{11}$$

Furthermore greatly affecting animation production is the deployment of CNNs in image processing. Through multi-layer convolutional layers, CNNs are adept in extracting local features in an image and feature extraction and processing. CNNs are extensively applied in holiday celebration animation production for tasks including scene element detection, character behaviour recognition, and image style migration. For instance, CNNs may automatically recognise character actions and create seamless animation sequences depending on the behavioural data of festival celebrations in character action creation. Assume we have a dataset for action recognition, learning the characteristics of this dataset helps the CNN to detect and create fresh behavioural sequences. One may define the CNN's training process by means of the following equation:

$$f(x) = \sigma(W \cdot x + b) \tag{12}$$

where x is the input image or video frame; W is the convolution kernel; b is the bias term; σ is the activation function. By means of multi-layer convolutional operations, the CNN is able to extract higher-order characteristics of character actions from the input image (Duan et al., 2018), thereby augmenting realistic character behaviour.

CNNs can be applied not only for behaviour recognition but also for style migration in scenes of a holiday party. To create animation frames with a designated style, the style migration technique can move the style of one image (e.g., traditional painting style, cartoon style, etc.) to another image. CNN can be utilised for style migration to display the components of traditional festival culture (e.g., lanterns, fireworks, dragon dance, etc.), in a particular style in the development of festival celebration animation. One can characterise the style migration process with the following formula:

$$L_{\text{total}} = \lambda_{\text{content}} L_{\text{content}} + \lambda_{\text{style}} L_{\text{style}} \tag{13}$$

where L_{style} marks style loss; L_{content} marks content loss; λ_{content} and λ_{style} are weighting coefficients. Optimising this loss function helps the model to preserve the substance and style of the image, therefore producing pictures that complement the holiday celebrations' theme.

Apart from GAN and CNN, recurrent neural networks (RNN) find great use in animation production's time series modelling. RNNs particularly in character behaviour simulation may manage behaviour sequences including temporal dependencies (Liu et al., 2017). For a festival celebration, for instance, a character's dance motions show strong temporal correlations; RNNs might thus produce the motions of the following frame depending on past frames. In RNN, the state of the previous time step determines in addition to the current input the output of every time step. One may write the mathematical model of RNN as:

$$h_t = f\left(W_h h_{t-1} + W_x x_t + b\right) \tag{14}$$

where W_h and W_x are the weight matrices, b is the bias term, f is the activation function, h_t is the hidden state at the present moment; h_{t-1} is the hidden state at the previous moment; x is the current input. By means of ongoing training, the RNN learns the temporal dependencies in the action sequences of the character, therefore producing lifelike and seamless animation behaviours.

At last, neural network technology can be merged with other techniques to improve animation creation's efficiency and inventiveness. For instance, neural networks can maximise created animation material depending on input by merging with reinforcement learning (RL) approaches. In reinforcement learning, the reward function R may be stated assuming our neural network-based animation generating model f_θ as:

$$R = \sum_{t=1}^{T} \gamma^t r_t \tag{15}$$

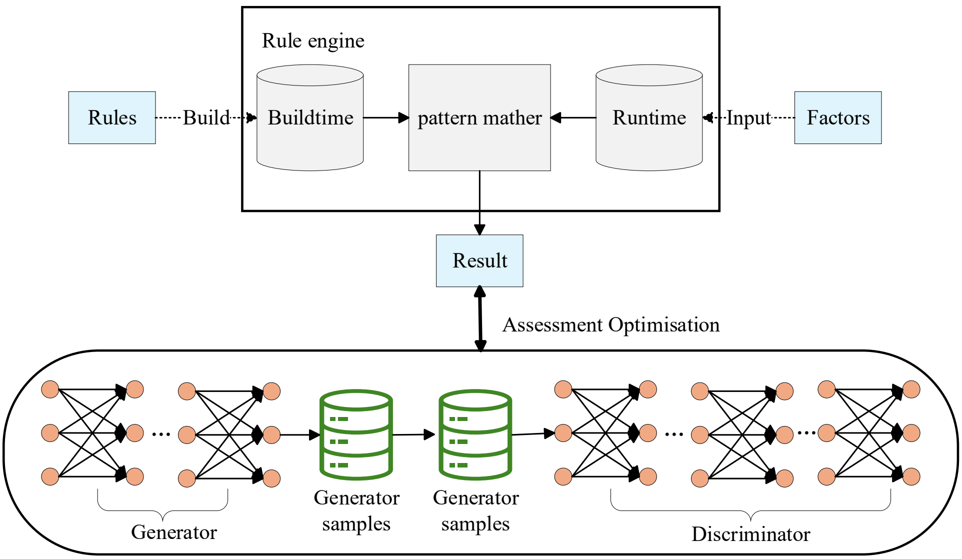
where T is the number of time steps; γ is the discount factor; r_t is the reward earned at time t. By means of reinforcement learning, the model can progressively optimise the produced animation, thereby aligning the generated material with the theme of the festival celebration and the audience expectations.

By means of these neural network approaches, animators can attain a great degree of automation and customised creation in terms of scene development, character behaviour simulation, and style migration of festival celebrations. Apart from increasing the efficiency of animation production, neural networks give greater creative freedom for creators to create festival celebration animation more colourful and expressive.

3 Architecture of the Drools-GAN

Tightly combining the Drools rule engine with GAN, the Drools-GAN framework achieves the reproduction and analysis of classic festival celebration aspects in animation. Three main modules form the framework: the GAN module, the Drools rule engine module, and the feedback optimising module. See Figure 1; each module contributes differently to the framework and collaboratively creates and maximises the classic festival celebration components.

Figure 1 Structure of drools-GAN (see online version for colours)



3.1 Drools rules engine module

The Drools rule engine module's main goal is to match the given holiday cultural and visual criteria by optimising the produced holiday celebration visuals via rule-based reasoning. The module dynamically changes several picture parameters (e.g., colour, size, form, alignment, etc.), therefore limiting the produced image by meeting predefined rules from the rule base. The Drools rule engine guarantees that every created element fits the particular criteria of the festival by use of a backward thinking process.

If a generated image x_{gen} has some sort of festival element – such as lanterns or fireworks – the rule engine will follow this direction:

$$R : \text{if } x_{gen} \text{ contains lantern, then adjust color } (x_{gen}, \text{red}) \tag{16}$$

The formula suggests that, should the produced image have a lantern element, the rule engine modulates the lantern's colour to red.

One may represent the rule engine's output as:

$$x_{new} = \text{Drools}(x_{gen}) \tag{17}$$

where x_{new} is an image that has been optimised by the rules engine to ensure it meets the cultural and visual requirements of the festival.

3.2 GAN module

Holiday celebration images first generated are the result of the GAN module. A generator and a discriminator make up the GAN. While the discriminator assures the validity of the photographs and provides feedback to the generator to drive its optimisation, the generator creates holiday images from random noise.

The generator creates the image depending on the input noise vector z. The festival image's initial creation is under the generator's purview:

$$x_{\text{gen}} = G(z) \tag{18}$$

where G marks the generator; z is the random noise.

Based on it, the discriminator establishes the created image's genuineness:

$$D\left(x_{\text{gen}}\right) = p\left(\text{real} \middle| x_{\text{gen}}\right) \tag{19}$$

The output is the likelihood that the produced image is real; $D(x_{gen})$ is the outcome of the discriminator's assessment on whether the image x_{gen} is real or not.

Through adversarial training, the generator and discriminator are constantly tuned to produce images and raise image quality.

3.3 Feedback optimisation module

Between Drools and GAN, the feedback optimisation module serves as the link and feeds back the optimised images from the rule engine to the generator as fresh inputs, hence driving the generator to further image optimisation. By means of an iterative procedure, the feedback optimisation module guarantees that the produced image constantly satisfies the rule criteria.

The optimised picture x_{new} is specifically supplied back to the generator as a fresh input:

$$z_{\text{new}} = \text{Feedback}\left(x_{\text{new}}\right) \tag{20}$$

The picture x_{new} optimised by the rule engine is input to the generator and drives it to generate a new image where z_{new} is the new noise vector provided back to it.

The generator modulates the content of the produced image using the feedback image x_{new}:

$$x_{\text{new}} = G\left(z_{\text{new}}\right) \tag{21}$$

By means of this feedback system, a closed loop between the generator and the rules engine develops and the produced images progressively fit the visual and cultural criteria of the festival.

3.4 Framework assessment

Two main factors of the frame evaluation are rule compliance and quality of the created images. The output of the discriminator helps to evaluate the produced images:

$$Q = \frac{1}{N}\sum_{i=1}^{N} D(x_i) \tag{22}$$

where N is the total number of photos assessed; Q is the average rating of the image quality; $D(x_i)$ is the discriminator's rating for the i^{th} image x_i.

By use of the Drools rule engine, one evaluates rule compliance by seeing whether the produced images follow the established guidelines:

$$C = \frac{1}{M}\sum_{j=1}^{M} \mathbb{I}\left(R_j(x)\right) \tag{23}$$

where C is the rule compliance score; $\mathbb{I}(R_j(x))$ is the judging result of rule R_j on image x (1 for rule compliance and 0 for non-compliance); M is the number of rules.

The framework's ultimate assessment outcome is:

$$F = \alpha Q + (1-\alpha)C \tag{24}$$

where F is the general assessment score; α is a weighting element regulating the relevance of image quality and rule compliance.

Through the cooperative work of three main core modules – the GAN module is in charge of the first generation of the images, the Drools rule engine module optimises the images according to the rules, and the feedback optimisation module guarantees that the images are constantly improved via a feedback mechanism – thus, the Drools-GAN framework generates and optimises traditional festival celebration elements. By means of thorough evaluation of the quality and rule compliance of the produced photos, the framework guarantees high-quality reproduction of the festival celebration elements.

4 Experimental results and analyses

4.1 Experimental data

The Flickr Creative Commons (FlickrCC) dataset is selected to test the efficacy of the Drools-GAN architecture by means of a trustworthy and extensively used dataset for computer vision tasks. Particularly suited for picture generating activities connected to holiday celebrations, FlickrCC features a lot of Creative Commons photographs covering a broad spectrum of scenes and topics. Images of several holidays, including Chinese New Year, Christmas, Halloween, Lantern Festival, etc., encompassing a range of festive celebration elements, including lanterns, fireworks, Christmas trees, snowflakes, etc., abound in this collection. Images of the Chinese New Year, Christmas, Halloween, and the Lantern Festival abound in the collection as well.

Apart from offering a range of holiday celebration components, FlickrCC tags the themes and parts of every photograph, therefore facilitating the classification and creation of photos process. In this experiment, we picked photographs connected to holiday celebrations and categorised them depending on their tags for Drools-GAN-based image generation and rule engine optimisation.

Table 1 lists some of the datasets' sample contents.

Table 1 Sample data from the FlickrCC dataset for holiday celebrations

Image ID	*Holiday type*	*Key elements*
0001	Spring Festival	Lanterns, fireworks, red envelopes
0002	Christmas	Christmas tree, snowflakes, gifts
0003	Halloween	Jack-o'-lanterns, ghosts, bats
0004	Spring Festival	Couplets, lanterns, firecrackers
0005	Christmas	Santa Claus, snowman, snowflakes
0006	Lantern Festival	Lanterns, fireworks, dumplings
0007	Thanksgiving	Pumpkins, autumn leaves, roast turkey
0008	Easter	Easter eggs, rabbits, flowers

Drools-GAN was able to train a varied and high-quality generative model using this dataset to create images that complement the festival theme, therefore enhancing the accuracy and optimisation of the rule engine in producing images. This information not only evaluates the generative model's performance but also offers data support to confirm how the rule engine runs during the image generating process.

4.2 Experimental procedure

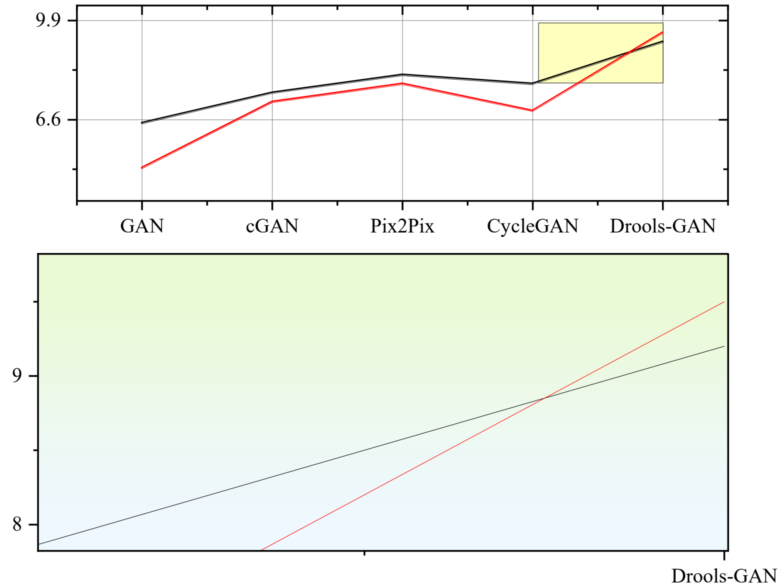
To assess the performance variations of the Drools-GAN framework under various methodologies and the contribution of the separate modules to the effect of the system respectively, we performed two related experiments: a comparison experiment and an ablation experiment.

We compared with Drools-GAN different generative models in the comparison studies. These techniques for comparison consist in traditional GAN, conditional GAN (cGAN), Pix2Pix, and CycleGAN. Every technique was taught exactly; the produced photographs were assessed for rule compliance and quality. These comparison approaches validate the improvement of the rule engine in image generation and enable us to have a thorough knowledge of the performance of several GANs in the generation of holiday festival images.

GANs are basic generative adversarial networks that are trained with a standard generator and discriminator without introducing any specific conditions or rules. cGANs, on the other hand, are conditional generative adversarial networks that generate images that are constrained by input conditions (e.g., type of holiday), and are therefore capable of generating holiday-specific images. pix2Pix is an image-to-image translation model based on image-to-image translations that is suitable for generating mappings from one kind of image to another. mapping from one type of image to another. CycleGAN is an unsupervised image-to-image translation model that can be trained without pairwise data to generate style-transformed images.

The experimental results are shown in Figure 2.

Figure 2 Results of the comparison experiment (see online version for colours)



In terms of image quality and rule compliance, Drools-GAN much exceeds other techniques. With a 9.2 for image quality, Drools-GAN gets far better than other techniques. With the colours complementing the festive mood, the created graphics shone in the integration of features and details. GAN, on the other hand, only scored 6.5, producing poor quality photos with hazy and devoid of detail festive elements. Although the image quality has improved, cGAN and Pix2Pix are still not as good as Drools-GAN mostly owing to their lack of control of a rule engine to precisely create images that meet the festive theme. With a score of 7.8, CycleGAN produces photographs of higher quality but does not fully highlight the festive theme or provide the precise control of holiday features.

With a rule compliance score of 9.5, Drools-GAN demonstrated rigorous management of holiday aspects. Drools-GAN is able to create images that fit the holiday theme by including the Drools rule engine, therefore ensuring that the location and proportion of every element in the picture follow the given guidelines. Poor rule compliance characterises the other approaches. Though they can produce something in keeping with the holiday theme, cGAN scores 7.2 and Pix2Pix 7.8 lack the direction of the rule engine, which produces images with inadequate element locations and synchronisation. Although the pieces are inadequately aligned and united and the rule compliance is minimal, cycleGAN gets 6.9 even if it can create graphics roughly in line with the festive theme.

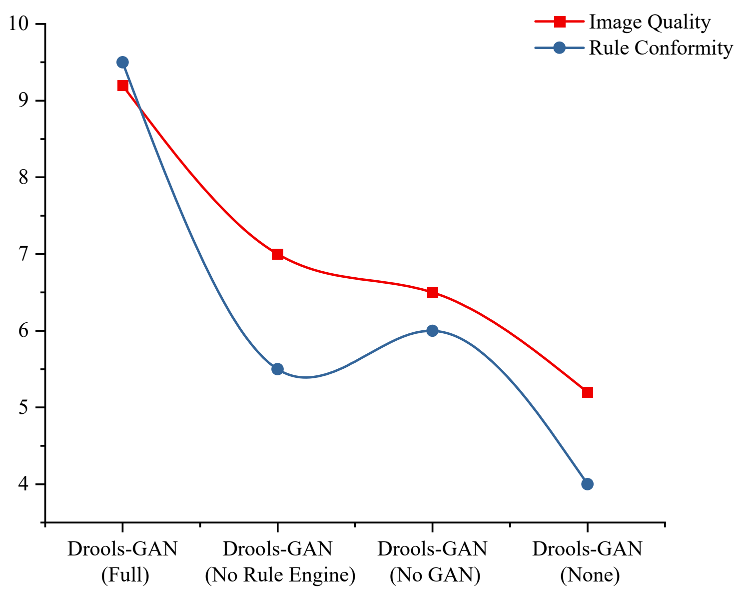
All taken together, the Drools-GAN architecture excels in producing visuals of holidays. Drools-GAN not only produces the best quality photographs but also guarantees the coordination and consistency of the seasonal aspects in the images by mixing GANs with the Drools rule engine, hence surpassing the other examined approaches.

We seek to validate the contribution of the several components of the Drools-GAN architecture in the ablation studies, especially the effect of the Drools rule engine on the quality of picture generating and rule compliance. We may evaluate the effect of every module on the general system performance by gradually eliminating some important parts.

There exist the following versions in the experimental design: deleting the Drools rule engine and depending just on the conventional GAN. In this variation, there are no restrictions on the image generation yet the generator and discriminator still function as intended. Remove the GAN and generate images just using the Drools rule engine. In this variation, we directly control image production using the Drools rule engine independent of any deep learning support. A comparison of the fundamental techniques is removing the Drools rule engine and GAN and doing merely simple image generating. These versions respectively assist us to evaluate their relevance for picture quality and rule compliance and to assess the synergy between the GAN and the rule engine.

Figure 3 shows the experimental findings.

Figure 3 Results of the ablation experiment (see online version for colours)



The produced photographs suffered greatly in quality once the rule engine was removed; the score dropped to 7.0 and the rule compliance score dropped to just 5.5. This indicates that, even if the generated images were produced by the GAN, their inability to guarantee the unity of the festival parts and the thematic consistency of the photos after removing the rule engine shows.

The experiment with the removal of the GAN shows the lower quality of the images without the GAN as well as the fact that the rule engine failed to totally compensate for the shortcomings in the generating process. The quality of the generated images scored 6.5 and the rule compliance scored 6.0.

At last, the most fundamental generating technique received the lowest score. Without the support of the rule engine and the GAN, the produced photos are not only of poor quality but also fail to meet the fundamental criteria of the festival topic, according to 5.2 for image quality and 4.0 for rule compliance.

These results clearly show how important it is to combine GANs with rule engines in the Drools-GAN system. While the rule engine makes sure the festive aspects in the photographs follow the given guidelines, the GAN is in charge of the generated image quality. Removing any one of the components drastically reduces the system's performance, thereby proving the need of the synergy between the GAN and the rule engine for the creation of holiday celebration graphics.

Figure 4 Example of visual presentation under Drools-GAN framework 1 (see online version for colours)

Figure 5 Example of visual presentation under Drools-GAN framework 2 (see online version for colours)

Figures 4 and 5 then show a sequence of images created based on Drools-GAN to further graphically show the practical efficiency of the framework.

In these images, we can clearly observe that the iconic elements of traditional festivals, such as the Dragon and Lion Dance of the Spring Festival, the Dragon Boat of the Dragon Boat Festival, and the Moon Cake of the Mid-Autumn Festival, are not only accurately reproduced, but also highly compatible with the cultural connotations and rules of the corresponding festivals in terms of the overall visual effect and layout of the images, which is a strong manifestation of the powerful function of the Drools-GAN framework.

5 Conclusions

In this work, we offer the Drools-GAN framework, which combines GAN with Drools rule engine to enhance the quality of reproduction and generating of traditional festival celebration elements in animation. By means of tests, it is confirmed that the Drools-GAN framework is successful in guaranteeing the quality of the photographs and in ensuring that produced images follow the particular guidelines and festival aspects.

In the experimental part, we first validate the performance variations of the Drools-GAN framework under various approaches by means of comparative experiments; the results reveal that Drools-GAN outperforms the approaches using GANs or rule engines alone in terms of both image quality and rule compliance. We next investigated the contribution of every module in the framework to the generation effect in the ablation experiments; the results revealed that attaining quality image production depends on the synergy between the GAN and the rule engine.

Still, this study has several limits. First of all, even although the Drools rule engine can efficiently control the rule compliance of the produced images, in some complicated situations its flexibility and adaptability still has to be enhanced. Second, GAN’s training procedure calls for a lot of processing resources, thus the quality of image generation could be very restricted while handling more difficult festival components.

Future investigations in the following spheres is possible:

1 Improving the rule engine’s performance. The adaptability and flexibility of the Drools rule engine still need work in some challenging situations. By improving its intelligence and adaptive capacity, the rule engine can be strengthened in the future to better manage several festival components and scene demands.

2 Raising the GAN’s image quality. Even if the produced photographs in this investigation already show great quality, while handling more complicated festival components the image quality could still be restricted. More effective GAN topologies can be investigated in the future, and more advanced approaches (e.g., Transformer or multi-scale generating methods) can be applied to progressively improve the clarity and detail performance of the images.

Further investigation of the aforesaid research directions should help the Drools-GAN framework to generate more creative ideas for related applications and create bigger discoveries in the domains of picture generating and rule control.

Declarations

All authors declare that they have no conflicts of interest.

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