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Auxiliary Generative Adversarial Networks with Illustration2Vec and Q-Learning based Hyperparameter Optimisation for Anime Image Synthesis

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Abstract— **Harnessing the power of Generative Adversarial Networks (GANs) for the specialised task of anime face generation, this study introduces enhanced models of Auxiliary Classifier GAN (AC-GAN) and Wasserstein Auxiliary Classifier GAN (WAC-GAN) with modified network architectures and reinforcement learning-based hyperparameter optimisation. These models are uniquely adapted to handle the distinct nuances of anime-style imagery, a domain where conventional GANs often stumble due to complex stylistic variations and a heightened risk of mode collapse. Novel elements of our approach include, (1) modification of existing generator and discriminator architectures of both AC-GAN and WAC-GAN, (2) Q-learning based optimal hyperparameter selection, and (3) Illustration2Vec (I2V)-based automated attribute label extraction. Specifically, the Q-learning method is employed for hyperparameter search which effectively explores the search space of key network configurations by fulfilling the principles of Bellman optimality. Besides that, a deep learning-based I2V's method is utilised to generate attribute class labels and latent vectors to inform the generation process. Furthermore, we augment AC-GAN and WAC-GAN with additional layers to enhance their feature learning and generative capabilities. The insertion of these additional layers is calibrated based on the optimised network learning settings as well as the class labels derived from I2V, to fine-tune model scalability and diversity. Our experimental studies indicate that the conjunction of these techniques has led to a significant improvement in generating high-fidelity anime faces, adeptly handling the diverse and complex attributes inherent in anime-style imagery. The proposed strategies also showcase the potential of our customised AC-GAN and WAC-GAN models to master the nuanced art of anime face generation.**

I. Introduction

Fast growth of Japanese animation industry has resulted in the production of many animated shows that have piqued the attention of diverse audiences. Each anime has a unique trait that caters to a distinct user taste. As such, generating custom faces is a challenge on its own. It takes tremendous efforts to master this skill, to draw and generate concise facial data. To bridge this gap, we have the principle of automatic generation of characters based on prior datasets. Due to the powerful ability of generative models, Generative Adversarial Networks (GANs) have achieved great success in manipulating and generating images, with up-scaling and image generation being prime examples.

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The development of anime faces using generative networks presents several challenges, primarily due to the complexity and diversity of facial structures. Two essential requirements must be met to ensure success: I) Each generated face must possess unique traits sufficiently distinct from the initial training batch, and II) The quality of the generated faces must be high [1]. These challenges are compounded by the non-linear nature of facial structures, which can lead to inconsistencies and artifacts, as well as the high dimensionality of the feature space, making it difficult to control specific attributes like hair and eye colours [2]. To verify adherence to these standards and evaluate performance, this research will quantify the variety of produced and input data using several strategies. These include comparing generated images to the presented dataset, assessing image quality using inception distance measure, attribute classification accuracy, and user evaluation scores. Despite the availability of large datasets such as Danbooru2021, challenges persist regarding dataset dependability, quality, and biases. Ensuring accurate labeling and consistency in the dataset is critical, as GANs can be notoriously difficult to train.

We propose a novel approach to overcome these limitations and generate high-quality anime faces by leveraging Illustration2Vec (I2V) for active label synthesis and Auxiliary Classifier GAN (AC-GAN)/Wasserstein Auxiliary Classifier GAN (WAC-GAN) for image generation. To increase model robustness, reinforcement learning-based hyperparameter optimisation and atchitecture augmentation are also employed in this research. Firstly, the use of I2V allows us to automatically and accurately label the dataset with potential tags corresponding to style, gender, hair colour, and eye colour which are particulate to animated faces. These labelled attributes are essential for training AC-GAN and WAC-GAN, which in turn facilitate the generation of more diverse and high-quality anime faces while maintaining control over desired attributes [3].

Besides using attribute class labels extracted by I2V, the introduction of augmented extra layers to the generators and discriminators in both AC-GAN and WAC-GAN enhances the model's learning capacity, improving results, and maintaining a soft limit concerning the number of classes.

Moreover, another key distinction in our research is the application of a reinforcement learning-based hyperparameter optimisation process. This approach significantly diverges from traditional methods, focusing on identifying the optimal settings for momentum, learning rate, and weight decay. Our strategy involves a thorough exploration and iterative adjustment of hyperparameters, guided by a reward mechanism that assesses their performance impact. This process has proven instrumental in enhancing model stability and image quality, as well as in ensuring the accurate preservation of conditioned attributes.

Our research contributions are as follows.

- We propose new modified versions of two Conditional Generative Adversarial Networks (CGAN) models, namely AC-GANs and WAC-GANs, by adding additional layers. Specifically, for additional classes required, we introduce extra numbers of (transposed) convolutional layers, with each followed by a ReLU activation layer and a batch normalisation layer, in accordance with the extra attribute classes. This modification aims to explore how the models would perform based on the attributes fetched from I2V, enhancing the generation of anime faces in accordance with the core objectives.
- Hyperparameter optimisation utilising reinforcement learning (Q-Learning) principles is performed on the modified AC-GANs and WAC-GANs with customised additional layers to further enhance its generative capabilities. This advanced strategy focuses on optimising key network hyperparameters, i.e. momentum, learning rate, and weight decay, by performing a systematic exploration of the hyperparameter space. This reward-driven approach identifies optimal configurations by following the principles of Bellman equation to maximise model performance, measured in terms of image quality and attribute classification accuracy. This approach has proven highly effective, leading to a marked improvement in the stability of the training process, enhanced image fidelity, and more accurate preservation of conditioned attributes.
- Integrating the Convolutional Neural Network (CNN)-based I2V model for active label synthesis serves as another novel element which facilitates precise and automated labelling of datasets, a critical precursor for training the proposed AC-GANs and WAC-GANs. This I2V model automatically generates diverse attribute class labels to diversify the generation process. The synergy of the Q-learning based hyperparameter optimisation, architectural modifications/advancements, together with I2V class attribute label generation, positions our proposed AC-GAN and WAC-GAN models at the forefront of controlled anime face generation.

II. Related Literature

In this section, we discuss variants of GAN models used in image generation tasks.

a) Conditional GAN (CGAN): Mirza and Osindero [4] introduced CGAN to generate images conditioned on specific class labels by incorporating conditional information into both the generator and discriminator networks, allowing for more controlled and diversified results.

b) Conditional Auxiliary Classifier GAN (AC-GAN): Odena et al. [5] proposed AC-GAN, which integrates CGAN [4] and auxiliary classifiers. The discriminator predicts both the realness and class label, encouraging the generator to produce accurate, diverse, and realistic images.

c) AnimeGAN and AnimeGANv2: Proposed by [6], [7], these models generate anime-style images from real photos using new loss functions such as color reconstruction and adversarial losses. Further enhancements could include adaptive learning configurations fine-tuned with evolutionary or reinforcement learning methods [8], [9].

d) Illustration2Vec: Proposed by Saito and Matsumoto [3], I2V is a model designed to extract semantic information from illustrations. It utilises a deep CNN to learn feature representations of illustrations, enabling various applications such as annotation, retrieval, and generation. By incorporating I2V into the image generation process, it is possible to leverage the semantic information to create more accurate and versatile images. For example, combining I2V with a GAN model allows the generator to produce images that not only look visually appealing but also possess meaningful semantic content. This can lead to more realistic and contextually appropriate image generation outcomes.

e) Wasserstein Auxiliary Classifier GANs (WAC-GAN): Liao and Dong [10] combined WC-GAN and AC-GAN, integrating the Wasserstein loss function and gradient penalty scheme with the auxiliary classifier. This results in more stable training and improved image generation, especially for imbalanced datasets, making it suitable for anime-style image generation.

III. Pre-Processing

The quality of an image dataset is a well-recognised determinant of the success in image generation tasks. Online platforms such as Danbooru and Safebooru, hosting image boards, are renowned for their vast image collections. Given the diverse datasets utilised in this research, the implementation of the Danbooru dataset presented potential quality-related challenges. These emerged due to variations between the quality of images and the information contained in the labels, such as distinguishing between people and objects. To tackle these issues, an extensive data cleansing protocol was deployed, and a custom label for *High Quality* images was introduced, thereby ensuring increased reliability and consistency in the generation process.

A. Danbooru2021

The Danbooru2021 dataset, a large collection of high-quality images sourced from the Danbooru image board, was chosen as the primary dataset for this research. Owing to the vast sample size in this dataset, which could be computationally expensive, we implement an attribute class extraction process to make the dataset more manageable.

Attribute extraction involved manually assigning labels to each image, a labour-intensive task that demanded a considerable amount of time and effort. Despite the challenges, this process was crucial in ensuring a consistent quality across the dataset. It enabled the identification and removal of low-quality images, as well as the introduction of a custom label for *High Quality* images.

B. Filtered Danbooru2021+

To address the computational challenges associated with the raw Danbooru2021 dataset, we opted to use a filtered version of the dataset, referred to as Filtered Danbooru2021+. This dataset had already undergone feature extraction and preprocessing, allowing us to bypass the resource-intensive tasks while still benefiting from the rich collection of images.

Besides the aforementioned Danbooru2021 dataset, another dataset, i.e. AnimeFaces, a collection of 100K anime faces obtained from Kaggle, is also used in this research. As such, two core datasets were employed, Dataset A (DanBooru2021) consisting of 20K images and Dataset B (AnimeFaces) of 100K, for our experimental studies.

IV. The Proposed Image Generation Systems

This research proposes two modified CGAN architectures, i.e. AC-GAN and WAC-GAN with additional (transposed) convolutional blocks, for controlled generation of diverse high-quality anime face images. By integrating I2V for automated feature extraction and attribute class prediction, it enhances the generation of anime faces in accordance with fetched class labels. Architecture modification and reinforcement learning-based hyperparameter optimisation are also exploited to improve model robustness and generation diversity. To test the quality of the generated images, we subsequently classify auxiliary attributes such as hair and eye colours using the generated images to measure the impact of insertion of additional layers to the generators, as well as optimal hyperparameter optimisation using Q-learning.

A. Auxiliary Classifier GAN (AC-GAN)

AC-GAN comprises:

- **Adversarial loss** $\mathcal{L}_{adv}$: It encourages the generator to produce realistic images.
- **Classification loss** $\mathcal{L}_{cls}$: It trains an auxiliary classifier to predict class labels, such as hair colour and/or eye colour.

The AC-GAN loss function is defined in Equation 1:

$$\mathcal{L}_{ACGAN}(G, D, C) = \mathcal{L}_{adv}(G, D) + \lambda \cdot \mathcal{L}_{cls}(G_{ext}, C) \quad (1)$$

where G_{ext} denotes the generator with extra layers, and λ controls the classification loss.

For anime face generation, the class labels are corresponding to hair colour, eye colour, and other stylistic attributes. By training the auxiliary classifier with I2V, the generator learns to associate certain stylistic attributes, allowing explicit control over the generated attributes. The introduction of extra layers to the generator (denoted as G_{ext}) enhances the general learning capacity, improving results with respect to classifiers and considering a soft limit related to the number of classes.

B. Wasserstein GAN with Gradient Penalty (WAC-GAN)

WAC-GAN further extends the AC-GAN framework through key enhancements and a nuanced understanding of the interplay between the generator and discriminator layers through the following aspects.

- Wasserstein distance as adversarial loss instead of the original GAN formulation: This results in more stable training by using Equation 2.

$$\mathcal{L}_{adv}^{W} = \mathbb{E}x \sim p_{data}[D(x)] - \mathbb{E}_{z\sim p_z}[D(G(z))] \quad (2)$$

- Gradient penalty regularisation: This term is introduced in the critic/discriminator loss to enhance the smoothness of gradients and ensure Lipschitz continuity, a mathematical property that helps stabilise training as defined in Equation 3.

$$\mathcal{L}_{gp} = \lambda_{gp}\mathbb{E}_{\hat{x}}[(||\nabla\hat{x}D(\hat{x})||_2 - 1)^2] \quad (3)$$

Here, $\hat{x}$ represents interpolated samples between real and generated data distributions, $\nabla\hat{x}$ denotes the gradient with respect to $\hat{x}$, and λ_{gp} is a weighting hyperparameter. The normaliser $(||\nabla\hat{x}D(\hat{x})||_2 - 1)^2$ enforces that the gradient norm of the discriminator's output with respect to $\hat{x}$ is close to 1. By controlling how the discriminator's output changes with slight variations in input, this penalty helps prevent the model from becoming overly confident in regions where it has little data, thus mitigating issues like mode collapse. This regularisation plays a crucial role in enhancing training stability and convergence.

The full WAC-GAN loss functions are defined in Equations 4 and 5.

$$\mathcal{L}_D = \mathcal{L}_{adv}^{W} + \mathcal{L}_{cls} + \mathcal{L}_{gp} \quad (4)$$

$$\mathcal{L}_G = \mathcal{L}_{adv}^{W} + \mathcal{L}_{cls} \quad (5)$$

By incorporating Wasserstein distance and gradient penalty, WAC-GAN makes the GAN training more stable. The gradient regularisation mitigates issues like mode collapse and vanishing gradients [11], [12]. This leads to improved sample diversity. The conditioning through auxiliary classifier is maintained similar to that of AC-GAN.

For anime image synthesis, WAC-GAN allows training highly stable models that produce varied samples with control over hair, eyes, and other facial attributes. The enhanced training stability and sample diversity make WAC-GAN well-suited for this application.

C. The Modified AC-GAN and WAC-GAN Models

To further improve the model representation capacity, as discussed earlier, AC-GAN and WAC-GAN with additional transposed and normal convolutional blocks are proposed. To be specific, in each model, we extend the generator and discriminator with additional transposed and normal convolutional layers, respectively, increasing the depth of both networks. The impact of adding these optional extra layers was analysed experimentally. As per Odena et al. [5], increasing model capacity with deeper generators

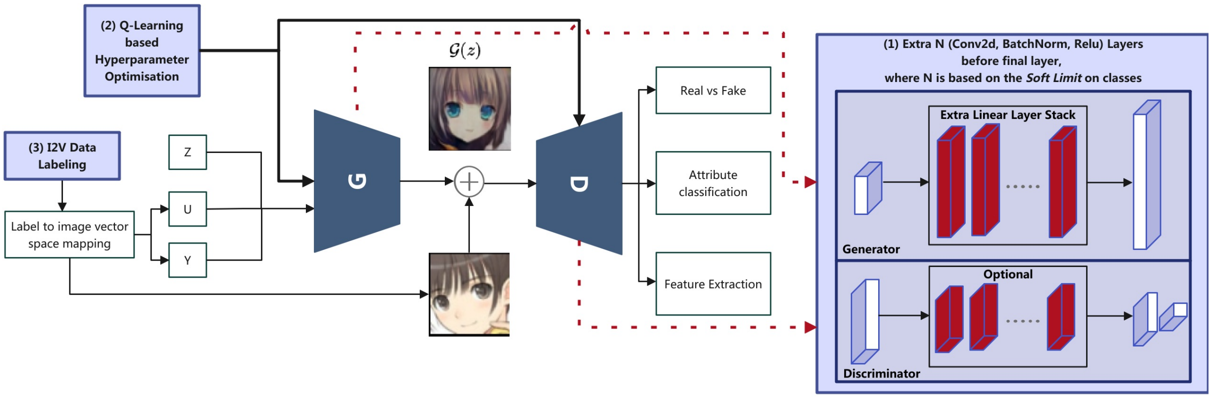

Fig. 1. The proposed modified WAC-GAN model. The proposed research novelties include, (1) additional layers in both generator and discriminator represented by red rectangles, for enhancing generative feature learning, (2) reinforcement learning (Q-learning)-based hyperparameter optimisation, and (3) a CNN-based I2V network for attribute class label generation. These three novel elements are marked as 1, 2 and 3, in the respective light blue boxes. Three model inputs include, noise vector (z), class vector (y), and latent info vector (u). G and D denote generator and discriminator, respectively.

and discriminators can potentially improve AC-GAN performance. Similarly, extra layers may in turn benefit WAC-GAN training and image synthesis quality, significantly. However, overly complex models can also lead to overfitting. So a comparative assessment was conducted with and without the extra layers with respect to both datasets. The number of optional extra convolutional layers was a hyperparameter that will be set when instantiating the generator and discriminator models.

Specifically, we elaborate the proposed modified AC-GAN and WAC-GAN models in detail below. Initially, the generator architectures for both models comprised four transposed convolutional layers, with each augmented by a batch normalisation layer and a ReLU activation. The input to the generator is a concatenation of the noise vector and a class vector which are processed by a sequence of dense layers before being fed to the convolutions layers. To increase feature learning capabilities, a set of two additional customised 2D transposed convolutional layers, each followed by batch normalisation and ReLU, is inserted before the final transposed convolutional layer to the base generator architecture in AC-GAN or WAC-GAN. The insertion of these additional layers allows the generator to adapt to different numbers of classes pertaining to the generation tasks. To optimise model performance, in this research, the number of customised transposed convolutional blocks can be fine-tuned based on each generation task, adhering to the "soft limit" principle.

On the other hand, each discriminator in both models relies on a quartet of standard 2D convolutional layers for the feature extraction, such that each layer is followed by batch normalisation and LeakyReLU. Upon extracting the relevant features, they are passed through additional dense layers that prepare the data for the final classification stage, such that the discriminator yields a scalar value approximating the authenticity of the input image, as well as a set of selected class probabilities categorising attributes such as hair or eye colours.

Similarly to the generator, the discriminator architecture in each model is designed to be extendable. Precisely, a set of extra 2D convolutional layers, with each followed by batch normalisation and leaky ReLU, is added to the network depending on the current limit of the classes. The attachment of the additional layers can be adaptable based on the complexity of the task at hand. In other words, the number of extendable extra layers can be diversified to enhance the discriminator's performance based on different application contexts.

D. Model Overview

Figure 1 illustrates the proposed WAC-GAN model with additional customised layers and Q-learning based parameter optimisation. Our model has three novel aspects, i.e. (1) the insertion of additional layers in both generator and discriminator to enhance feature learning capabilities, (2) reinforcement learning (Q-learning)-based hyperparameter optimisation, and (3) attribute prediction using a CNN-based I2V network for constraining the generation process. In addition, our WAC-GAN model is specifically tailored to design and synthesise anime characters to a high degree of control over specific attributes. In this research, we use gender, hair and eye colours as controllable attributes to constrain image generation.

The model commences with a 12-dimensional vector encoding, which is responsible for mapping categorical labels such as hair and eye colours into a continuous vector space. This mapping was modified to also define a "soft limit" for the class categories, culminating in 22 distinctive classes that integrate various hair and eye colours along with gender, all of which are malleable.

Moreover, as indicated in Figure 1, the label-to-image vector mapping modulates both the class vector $\mathbf{y}$ and the latent info vector $\mathbf{u}$, alongside the actual image data. This ensures that the generated images replicate the desired attributes encoded within this input vector.

A pre-training hyperparameter optimisation phase employs a reinforcement learning algorithm, i.e. the Q-Learning algorithm, to fine-tune key parameters such as the learning rate, momentum, and weight decay of the AC-GAN and WAC-GAN models with architectural modification. This optimisation process is actively maintained throughout the training, ensuring that both the generator and the discriminator are operating under optimal settings. We present the Q-learning based optimal hyperparameter selection in the next section.

V. Reinforcement Learning-based Hyperparameter Optimisation

We introduce a refined approach to hyperparameter optimisation in our AC-GAN and WAC-GAN models, leveraging the capabilities of Q-learning [13]. A key feature of our method is the dynamic and real-time updating of the Q-table, which adapts continuously based on both immediate performance outcomes and long-term cumulative rewards, ensuring perpetual alignment with optimal hyperparameter configurations. We strike a careful balance between exploring new hyperparameter combinations and exploiting known effective settings, thus avoiding premature convergence and thoroughly canvassing the hyperparameter landscape.

A. Adoption of Q-Learning for Hyperparameter Selection

Our optimisation framework treats hyperparameter tuning as a sequential decision-making process [13] [14] [15] [16] [17]. In this context, Q-learning plays a key role in systematically determining the most effective hyperparameter configurations, thereby optimising the generative capability of the proposed CGAN models.

Furthering to this, this approach is employed to navigate the hyperparameter space. The reinforcement learning method operates by iteratively choosing hyperparameters, transitioning between states based on these choices, and accruing rewards corresponding to the effectiveness of each decision. The primary aim is to accumulate the maximum possible reward over a series of actions, leading to the identification of the most advantageous hyperparameter policy.

1) Theoretical Formulation of Q-learning: The algorithmic foundation of the Q-learning method is based on the Bellman equation, which is crucial for calculating the expected utility of actions. Adapted to our specific context, the equation is represented as:

$$Q^{new}(s_t, a_t) = Q(s_t, a_t) + \rho \times \Big(r_t + \gamma \times \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\Big) \tag{6}$$

where $Q^{\text{new}}(s_t, a_t)$ is the updated Q-value, s_t and s_{t+1} are the current and next states, respectively, a_t is the action taken at state s_t, ρ is the learning rate, γ is the discount factor, r_t is the immediate reward, and $\max_a Q(s_{t+1}, a)$ represents the maximum future reward.

A Q-table is maintained, encoding the Q-values for various state and action combinations. This table is dynamically updated, reflecting the evolving understanding of the hyperparameter landscape. Each state/action in the table corresponds to a unique hyperparameter set.

Our Q-learning process involves the following procedures [14] [18] [19]:

1. **Initialisation**: Starting with a baseline hyperparameter set, the initial Q-values are set to 0. 2. **Exploration and Exploitation**: The algorithm explores the hyperparameter space by selecting actions and exploiting the existing knowledge encapsulated in the Q-table. 3. **Reward Assessment**: After each action, the immediate reward is assessed based on the impact of the hyperparameter change on model performance. 4. **Q-value Update**: The Q-values are updated using the Bellman equation, integrating the immediate and estimated future rewards.

This iterative process continues until convergence or a predefined number of iterations is reached, leading to the identification of an optimal set of hyperparameters.

B. Impact on Generative Model Performance

By implementing this Q-learning based hyperparameter optimisation process, we observed a substantial improvement in the performance of both AC-GAN and WAC-GAN models. The optimised hyperparameters led to a more stable training process, higher image fidelity, and better preservation of conditional attributes.

The Q-learning algorithm is used to fine-tune three core hyperparameters, i.e. momentum (m), learning rate (lr), and weight decay (wd), to identify the most effective training configurations for enhancing scalability and robustness of both proposed AC-GAN and WAC-GAN models. This reinforcement learning method has allowed us to advance beyond traditional hyperparameter tuning methods. As such, it employed immediate and long-term rewards to iteratively adjust and evaluate the hyperparameters, guiding the models towards the most effective configurations with accelerated convergence for the generation task at hand.

VI. Experimental Studies

To evaluate the efficiency of our proposed CGAN models, two distinct datasets, i.e. Datasets A and B, are employed for model evaluation.

A. Datasets

The two anime face datasets employed in our experimental studies are introduced in detail below.

- Dataset A (DanBooru2021): This dataset is a curated subset of the large DanBooru2021 collection by recruiting higher quality images.
- Dataset B (AnimeFaces): This dataset is a collection of 100K anime faces obtained from Kaggle. Originally sourced from getchu.com, these images have a lower resolution of 64x64 pixels.

B. Experimental Details

We employed the AC-GAN and WAC-GAN models, training each for 100 epochs using the Adam optimiser. The initial learning rate was set at 2×10^{-4}, with the first and

TABLE I

DETAILED RESULTS OF THE PROPOSED WAC-GAN AND AC-GAN MODELS ON DATASETS A AND B (NOTE: LOWER FID SCORES INDICATE BETTER PERFORMANCE).

Dataset	Model	Optimisation Strategy	Parameters	FID ↓	Hair Colour Acc ↑	Eye Colour Acc ↑
A	AC-GAN (Baseline)	None	lr=0.0002, m=0.5, wd=0.0001	74.3	0.67	0.71
A	WAC-GAN (Baseline)	None	lr=0.0002, m=0.5, wd=0.0001	70.6	0.73	0.76
A	AC-GAN (Add. Layers)	Layer Optimisation	lr=0.0002, m=0.5, wd=0.0001	68.7	0.82	0.85
A	WAC-GAN (Add. Layers)	Layer Optimisation	lr=0.0002, m=0.5, wd=0.0001	65.4	0.86	0.88
A	AC-GAN (Add. Layers + Opt.)	RL-based Optimisation	lr=0.000234, m=0.313, wd=0.00765	64.2	0.87	0.90
A	WAC-GAN (Add. Layers + Opt.)	RL-based Optimisation	lr=0.000234, m=0.313, wd=0.00765	60.3	0.90	0.92
B	AC-GAN (Baseline)	None	lr=0.0002, m=0.5, wd=0.0001	73.5	0.74	0.76
B	WAC-GAN (Baseline)	None	lr=0.0002, m=0.5, wd=0.0001	69.8	0.78	0.80
B	AC-GAN (Add. Layers)	Layer Optimisation	lr=0.0002, m=0.5, wd=0.0001	67.9	0.84	0.86
B	WAC-GAN (Add. Layers)	Layer Optimisation	lr=0.0002, m=0.5, wd=0.0001	63.2	0.87	0.89
B	AC-GAN (Add. Layers + Opt.)	RL-based Optimisation	lr=0.000234, m=0.313, wd=0.00765	62.1	0.88	0.91
B	WAC-GAN (Add. Layers + Opt.)	RL-based Optimisation	lr=0.000234, m=0.313, wd=0.00765	58.7	0.91	0.93

second moment parameters (β_1 and β_2) both configured at 0.5. A batch size of 128 was utilised, optimising the balance between computational load and network performance.

C. Evaluation Metrics

1) Fréchet Inception Distance (FID): The FID was used to measure the similarity between the distributions of generated and real images. This was done using deep feature representations extracted by a pretrained I2V model. The FID was computed between 10,000 generated and 10,000 real samples in this research.

2) Attribute Classification Accuracy: In the post-training phase, we used the VGG16 network for attribute prediction to evaluate hair and eye colour qualities in our generated samples. The classification accuracy was used to measure how well the generator preserved the conditioned attributes.

3) User Study: A user study was conducted in which participants were asked to rate the realism of the generated anime faces on a scale of 1 to 5, with 5 being the most realistic. The average user rating was used to compare the performance of the proposed models.

TABLE II

USER STUDY OF THE PROPOSED AC-GAN AND WAC-GAN VARIANTS WITH RESPECT TO ANIME FACE REALISM

Model	Average User Rating (1-5)
Prop. AC-GAN	3.21 ± 0.18
Prop. WAC-GAN	3.92 ± 0.23

D. Evaluation Results

We subsequently employ Datasets A and B for quantitative experimental studies. Specifically, we evaluate the proposed WAC-GAN and AC-GAN models with Q-learning based hyperparameter optimisation and additional embedded layers (for both generators and discriminators), against the modified GAN models with additional layers only, as well as the original WAC-GAN and AC-GAN methods. The detailed results are provided in Table I.

As shown in Table I, for Datasets A and B, both proposed models with additional layers and Q-learning hyperparameter optimisation perform the best against the counterparts with additional layers only and the original networks, in terms of both FID scores and attribute classification accuracy rates. In addition, our proposed WAC-GAN model with additional layers and hyperparameter fine-tuning outperformed the proposed AC-GAN with both strategies, on both datasets. This suggests that our optimised WAC-GAN was more effective at modelling data distribution and preserving the conditional information. The optimised hyperparameters obtained using Q-learning also enhanced the training process by adopting effective learning steps and sufficient regularisation to help tackle overfitting.

Moreover, our proposed WAC-GAN also demonstrated a higher attribute classification accuracy than those of our optimised AC-GAN, indicating that it was more effective at preserving the conditioned attributes in the generated images. This is a crucial aspect of signalling model performance, as it allows for the controlled generation of anime faces with specific attributes. The results suggest that our proposed WAC-GAN model is a promising approach for the controlled generation of high-quality anime faces.

Besides the above quantitative studies, Table II summarises the results of a user study with 50 participants rating the realism of anime faces generated. A two-sided t-test is used to determine the difference in mean ratings between the proposed AC-GAN and WAC-GAN variants. Specifically, the proposed WAC-GAN received a higher average realism rating (3.92 ± 0.23 out of 5) compared to that of the proposed AC-GAN model (3.21 ± 0.18 out of 5). This indicates that the participants found the images generated by the modified WAC-GAN model to be more realistic. An inspection of the generated images also revealed that our optimised WAC-GAN model produced fewer artifacts and failures with sufficient robustness and generation diversity.

E. Visualisation Results

After performance comparison in Table I, we provide illustrative comparison between our proposed WAC-GAN and AC-GAN models in this section.

1) Fixed Hair/Eyes, Varying Eyes/Hair: Analysing image generation by fixing one attribute (hair or eye colours) while varying the other provides insights into model control over colour variations. As shown in Figures 2 and 3, when fixing

TABLE III

FID Score Comparison of Various GAN Models (Lower FID scores indicate better performance)

Model	Source	FID ↓	Dataset	Domain
AniGAN	[7]	38.45	Custom Anime based on Danbooru	Human-to-Anime
AniGAN	[7]	86.04	Custom Dataset	Human-to-Anime
Pix2Pix	[20]	69.863	Various	Artistic Translation
CycleGAN	[20]	59.424	Various	Unpaired Translation
StyleGAN	[21]	119.83	Danbooru2019	Anime Faces
StyleGAN2 ADA	[21]	14.55	Danbooru2019	Advanced Anime Faces
SGA-GAN (Male)	[1]	58.8	Custom Anime	Gender-Specific (Male)
SGA-GAN (Female)	[1]	61.9	Custom Anime	Gender-Specific (Female)
GA-GAN (Male)	[1]	77.7	Custom Anime	Gender-Specific (Male)
GA-GAN (Female)	[1]	77.8	Custom Anime	Gender-Specific (Female)
ACFE-GAN	[22]	96.8	Selfie2Anime Custom Danboru	Selfie-to-Anime
DCGAN	[23]	84.94	Danbooru2021	Anime Attributes
AC-GAN (Add. + Opt.)	Ours	64.2	Dataset A (Danbooru2021)	Enhanced Anime Attributes
WAC-GAN (Add. + Opt.)	Ours	60.3	Dataset A (Danbooru2021)	Enhanced Anime Attributes
AC-GAN (Add. + Opt.)	Ours	62.1	Dataset B (Kaggle AnimeFaces)	Enhanced Anime Attributes
WAC-GAN (Add. + Opt.)	Ours	58.7	Dataset B (Kaggle AnimeFaces)	Enhanced Anime Attributes

*Results for DCGAN are from our experiments for comparison purposes.

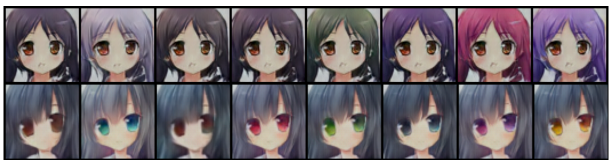

Fig. 2. Generated images with hair and eye variations using the proposed WAC-GAN model with a batch size of 128

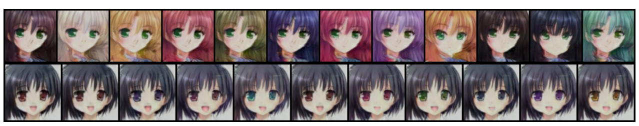

Fig. 3. Generated images with hair and eye variations using the proposed AC-GAN model with a batch size of 128

hair and varying eye colours, our optimised WAC-GAN model generates more realistic and nuanced eye colours compared to those produced by the devised AC-GAN model. Similarly, varying hair colour while keeping eyes fixed also results in enhanced hair texture and strand details from the proposed WAC-GAN model. The gradient penalty appears to act as a regulariser that enables our proposed WAC-GAN to render finer attribute changes.

2) Fixed Noise: We also conduct evaluation by using fixed noise for both proposed models. Figure 4 validates the capabilities of our optimised WAC-GAN in producing higher quality anime faces given fixed noise inputs. As shown in Figure 4, the generated images of our optimised WAC-GAN model appear visibly sharper and higher quality. The Q-learning based hyperparameter optimisation as well as the incorporation of additional layers in the generator and discriminator accounts for the efficiency and robustness of the proposed WAC-GAN, which lead to enhanced generated image quality. The proposed strategies along with the Wasserstein objective and gradient regularisation enable the network to balance well between scalability and diversity to mitigate artifacts.

Fig. 4. The generated images using the proposed WAC-GAN model with fixed noise

F. Comparison with Existing Studies

In analysing the performance of various existing GAN models, as presented in Table III, varying conditions have been used for model training and evaluation in these existing studies. As an example, some methods such as AniGAN, Pix2Pix, and CycleGAN have been trained and tested across different datasets and application targets, while some methods such as SGA-GAN, GA-GAN and DCGAN have been developed and evaluated using similar-style databases in identical application contexts. Therefore, we perform a loose comparison with these existing state-of-the-arts. As indicated in Table III, our models achieved competitive performance with comparatively lower FID scores for anime face generation than those of most methods. In particular, compared to SGA-GAN, GA-GAN, and DCGAN, our models exhibit a significant edge, in terms of both versatility and image quality.

For instance, SGA-GAN and GA-GAN, focusing on gender-specific anime faces, obtained FID scores ranging from 58.8 to 77.8, while DCGAN held an FID score of 84.94 for anime image generation. Both of our optimised models achieve lower FID scores, where our devised WAC-GAN model achieves **60.3** and **58.7** on Datasets A and B, with the optimised AC-GAN model obtaining 64.2 and 62.1 on Datasets A and B, respectively. This in turn indicates superior image quality and realism as compared with those from the above existing methods. Additionally, our models are capable of handling a broader range of attributes and can adapt to various image qualities, including lower fidelity images.

VII. Conclusions and Future Work

This research has proposed enhanced AC-GAN and WAC-GAN models with additional layers and Q-learning based hyperparameter optimisation, as powerful tools for the generation of anime faces, highlighting their capacity for explicit control over critical facial attributes like hair and eye colours. The integration of reinforcement learning through Q-learning for hyperparameter fine-tuning, alongside the use of a CNN-based Illustration2Vec method for accurate attribute extraction, and customised network augmentation for discriminative feature learning, has markedly enhanced the performance of our models. This combined approach not only facilitates the fine-tuning of learning configurations to mitigate gradient descent oscillations but also imbues the model with sufficient regularity to stabilise training and address over- and under-fitting issues effectively. Such advancements are evidenced by the superior quantitative and qualitative results of our models, as detailed in Tables I and II.

Future work aims to enhance model generalisation for a wider range of facial attributes. Exploring model applications in other domains like text-to-image generation and style transfers could lead to new advancements. Other deep network architecture and hyperparameter optimisation methods will also be exploited [24] [25] [26] [27].

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