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Generative adversarial networks (GANS) for generating face images

Dolly Indra[a], Muh. Wahyu Hidayat[b], Fitriyani Umar[c]

[a]Department of Information System, Faculty of Computer Science, Universitas Muslim Indonesia, Makassar, 90234
[b,c]Department of Informatics Engineering, faculty of computer science Universitas Muslim Indonesia, 90234
E-mail: dolly.indra@umi.ac.id, Muhwahyuhidayat28@gmail.com, fitriani.umar@umi.ac.id

Abstract

The advancement of artificial intelligence technology, particularly deep learning, presents significant potential in facial image processing. Generative Adversarial Networks (GANs), a type of deep learning model, have demonstrated remarkable capabilities in generating high-quality synthetic images through a competitive training process between a generator, which creates new data, and a discriminator, which evaluates its authenticity. However, the use of public facial datasets such as CelebA and FFHQ faces limitations in representing global demographic diversity and raises privacy concerns. This study aims to generate realistic synthetic facial datasets using the StyleGAN2-ADA architecture, a specialized variant of GAN, with two training approaches: training from scratch on two types of datasets (private and public), each containing 480 images. The public dataset used is FFHQ (Flickr-Faces-HQ), known for its broader facial variation and high-quality images. Evaluation is conducted using the Frechet Inception Distance (FID), a metric that assesses image quality by comparing the feature distributions of real and generated images. Results indicate that training from scratch with the public dataset (FFHQ) using a batch size of 16 and a learning rate of 0.0025 achieves an FID score of 85.67 and performance of 86.46% at Tick 100, whereas the private dataset, under the same conditions, results in an FID score of 98.59 with a performance of 18.54%.. The training from scratch approach with the public dataset proves more effective in generating high-quality synthetic facial images compared to the private dataset. In conclusion, this approach supports the optimal generation of realistic synthetic facial data.

Key words: Dataset, Generative Adversarial Network, StyleGAN2-ADA, Face.

INTRODUCTION

Along with the rapid advancements in artificial intelligence (AI) technology, many parties from various fields show interest in studying and developing this technology. One branch of AI experiencing significant growth is deep learning [1][2][3][4]. Among its many applications, image processing, particularly facial image processing, has garnered considerable attention. This technology is not only pivotal in research but also in industries that leverage visual data for analysis and application development, such as social media [5], facial security enhancement [6], face recognition [7][8][9], entertainment industry[10] and healthcare [11].

The face is a primary feature used to identify individuals and is central to social interaction. This is supported by specialized regions in the human brain dedicated to recognizing facial patterns and subtle changes in facial expressions or features [12]. Characteristics such as feature variations, expressions, and other specific details make human faces essential not only for identification but also for providing rich information about an individual's identity and emotions. The complexity of facial features makes them a focal point in social interactions and technological research, particularly in artificial intelligence. The face's uniqueness and complexity are crucial not only for identifying individuals but also for driving the development of modern technologies.

However, facial data processing comes with ethical and technical challenges. Protecting individual privacy is a recurring concern when collecting facial data [13]. Commonly used datasets, such as CelebA [14] and FFHQ [15] while extensive, still fall short in representing global demographic diversity. Consequently, there is a growing need to create realistic synthetic data as an alternative for training AI models without compromising individual privacy. The collection of representative facial datasets demands diversity in expressions, viewpoints, and variations. The primary challenge lies in the imbalance of facial data distribution in available public datasets, which can result in gaps in representation and model performance. When datasets lack sufficient variation in terms of age and ethnicity, models trained on such data tend to have limited generalization capabilities.

Generative Adversarial Network (GAN) [16] are among the deep learning methods capable of high-quality image synthesis. GANs function by leveraging a generator (G) to improve the capabilities of a discriminator (D), enabling the generation of more realistic data that closely resembles the original data distribution [17]. The generator is responsible for producing fake data, while the discriminator distinguishes between real and fake data originating from the training data [18].

Generative Adversarial Network (GAN) utilize competitive iterations between these two models, where the generator continuously learns to produce more realistic data to "trick" the discriminator, while the discriminator becomes increasingly adept at distinguishing between real and fake data [19] [20]. This iterative mechanism gradually improves the quality of synthetic data, making GANs highly effective tools for generating images, such as human faces, modifying facial attributes, and applications in text, audio [21] and healthcare [22].

Research by [23] trained and evaluated four GAN models DCGAN, PGGAN, StyleGAN2, and CoCoGAN on the Inria Aerial Image dataset. The results, measured using *Fréchet Inception Distance (FID)*, show that StyleGAN2 achieved the best performance with a FID score of 16.59, followed by PGGAN (27.24), CoCoGAN (141.10), and DCGAN (283.72). Similarly, the study by [11] also tested several GAN models to generate synthetic fundus images for improved AMD detection. StyleGAN2-ADA, BEGAN, WGAN-GP, LSGAN, and WGAN achieved the best results based on Fréchet Inception Distance (FID), with StyleGAN2-ADA recording the lowest FID (166.17), followed by BEGAN (225.89), WGAN-GP (295.23), LSGAN (305.59), and WGAN (307.00). These results indicate that StyleGAN2-ADA produces the highest-quality synthetic images compared to other models.

Therefore, this study focuses on creating datasets by implementing GANs, using the StyleGAN2-ADA architectural model..

MATERIAL AND METHODS

Dataset

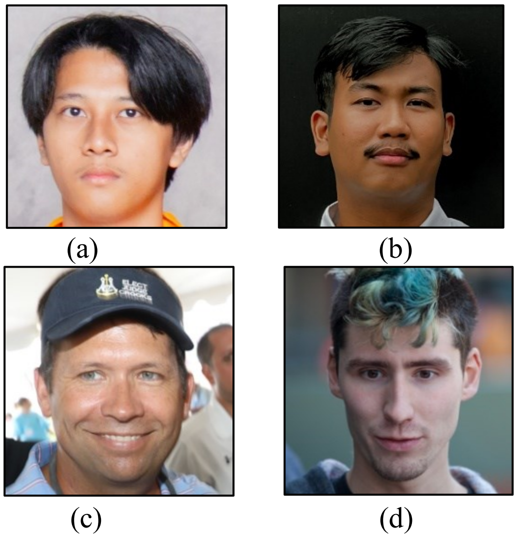


Fig. 1. Images (a) and (b) represent the private dataset, while images (c) and (d) represent the public FFHQ dataset

This research utilized a facial dataset consisting of 960 images, comprising 480 images from a private dataset and 480 images from the publicly available FFHQ dataset, trained separately. Each image was resized to a resolution of 256 x 256 pixels prior to processing [24]. Examples of images from both the private and public datasets are shown in Fig. 1.

Deep Learning

Deep learning [25] a branch of artificial intelligence, is designed to enable computers to autonomously learn patterns and information from data. By employing a hierarchical structure of concepts, this system builds understanding of complex ideas by combining simpler ones. This approach eliminates the need for manual human intervention to define all required knowledge, making it more flexible and effective for handling complex tasks such as pattern recognition, data analysis, and natural language processing.

Essentially, deep learning constructs an understanding of complex concepts gradually. For instance, in image recognition, the system initially learns to identify basic elements such as colors or lines. From these elements, it constructs an understanding of more complex patterns, like facial shapes or specific objects. This hierarchical approach enables the system to integrate simpler elements into higher-level concepts, allowing for a comprehensive understanding of data [26].

Generative Adversarial Network (GAN)

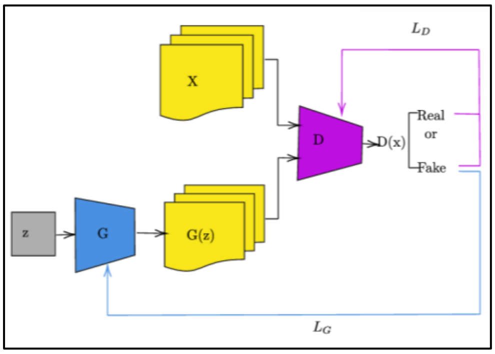


Fig. 2. Generative adversarial network (GANs) architecture [16]

Generative Adversarial Networks (GANs), introduced by Ian Goodfellow in 2014 [27], are a type of deep learning model that employs two competing neural networks: a generator and a discriminator (can be seen in Fig. 2). The generator creates fake data resembling real data, such as images or text, while the discriminator differentiates between real and fake data. Both networks train simultaneously, with the generator improving its ability to produce realistic data and the discriminator becoming more adept at distinguishing real data from fake data. This process enables GANs to generate new data that closely mirrors existing data, even when the original dataset is limited [13] [21].

In a GAN, the generator is responsible for creating synthetic data $G(z)$ from input noise z, aiming to replicate the distribution of real data. It minimizes the loss function:

$$L_G = -log(D(G(z))) \quad (1)$$

where $D(G(z))$ represents the probability assigned by the discriminator that the generated data is real. Meanwhile, the discriminator is a binary classification model designed to distinguish between real data x and synthetic data $G(z)$. Its loss function,

$$L_D = -[log(D(x)) + log(1 - D(G(z)))] \quad (2)$$

optimizes the ability to identify real data and reject fake samples. Training proceeds iteratively, with both models improving until the generator produces outputs indistinguishable from real data, reaching a Nash equilibrium between the two [16].

One of the primary applications of GANs is creating new datasets, particularly facial images. In this context, GANs can produce realistic facial images even with minimal or no original data. The generator learns to create various realistic facial image variations, while the discriminator ensures that the generated images resemble authentic facial data.

This capability makes GANs invaluable for research requiring large-scale facial datasets, particularly when collecting real facial images is challenging due to privacy concerns or limited access. GANs also facilitate the creation of more diverse datasets, which are essential for training AI models with higher accuracy in facial recognition and processing tasks [12].

StyleGAN

StyleGAN, an evolution of GANs introduced by NVIDIA in 2020 [28]. consists of two main components: the generator and the discriminator. These components work competitively to produce increasingly realistic images. One of StyleGAN2's strengths is its ability to control various visual aspects of images with great precision, resulting in high-quality, detailed images, particularly for facial synthesis.

Due to its capability to generate facial images that closely resemble real ones, StyleGAN is highly effective for creating synthetic facial datasets. The model can produce faces with a wide range of variations, including expressions, ages, and genders [26]. This makes StyleGAN an ideal choice for generating large-scale facial datasets, which can be used to train AI models for facial recognition and other visual modeling applications.

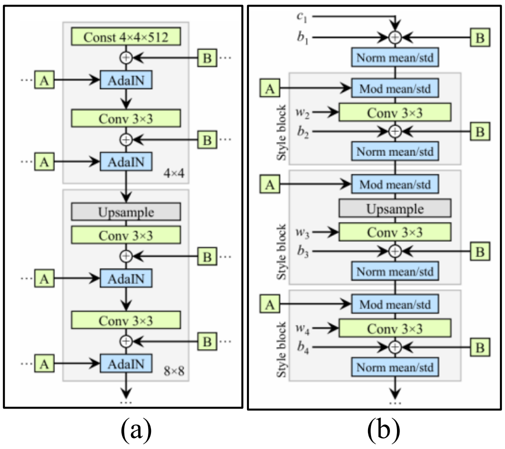


Fig. 3. StyleGAN architecture (a) StyleGAN, (b) Detailed StyleGAN [28]

Fig. 3(a) shows the basic StyleGAN architecture, where a generator progressively produces images from low to high resolution. It starts with a 4×4×512 constant tensor processed through Adaptive Instance Normalization (AdaIN) layers, which adjust image features based on style parameters. Each stage involves a 3×3 convolution followed by upsampling to increase resolution. Style parameters, derived from a style vector transformation, control normalization at each layer, allowing realistic and controlled image generation. This process allows the generator to modify the image according to the desired style, producing realistic and controlled image variations.

Fig. 3(b) details each style block in StyleGAN. Key components include mean and standard deviation normalization, style vector modulation, 3×3 convolution, and noise injection. Style vectors are processed via a weight matrix to generate modulation parameters that adjust feature distributions. Noise adds fine detail variation, such as textures, ensuring each layer enhances style control and produces high-quality, detailed images. This ensures that each layer contributes to style control and detail enhancement, enabling the generation of high-quality images rich in variations and fine details.

Adaptive Discriminator Augmentation

Adaptive Discriminator Augmentation (ADA) is a technique designed to address challenges in training generative models with limited datasets [22] [29]. ADA introduces adaptive data augmentation to the discriminator, applying transformations such as rotation, color changes, or geometric distortions to enrich data variation without directly increasing the training data. The intensity of augmentation increases when the discriminator struggles to differentiate real and fake data and decreases as the discriminator improves. This dynamic approach prevents overfitting, a common issue with small datasets, and enables the model to generate high-quality synthetic data.

A key aspect of ADA is its dynamically adjustment of augmentation probability p, which ensures that augmentation is neither excessive nor insufficient. This adjustment is guided by the classifier retention metric Rt, which measures how well the discriminator retains its classification decisions when distinguishing between real and augmented images. Mathematically, R_t is computed as the ratio of the discriminator's output for real and augmented images:

$$R_t \frac{D(x)}{D(A(x))} \quad (3)$$

Based on this metric, the augmentation probability is updated using the following formula:

$$P_t + 1 = P_t + k \cdot (R_t - R_{target}) \quad (4)$$

If R_t is too high, indicating that the discriminator is overfitting, the augmentation probability increases to introduce more variability. Conversely, if R_t is too low, suggesting that augmentation is too strong and hindering learning, the probability decreases to maintain a balance.

This adaptive mechanism ensures that augmentation remains effective in enriching the dataset while preserving its original distribution. By dynamically regulating augmentation, ADA stabilizes GAN training, improves generalization, and enhances the quality of generated images, making it particularly beneficial for training with limited data.

StyleGAN2-ADA

StyleGAN2-ADA (Adaptive Discriminator Augmentation) is an enhancement of StyleGAN2, developed to improve the stability and quality of GAN training, particularly with small datasets. This technology employs adaptive augmentation on the discriminator, dynamically adjusting augmentation levels based on discriminator performance to prevent overfitting [30] [31]. Despite these improvements, StyleGAN2-ADA retains the core architecture of StyleGAN2, which relies on style modulation to generate high-quality images with precise style control. With the addition of ADA, StyleGAN2 can produce realistic images even with limited training data, making it a popular choice for creative applications such as synthetic facial generation.

To further enhance training efficiency, StyleGAN2-ADA incorporates several additional techniques. Transfer learning allows the model to leverage knowledge from larger datasets like FFHQ, accelerating and improving training on smaller datasets. The model also employs a progressive growing approach, where image resolution increases over time, ensuring stable learning. Additionally, noise regulation mechanisms help maintain training stability by preventing artifacts and preserving image quality.

Another key feature of StyleGAN2-ADA is style control (style mixing), which enables interpolation between different styles to create unique image variations. This capability enhances the flexibility of the model, making it ideal for creative experimentation and research in generative deep learning.

The blue elements in Fig. 4, highlight operations related to augmentations, while the rest implement standard GAN training with generator G and discriminator D. The orange elements indicate the loss function, and the green boxes mark the networks being trained [30]. In this architecture, G generates synthetic data from latent vectors, while D evaluates both real and augmented data. Data augmentations (Aug) are applied probabilistically with probability p, ensuring diversity and preventing overfitting. The generator loss (G loss) is computed as

$$G\ loss = -E[log(D(G(z)))] \quad (5)$$

while the discriminator loss (D loss) is split between real and fake data:

$$D\ loss = -E\left[log(D(x))\right] - E\left[log\left(1 - D\left(G(z)\right)\right)\right] \quad (6)$$

These combined augmentations and loss formulations ensure the generator produces realistic outputs while training the discriminator effectively.

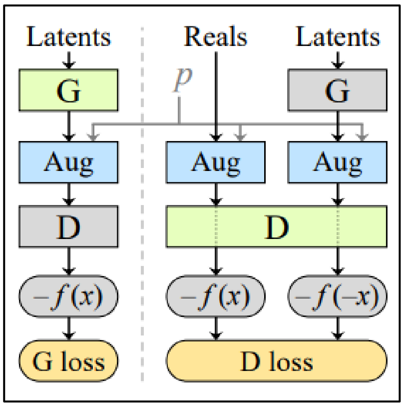


Fig. 4. StyleGAN-ADA architecture [30]

RESULT AND DISCUSSION

In this study, we conducted model training under two scenarios to evaluate the model's performance based on the type of dataset used. Both scenarios employed a training-from-scratch approach with an equal amount of data, namely 480 images each, to ensure a fair comparison.

In Fig. 5(a), the first scenario involved training with 480 images from the private dataset. This dataset comprises unique images captured using Samsung, iPhone, and Photographer cameras. This scenario was designed to explore how the model learns unique patterns inherent in the private dataset and generates images that reflect its characteristics.

In Fig. 5(b), the second scenario utilized 480 images from the public FFHQ dataset. The selection of 480 images from FFHQ was performed to ensure balance with the first scenario, so that model performance comparisons would not be influenced by differences in data quantity.

Table 1 outlines the training process for StyleGAN2-ADA in two scenarios, differing in dataset type and gamma values. First Scenario Training was conducted using the private dataset with 480 images, a gamma value of 20, 100 ticks, and a batch size of 16. A gamma of 20 was chosen because private datasets tend to have lower variability compared to public datasets. With a higher gamma value, gradient penalties on the discriminator are strengthened, preventing the discriminator from dominating too quickly and allowing the model to capture more specific details of the private dataset.

Second Scenario Training was conducted using the public dataset, also with 480 images but with a gamma value of 10. A lower gamma was selected for the public dataset due to its generally higher diversity. This lower gamma helps reduce gradient penalties, enabling the generator to be more flexible in producing realistic images without being overly constrained by the discriminator.

Other parameters, such as the number of ticks and batch size, were kept consistent across both scenarios to ensure a fair comparison of model performance.

Table 1. Training scenarios and configuration

Scenarios	Dataset	Training Method	Number of Images	Tick	Gamma	Batch Size
1	Private	Training from Scratch	480	100	20	16
2	Public	Training from Scratch	480	100	10	16

(a)

(b)

Fig. 5. (a) Private dataset, (b) Public dataset

Performance of Generator and Discriminator Loss Stability

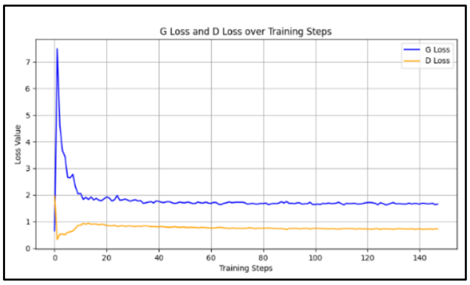
In Scenario 1 (Private Dataset), the training process demonstrated reasonable stability, although in the early stages, the generator loss could be considered unstable. The higher generator loss at the start of training could be due to the challenges of learning from the private dataset, which might be more complex or less diverse than the public dataset. However, as training progressed, the generator loss gradually decreased and reached a more stable value in later stages. This indicates that the model began producing more realistic images and achieved better convergence after several iterations.

On the other hand, in Scenario 2 (Public Dataset), the training process exhibited faster and more consistent stability compared to the private dataset scenario. Both the generator and discriminator losses decreased more steadily and converged more quickly, indicating that the model learned more efficiently from the public dataset. With its greater diversity and well-structured nature, the public dataset enabled the model to achieve better stability in a shorter time, reflecting a more optimal training process.

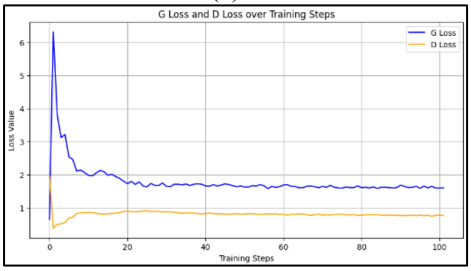
Table 2. Generator and discriminator loss stability on private and public datasets

Scenarios	Kimg	Loss	
		Generator	Discriminator
1	80	1.92622	0.84807
	160	1.75492	0.80288
	240	1.68499	0.75642
	320	1.67512	0.75590
	400	1.64531	0.75065
2	80	1.73146	0.90603
	160	1.66479	0.83015
	240	1.69320	0.80532
	320	1.61029	0.78459
	400	1.60135	0.78599

As illustrated in Fig. 6(a) and Fig. 6(b), the visuals provide insights into the performance of the Generator and Discriminator losses, which consistently strive to maintain stability throughout the training process. This balance ensures that overfitting is avoided, which could occur if one component becomes excessively dominant during the training phase.



(a)



(b)

Fig. 6. Performance graph of stability for generator and discriminator loss on (a) Private dataset and (b) Public dataset.

Training Performance From Scratch Based on Fréchet Inception Distance (FID) Metric

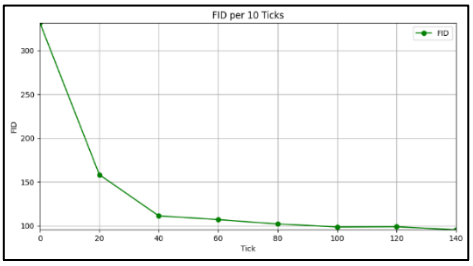
In StyleGAN2-ADA, the evaluation of training results is conducted using various metrics, with one of the most common being the Fréchet Inception Distance (FID). FID measures how closely the distribution of images generated by the model matches the distribution of real images. This metric operates by comparing the high-level feature representations of these images using an Inception network. The lower the FID score, the better the quality and realism of the generated images, making it a key indicator for assessing the success of generative model training.

Table 3 presents the evaluation of Fréchet Inception Distance (FID) for two scenarios using private datasets (Scenario 1) and public datasets (Scenario 2) during the training of StyleGAN2-ADA. Generally, the FID value decreases as the number of training steps (kimg) increases, indicating that the model becomes progressively better at generating images with a distribution closer to the real data.

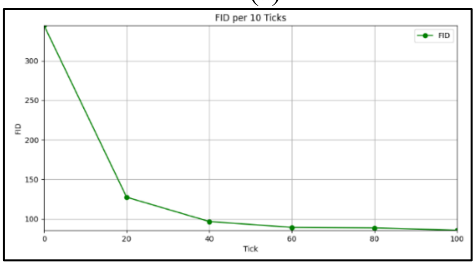
Table 3. Evaluation of fréchet inception distance (FID) on private and public datasets

Scenarios	Kimg	Fréchet inception distance (FID)
1	80	158.30124
	160	111.23192
	240	106.97159
	320	101.99316
	400	98.59394
2	80	127.47809
	160	96.70023
	240	89.25078
	320	88.61752

In the public dataset scenario, FID values are consistently lower than those of the private dataset across all training stages. This suggests that models trained with public datasets produce images of higher quality and realism. The decline in FID values in both scenarios also demonstrates stable training progress and the model's capability to effectively learn from the data.



(a)



(b)

Fig. 7. Evaluation graph of fréchet inception distance (FID) for (a) Private dataset and (b) Public dataset

As shown in Fig. 7(a) and Fig. 7(b), the graphs of both training processes exhibit a downward trend, indicating improved training performance at each stage in creating realistic synthetic facial data. However, the performance in Scenario 2 outperforms Scenario 1, owing to the superior image quality and greater diversity of the public dataset.

Performance Evaluation Based on Visual Perception

In evaluating the quality of images generated by generative models like StyleGAN2-ADA, in addition to using objective metrics such as Fréchet Inception Distance (FID), human visual perception-based evaluation also becomes important. This evaluation involves direct assessment by human observers to judge the realism, naturalness, and visual detail of the generated images compared to real images. This approach provides a subjective perspective that complements objective metrics, especially in assessing visual aspects that are difficult to quantify numerically.

Table 4 shows the results of visual perception evaluation based on image classification performance in two scenarios: the private dataset (Scenario 1) and the public dataset (Scenario 2), with the model trained from scratch. The performance is measured based on the number of generated images correctly classified by human observers.

Table 4. Visual perception evaluation

Scenarios	Kimg	Generate	Wrong Generate	Performance
1	20	0	480	0%
	40	13	467	2.71%
	60	64	416	13.33%
	80	70	410	14.58%
	100	89	391	18.54%
2	80	0	480	0%
	160	195	285	40.63%
	240	377	103	78.54%
	320	388	92	80.83%
	400	415	65	86.46%

In Scenario 1 (private dataset), performance gradually improved as the training steps (kimg) increased, but the rate of improvement was relatively slow, with the final performance reaching 18.54%. This indicates that the model required more time and training steps to generate more realistic images on the private dataset.

In contrast, in Scenario 2 (public dataset), visual performance improved much faster and more significantly. After a few training steps, performance reached 86.46% by the final kimg step, reflecting the higher quality of the generated images compared to the private dataset. Training from scratch on the public dataset allowed the model to learn more quickly and efficiently, resulting in more realistic images and much better visual classification performance within the same training time. Examples of images that can be considered as "generated" and "wrong generated" can be seen in Fig. 8(a) and Fig. 8(b) for the private dataset, and Fig. 9(a) and Fig. 9(b) for the public dataset.

(a) (b)

Fig. 8. Example of public dataset for (a) Generate and (b) Wrong generate.

(a) (b)

Fig. 9. Example of public dataset for (a) generate and (b) Wrong generate

CONCLUSION

Based on the research results evaluating the performance of the StyleGAN2-ADA model from three main aspects loss stability, Fréchet Inception Distance (FID) metrics, and visual perception evaluation it can be concluded that the characteristics of the dataset play a crucial role in the success of training generative models. The public FFHQ dataset, which is more diverse and structured, enabled the model to achieve an FID value of 85.67 with a performance of 86.46% at Tick 100, demonstrating faster training stability and image quality recognized by human observers. On the other hand, the private dataset, despite its uniqueness, required more iterations to reach comparable results, with an FID of 98.59 and a performance of only 18.54% at Tick 100. This indicates that dataset variation significantly impacts the model's learning efficiency.

In training from scratch, dataset diversity proved to be the key factor supporting the generator's ability to create realistic images. The public dataset provided the model with more patterns to learn from, speeding up stability and reducing the FID value, while a dataset with limited variation tends to slow down the training process and produce lower-quality images. The results of this study emphasize the importance of selecting a high-quality and diverse dataset to achieve optimal performance in generative model training. Additionally, for applications using specialized datasets like private datasets, additional strategies such as data augmentation or parameter tuning are required to approach the results achieved with public datasets.

FUTURE WORK

For researchers aiming to conduct similar studies, it is recommended to use a more diverse dataset, such as FFHQ, to support training stability and improve the quality of results. When using a private dataset with limited variation, strategies such as data augmentation, training parameter adjustment, or a combination with transfer learning should be considered to address challenges in model generalization. Additionally, the selection of evaluation metrics like FID should be aligned with the research objectives to ensure more measurable and relevant results.

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