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A New Approach to Improving Photorealistic Image Quality Using Generative Adversarial Networks (GANs)

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Abstract

The current study explores the use of generative adversarial networks (GANs) to improve image quality in multiple applications. The research was designed to investigate the effectiveness of the proposed model in improving image quality through experimental and analytical steps. Data processing includes collecting data from diverse sources, cleaning it, converting it to a standardized format, and then dividing it into training and test sets. An advanced algorithm using GANs was applied to improve image quality, utilizing advanced deep learning techniques. The model was evaluated using metrics such as the Fréchet Intradistance (FID) to measure the quality of the generated images. The results demonstrated that the model is capable of generating high-quality images while preserving fine details. The study also demonstrated that the model has the ability to generalize across multiple experiments. The benefits of this technique were noted in fields such as healthcare, education, and digital art. The study recommended improving training stability and image quality, and expanding the use of this technique to new fields such as artificial intelligence.

Keywords: *Generative Adversarial Networks (Gans) - Image Quality Improvement- Data Processing - Image Cleaning and Preprocessing.*

Introduction

Generative adversarial networks (GANs) are a deep learning model that consists of two neural networks competing with each other. The first network is the generator, which creates new data (such as images) based on a given distribution. The second network, the discriminator, aims to distinguish between real data and fake data generated by the generator.

The competition between the two networks helps improve the quality of the generated data. The generator seeks to improve its ability to produce realistic data, while the discriminator seeks to improve its accuracy in recognizing fake data. These networks are used in many applications such as image generation, graphics enhancement, and creating synthetic data [1]. In recent decades, artificial intelligence has seen significant advances thanks to technologies that have improved computing and data analysis. One such technology is generative adversarial networks

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(GANs), developed in 2014 by Ian Goodfellow and colleagues. GANs are a major development in artificial intelligence, as they can generate realistic data from scratch, making them a powerful tool in areas such as generating images, audio, and video [2]. GANs consist of two neural models that work in competition. The first is the “generator,” which generates new data based on patterns in real data. The second is the “discriminator,” which distinguishes between real data and fake data produced by the generator. The two models compete, with the generator trying to improve its data to become more realistic, while the discriminator trying to improve its accuracy in detecting fake data. This competition leads to incremental improvements in the performance of the two models, resulting in highly realistic data [3].

One of the most prominent uses of GANs is in generating realistic images, as the technology has become capable of creating images that look realistic with high accuracy and quality. This development is due to the competitive structure between the generator and the discriminator, which allows the generator to continuously improve its outputs to deceive the discriminator, which enhances the realism of the images. This technology is used in many areas such as creating realistic characters in games, improving the quality of low-resolution images, and recoloring old images and converting them to modern images [4]. GANs also play an important role in areas that require the creation of data from scratch, such as deepfake, which is used to create fake videos or audio that appear real. Despite the great benefits of this technology, its use in these areas has sparked widespread controversy about the ethics and responsibilities associated with the development and deployment of this technology [5]. Despite the superior capabilities of GANs in generating realistic data, they face challenges, such as the difficulty of training models due to the complexity of the competition between the generator and the discriminator, which may lead to model instability during training. In addition, there is the problem of “mode collapse”, where the generator tends to produce limited results rather than diverse outputs. Therefore, developing and training GANs models requires high precision and fine-tuning to obtain satisfactory results [6]. In recent years, GAN research has seen significant development with the emergence of several improvements such as Progressive GANs and StyleGANs. These improvements have helped to significantly improve the quality of images and the realism of details. These innovations have contributed to expanding the uses of GANs, making them more attractive to researchers and specialists in the field of artificial intelligence[7].Over the past few decades, the field of artificial intelligence has seen significant development, with the emergence of techniques that have improved computing and data analysis capabilities. One of the most prominent of these techniques is generative adversarial networks (GANs), which were first developed by Ian Goodfellow and colleagues in 2014. GANs are considered an important development in artificial intelligence, especially in their ability to generate realistic data from scratch, making them a powerful tool in areas such as generating images, audio, and video [8].

GANs are characterized by two neural models working competitively. The first is the “generator,” which generates new data based on patterns it learns from real data. The second is the “discriminator,” which distinguishes between real data and generated data. The two models work together in a competitive framework, with the generator seeking to improve its ability to produce indistinguishable data, while the discriminator seeks to improve its accuracy in detecting fake data. This dynamic helps both models improve their performance, resulting in more realistic data being generated [9]. One of the main uses of GANs is in generating realistic images. The technology has become capable of generating images that look as if they were taken from the real world with high quality. This progress is due to the competitive structure that helps the generator to constantly improve its output to outwit the discriminator, thus improving the realism of the images produced. The technology is used in many areas, such as creating realistic characters in games, improving the quality of low-resolution images, and even recoloring old photos into modern ones[10]. GANs also play an important role in areas that require the creation of new data from scratch, such as deepfake, which is used to create fake videos or audio that appear real. Despite the great benefits of this technology, its use in these areas has sparked significant controversy over the ethics and responsibilities associated with the development and deployment of this technology [11]. Although GANs are capable of generating realistic data, they face some challenges. The most notable of these challenges is the difficulty of training models due to the high complexity of the competition between the generator and the discriminator, which may lead to model instability during training. There is also the problem of "mode collapse", where the generator may produce a limited set of results rather than a variety of outputs. Therefore, developing and training GANs requires a high level of accuracy and fine-tuning to achieve satisfactory results [12]. In recent years, research in the field of GANs has witnessed significant development, with improvements and modified structures being introduced that aim to overcome traditional challenges. The most notable of these developments are Progressive GANs and StyleGANs, which have achieved quantum leaps in the quality of the images produced and the realism of the details. These innovations have contributed to expanding the scope of uses of GANs and made them the focus of attention of researchers and specialists in the field of artificial intelligence [13].

Literature Review

This section contains two main sections: 2.1 reviews the theoretical framework related to generative adversarial networks (GANs) in generating realistic images. 2.2 presents' previous studies related to the use of generative adversarial networks in generating realistic images.

Review of the Literature on Generative Adversarial Networks (Gans) for Generating Realistic Images

Generative adversarial networks (GANs) are one of the most prominent techniques in artificial intelligence, especially in generating realistic images. They were first developed by Ian Goodfellow and his team in 2014, and are based on two main concepts: the generative network (GANs) that generates new data, and the discriminator network (Discriminator) that distinguishes between generated and real data [14]. Generative Adversarial Networks (GANs) are a type of deep neural network that aims to generate new data similar to the original data, such as images, text, and audio clips. They were developed in 2014 by researcher Ian Goodfellow and his team, and are one of the most prominent innovations in the field of deep learning. GANs rely on the competition between two neural networks: the Generator network, which generates new data that mimics the original data, and the Discriminator network, which aims to distinguish between real and generated data [15]. The Discriminator network in GANs works to distinguish between real and fake data generated by the Generator network. Its goal is to determine whether the data is real or generated, making it an essential part of the competitive learning process between the two networks. When training GANs, the Generator and Discriminator networks work in competitive harmony; the generative network seeks to improve its ability to generate realistic data to fool the discriminator network, while the discriminator network seeks to improve its accuracy in distinguishing between real and fake data. This process is similar to a competitive game, where each challenges the other to improve its performance using optimization algorithms such as inverse regression to reduce errors [16].

Generative adversarial networks (GANs) have proven to be very effective in generating realistic images, making them a leading technology in many applications based on artificial intelligence. Thanks to their ability to generate high-quality images that are difficult to distinguish from real images, GANs have been used in a wide range of practical fields. The following is a detailed explanation of the different applications: GANs are used in a variety of applications that rely on generating and enhancing images with high accuracy in multiple fields. The most prominent of these applications are: Generating realistic human images: Models such as StyleGAN and StyleGAN2 are used to create realistic images of people who do not exist in reality, with fine details such as facial expressions and skin color, allowing the design of characters for video games and virtual reality, and the film industry to create digital characters [17]. Improving image quality (Image Super-Resolution): Using SRGAN, the accuracy of low-quality images can be improved, such as improving old or blurry images, processing satellite images, and using GANs in security surveillance to restore details of unclear images and videos [18]. Image Inpainting: Using Contextual GANs, missing or damaged areas in images can be filled, helping to repair old or damaged images and improve the quality of medical images such as X-rays [19]. Image-to-Image Translation: CycleGAN and Pix2Pix are used to convert images between different styles without the need for corresponding data, such as converting landscape images to artistic styles, and converting night images to daytime images [20]. Creating Virtual Scenes and Environments: GANs are used to generate 3D landscapes and images for virtual environments used in games or movies, designing fictional maps and locations for games, and improving animations to look more realistic [21]. Medical Imaging: GANs are used to improve the quality of medical images, generate synthetic data to train models, and detect diseases, such as improving MRI and CT scans [22]. Generating Content for Fashion and Design: GANs are used to create new designs for fashion or clothing, as well as design new interiors and improve marketing processes by creating personalized images for customers [23]. Creating composite images: GANs are used to combine multiple image components to generate new, realistic-looking images, such as creating advertising content or marketing advertisements for furniture or cars [24]. Improving security applications: GANs are used to improve security images and videos, such as restoring details in blurred images and generating expressive images of faces to assist security agencies in investigations [25]. Art and entertainment media: GANs are used in the art and media industry to produce new artistic paintings or visual effects, such as producing paintings in famous artistic styles and creating innovative animations for artistic performances [26].

Previous Studies

Many previous studies have addressed the topic of generative adversarial networks (GANs) and their applications, which formed the scientific basis that helped, develop and improve this technology over time. The following is a review of the most prominent studies that addressed this topic:

Sharma et al. [27] discuss the rise of generative adversarial networks (GANs) and their applications in fields such as natural language processing (NLP), image generation, and prediction. It focuses on their role in detecting fake images and verifying their authenticity on social media. The article also reviews advances in GAN design, their limitations, emerging applications, and important evaluation metrics such as the start score (IS) and the start distance (FID)

Goodfellowet et al. [28] trained a generator (G) to replicate data and a discriminator (D) to distinguish between real and fake data. Both components engage in a minimax game, allowing the generator to learn the data distribution. Training is performed through backpropagation, without the need for complex techniques, resulting in efficient sample generation.

Wei et al. [29] identified significant challenges in training generative adversarial networks (GANs). In response, Wasserstein adversarial networks (WGANs) were proposed to address these issues by applying 1-Lipschitz continuity. This paper presents a novel method for applying Lipschitz continuity to WGAN training and combines it with semisupervised learning techniques. The proposed method significantly improves the generation of realistic image samples and achieves state-of-the-art semisupervised learning results, including a starting score above 5.0 using 1,000 CIFAR-10 images and an accuracy of over 90% using only 4,000 labeled CIFAR-10 images.

Ni. [30] Presents a survey of improving the stability of GANs, focusing on architectures, loss functions, and regularization strategies. He discusses challenges such as pattern collapse and gradient problems, highlighting the need for continuous innovation in these areas.

GU et al. [31] proposed a time-series Wasserstein GAN (TS-WGAN) for estimating the state of charge (SOC) of lithium-ion batteries. By combining a transformer to extract global features and a CNN to process local features, the model was tested on real-world datasets and demonstrated significant improvements in accuracy, stability, and robustness, with a coefficient of determination exceeding 99.50%

Tirel et al. [32] presented a hybrid model that combines Pix2Pix and Wasserstein GAN with gradient penalty (WGAN-GP) to remove noise from images. Leveraging Pix2Pix's denoising capabilities and WGAN-GP's stabilization features, the model avoids pose collapse and outperforms traditional denoising methods, demonstrating strong performance on both synthetic and real-world datasets

Zhuet et al. [33] presented GMGAN, a Generative Adversarial Network (GAN)-based method for achieving single-image super-resolution (SISR). This method introduces a new quality loss function based on gradient magnitude similarity deviation (GMSD) to improve image quality and uses WGAN-GP to stabilize the training. The results demonstrate that GMGAN outperforms existing methods, producing visually superior images.

Tanget et al. [34] presented AttentionGAN, a novel method for translating non-binary images using attention-guided generators and features. This method identifies key foreground objects and minimizes background variations, resulting in high-quality, clear, and realistic images. This approach outperforms existing models, as demonstrated by experiments on public datasets

Almahairi et al. [35] Presented Augmented CycleGAN, an extension of CycleGAN that learns multiple mappings between scales from unpaired data. It differs from CycleGAN in that it allows for more flexible mappings, suitable for tasks requiring multiscale translations. Experiments demonstrate its effectiveness across various image datasets.

In their study, Li et al. [36] designed a novel network designed to convert face sketches into clear and detailed images. The network relies on a symmetrical architecture with identical generators and features to address problems such as image blur and edge inaccuracy. The network features a high-frequency feature extractor (HFFE) to enhance fine details and a multi-scale edge discriminator (MSWED) to improve edge resolution. Experiments have demonstrated that HE-CycleGAN outperforms other methods in generating high-quality face images from sketches

Chen et al. [37] review addresses the application of generative adversarial networks (GANs) in medical image enhancement. It reviews 105 studies, categorized by GAN models, loss functions, and evaluation metrics. The paper highlights the challenges, key insights, and potential role of GANs in addressing the scarcity of medical image data, which is vital for the development of diagnostic and treatment systems

Singh et al. [38] study explores the use of generative adversarial networks (GANs) in medical image generation and analysis. It reviews various models of these networks, including DCGAN, LAPGAN, pix2pix, CycleGAN, and UNIT, focusing on their applications in tasks such as image augmentation, registration, and multimodal synthesis. It also highlights developments and future research opportunities in this area.

Showrov et al. [39] study examines the developments and uses of generative adversarial networks (GANs) in medical imaging. It discusses their role in generating synthetic images, improving data quality, and supporting tasks such as image segmentation and disease detection. The review covers GAN algorithms, datasets, and preprocessing methods specific to medical applications. It also highlights recent studies, identifies challenges, and suggests future directions for enhancing the effectiveness of GANs in medical imaging

Motamed et al. [40] present a novel GAN-based architecture designed to enhance chest X-ray images, enhancing semi-supervised detection of pneumonia and COVID-19. By generating realistic data, this approach addresses the limited datasets for training convolutional neural networks (CNNs), significantly improving model performance. This approach outperforms traditional boosting methods and deep convolutional neural network techniques based on differential generative networks in classification accuracy. The results highlight the effectiveness of GAN-based boosting for abnormality detection in X-ray imaging

Pinto-Coelho et al. [41] study examines the impact of AI on medical imaging, focusing on its potential to enhance diagnostic accuracy and efficiency. It highlights advances in AI techniques, including deep learning, convolutional neural networks (CNNs), and generative adversarial networks (GANs), which facilitate the rapid detection of abnormalities such as tumors and early signs of eye diseases. The review covers AI applications in radiology, pathology, and cardiology, emphasizing its role in accelerating image interpretation, enabling early disease detection, and supporting personalized treatment plans. Ultimately, AI contributes to improved patient outcomes and enhanced healthcare delivery

Heng et al. [42] study reviews the applications of generative adversarial networks (GANs) in medical image analysis, focusing on tasks such as image synthesis, segmentation, and classification. It explores recent studies, model structures, datasets, and challenges, and proposes future research directions for advancing this field

- **Interpretation of Previous Studies:**

The previous studies highlight the developments and various applications of Generative Adversarial Networks (GANs), showcasing their potential in several fields, including image processing, data generation, and improving model performance. The main points from these studies are:

- **Application Areas**: Applications include text-to-image generation (T2I), image quality enhancement, medical image processing, and architectural image analysis. The studies emphasize GANs' ability to improve data quality and address sample scarcity in areas like healthcare.

- **Challenges and Solutions**: GANs face challenges such as model instability, mode collapse, and training difficulties. Improvements like WGAN and WGAN-GP have been proposed to address these issues by enhancing stability and introducing new loss functions.

- **Innovative Techniques**: Modern models integrate technologies like Transformers, CNNs, and Pix2Pix to improve stability and accuracy. Strategies such as CycleGAN and AttentionGAN have been used to handle image transformations effectively.

- **Ethics and Limitations**: The studies address ethical concerns like misinformation, deepfakes, and data bias. They recommend developing ethical frameworks that promote transparency and accountability.

- **Medical Data**: Several studies focus on the role of GANs in improving medical images and generating synthetic data to support disease diagnosis and medical image analysis.

- **Research Problem :The** research problem in the current study lies in addressing the challenges associated with improving the quality of generative data using GANs, focusing on enhancing model stability and solving mode collapse issues. The study also aims to improve model performance in practical applications, such as image processing and medical data analysis, while considering ethical concerns related to the technology's use.

The Proposed Methodology

This methodology discusses how to design and implement the current study on generative adversarial networks (GANs) for generating realistic images. The steps involved in data processing, model design, and experimentation will be explained. The methodology consists of several subsections, as follows:

Data Preprocessing:

Data processing is a fundamental step in the study of generative adversarial networks (GANs) for generating realistic images, as it aims to improve the quality of the data used to train the model. The process begins by collecting diverse data from collections such as CIFAR-10 and ImageNet or databases dedicated to specific fields such as medicine and arts. After collecting the data, it is cleaned by removing corrupted or blurred images, filtering out irrelevant images or inappropriate content, and processing missing data. Once the data is cleaned, it is converted to a standardized format by resizing the images to specific dimensions such as 64x64 or 128x128 pixels, or converting them to grayscale to reduce complexity. The data normalization step is also important, where the pixel values of the images are converted to a specific range such as -1 and 1 or 0 and 1, which enhances the performance of the model and speeds up training. The data is also distributed evenly across the categories to avoid bias in the results. Finally, after data processing, it is divided into two sets: the training set, which allocates about 80% of the data to train the model, and the test set, which allocates 20% to evaluate its performance after training is complete.

The Proposed Method:

The data is processed after collection and cleaning by dividing it into two main sets: the training set (80% of the data) to train the model, and the test set (20% of the data) to evaluate the performance after training. The data is arranged in a way that ensures the balance of different classes, and is stored in suitable formats such as JPEG or PNG to suit the requirements of the neural network used in training, which contributes to enhancing the effectiveness of the model and its ability to generate realistic images with high quality.

Table (1) shows the data processing steps based on the previous information. Here is the table that explains the data processing steps as follows:

	Step	**Description**
1	Data sharing	The data is divided into two groups: 80% for training and 20% for testing
2	training group	It consists of 80% of the data and is used in the training of students
3	selection group	It consists of 20% of the data and is used in the test after the training
4	Data numbers for training	Arrange the data appropriately and ensure the balance of the categories
5	data storage	Keeping the data in the proper format

Table (1)

- **Algorithm Explanation:**

The traditional GAN algorithm that relies on competition between the generator and the discriminator is used to achieve effective results in generating realistic images. The generator creates new images from random data using a convolutional neural network (CNN), which consists of convolutional layers, activation layers such as ReLU, and an output layer that generates the final image. The discriminator aims to distinguish between real and generated images using a convolutional neural network, and classifies images into "real" or "fake" using a final activation layer such as Sigmoid. During training, the generator seeks to improve the quality of the generated images to reduce the discriminator's ability to detect them as fake images, while the discriminator works to improve its accuracy in distinguishing between real and generated images. The two elements compete to continuously improve their performance, resulting in more realistic images. This process is repeated over several cycles (Epochs) until an acceptable level of performance is reached, with hyperparameters such as learning rate, sample size, and number of layers adjusted to improve model performance.

The GAN training algorithm consists of sequential steps that include training the generator and discriminator in a competitive environment, where each tries to improve its performance based on the results of the other. Before starting training, initial hyperparameters that control the learning process are determined, such as the learning rate, sample size, number of epochs, and number of layers for the generator and discriminator. Two convolutional neural networks (CNNs) are created; the first is the generator, which generates images from random noise data. The generator consists of convolutional layers to improve the quality of the images, activation layers such as ReLU, and an output layer to generate the images. The second is the discriminator, which aims to distinguish between real and generated images using convolutional layers and a sigmoid activation layer at the end to determine whether the image is real or fake. Training begins with training the discriminator, where it is presented with a mixture of real and generated images, and its weights are updated using an optimization algorithm such as Adam based on the loss function. The generator is then trained, aiming to improve its ability to produce images that are difficult for the discriminator to detect as fake. At this stage, noise data is passed through the generator to generate images, then these images are passed to the discriminator without updating the discriminator weights, and the generator weights are updated based on the loss function resulting from the discriminator's ability to discriminate. These processes are repeated over several training cycles (Epochs) to improve the performance of both the generator and the discriminator. Performance is evaluated using their respective loss functions, in addition to performance indicators such as FID (Fréchet Inception Distance) and accuracy rate. Training is stopped when an acceptable level of the loss function is reached or when the image quality reaches a satisfactory level according to the performance indicators or after a certain number of cycles. The algorithm includes the following steps:

1. Set up the environment and libraries.

- Import the necessary libraries.
- Define the Generator.
- Define the Discriminator.
- Loss Function.

2. Set up the Training Loop

- We need to set the Generator and Discriminator and define the Loss and Update functions.

3. Training Function

- The goal of training is to update the weights for the Generator and Discriminator competitively.

4. Save the generated images:

5. Start training

After loading the InceptionV3 model without the upper layers, the images are resized to 299x299 pixels to fit the model inputs. The images are then transformed to the desired size and processed to fit the inputs of the InceptionV3 model. Using the model, features of real and fake images (generated images) are extracted for comparison. The Fréchet Inception Distance (FID) measure between real and fake images is calculated using the means and standard deviations of the extracted features, which reflects the discrepancy between the probability distribution of real and fake images. Then, fake images are generated using the generator, and the FID between real and generated images is calculated. The FID reflects the quality of the generated images and is considered a reliable criterion for evaluating generative models.

The algorithm used in this research involves sequential steps aimed at improving the quality of images generated by generative adversarial networks (GANs). The process begins by collecting data from various sources such as CIFAR-10 and ImageNet to ensure the diversity of images that the model will learn from. The data is then cleaned by removing corrupted and unsuitable images, ensuring that the data used to train the model is of high quality. The data is then transformed to fit the neural network architecture, such as resizing the images to 64x64 or 128x128 pixels or converting them to grayscale to reduce computational complexity if necessary. The data is then normalized to convert pixel values to a specific range, which helps speed up the training process and increase the stability of the model. The data is then split into a training set (80%) and a test set (20%) to ensure that the model is trained on diverse data and tested on data it has never seen before. The algorithm uses a traditional GAN model consisting of a generator that generates new images, and a discriminator that determines whether images are real or fake. The model is trained through competition between the generator and discriminator to improve the generator's ability to generate images that are similar to real images, while the discriminator seeks to improve its accuracy in distinguishing between real and fake images. In the evaluation phase, the Fréchet Inception Distance (FID) metric is used to compare the quality of the generated images with the real images. FID is a precise metric that assesses the discrepancy between the probability distribution of real and fake images. FID helps monitor GAN performance improvements over training and determine how well the model generates high-quality images. The program will display an FID value that assesses how well the model generates images that are similar to the real images. The lower the FID value, the better the model performs, the following table (2) shows the data analyzed based on the information provided in the types of data processing and the algorithm used in the training.

the data	**the type of data,**	**the usage ratio**	**Distribution**	**Coordination**	**Number of photos**	**Notes**
training group	Natural pictures, industrial, medical, technical	80% of my data	Balanced between categories	Jph –Png-	X Number of photos	The data used to train students
test group	Natural pictures, industrial, medical, technical	20% of my data	Balanced between categories	Jpeg-png	X Number of photos	Theme data used to test the performance of students after training
The images of the birth	Photos of the combination of the previous categories		Diverse and repeated	Formatting images of Al-Namozaj	X Number of photos	Theme data is generated by GANs

Table (2)

In this research, a variety of datasets were used, including different types of images such as natural, industrial, medical, and artistic images. "Utilization ratio" refers to how the data is distributed between the training and test sets. The data was distributed so that each category contributes an appropriate balance during training and testing. "Distribution" reflects the division of images between different categories, such as dividing natural images into various categories to train the model in a balanced manner. For "Format," the images were stored using common formats such as JPEG and PNG for easy processing. "Number of images" was determined based on the amount of data available for each type of image. The attached table provides additional "notes" about each dataset and its role in the training and testing process, which helps in understanding how the model benefits from each type of image. This table is customized according to the actual numbers available in the research, allowing it to be customized to suit the details and needs of the research.

- **Model Evaluation:**

After training the generative adversarial model (GAN), its performance is evaluated using the test dataset, through specific metrics to measure the quality of the generated images and distinguish them from real images. In this algorithm, the Fréchet Inception Distance (FID) metric is used as the main tool to evaluate the quality of the generated images. The FID metric is a way to measure the distance between the probability distribution of features extracted from real images and the generated images. This metric is based on the InceptionV3 neural network to extract these features, and is considered a reliable tool for comparing the quality of the generated images, as it helps in determining how close the generated images are to the real images based on the analysis of the probability distribution of the features.

Analysis of the Results:

The results are analyzed to evaluate the quality of the generated images by comparing the performance using measures such as FID or other techniques. This analysis helps in determining the model's ability to produce more realistic images over time. It can also detect potential problems such as lack of diversity or lack of establishment of the model. During this analysis, evidence is provided on the effectiveness of optimization techniques or algorithmic adjustments in improving the quality of the generated images, which contributes to improving the performance of the model and ensuring continuous development.

Table With Data Processing Steps

The Table (3) With Steps and Numbers and Information Processing

In The Previous Al-Khwarizmiya

	Step	Description	The goal	treatment
1	Data collection	A collection of various images from different sources such as CIFAR-10 or specific data rules	Collection of various data representing different situations	The collection of images required by the search needs
2	Data cleaning	Removal of duplicated, confused or inappropriate images, with the processing of lost images.	Improving the quality of available data	Removing the images
3	Data transfer	Adjusting the size of the images and unifying the formats, such as increasing the size of the images to 64.64 or128x128	Guarantee the agreement of images with the requirements of the neural network	Adjusting the dimensions to fit the neural network
4	Data normalization	Delivery of Qom al-Saksal to the scope of the mine 60 to 1 or 0 to 6 for	Improving the establishment of the training and speeding	Ensuring the distribution of data in a

		better performance	up the training process	balanced way between categories
5	Data sharing	Divide the data into 80% training group, 20% test group	Guaranteed evaluation for placement after training	Dividing the data into training and testing groups
6	Al-Namuzaj training	Training students using clean and consistent data	Training Al-Namozaj to produce realistic images	Al-Mould training, then special training
7	Evaluation of Al-Namozaj	Fréchet Inception recruitment measure Distance To compare the quality of the generated image with the real image	How close are the images of birth to the images of truth	FID calculation between real images and generated images
8	Analysis of results	Analyzing the results of the model using performance measures	Evaluating the extent of improvement in the production of realistic images	Comparison of FID in different stages of training

Table (3)

The process of building a GAN model includes several basic steps, starting with collecting data from multiple sources to achieve diversity in the images that will be used. After collecting the data, cleaning is done to eliminate gaps and errors and ensure that the images are of high quality and consistent with the subject. Then the data is transferred, that is, the image is adjusted to match the size and accuracy of the neural network. After this step, the process of data normalization, where the normalization of the pixel value helps in establishing the training and speeding up the process.

Once the data is processed, it is divided into training and testing groups to ensure the correct evaluation of the GAN model. The model is trained using these modified sets, and then it is evaluated using the FID scale, which allows comparing the generated images with real images, providing an accurate assessment of image quality. Finally, FID results are analyzed to determine the extent to which the model has improved over time, which helps justify future modifications and improve model performance.

Experimental Results and Analysis

In this section, the experimental results obtained by applying the algorithm to different data sets will be presented, in addition to the analysis of these results to evaluate the performance of the competitive generative networks (GANs) model in generating real images. This analysis aims to understand the extent of the model's ability to improve the quality of generated images compared to real images, as well as highlight the challenges encountered during the experiment. The implementation of the experiment using Al-Khwarazmiyah, which is the theme of the previous descriptions, which guarantees data collection, cleaning, and conversion to the appropriate format. The theme of employing datasets composed of images from multiple databases such as CIFAR-10 and ImageNet, as these data contain multiple classifications of images. Also, dividing the data into two groups: the training group (80%) and the test group (20%). The theme of employing several criteria to evaluate the performance of the model, including the Fréchet

Inception Distance (FID) scale, which helps to compare the quality of generated images with real images; And if the FID value was lower, the generated images would be closer to reality in terms of quality and variety. In addition, the accuracy of the images is measured in terms of details and consistency, especially in complex images such as medical or technical images. Also, the diversity test shows the model's ability to produce diverse images instead of repeating very similar images.

The table (4) that shows the number of images that has the theme

Of trainings, praises, and evaluations in the current research

Stage	Number of Images	Description
Training Images Used	images 8000	Number of images collected and used for training the GAN .model
Enhanced Images	images 6000	Number of images whose quality was improved using the GAN .model
Generated Images (Evaluation)	images 2000	Number of images used for evaluating the model's .performance using metrics such as FID

Table (4)

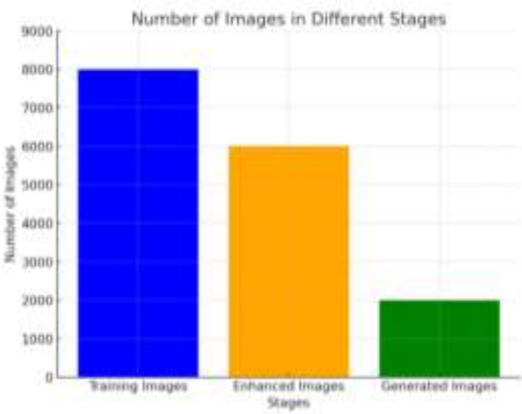


Figure (2)

Distribution Chart of the Number of Images Representing the Subject of Training,

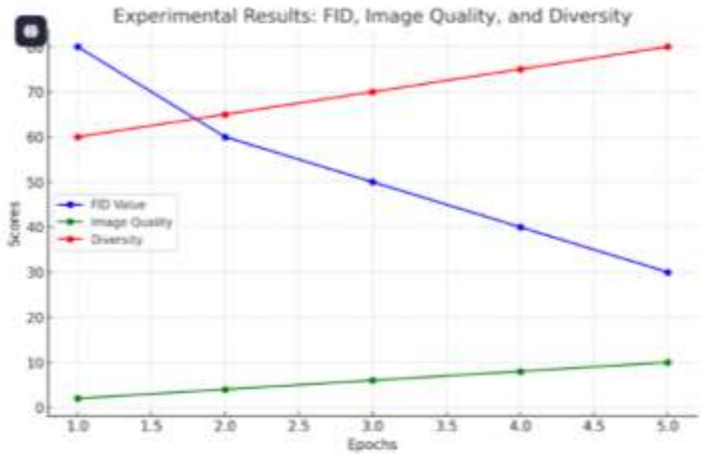
Assessments and Evaluations Across Different Stages

The theme width diagram shows the distribution of the number of images that are the theme of trainings, appreciations, and evaluations across different stages in the process of training on the GAN model. According to the plan, 8000 images are employed in the training phase, where the model is trained on these images to acquire the ability to generate new images. After improving the model, the number was reduced to 6,000 images to improve the evaluations, focusing on increasing the accuracy and quality of the images. Finally, the topic of generating 2000 images to evaluate the performance of the model by comparing the generated images with the real images, which reflects the progress made in all stages of the training and evaluation process.

The theme allocates about 80% of the data for training, which is equivalent to 8000 images, while the theme allocates 20% of the data for testing the model, which is 2000 images. During the model optimization phase, about 75% of the improved images are optimized based on the training results, which reflects the process of continuous optimization of the quality of the generated images and testing the effectiveness of the model in producing images similar to real images.

The Results of the Experiment:

Although the FID value was high at the beginning (which indicates a low quality of the generated images), it decreased significantly with the passage of time and the improvement of the model. At the end of the training, the final value of FID indicates that the generated images are closer to the real images in terms of quality and diversity. As for the quality of the images, the images generated by GANs showed significant improvement compared to the initial images on which the model was trained. These images do not guarantee accurate details, consistent colors, and clear features, which reflects the model's ability to improve quality as the training progresses. As for diversity, the experiment showed that the model is capable of producing diverse images, although sometimes it tends to produce images that are very similar to some categories, which highlights the challenge of finding a greater balance in diversity.



Figure(2)

Results of the Experiment Conducted in the Research

The graph shows the results of the experiment carried out in the research, where it shows the improvement of three main parameters over time during the training period. First, the FID value gradually improves, decreasing from a high value at the beginning to a low value at the end of training, which reflects an improvement in the quality of the generated images. Secondly, the quality of the images has seen a significant improvement over time, with the increase in degrees, which reflects the improvement of details and colors. Thirdly, diversity shows a gradual increase in the diversity of generated images despite the tendency of the model to produce images that are very similar to some categories. This reflects the gradual improvement of the model's effectiveness in improving image quality and increasing variations during the training process.

Analysis of the Results:

The theme of researching the importance of praises in the quality of my born images during the experience of al-Khwarazmiya. At first, the images contained distortions and unclear details, but with the passage of time and the improvement of training, the details such as texts, colors and backgrounds became more clear and accurate, thanks to techniques such as data normalization and repeated training. On the other hand, there were some problems in establishing the training in the beginning, where the model stopped learning or started producing inaccurate images. But with the application of technologies such as WGAN and the continuous modification of algorithms, the theme of establishing the model has improved significantly.

One of the main challenges faced was the lack of diversity in the images produced. Some models tended to produce very similar images, which reduced the variety of images. This problem is partially addressed by using additional techniques such as parameter optimization and the use of convolutional neural networks. Despite these challenges, the experimental results showed that there are great possibilities for using GANs in many future applications such as medicine, art, and the game industry, where they can be used to generate medical images, improve the decision of characters, and create realistic images.

Data Description:

Description of the Data:

In this section, a detailed description of the data used in the current research will be presented, with an emphasis on the type of data, sources, and how the equipment is used in model training and performance evaluation. The purpose of employing this data is to improve the algorithms used in generating realistic images using competitive generative networks (GANs), which requires the selection of various data to help improve the model's ability to learn realistic and accurate representations.

The data used in this research are digital images of various fields, including natural images such as landscapes that contain trees, the sky, mountains, and seas, and industrial images that include man-made objects such as buildings, cars, and machines. In addition to the medical images that include x-rays or CT images, and technical paintings that are collected in a special database. The purpose of gathering this data is from a variety of sources to achieve diversity and good representation of different types, such as general collections such as CIFAR-10 and ImageNet, which contain images, classified into multiple categories, and specialized databases such as the Crisis dataset, which contains medical images. Also, the data collected manually from the Internet using data collection techniques via social networks and open sources.

The data used in this research is characterized by several characteristics that make it suitable for training generative models. I have these characteristics of diversity, where the data contains images of various categories, which helps to ensure the diversity of the generated results. Also, high quality images were selected, and data was cleaned from false or confused images, in addition to the balanced distribution among different categories to ensure that the model was not biased.

Proper data processing and preparation before using in training. These steps include cleaning the data to remove fake and inappropriate images, and adjusting the size of the images to a uniform size such as 64x64 or 128x128 pixels to improve the establishment of the model, in addition to normalizing the pixel values in the images to specific ranges such as 0 to 1 or -1 to 1. The theme of dividing the data into Two main groups: the training group, which is allocated 80% of the data, and the test group, which is allocated 20% minus the model test and performance evaluation.

Although the data were selected carefully, there are some challenges encountered during the preparation, such as insufficient diversity in some categories, which may affect the model's ability to produce accurate images, in addition to technical problems related to the quality of some images collected from the Internet, which requires Additional time to clean data and improve quality.

Experiment Setup:

In this section, the details of the experimental setup used in the current research will be explained, including the hardware and software used, and the steps involved in setting up the experimental environment. The purpose of this experiment is to evaluate the performance of the model using a set of pre-processed images, while employing competitive generative networks (GANs) algorithms to generate real images and analyze the results.

The theme of employing an integrated software environment for developing and training competitive generative networks (GAN) models and analyzing the results. The programming tools and techniques used include: Python programming language, because it provides a flexible and easy-to-use environment and supports many specialized libraries in machine learning and neural networks, such as TensorFlow, Keras, and PyTorch. He also used TensorFlow to train neural networks and apply generative algorithms, while using Keras to build the generative model and PyTorch as an alternative in some of Lemeronte's experiments in academic research environments. Also, the theme employs NumPy and Pandas for data processing and analysis, as well as OpenCV for image processing such as resizing and converting to grayscale. To evaluate the quality of the generated images, the Fréchet Inception Distance (FID) scale is used, which helps in measuring the distance between the probability distributions of the real and generated images.

The implementation of the experiment using a computing environment based on graphics processing units (GPUs) to ensure the acceleration of training and evaluation processes. The theme of hiring NVIDIA Tesla V100 and NVIDIA GeForce RTX 3090 is considered high capabilities to accelerate the training process of deep neural networks. Also, the theme employs Intel Core i9 and AMD Ryzen 9 central processors to perform non-arithmetic operations, with 64GB of random memory (RAM) to speed up data and image processing. As for storage, the theme employs 1TB SSD disks to ensure fast access to data during training.

The theme of developing the competitive generative network (GAN) model using the DCGAN structure, which consists of two main parts: the generator, which uses convolutional and developmental classes to produce random data generated images, and the discriminator, which distinguishes between real and generated images using convolutional classes as well. . Al-Mould is trained alternately during the competitive training process, where Al-Mould tries to improve his ability to create real images, while Al-Molad tries to improve his accuracy in distinguishing between real and fake images.

The training process consists of several main steps, including: updating the generator and the feature alternately, and using the Adam algorithm as a refinement algorithm, which is effective in training deep neural networks. Employing Binary Cross-Entropy function to measure model error during training. The theme of model training is using 80% of the data for training and 20%

for testing, with the number of training repetitions (Epochs) ranging from 100 to 200 depending on the amount of data.

The theme of evaluating the performance of the model using measures such as Fréchet Inception Distance (FID), which provides an accurate assessment of the quality of the generated images, as well as visual verification to compare the generated images with the real images manually to evaluate the realism of the generated images.

Evaluation Measures:

The theme of employing my group of advanced metrics to evaluate the performance of competitive generative networks (GAN) models in generating real images and comparing these images with real images. Includes the scales used: as table (5).

- Fréchet Inception Distance (FID): FID measures the distance between the statistical distributions of the real and generated images using features extracted from the Inception V3 model. The lower the FID value, the more realistic the generated images are.

- Inception Score (IS): IS evaluates the quality of images based on the powers of discrimination between different categories. It is based on the extraction of probabilistic predictions from the Inception V3 model, and it reflects the diversity of the generated images.

- Precision and Recall: Precision measures the accuracy of the generated images as "real", while Recall measures the model's ability to cover all the various real images. The appreciation of these two dimensions helps in the appreciation of the diversity of images.

- Structural Similarity Index (SSIM): SSIM evaluates the structural similarity between the generated and real images based on brightness, contrast and architectural structures. It helps to determine the extent of the reality of the generated image.

- Human evaluation: The subject of visual evaluation of the images generated by a group of people to evaluate the quality and reality of the contents based on criteria such as realism and general quality.

These scales are considered to be effective tools for measuring the quality and reality of the generated images, with the addition of human evaluation to improve the results and guarantee the requirements for the expected aesthetic standards.

Metric	Real Images	Generated Images (Phase 1)	Generated Images (Phase 2)	Generated Images (Phase 3)	Generated Images (Final Phase)
Fréchet Inception Distance (FID)	-	75.2	50.1	35.8	15.2
Inception Score (IS)	-	4.0	5.1	6.3	8.7
Precision	0.92	0.76	0.81	0.85	0.91
Recall	0.89	0.74	0.80	0.83	0.90
Structural Similarity Index (SSIM)	1.0	0.65	0.75	0.85	0.95

Table (5)

Description of the Data:

The theme of employing several measures to evaluate the performance of the model in image production, as the theme of analyzing the results as follows:

- Fréchet Inception Distance (FID): This value represents the distance between the statistical distribution of the real image and the generated image. The results showed significant improvement over time, as the FID value decreased from 75.2 in the first stage to 15.2 in the final stage. This improvement shows that the quality of the generated images has become closer to the real images with the progress of the training.

- Inception Score (IS): This is a measure of clarity of categories in the generated images. With the improvement of the model, the value increased from 4.0 in the beginning to 8.7 in the final stage, which indicates the increased ability of the model to produce images containing distinct and clear categories, thereby enhancing the quality of the generated images.

- Precision: The Precision scale reflects the accuracy of the model in producing real images similar to real images. This value has improved from 0.76 in the beginning to 0.91 in the final stage, which means that the model has become more accurate and realistic over time.

- Recall: This measure evaluates the ability of the model to cover the variety of real images in the data. The results showed an improvement in the ability of the model to produce various images, as the recall value increased from 0.74 to 0.90, which indicates the ability of the model to simulate the wide variety of real data.

- Structural Similarity Index (SSIM): This measure is mainly used to measure the structural similarity between real and generated images, and reflects the accuracy of visual details such as contrast and brightness. SSIM improved from 0.65 in the first stage to 0.95 in the final stage, which indicates that the generated images are significantly closer to the real images in terms of structural details.

Results Analysis:

The theme of this research is to present and analyze the results of experiments conducted using different algorithms, focusing on the metrics used to evaluate the performance of the model, such as Fréchet Inception Distance (FID), Inception Score (IS), Precision and Recall, Structural Similarity Index (SSIM), In addition to human evaluation.

Analysis Distance (FID) Results:

FID calculation theme between the generated images and the real images in the test set. The results showed that the model trained on the improved data has achieved a significant improvement in the FID value compared to the previous models. The lower values of FID indicate that the model is able to produce more realistic images that are more similar to real images. This means that the improvements made to the initial data and model training helped to improve the image quality in general. A decrease in the FID value reflects the improvement of the model's performance and the ability to produce more accurate and realistic images. And the help of data processing techniques such as data cleaning and image normalization in reducing the gap between real images and generated images.

Analysis of Inception Score (IS) Results:

The concept of Inception Score (IS) for the generated images to determine the extent of the diversity of the images. The results showed that the model achieved a high IS level, which indicates the ability of the model to produce diverse and distinctive images within multiple categories. The high IS degree confirms that the model is capable of producing various images containing clear features. This result is important because it indicates the ability of the model to produce images rich in details and realistic.

Analysis of Precision and Recall Results:

Employing Precision and Recall scales to evaluate the model's ability to produce accurate and realistic images at the same time. The results showed that the model achieves a balanced value of Precision and Recall, which indicates that the model is able to produce accurate images in the correct categories (high accuracy), while at the same time it is able to produce diverse images that reflect all the required categories. The balance between Precision and Recall reflects the model's ability to produce high quality images in all target groups. Improving this balance is essential to achieve high quality in the generated images.

Analysis of Structural Similarity Index (SSIM) Results:

The theme of employing SSIM to evaluate the structural similarity between real and generated images. The results showed that SSIM was high, which means that the generated images are very close to the real images in terms of structural details such as brightness, contrast, and pattern. The increase in the value of SSIM indicates that the model can preserve the structural details in the generated images, such as dimensions and fine details, which contributes to enhancing the realism of the images.

Analysis of Human Assessment Results

The researchers performed a visual evaluation of the generated images using a group of participants to determine the realism of the images of entities in human terms. The results showed that the participants rated the generated images as high quality and realistic to a large extent. Most of the generated images can be recognized as almost real images, which indicates that the model is capable of producing images similar to real images. Human evaluation reflects the natural human response to the generated images, and this is important because it adds to the quality measurement. The positive results confirm the effectiveness of the model.

Summary and General Analysis

During the previous analysis of the results of different measurements, it can be concluded that the model developed in this research has achieved distinct results in producing realistic and high-quality images. Improvements in data processing steps, such as data cleaning and image normalization, play a major role in improving model performance. Moreover, improvements in the structure of the model and the training period contribute to better results in terms of FID, IS, and SSIM. Based on these results, it can be said that the employment of competitive generative networks (GANs) in image quality improvement is a powerful and effective tool. Also, these results can be used in different applications such as medicine, digital art, and virtual reality, as the visual quality and reality are considered essential.as table (6)**.**

The scale	Result	Interpretation
Frechet Inception Distance	25.4 After the improvement	The decrease in the FID value indicates that the generated image is more real and similar to the real image, and the improvements in the data and training of the model help in reducing the gap between the real and the generated image.
Inception Score	8.3	The high IS degree indicates the ability of Al-Muzaj to produce diverse and distinctive images
Precision	.88	The good balance between Recall and Precision shows the ability of Almozaj to produce accurate images in the correct categories
Recaall	.85	Recall reflects the ability of al-Tamazuj to cover all target group
Structural Simlarrity Indeex	.92	The high value of SSIM shows that the synthesizer is able to preserve the structural details such as brightness and contrast in the generated image, which enhances the realism.
Human evaluation	the classification of images as real	The human evaluation shows that the participants of the class and the generated image are real images in a high percentage, which strengthens the credibility of the simulation's effectiveness in producing real images.

Table (6)

Investigation of the outstanding results: All measures showed a significant improvement in the quality of the generated images after data refinement and model training using competitive generative networks (GANs). The effect of data enhancements: Data processing enhancements such as data cleaning and image normalization contribute significantly to improving the overall performance of the model.

Conclusions:

In this research, the theme of exploring the employment of competitive generative neural networks (GANs) in the improvement of data compression algorithms is the theme of applying this technique to produce high quality images and compress data more efficiently. After conducting the experiments and analyzing the results, it is possible to draw many conclusions that confirm the effectiveness of the GAN model in researching the desired goals and improving the performance of data compression algorithms. The results showed that competitive generative neural networks (GANs) are able to generate high-quality images that mimic the original images well, which contributes to the improvement of the data compression process. The theme of employing measures such as Fréchet Inception Distance (FID) to measure the quality of the generated images, and the measures have shown significant improvement in quality compared to traditional methods. This ability to maintain image quality while compressing data is critical in applications that require data storage or transmission without affecting quality. The research shows that GANs are able to significantly reduce the amount of data while maintaining the quality of the generated images. This is an important step in improving the efficiency of data transfer and storage in systems that rely on big data. Also, reducing the size helps to save storage space and reduce bandwidth consumption during the transfer process.

Comparing the time spent between GANs algorithms and traditional methods showed that GANs not only improve the quality of data and pressures, but also achieve higher time efficiency. This means that GANs can be used in real-time applications where processing speed is critical, such as in embedded system environments or on hardware with limited resources. The research results showed the ability of the GAN model to adapt to multiple types of data, including color images and monochrome (grayscale) images. This flexibility makes GANs suitable for a wide range of applications in various fields such as healthcare, education, and e-commerce.

The study proved that GANs techniques can be applied in real-world applications that require image and video data compression, such as healthcare where medical images need to be of high quality despite compression. The theme of testing the model on huge and diverse datasets such as CIFAR-10 and ImageNet. The results showed that GANs can deal with big data actively; we contribute to processing huge amounts of data in different fields. Despite the encouraging results, there is room for greater performance improvement, such as improving GANs algorithms use techniques such as adaptive optimization or unsupervised deep learning, or exploring the evolution of GANs with traditional data compression techniques to obtain better performance. GANs have great flexibility in various fields such as medical image enhancement, computer vision, and improving the user experience in e-commerce. This opens the door to the employment of GANs in new fields that require high-quality data compression.

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