Blind Image Restoration and Data Augmentation

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***Abstract*— This paper introduces an innovative method and system that harnesses the collaborative potential of Generative Adversarial Networks (GANs), specifically GFP-GAN (GFP Generative Adversarial Network), and StyleGAN, to significantly enhance image pixel quality, with a primary focus on facial images. Concurrently, it facilitates the streamlined creation of augmented datasets, fostering advancements in a multitude of applications. At its core, the proposed method embodies two pivotal functions: Leveraging the capabilities of GFP-GAN; this function orchestrates the intricate process of pixel-level detail restoration, imperfection rectification, and visual quality enhancement in facial imagery. The outcome is a transformative enhancement of pixel precision, revolutionizing the landscape of image processing. Seamlessly integrating StyleGAN with GFP-GAN's output; this function efficiently generates augmented datasets. These datasets, marked by their dynamism and complexity, emerge as indispensable assets in the realm of machine learning, powering applications ranging from facial recognition to object detection and image synthesis. The proposed method's inherent strengths encompass its ability to redefine image pixel enhancement, elevate the standards of facial imagery, and expedite the production of augmented datasets. It capitalizes on the harmonious synergy between GFP-GAN and StyleGAN, delivering a comprehensive and cohesive solution that transcends traditional image processing boundaries. As an outcome, the paper represents a pioneering leap forward in image processing and machine learning, offering an unprecedented combination of pixel enhancement and dataset augmentation capabilities, particularly in the context of facial imagery and its multifaceted applications.**

Keywords*— *Data Augmentation, Face restoration, GFPGAN, Latent Codes, StyleGAN3.

I. Introduction

Technology and Technological developments in this decade have led to some of the most awe-inspiring discoveries. With rapidly changing technology and systems to support them and provide back-end processing power, the world seems to be becoming a better place to live day by day. One of the biggest challenge from the times is Image restoration. Image restoration is the operation of taking a corrupt/noisy image and estimating the clean, original image. Corruption may come in many forms such as motion blur, noise and camera misfocus. The restoration process improves the image's appearance, and the main goal is to restore it to how it looked when it was first synthesized originally. Image restoration plays an important role in the real life- medical field different cancerous cells images can be restored and studied by the process, astronomical aspects obtained satellite image can be restored, face image restoration- detects the criminal activities etc. Here, we are using the Generative Adversarial Network(GAN) models to achieve the mention goals. GAN prior embedded network helps us to generate a fine-tuned and smooth image which can be further used to draw some insights.

II. Literature Review

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Ian J. Goodfellow et al.[1] have implemented Generative Adversarial Network. Author employed this model with the help of two functions Generator and Discriminator. Here both functions have different meanings. According to the research Generator is responsible for capturing the data whereas Discriminator is responsible for estimating the probability that the feature comes from training data or captured image. Author has trained model on various famous datasets that are MNIST, CIFAR-10, TFD etc. Author had not used any Markov chains or unrolled approximate inference files during the training of model. The study completes with a note that it can be improved by taking better devising methods for Generator G and Discriminator D. This is how the whole study takes place.

Tao Yang et al.[2] have worked upon "Blind Face Restoration" by using GAN prior embedded network (GPEN). The author has researched that GAN models are used to improve the quality of degraded image but they make the image over smooth which is not a better result. That's why concept of GPEN came in which GAN model is mapped with U shaped Deep neural network to achieve better results in terms of quality and quantity as well. In the research, U-shaped Deep neural network is trained by using U-net model to make the results better. This model basically works on converting low quality face image to higher quality face image. According to their research they employed that GAN prior embedded network is able to generate photo realistic results. The model overall work on following a U-shaped encoder decoder architecture for being capable to generating high quality face images. StyleGAN convolutions and U-net model is used for making of GPEN model for real world blind face restoration.

Feida Zhu et al.[3] aims to reconstruct high quality images from low quality images. It was founded that real world is suffering from degradation of low quality face images during data acquisition and Internet transmission. So, Author has employed SGPN Shape and Generated prior integrated network to solve this problem. Approach of the whole methodology starts with the shape restoration module to balance the face geometry. After that by following D3DFR author regress 3DMM coefficients with Resnet50. Then, shape S and 12 coloured texture C formed which is used to make 2D image plane to obtain 3D image. Author has utilized

StyleGAN2 model as the generative prior to improve the model capability as well as results. The main focus of this study is to restore low quality face images in the wild. The model overlooks only the facial part and little about background part.

Tero Karras et al.[4] has proposed a different generator architecture for Generative Adversarial Network that is style based generator. Author has introduced new dataset of human faces as well like Flickr-Faces-HQ, FFHQ that offers a great quality content. Study says that most of the work is to focus on improving discriminator by using multiple types of discriminator. Author has considered stochastic variation of the image to get the best outcomes. The study mainly focuses on making great content in the field of StyleGAN network by adding some latent space in between the layers to improve. Firstly, author has compared various methods of generator function like traditional, style based, noise addition according to their separability and path length to analyse their dependencies for enhancing the performance in a better way. The conclusion of the study is that Traditional GAN generator architectures are subordinate in every regard to style-based network architecture.

Tero Karras et al.[5] have find out a generative adversarial network model that is better suited for video and animation category. Author has matched the FID of style-gan2 model with their resulting model, then they know that their model performs better. In the proposed methodology author has converted the StyleGAN2 model generator to be fully equivariant to translation and rotation. During the whole research author has implemented alias free generator model that contains implicit assumptions about the behaviour of training dataset. In StyleGAN3-R, the emergent positional encoding patterns appear to be somewhat more well-defined. Author believe that the existence of a coordinate system that allows precise localization on the surfaces of objects will prove useful in various applications, including advanced image and video editing.

JIAWEI YOU et al.[6] have introduced an integrated framework designed for efficient face image restoration and the generation of multiple samples from the same image. This framework combines two well-established algorithms, Generative Prior and StyleGAN3, with the primary objective of producing high-fidelity image data. To guide a pre-trained generative model effectively, they have made modifications to the U-Net architecture, enabling it to predict latent code biases and feature maps for the generator, thus facilitating the production of high-quality image outputs. With a view simplify the training process, the authors have introduced a novel module called the Difference Extractor, alongside a series of mappers. These additions serve to enhance the training data. Additionally, the authors have explored various restoration and interpolation effects to further enrich the data, allowing for a detailed pixel-level study of facial features.

Xin Jin et al.[7] describes a novel image restoration method that combines Generative Adversarial Networks (GANs) and multi-scale feature fusion. It addresses the limitations of existing algorithms by emphasizing accuracy and visual consistency. The method employs a standard encoder-decoder structure, with the VGG-16 full convolutional neural network serving as the encoder. Notably, it improves deep convolution inputs by fusing features at different scales. The paper employs Wasserstein GAN (WGAN) principles to improve training stability and image similarity while mitigating issues such as error oscillations and gradient problems. Furthermore, an L1 loss term improves the similarity between restored and target images. Empirical tests on a facial dataset show
that image restoration accuracy and realism have improved significantly. However, there is some clarity loss when compared to the original images. Future research will investigate more complex backgrounds to further enhance the restoration process.

Raymond A. Yeh et al.[8] has explained that fixing missing parts of an image based on its content is a difficult task in the field of image processing known as "semantic inpainting." There are various methods for accomplishing this, but each has limitations. When there are large missing areas, learning-based methods struggle, whereas traditional methods rely on local or non-local information and image patterns. Some methods even require an exact match, making them inefficient in certain situations.

Although the Context Encoder (CE) is effective at semantic inpainting, it occasionally produces ambiguous results. This study introduces a new method for repairing corrupted images using generative modeling and a combination of context and prior knowledge. Unlike CE, this method can handle a wide range of missing areas and does not require any special masks during training. This technique outperforms other methods in challenging semantic inpainting tasks in tests using datasets such as Celebs Faces, SVHN, and Stanford Cars. This is a significant advancement in image restoration.

Sheng Li et al.[9] investigated deep learning techniques for image reconstruction, focusing and discovered network called X-GANs (Generative Adversarial Networks). Image reconstruction is essential in areas such as image restoration and de-noising. However, GANs may face difficulties due to the requirement for high-quality training data. The goal of this study was to reconstruct images with minimal input, even when much of the image was corrupted. GANs have limitations, particularly when dealing with large images and complex scenarios. The proposed framework has three key components: reconstructing images from limited discrete samples, strategic point placement using Sobel operators, and dealing with issues such as colour noise and cluttered blocks. The X-GANs network, a multidimensional loss function, and specific point distribution methods improve network robustness. In summary, the study demonstrated the framework's effectiveness in a variety of image reconstruction tasks, including low sampling, colour noise, and severe corruption, making it useful for CT reconstruction and image compression.

Ngoc-Trung Tran et al.[10] majorly focused on the critical need for more data in the training of Generative Adversarial Networks (GAN). However, gathering data, particularly in domains such as medical applications, can be costly and time-consuming. The paper discusses Data Augmentation (DA) techniques commonly used in such applications to address this issue. According to the paper, traditional DA approaches may cause the GAN generator to learn a distribution that differs from the original data. To address this limitation, the authors present Data Augmentation Optimized for GAN (DAG), a principled framework. DAG adheres to the original GAN framework, minimizing JS divergence from the original distribution, and uses augmented data to improve the discriminator and generator. When DAG is integrated into certain GAN models, the experimental results show that it significantly improves various GAN models and achieves state-of-the-art Fréchet Inception Distance (FID) scores. Finally, the proposed DAG framework provides a promising solution for GAN training in domains with limited data availability, such as medical imaging, and has the potential to solve data challenges in a variety of applications. Table 1 shows the related work of the proposed system.

TABLE I. EXISTING WORK RELATED TO THE PROPOSED SYSTEM

Author, Year	***Paper Title***	***Objective***	***Tools/Technologies/Approach***	***Outcome***
I. Goodfellow et al.[1] 2014	Generative Adversarial Nets	Develop a novel generative model framework with adversarial training to capture data distributions and enhance sample generation quality efficiently.	Adversarial Training, Deep Learning, Multilayer Perceptron's, Parzen Window Likelihood Estimation, Convolutional Networks, Backpropagation, and GANs.	The results show competitive performance in generative modelling, achieving state-of-the-art or near-state-of-the-art log-likelihood scores on various datasets.
Tao Yang et al.[2] 2021	GAN Prior Embedded Network for Blind Face Restoration in the Wild	Develop a GAN-based method (GPEN) for blind face restoration, focusing on improving the quality of restored face images.	The approach combines GAN and DNN to address blind face restoration's one-to-many problem, enhancing image quality and details.	The paper presents GPEN, a GAN-embedded DNN model for blind face restoration, achieving high-quality results from degraded images, outperforming existing methods.
JIAWEI YOU et al. [6] 2022	A Unified Framework From Face Image Restoration to Data Augmentation Using Generative Prior	The objective is to develop a data enhancement framework using pre-trained generative models for image restoration and data augmentation in the context of face images, with a focus on improving downstream tasks.	The paper utilizes a pre-trained StyleGAN for face image restoration, with latent and feature biases and linear interpolation.	The research paper introduces a downstream-friendly face image restoration method with data augmentation capabilities.
Tero Karras et al. [5] 2020	Analysing and Improving the Image Quality of StyleGAN	The objective is to enhance StyleGAN, addressing artefacts, improving image quality, conditioning, and network attribution.	Redesign StyleGAN to address image artefacts, improve quality using demodulation, and enhance image evaluation with PPL.	StyleGAN2 enhances image quality, training performance, and attribution while consuming 132 MWh of electricity.
Sheng Li et al.[9] 2018	X-GANs: Image Reconstruction Made Easy for Extreme Cases	The objective of this abstract is to introduce X-GANs, a new image reconstruction method that significantly improves image quality and addresses various challenges, including denoising, restoration, inpainting, and compression.	The methodology involves training a conditional GAN using diverse datasets for image restoration and denoising.	The output demonstrates the efficacy of a conditional GAN-based network in image reconstruction, emphasizing restoration, denoising, inpainting, and handling high-colour noise and cluttered blocks.
Xin Jin et al.[7] 2020	Image restoration method based on GAN and multi-scale feature fusion	The objective is to enhance image restoration using GAN and multi-scale feature fusion, improving accuracy and visual consistency.	The methodology involves using GANs with a VGG-16 encoder, feature fusion, and L1 loss for image restoration.	The methodology involves using GANs with a VGG-16 encoder, feature fusion, and L1 loss for image restoration.
Ngoc-Trung Tran et al.[10] 2020	Towards Good Practices for Data Augmentation in GAN Training	The objective is to enhance GAN training with data augmentation to improve the learning of the original data distribution.	The proposed method introduces Data Augmentation Optimized for GAN (DAG) to address the issue of classical DA, ensuring the generator learns on the original data distribution while leveraging augmented data.	DAG framework enhances GAN stability, preserves JS divergence with invertible transformations, and achieves state-of-the-art FID scores in experiments.

III. Methodology

Figure 1 shows the proposed work in the form of model.

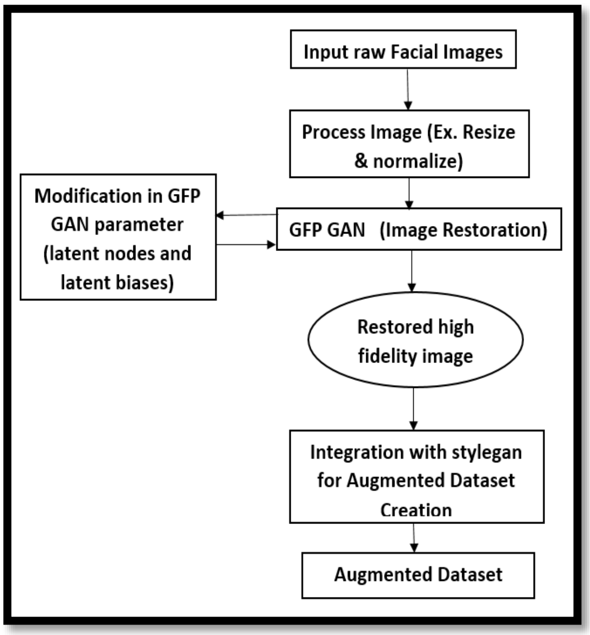

Figure 1. Proposed Approach

There are various related approaches to the proposed work which are highlighted below:

A. *GFP-GAN*

Generative Facial Prior Adversarial Network with an intricately designed architecture, is at the heart of this research methodology. GFP-GAN employs a conventional encoder-decoder structure, with the encoder component relying on the VGG-19 full convolutional neural network[11]. GFP-GAN can meticulously extract essential features from defective images using this architecture, capturing both low-dimensional and high-dimensional details. These features are then expertly fused to improve the input to deep convolutional layers. GFP-GAN's success in image restoration is dependent on the careful fusion of features at various scales. This study achieves significant improvements in image quality by leveraging the architectural prowess of GFP-GAN, which aligns with its goal of improving visual fidelity in the restoration process.

i. Fundamentals of GANs: At its core, GFP-GAN operates based on the principles of GANs. GANs consist of two key components: a generator and a discriminator[1]. The generator is responsible for creating synthetic images, while the discriminator evaluates these images for authenticity. Through a feedback loop, both components improve over time.

ii. Facial Image Generation: The primary focus of GFP-GAN is the generation of facial images. This network is meticulously trained using real facial images as reference data[11]. The goal is to create artificial images that are indistinguishable from real ones, achieving an unprecedented level of detail and realism [3].

iii. Architectural Insights: GFP-GAN relies on sophisticated neural network architectures. Convolutional Neural Networks (CNNs) play a pivotal role in processing and generating facial images. These architectures enable the network to capture intricate facial features and nuances[2].

iv. Training and Learning: The training process of GFP-GAN involves an iterative loop. The generator and discriminator continually learn and adapt to each other's outputs, enhancing the overall performance of the network[11][2].

v. Enhancing Visual Fidelity: A key objective of GFP-GAN is to improve the visual fidelity of facial images. This network employs advanced techniques to ensure that generated images exhibit high quality, accuracy, and realism in terms of facial details.

vi. Blind Image Restoration: Blind image restoration, an important process in digital image processing, attempts to recover clear and high-quality images from degraded or distorted inputs without prior knowledge of the degradation process. This "blind" approach is especially useful in scenarios involving unknown or complex degradation, such as medical imaging or surveillance. The blind image restoration process in this study is powered by GFP-GAN (GFP Generative Adversarial Network), an innovative neural network architecture [11]. GFP-GAN improves the restoration process by estimating a degradation model, recovering the blur kernel, and using it to de-convolute the degraded image, eventually restoring it to pristine condition. Techniques for regularization and quality assessment metrics are critical in stabilizing and evaluating the restoration process. Due to the uncertainties involved, blind image restoration remains a difficult task that necessitates iterative optimization and mathematical techniques for convergence to a satisfactory solution[12]. Advanced methods, such as deep learning models like GFP-GAN, continue to expand the capabilities and applications of the field [3].

B. *StyleGAN:*

StyleGAN, short for Style Generative Adversarial Network, is a type of generative model used in the fields of artificial intelligence and machine learning to create high-quality, realistic images. It was developed and introduced by NVIDIA in 2018 [4]. StyleGAN builds on the previous concept of generative adversarial network (GAN), which consists of two neural networks, a generator and a discriminator, trained together in a competitive process[17].

Some main components of StyleGAN:

a. Generator: The StyleGAN generator takes random noise as input and generates images. Unlike previous GAN models, StyleGAN generator generates images incrementally. It starts with a low-resolution image, then gradually adds more detail and complexity to the image as it goes through multiple layers [5]. This progressive approach allows for greater control over the style and structure of the images produced.

b. Map network: StyleGAN introduces a mapping network that transforms initial random noise into latent vectors, often called "style codes" or "style vectors"[13][14]. These style vectors control different aspects of an image's appearance, such as posture, facial features, and other features. This mapping network allows you to separate the high-level properties of an image from its low-level details.

c. Styles Mixing: One of StyleGAN unique feature is its ability to combine styles. This means we can combine style vectors from different images to create a new image that inherits features from both sources[4][]. For example, we can combine one person's face type with another person's face type, creating a new face that doesn't exist in real life.

d. Discriminators: The role of the discriminator is to differentiate between the real images in the dataset and the images generated by the generator. It provides feedback to the generator to help it improve over time [4][5]. The generator and discriminator are trained together in an adversarial manner, with the aim of generating images that are indistinguishable from real images, while the discriminator tries to better distinguish real from fake.

e. Progressive growth: StyleGAN uses a gradual growth mechanism where the resolution of the generated image increases over time. This process starts with a very low resolution image (e.g. 4x4 pixels) and gradually increases the resolution to double each step [5]. This allows for highly detailed images, which is a significant improvement over previous GAN models. Fig 2 shows the GAN Model.

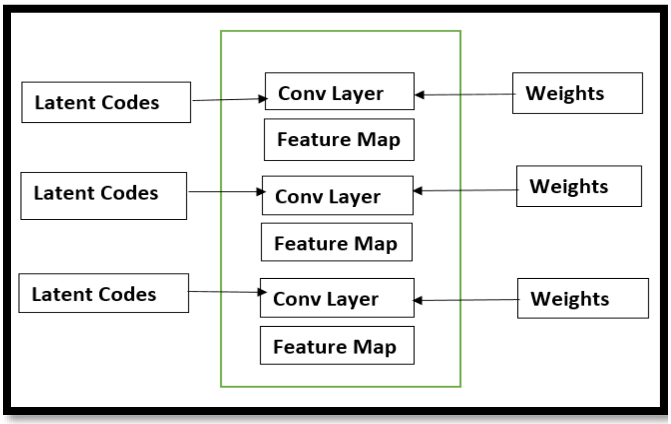

Figure 2. GAN Model for processing

f. Normalization Techniques: StyleGAN uses various normalization techniques, such as adaptive instance normalization (AdaIN), to control the style and appearance of generated images. [4][15] These techniques allow for more fine-grained control over features like color, brightness, and texture.

g. Style and Content Separation: StyleGAN effectively separates the style (high-level attributes) and content (low-level details) of an image, making it possible to manipulate these aspects independently [16]. This separation is one of the reasons StyleGAN is popular for artistic and creative applications. Fig 2 shows the StyleGAN Model.

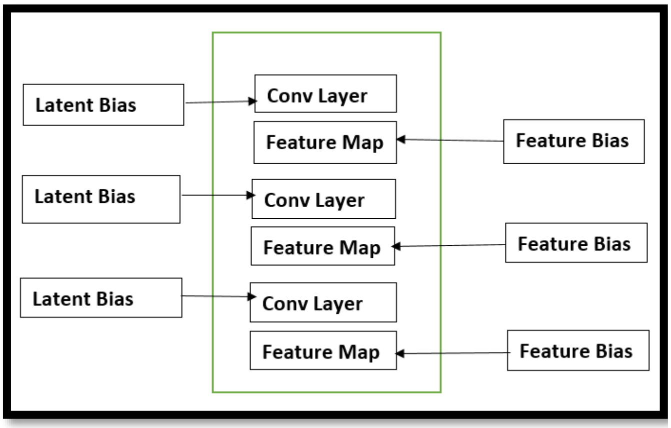

Figure 3. GFP-GAN Model for Computing

C. GFP-GAN and StyleGAN integration:

Authors strategically integrated the GFP-GAN[11] and StyleGAN[4] models to achieve the remarkable improvements in image quality observed in this project. This integration process necessitated significant changes to GFP-GAN's latent codes and feature biases. GFP-GAN initially produced lower-fidelity output images, which were attributed to its default settings.

Further authors decided to refine the latent codes and feature biases used by GFP-GAN, we made a significant breakthrough [6]. Authors were able to improve the output quality by optimizing these parameters, resulting in high-fidelity images. This critical change allowed GFP-GAN to generate images with significantly improved pixel quality and detail accuracy.

The integrated approach leverages the strengths of both GFP-GAN and StyleGAN, with GFP-GAN serving as the initial image restoration component and StyleGAN serving as the dataset augmentation component. We not only achieved remarkable visual fidelity as a result of this harmonious collaboration, but we also opened the door to a wide range of applications such as image synthesis, object detection, and facial recognition. To summarize, the integration of GFP-GAN and StyleGAN represents a strategic step forward in image quality enhancement. GFP-GAN's latent codes and feature biases have been modified, and this, combined with the dataset augmentation capabilities of StyleGAN, has resulted in a powerful approach for high-fidelity image generation and dataset enrichment.

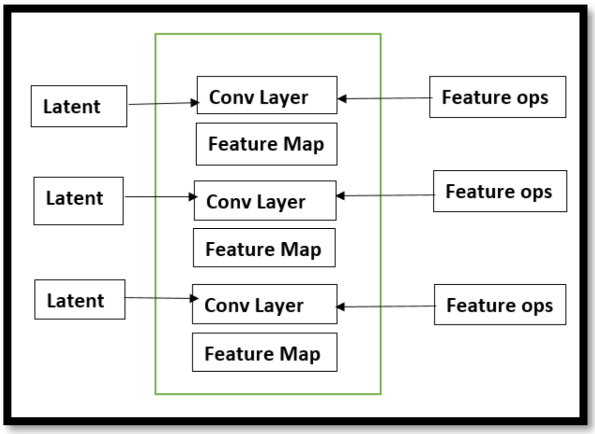

Figure 4. StyleGAN Approach

IV. RESULT AND DISCUSSION

The research centres on image enhancement, with a primary focus on facial images, employing state-of-the-art computer tools . We leverage the collaborative capabilities of two specialized tools: GFP-GAN and StyleGAN [18][19]. GFP-GAN, through advanced generative models, excels in pixel-level detail restoration, enhancing image clarity significantly, akin to transforming a blurry photograph into a sharp, high-resolution image [20][21]. On the other hand, StyleGAN efficiently generates augmented datasets suitable for training computer systems [22][23]. This synergy yields substantial benefits, particularly in improving the quality of facial imagery and enabling the development of datasets for machine learning, a pivotal aspect for applications such as facial recognition [24]. Our research marks a notable advancement in computer vision and artificial intelligence, with broad applications in various domains, including medical imaging and object recognition [25]. In essence, our work does not merely pertain to aesthetic image enhancement but underscores its vital role in enhancing the capabilities of computer systems, thus offering considerable potential for researchers and developers to achieve remarkable outcomes in diverse field[26].

V. Conclusion

This work represents a significant advancement in the field of image processing and machine learning. The combination of GFP-GAN and StyleGAN has not only resulted in significant improvements in image pixel quality, but has also paved the way for the creation of unprecedentedly rich augmented datasets. This project exemplifies field innovation by focusing on improving visual fidelity and harnessing the power of generative adversarial networks. The obtained results are not only promising, but also open the door to a wide range of applications, ranging from facial image restoration to broader machine learning tasks. As the world of AI and image processing evolves, the collaborative potential of GFP-GAN and StyleGAN promises to be a game changer, offering transformative solutions and advancements across multiple industries and domains

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