Enhanced Image Restoration Techniques Using Generative Facial Prior Generative Adversarial Networks in Human Faces in Comparison of PSNR with GPEN

D. Shravan and G. Ramkumar
Department of ECE, Saveetha School of Engineering, SIMATS, Chennai, Tamil Nadu, India

Keywords: Novel Generative Facial Prior Generative Adversarial Networks (GFPGAN), Image Restoration, GAN Prior Embedded Network (GPEN), Facial Prior, Peak Signal Noise Ratio (PSNR), Genetrative Adversarial Networks (GAN), Technology.

Abstract: The primary objective of this study is to discover whether or not Novel Generative Facial Prior Generative Adversarial Networks (GFPGAN) are capable of properly recreating human portraits from damaged face photographs. The purpose of this research is to assess the effectiveness of various image restoration techniques by contrasting the findings generated by the Generative Adversarial Networks (GAN) Prior Embedded Network (GPEN) approach with the quality of the restored pictures, as measured by the Peak Signal to Noise Ratio (PSNR). For the purpose of this study, a total of 464 samples were collected, split into two groups with 232 samples each. In Group 1, the researchers utilize a novel GFPGAN approach, whereas in Group 2, researchers use the GPEN method. The pre-trained models are imported as part of the process of the study, and the Novel GFPGAN code has been included into Google Colab and run. The size of the sample is determined with the use of a statistical tool found online (clincalc.com) by combining the F-score data obtained from earlier research with the results of the current study. In the computation, the pretest power is set at 80%, which is a number that is held constant, and the value of alpha is 0.05. As a direct result of the simulation, the Novel GFPGAN approach achieved the greatest PSNR value, which was measured at 0.32, while the GPEN PSNR value was measured at 0.30. There is a statistically significant difference in the accuracy provided by the two algorithms, as shown by significance values of 0.003 (P0.05). In terms of the PSNR values, the Novel GFPGAN performs better than the GPEN approach for the dataset that was presented.

1 INTRODUCTION

The technology that powers mobile phones and cameras has seen significant advancements over the last several years. Despite this, the availability of cameras has led to a rise in the issues that are faced while photographing persons at formal or informal events. The acquisition of these photographs is crucial in order to make use of them in the future; yet, doing so may be challenging owing to difficulties such as noise and blur caused by shaking the camera (R. R. Sankey and M. E. Read, 1973). The exposure value is rather high as a result of the sun's strong rays. This might result in the images being overexposed or noisy as a result of the camera sensor, which is something that typically only happens when there is not enough light (J. Q. Anderson, 2005). Image restoration is a method that may be used to address these faults and bring back the quality of the images. Human portraits, and more especially the facial region, comprise the primary focus of attention in the current piece of scholarly literature. A GAN, which stands for "Generative Adversarial Network," is used in the process of "blind face restoration." This GAN takes advantage of the wealth of previous data that is included inside the pretrained face GAN. The prior data comes from a variety of sources. The Generative Facial Prior (GFP) technique is employed in this study for the goal of doing realistic face restoration (T. Yang, P. Ren, X. Xie, and L. 2021). The aim of blind face repair is to revive faces of a high grade from portions of a lower quality that have been injured. These fragments may have deteriorated, become fuzzy, or contain noise, compression artifacts, or other problems of a similar kind. Alternatively, they may include various types of defects. The process of applying it to real-world occurrences is exceedingly challenging for a number of reasons, including the existence of problematic

Shravan, D. and Ramkumar, G.
Enhanced Image Restoration Techniques Using Generative Facial Prior Generative Adversarial Networks in Human Faces in Comparison of PSNR with GPEN.
DOI: 10.5220/0012561700003739

In *Proceedings of the 1st International Conference on Artificial Intelligence for Internet of Things: Accelerating Innovation in Industry and Consumer Electronics (AI4IoT 2023)*, pages 557-563
ISBN: 978-989-758-661-3

artifacts and a broad variety of locations and expressions. This is due to the fact that the actual world is full of complex situations. (Z. Teng, X. Yu, and C. Wu, 2022). The bulk of the techniques depend on face-specific priors in the process of restoring facial feature maps. This is done with the intention of restoring the proper information in the face. The priors are calculated based on the input photographs, which most of the time are of a very low quality. Only a limited amount of information on the texture that has to be repaired is provided by the priors. The usage of reference priors, the exploitation of high-quality face pictures, and the application of facial dictionaries are three more tactics that may be implemented in order to generate outputs that are realistic. However, this issue is only present in the facial characteristics section of that lexicon; the lack of variation is a problem in this regard. The Generative Adversarial Network (GAN) is able to build faces of a high quality by using a large amount of data on the face's texture, color, lighting, and other elements (T. Yang, P. Ren, X. Xie, and L., 2021). There are several obstacles to overcome when attempting to include such priors into the process of repair. In the past, most techniques relied on an inversion of the GAN algorithm, which, although being able to create realistic results, more often than not resulted in images with a low degree of realism. The last ten years have witnessed the development of a wide variety of distinct image restoration procedures and algorithms, each of which comes with its own unique set of pros and cons. A good number of them, including the use of SWINIR, GFPGAN, ESRGAN, and GPEN, have been included in recognized databases such as IEEE Xplore, ResearchGate, Google Scholar, and others. There are around 17200 publications relating to face image restoration that can be found in Google Scholar, 3945 face image restoration-related papers that can be found in IEEE Xplore, and 14552 face image restoration-related articles that can be found in Springer. The research that makes use of ESRGAN (X. Wang *et al.*, 2019) has been cited 2339 times, the research that makes use of GFPGAN (S. G and R. G., 2022) has been cited 72 times, the research that makes use of GPEN (T. Yang, P. Ren, X. Xie, and L., 2021) has been cited 115 times, and a study was carried out in which SWINIR (J. Liang, J. Cao, G. Sun, K. Zhang, L., 2021) was utilized to restore an image; this study was cited 429 times. These articles rank among the highest in terms of the number of citations received in their respective disciplines. The GFPGAN research stands out to me as the one that is likely to be of the most use to readers among these papers. This is due to the fact that the GFPGAN investigation is equivalent to this research and enlightens us about the procedures that need to be carried out. Because low-resolution images do not convey sufficient information about the colors and textures of the objects being photographed, problems have been found in the methods that are presently used to prevent restoration. The primary purpose of this research effort is to recover low-resolution photos that are blurry and then deblur those images while maintaining as little of the original photograph's information about its texture and colors as is realistically possible.

2 PROPOSED METHODOLOGY

Each kind of data has 232 different samples to choose from. The preparation of the sample size for Group 1 included utilizing a sample of 232 testing data that was trained using Novel GFPGAN. The GFPGAN combines the capabilities of traditional GANs with facial priors, which are the standard facial structures and characteristics that are present in the majority of faces. This technique contributes to the creation of faces that have a more natural and lifelike appearance (H. Lithgow *et al.)*.

A total of 232 training data points for Group 2 that are prepared following the methodology that is currently used by GPEN. The issue of picture restoration in the face of a wide variety of types of degradation, such as noise, blur, and compression errors, will be tackled by using GPEN. The system makes use of a generative adversarial network (GAN) as a preliminary step in the picture restoration process. It is based on a deep neural network.

For the purpose of the research, an electronic device that had a resolution of 1920 by 1080 pixels, an x64 CPU, and a 64-bit operating system was employed. The command and the model have both been executed with the help of Google Colab ("Google Colaboratory"). The collaborative laptop, as stated by nvidia-smi, is powered by a Tesla K80 with Compute 3.7, 2496 CUDA cores, 12GB GDDR5 VRAM, and a single-core hyper-threaded 2.3GHz Xeon CPU. In addition to that, it contains 13 GB of RAM. A free application for managing datasets called Kaggle (J. Li, 2018) is used to import the user's own dataset into the program once it has been launched. The data set is then trained using Novel GFPGAN and GPEN after this step. The evaluation is carried out using datasets that have been trained. After that, a comparison is made between the PSNR values of a satisfaction provided by the GFPGAN technique and the PSNR values acquired by the GPEN method. The performance is evaluated using the PSNR values that were generated as a consequence. The data visualization came after the analysis had been completed. It has been shown that Generative Adversarial Networks, often known as GANs, are effective tools for a variety of picture restoration tasks, including ones that include faces. GANs are made up of two separate neural networks known as the generator and the discriminator. These networks are trained concurrently with one another using a competitive method. GANs have been effectively used to tasks such as picture inpainting, super-resolution, and denoising. They may also be modified for face image restoration using generative facial priors, which is another application of their versatility. The following is an example of how GAN-based approaches may be used to restore face images: Inpainting is a technique that may be used with GANs for the purpose of restoring missing or damaged components of face pictures. The discriminator network is taught to differentiate between actual and inpainted pictures, while the generator network is trained to fill in missing areas of an input image during training. In order to fill in the gaps, the generator learns how to develop information that is both realistic and contextually consistent. This may be helpful in situations in which elements of a person's face are absent or are concealed. GANs may also be used for facial super-resolution, which involves enhancing photographs of the face with lower resolutions to produce images with greater resolutions. The generator network is trained to translate low-resolution photos to their high-resolution equivalents, which enables it to capture finer face information. This method is very useful for improving the quality of photos with a low resolution as well as for zooming in on certain facial characteristics to examine them more closely. It is possible to teach GANs to denoise facial photos by teaching them to understand the underlying clean structure of faces using noisy examples as training data. The generator's goal is to get rid of unwanted noise while preserving the fundamental face characteristics. This is especially helpful in situations when there is not enough light or when noisy sensors are being used to collect face photographs. GANs may be used to improve certain aspects of face photographs, such as the lighting, the skin tones, or the facial expressions. GANs can also be used to adjust skin tones. GANs may assist improve the aesthetic quality of face pictures by being taught to adjust specific qualities while maintaining the overall facial structure. This training is done in order to do this. GANs have the ability to create face pictures that show the acceleration or deceleration of an individual's aging process. It is possible to teach the generator to create faces of varying ages while ensuring that the created pictures maintain the individual's distinctive features of their appearance. Additionally, GANs may be used to artificially generate face emotions on still photos. The generator is able to alter the facial features to portray a certain emotion while maintaining the integrity of the rest of the face because it has learned the correlations that exist between the many facial expressions. When using GAN-based strategies for facial image restoration, it is essential to have a high-quality training dataset that contains both damaged face pictures and their matching clean counterparts. This is because the GAN-based techniques will learn from the differences between the two. The effectiveness of these approaches is strongly reliant on the high quality as well as the variety of the training data. In addition, optimizing the GAN architecture and the training parameters is very necessary in order to acquire the best possible outcomes for a given restoration endeavor.

The Novel GFP-GAN achieves success in both the realm of realism and the realm of authenticity because of the delicate balancing act that it employs in its design. The model incorporates both a degradation removal module and a GAN that has already been trained. All three of these concepts are interconnected: direct latent code mapping, channel split spatial feature, and prior. The restoration loss is computed after the degradation module identifies the areas of the face in the picture that have been damaged as a result of image deterioration. The facial prior from the pretrained generative adversarial network (GAN) is utilized to replace the facial features by using the channel split face spatial feature as a helper. Due to the production of this high quality face prior, the GAN will now construct priors, generators that will create synthetic facial feature pictures using the input photos supplied, and discriminators that will assess if the facial features are genuine or fake.

The current technique is solely concerned with the face area, but an existing approach (realESRGAN) will be included into the GFPGAN in order to provide more enhancements to the background and even to restore the complete image's texture. The GFPGAN outscale value has been increased to 4x, up from the previous value of 3.5x. This cutting-edge GFPGAN technology is able to recover pictures that are exceedingly blurry, which is a significant advancement in the field. The GFPGAN method has been given innovation by having a number of enhancements made to it in order to increase the PSNR values for the custom dataset that was supplied. After putting this novel GFPGAN technique through its training, the PSNR data are retrieved for analysis. The same custom dataset is put to use once again in the process of training the GPEN method to get PSNR values that are identical. After that, the PSNR values that were obtained are compared by using the Independent Samples T-test, and the validity is established by deciding whether or not the significance value is lower than 0.05.

2.1 Statistical Analysis

IBM SPSS Analytical 26 is the statistical tool that was employed (K. McCormick and J. Salcedo, 2017) in order to evaluate the mean average PSNR value of the intended research activity as well as the previous investigations. For the purpose of testing, the Independent Sample T-test is used. In this particular investigation, the mean average PSNR values serve as the dependent variables, while the blurriness of the face photos serves as the independent factors. As inputs for the analysis, the mean, the standard deviation, and the standard error mean were used.

3 RESULTS

Figure 1 Depicts the workflow for running the Novel GFPGAN method starting from the basic process of importing the source code and datasets to giving the results for the mean average PSNR

Figure 2 shows a simple bar chart of mean of PSNR by groups, where the individual PSNR of each picture in the dataset is noted by testing using both Novel GFPGAN and GPEN and the mean PSNR values are compared and mean average PSNR value is calculated using SPSS Analytics 26's independent samples T-test. For Novel GFPGAN the mean PSNR value is 0.32694 and GPEN has mean PSNR value of 0.255517, with error bars at 95%.

Table 1 shows the group statistics obtained from performing Independent Samples T-test in order to obtain the mean PSNR value for Novel GFPGAN as 0.326940 with standard deviation as +0.008760 and for GPEN as 0.255517 with standard deviation as +0.026297 using SPSS Analytics 26 tool.

Table 2 depicts the results of independent samples t-test conducted in the SPSS Analytics tool. This table shows the independent sample T-test performed for the two groups and noted that the significance level of the PSNR value of two groups is .000 which is less than 0.05.

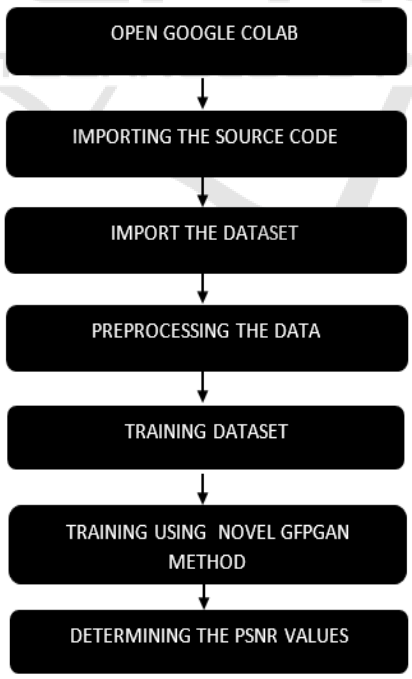

Figure 1: Process flowchart for determining the mean average PSNR.

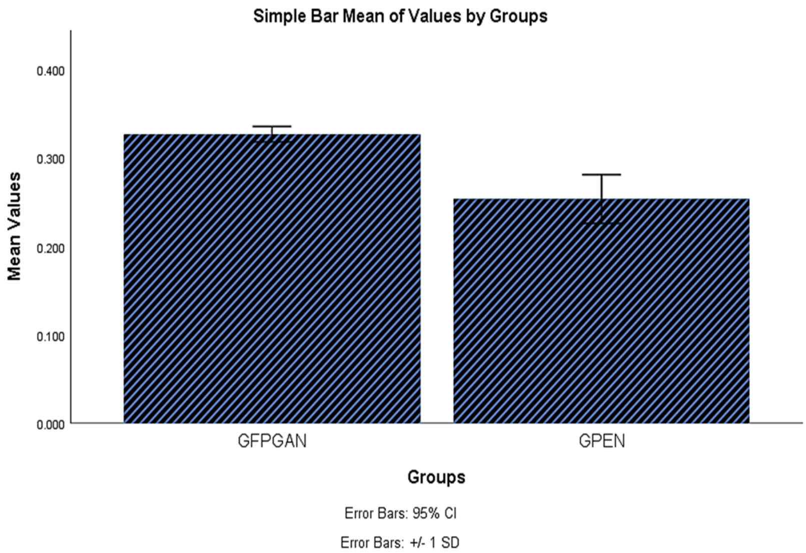

Figure 2: The simple bar chart of mean of PSNR by groups.

Table 1: Group statistics obtained from performing Independent Samples T-test.

	Groups	N	Mean	Std. Deviation	Std. Error Mean
PSNR	Novel GFPGAN	232	.32694	.008760	.000575
PSNR	GPEN	232	.30177	.007200	.000473

Table 2: Independent samples t-test.

		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. Error Difference	Lower	Upper
Accuracy	Equal variances assumed	16.1	.000	33.813	462	.003	.025172	.000744	.02370	.026635
	Equal variances not assumed			33.813	445.3	.003	.025172	.000744	.02370	.026636

4 DISCUSSION

The findings of the study indicate that the Novel GFPGAN is superior than Restormer in terms of PSNR by 3.5% in the restoration of face pictures from the dataset that was provided, with a significance of 0.003, which indicates that the findings should be considered reliable. The prior findings demonstrate that Novel GFPGAN works better as compared to the already used restoration method in terms of accurately and successfully recovering face images from a user-specified dataset. According to results that are comparable to those shown here, studies and research from various authors and researchers, which have also been included here, have shown that this technology is 86% more successful than other technologies in restoring low-resolution face images to high-resolution face images while maintaining the subject's identity. The topic of guided face restoration, which is also often referred to as blind face restoration from a corrupt picture (GFRNet), is investigated in this article (X. Li, M. Liu, Y. Ye, W. Zuo, L. Lin, and R. Yang, 2018). An technique to face restoration using vector quantization (VQ), known as VQFR, was conceived after being influenced by both the conventional dictionary-based approaches and the more recent vector quantization (VQ) technological advancements. Because of this, VQFR is able to recreate realistic facial features with the assistance of high-quality low-level feature banks that were derived from high-quality faces. This is a significant advantage for VQFR. (Y. Gu et al., 2022). DeblurGAN-v2 is a brand-new end-to-end generative adversarial network (GAN) for single picture motion deblurring. Its purpose is to dramatically increase the quality, flexibility, and efficiency of existing deblurring approaches (O. Kupyn, T. Martyniuk, J. Wu, and Z. Wang, 2019). The HiFaceGAN system is a multi-stage framework that is made up of a number of layered CSR units. These CSR units progressively add facial features utilizing the hierarchical semantic guidance that was collected from the front-end content-adaptive suppression modules as a consequence (Kumar M, M., Sivakumar, V. L., Devi V, S., Nagabhooshanam, N., & Thanappan, S. 2022). According to the findings of this research, highly trained GANs may serve as effective preprocessors for a variety of image processing applications if they are given multi-code GAN priors, also known as mGANpriors. They made use of a large number of latent codes in order to precisely invert a given GAN model. They then used adaptive channel significance at some point during the generator's construction at an intermediate layer in order to generate the features maps from these codes. The trained GAN models are able to leverage the resultant high-fidelity picture reconstruction for a wide variety of real-world applications, including image colorization, super-resolution, image inpainting, and semantic modification (J. Gu, Y. Shen, and B. Zhou, 2020). In addition, it has been discovered that putting the GFPGAN blind face restoration idea into practice might be a difficult task. Photographs of people's faces that were shot outside usually suffer from a variety of quality issues, such as compression, blurring, and noise. Due to the fact that the information loss caused by the degradation provides an unending number of high-quality (HQ) outputs that might have been produced from low-quality (LQ) inputs, it is very challenging to recover these kinds of photos. When doing blind repairs, in which the exact degree of deterioration is unclear, the inconvenience is amplified even more. Learning a LQ-HQ mapping in the large picture space is still intractable, which results in the mediocre restoration quality of previous approaches. Despite the breakthroughs brought about by the advent of deep learning, learning a LQ-HQ mapping in the huge image space is still intractable. (CodeFormer), a prediction network that is built on transformers (G. Ramkumar, R. Thandaiah Prabu, Ngangbam Phalguni Singh, U. Maheswaran, 2021). Due to the fact that just around 3000 photos were used to train GFPGAN, one essential facet to take into account is that the number of images used to train GFPGAN is rather high. This is an essential facet to take into consideration. The amount of time spent training the model with user-supplied data and photos results in a high-quality face image being used for the restoration of any elements of the image that have been damaged or corrupted. In addition, extremely poor quality photos cannot be retrieved if there is no information on the texture of the image. In the future, the scope should anticipate aiming the picture restoration for extremely low-quality image restoration with no information on texture or color.

5 CONCLUSION

From the obtained results, Novel GFPGAN performs better and delivers more accurate and realistic human face restoration in the facial region than the GPEN by PSNR value 0.02517, according to the above PSNR values.

REFERENCES

R. R. Sankey and M. E. Read,(1973) "Camera Image Degradation Due to the Presence of High Energy Gamma Rays in l23l-Labeled Compounds, "*Southern Medical Journal*, vol. 66, no. 11. p. 1328. doi: 10.1097/00007611-197311000-00053.

J. Q. Anderson, (2005). *Imagining the Internet: Personalities, Predictions, Perspectives*. Rowman & Littlefield Publishers,

T. Yang, P. Ren, X. Xie, and L. (2021). Zhang, "GAN Prior Embedded Network for Blind Face Restoration in the Wild," *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. doi: 10.1109/cvpr46437.2021.00073.

Z. Teng, X. Yu, and C. Wu, (2022). "Blind Face Restoration Multi-Prior Collaboration and Adaptive Feature Fusion," *Front. Neurorobot.*, vol. 16, p. 797231, Feb.

X. Wang *et al.*, (2019). "ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks," *Lecture Notes in Computer Science*. pp. 63–79, doi: 10.1007/978-3-030-11021-5_5.

S. G and R. G, 2022, "Automated Breast Cancer Classification based on Modified Deep learning Convolutional Neural Network following Dual Segmentation," 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, pp. 1562-1569, doi: 10.1109/ICESC54411.2022.9885299

J. Liang, J. Cao, G. Sun, K. Zhang, L. (2021). Van Gool, and R. Timofte, "SwinIR: Image Restoration Using Swin Transformer," *2021 IEEE/CVF International*

Conference on Computer Vision Workshops (ICCVW). doi: 10.1109/iccvw54120.2021.00210.

H. Lithgow *et al.*, "Protocol for a randomised controlled trial to investigate the effects of vitamin K2 on recovery from muscle-damaging resistance exercise in young and older adults-the TAKEOVER study," *Trials*, vol. 23, no. 1, p. 1026, Dec.

"Google Colaboratory." https://colab.research.google.com/ (accessed Mar. 15, 2023).

J. Li,2018 "CelebFaces Attributes (CelebA) Dataset." Jun. 01,. Accessed: Mar. 15, 2023. [Online]. Available: https://www.kaggle.com/jessicali9530/celeba-dataset

K. McCormick and J. Salcedo, 2017.*SPSS Statistics for Data Analysis and Visualization*. John Wiley & Sons,

X. Li, M. Liu, Y. Ye, W. Zuo, L. Lin, and R. Yang,(2018) "Learning Warped Guidance for Blind Face Restoration," *Computer Vision – ECCV* . pp. 278–296, 2018. doi: 10.1007/978-3-030-01261-8_17.

Y. Gu *et al.*,2022. "VQFR: Blind Face Restoration with Vector-Quantized Dictionary and Parallel Decoder," *Lecture Notes in Computer Science*. pp. 126–143, doi: 10.1007/978-3-031-19797-0_8.

O. Kupyn, T. Martyniuk, J. Wu, and Z. Wang,(2019) "DeblurGAN-v2: Deblurring (Orders-of-Magnitude) Faster and Better," *IEEE/CVF International Conference on Computer Vision (ICCV)*. 2019. doi: 10.1109/iccv.2019.00897.

Kumar M, M., Sivakumar, V. L., Devi V, S., Nagabhooshanam, N., & Thanappan, S. (2022). Investigation on Durability Behavior of Fiber Reinforced Concrete with Steel Slag/Bacteria beneath Diverse Exposure Conditions. Advances in Materials Science and Engineering, 2022..

J. Gu, Y. Shen, and B. Zhou, (2020). "Image Processing Using Multi-Code GAN Prior," *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. doi: 10.1109/cvpr42600.2020.00308.

G. Ramkumar, R. Thandaiah Prabu, Ngangbam Phalguni Singh, U. Maheswaran, (2021) Experimental analysis of brain tumor detection system using Machine learning approach, Materials Today: Proceedings, ISSN 2214-7853, https://doi.org/10.1016/j.matpr. 2021.01.246.