ISSN: 2581-3404 (Online) **IF: 5.445 (SJIF)**

International Journal of Innovative Research in Technology and Management, Volume-6, Issue-3, 2022.

A Cascaded Method for Real Face Image Restoration using GFP-GAN

Anamika Kumari [1], Prof. Ratnesh Kumar Dubey[2], Dr. Sadhna K. Mishra[3]

[1]M. Tech. Research Scholar, Department of CSE, LNCT, Bhopal (M.P.), India.

[2]Assistant Professor, Department of CSE, LNCT, Bhopal (M.P.), India.

[3] Head & Professor, Department of CSE, LNCT, Bhopal (M.P.), India.

Abstract: *Blind face restoration is referred as the process which recovers the high quality images (HQ) from images having low quality (LQ) input. Generally LQ images experience defects of obscure degradation like low resolution, noise, blur as well as lossy compression. Latest restoration strategies actually centered on particularly super resolution method. Very few image restoration techniques work well to real LQ images except the same. When applied to genuine situations, it turns out to be really difficult, because of more convoluted degradation, different poses and articulations. In this paper, a cascaded method for real face image restoration using GFP-GAN has been proposed. For experiment on combined approach of GFP-GAN, FFHQ dataset has been used. All images which are used here are much authentic in the terms of their feature originality, hence it improves the results. Our GFP-GAN method has been trained on synthetic data which estimates LQ images. Training data have been generated by degradation model by passing high quality images through Gaussian blur kernel. At time of training for color enhancement color jittering has been used. FID and NIQE metrics was calculated on CelebChild image dataset for strongly verify our proposed work against available restoration model. Based on evaluation metrics it is shown that GFP-GAN works well comparative to other existing methods and can be adapted by different face image restoration applications.*

Keywords: Face image restoration, GFP-GAN, Cascaded, Resolution, FID, NIQE, Celeb Child.

Introduction

Digital images are electronic depictions of a scene, which made out of commonly picture elements in a lattice development known as pixels [1]. Every pixel holds a worth which is quantized that addresses the tone at a particular point. Images are acquired in areas going from regular photography to astronomy, remote sensing, microscopy, medical imaging and so on. Image restoration utilizes a priori knowledge of the degradation [2]. It forms and assesses the objective rules of goodness. The distortion in image can be modeled as noise or blur or a degradation function [3]. It is very unfortunate that all images are pretty much blurry [4]. This is because of the explanation that there is a great deal of interference in the camera as well as in the climate. Blurring of an image can be brought about by many factors, for example, development during the capture cycle, utilizing wide angle lens, utilizing long exposure times, and so on [5]. Photos are taken to freeze the cheerful minutes that generally gone [7]. Notwithstanding the way that time elapses by, one can regardless bring out memories of the past by survey them. Notwithstanding, old photograph prints disintegrate when kept in poor natural condition, which causes the significant photograph content forever hurt. Fortunately, as portable cameras and portable scanners become more accessible, people

ISSN: 2581-3404 (Online) IF: 5.445 (SJIF)
International Journal of Innovative Research in Technology and Management, Volume-6, Issue-3, 2022.

can now digitalize the photos and welcome a skilled master for restoration. Anyway, manual modifying is ordinarily laborious and tedious, which leaves heaps of old photos challenging to get restored. Hereafter, it is fascinating to design programmed algorithms that can promptly fix old photos for individuals who wish to restore old photos. Going before the deep learning time, there are a couple of tries that restore photos through normally recognizing the confined disfigurements like scratches and flaws, and filling in the hurt regions with inpainting strategies. Anyway these methods revolve around completing the missing substance and not a single one of them can fix the spatially-uniform disfigurements, for instance, film grain, sepia influence, assortment blurring, etc, so the photos after restoration really appear to be outdated diverged from present day visual images. With the rise of deep learning, one can address a combination of low-level picture restoration issues by exploiting major areas of strength for the limit of convolutional neural networks, i.e., learning the planning for a specific task from a ton of engineered images. A similar framework, in any case, doesn't have any significant bearing to old photograph restoration. In any case, the degradation pattern of old photographs is fairly mind boggling, and there exists no degradation model that can basically deliver the old photograph antiquity. Thusly, the model acquired from those engineered data sums up insufficiently on certified photographs. Old photographs are tormented with a compound of degradations and innately, requires different strategies for fix unstructured disfigurements that are spatially homogeneous, e.g., film grain as well as color blurring, should be restored by involving the pixels nearby, while the coordinated blemishes, e.g., scratches, dust spots, etc, should be fixed with an overall picture setting. A few aftereffects of restoration of old images are displayed in Figure 1.

Figure 1: Old image restoration results.

II. Classification Techniques

Inthe image processing research area, blind restoration grants recovery of the objective scene from a solitary or set of "blurred" images within the sight of not set in stone or obscure point spread function (PSF), which is used by regular linear and non-linear restoration techniques. For blind restoration, the PSF is estimated from the image or image setfollowed by the restoration process. Types of filter used in Blind restoration techniques with their characteristics and working principles are illustrated in table 1.

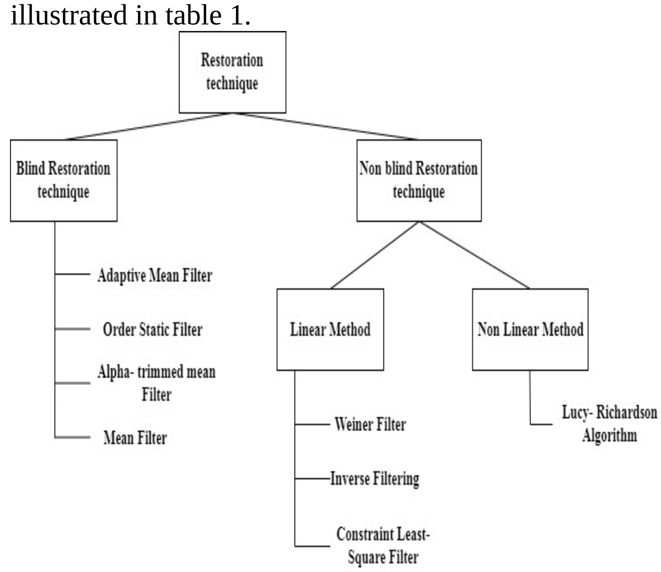

Figure 2: Classification of Restoration techniques.

ISSN: 2581-3404 (Online) IF: 5.445 (SJIF)
International Journal of Innovative Research in Technology and Management, Volume-6, Issue-3, 2022.

Table 1: Types of filter used in Blind restoration techniques with their characteristics and working principle

Filter used in Blind Restoration Technique	Characteristics and working principle
Adaptive Mean Filter	Filter size is flexible. In less noise density images, it can be used. It can eliminate high density noise.
Order Static Filter	It depends on the image pixel sequences. Its reaction cannot be settled by ranking results. It is a type of spatial filter.
Mean Filter	It replaces the middle value in the window with the average of all the adjoining pixel values including it. It is a type of spatial filter.
Alpha (α) trimmed mean Filter	It is a hybrid of mean and median filter. It removes the uncommon pixel and calculate mean from the remaining. Alpha is a parameter.

1.2.2 Non-blind restoration techniques

A non-blind method relies upon the estimation of PSF which ought to be priorly known. In light of PSF estimation it restores the input image. As referenced above other two sorts of non-blind strategies are linear restoration techniques, for example, Weiner channel, Inverse channel, and Constrained Least square channel. Lucy-Richardson algorithm is a Non-linear kind of restoration technique. Types of filter used in Non-Blind restoration techniques with their characteristics and working principle is illustrated in table 2.

Table 2: Types of filter used in Non-Blind restoration techniques with their characteristics and working principle

Filter used in Non-Blind Restoration Technique	Characteristics and working principle
Weiner Filter	It finds an estimated value of the uncorrupted image value to such an extent that the mean square values between them are limited
Inverse Filter	Estimation of the Fourier transform of the image is derived by partitioning the Fourier transform of the degraded image by the Fourier transform of the degradation function.
Constraint Least-Square (CLS) Filter	It is a kind of an approximation of a Weiner filter. The blurred and noisy images are recovered by a regularized filter CLS restoration method.
Lucy-Richardson Algorithm	It can derive remadeimages of good quality within the sight of high noise level

III. Review of Face Restoration Techniques

Face restoration is critical in face picture dealing with, and has been by and large focused recently. Blind face restoration insinuates recovering the incomparable (HQ) pictures from the mediocre quality (LQ) inputs which experience the evil impacts of dark degradation like low resolution, commotion, obscure and lossy compression. It has drawn progressively more interest on account of its wide applications. In this fragment, we quickly survey the ongoing procedures for face super-resolution; blind face restoration and HQ face age considering generative adversarial networks. Their relative rundown is likewise displayed in table 3.

Table 3: Summary of some current Face Restoration techniques

Authors and Year	Proposed Technique	Application Areas
Xintao Wang et.al. in [1], 2021	GFP-GAN (Generative Facial Prior-Generative Adversarial Network)	Blind face restoration
Chaofeng Chen et al. in [2], 2021	PSFR-GAN framework	Used for Face restoration
Jinjin Gu et al. in [3], 2020	Multi Code GAN Prior (mGANprior)	Used for image colorization and inpainting. Also used for super resolution,
Orest Kupyn et al. in [4], 2020	DeblurGAN-v2	Real-time video enhancement,
Xiaoming Li t al. in [5], 2020	DFDNet)	Used to solve the limitation of reference-based methods.
Sachit Menon et al. in [6], 2020	Photo Up-sampling via Latent Space Exploration (PULSE)	Face hallucination

IV. Problem Statement

Face super-resolution (FSR), is a domain-specific image super-resolution issue that aims to improve the resolution of face photographs having less-resolution (LR) in order to generate high-resolution face images. FSR has recently got a lot of attention and has been seen some amazing advancements thanks to the emergence of deep learning algorithms. A blind Face Restoration is a related field of research which is used in smart devices, as improved era of image related applications. To restore realistic and true details, blind face restoration typically uses facial priors such as facial geometry prior or reference prior. Lot of model of digital image processing techniques has already adapted by application time to time as per need. But these restoration techniques need improvements as per need of application and improvement in image quality of restored images. However, because very low-quality inputs cannot provide correct geometric priors and high-quality references are unavailable, the applicability of restoration of images in real-world applications is very large. Moreover, degradation of image quality depends on many artifacts like spatial feature transformation, and channel split. Some of the times application needs the use of unrealistic or Synthetic dataset. GFP is a technique which uses fair mix of realism and fidelity by including Generative Facial Prior (GFP) into the face restoration process via spatial feature transform layers. A generative adversarial network (GAN) is a machine learning (ML) model in which two neural networks compete to improve restored image quality. Image synthesis is the well-studied of the various applications of GAN, and research in this area has already shown the immense potential of using GAN in image synthesis. GAN along with GFP can be used to restore more images with the help of single forward path. The work to be carried is oriented towards improvement of quality of restoration of images using GFP-GAN on balanced dataset taken for natural and synthetic dataset.

V. Experimental Result

For experiment on combined approach of GFP-GAN, FFHQ dataset has been used. The FFHQ is a Flickr-Faces High Quality image dataset consist 72000 images on high resolution above 512x512 pixels. This data set have a balanced mix faces having considerable variation in age. All images are authentic in terms originality of their feature, so it improve the results also. The proposed GFP-GAN is trained on synthetic data that approximates low-quality real-world photos and extends to real-world images during inference. To generate training data, proposed model follow degradation model where high quality image are passed through Gaussian blur kernel and then convolved images are down sampled with some factor (Scale factor- r). In next part of training phase the additive white Gaussian noise is added to image and compressed the images in JPEG format using appropriate quality factor (say –q). At time of training for color enhancement color jittering has been used.

Training bias

Because it leverages both the pre-trained GAN and input picture characteristics for modulation, this suggested technique works well on most black skinned faces and different population groups. Furthermore, the suggested technique uses reconstruction loss and identity preservation loss to limit outputs while maintaining input integrity. When the input images are grayscale, however, the face color may be skewed since the inputs lack adequate color information. As a result, a diverse and well-balanced dataset is required.

For testing results of implemented proposed method uses random images shown in figure 3 which was a mix of all worst cases of blur images to test. In the preprocessing part of the model crops the images. The results of cropped faces are given in figure 4, in cropped images input image no 5 has two faces so the cropped image contains 5_00, 5_01 has cropped faces respected to input image 5 of figure 3.

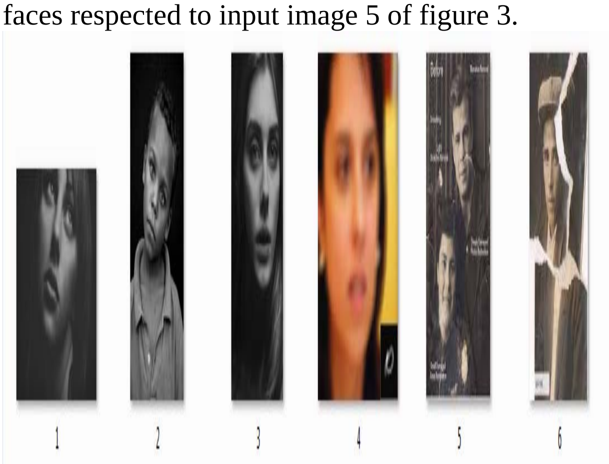

Figure 3: Input Test Images.

Figure 4: Cropped Faces.

Figure 5: Restored Cropped Faces.

The restored cropped faced of referenced cropped faces after applying GFP-GAN techniques has been shown in figure 5. The comparison of cropped face and restored images has been shown in figure 6 where clear features of faces and clear comparison can be understood.

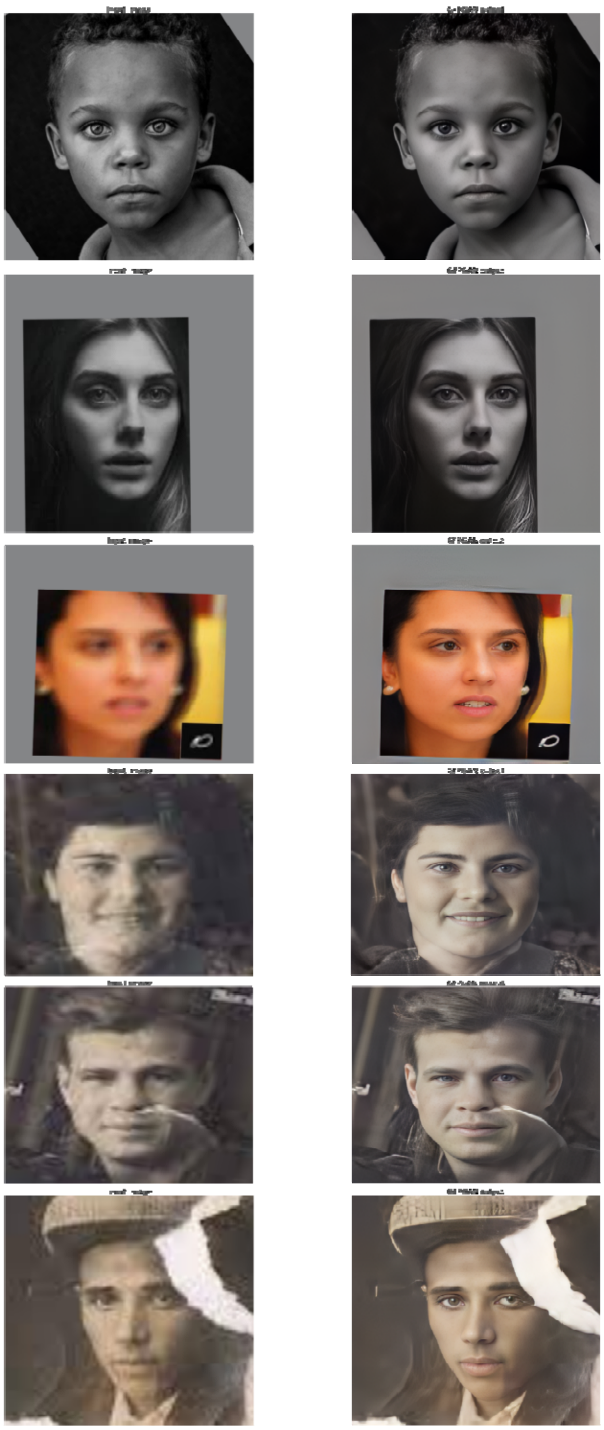

Figure 6: Comparison of Cropped Faces and Restored after GFP-GAN.

The final restored face image has been shown in shown in figure 7. In this figure, full blur image has been restored as referenced with input images of figure 3. Image no 5 in figure 7 is a combination of two restored faces that is clearly recognized.

Figure 7: Final Restored Images.

Figure 8: Comparison of various image restoration techniques by various researchers.

Practically it is impossible to decide the better image quality based on appearance some time features of images has been degraded by noise as well. In GAN some random noise is gathering to improve the restoration of image to look image as real as possible. So for identifying quantity of realism achieved following evaluation metrics can be used.

1. Frechet Inception Distance(FID):

This is one of the most widely used metrics for comparing real and produced images in terms of feature distance. Frechet Distance is a measure of the linear correlation between curves that takes the placement and ordering of points along the curves into account. It can also be used to calculate the difference between two distributions. Some conclusive observations for FID are:

Table 4: CelebChild Face Image Dataset FID & NIQE Metrics

Dataset Methods	CelebChild	
	FID	NIQE
Input	144.42	9.170
DeblurGANv2	110.51	4.453
Wan	115.70	4.849
HiFaceGAN	113.00	4.855
DFD-Net	111.55	4.414
PSFRGAN	107.40	4.804
PULSE	102.74	5.225
GFP-GAN	111.78	4.349

- The FID score lowers as the model checkpoint improves. A model checkpoint with a low FID score for inference can be chosen.
- Because the Inception model is trained on Imagenet, which contains natural images, the FID score is relatively high.

2. **Naturalness Image Quality Evaluator (NIQE):** Only a Deep Quality Assessment (QA) model trained on human evaluations was sensitive to the minor variations between higher-quality images, showing good overall agreement with human evaluation for lower-quality images (i.e. photos from early stages of GAN training). The picture statistics are fitted with a multivariate Gaussian distribution, and the Mahalanobis distance to a fit derived on a corpus of natural images is determined. For the better fitted model NIQE value must be low as possible.

FID and NIQE metrics was calculated on CelebChild image dataset for strongly verify our proposed work against available restoration model. The comparison has been shown in table 4 and respective line graph has been shown in figure 9 & figure 10.

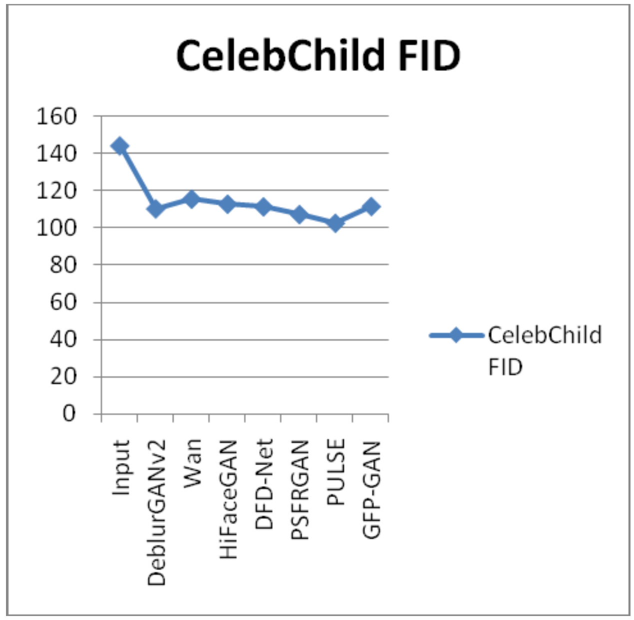

Figure 9: FID Comparison of Different methods.

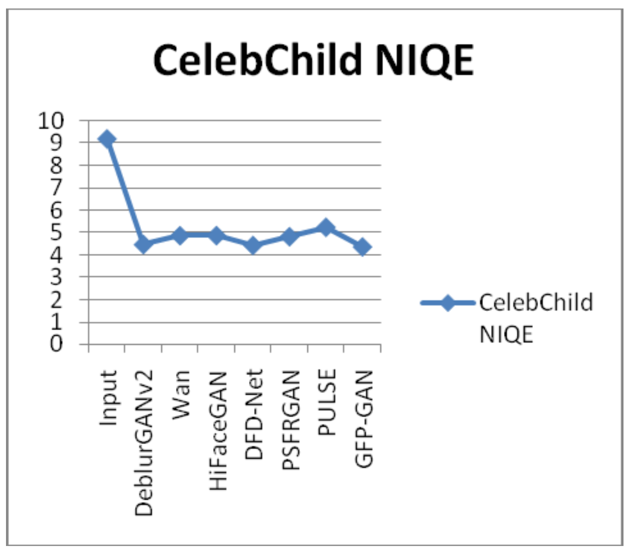

Figure 10: NIQE Comparison of Different methods.

Based on these metrics values it has been clear that GFP-GAN has batter results as compared to previous mentioned research in referred area. All Comparison mentioned in restored images and based on metrics shows that GFP-GAN works well comparative to other method and can be adapted by different face / image restoration applications.

VI. Conclusion

GFP-GAN's restored facial details become warped with parameters when real-world pictures are substantially damaged. This method also produces weird effects when used for extremely large poses. This is because synthetic deterioration and training data has a different distribution than real-world data. One possibility is to acquire that distribution from real data rather than synthetic data, which will be left for future study. When real-image degradation is extreme, GFP-GAN's reconstructed facial details become distorted with artifacts. For excessively large poses, our technology also gives strange effects. This is because the distribution of synthetic degradation and training data differs from that of real-world data. One option is to learn those distributions from real data rather than synthetic data, which will be left for future research.

References:

[1] Xintao Wang Yu Li Honglun Zhang Ying Shan, "Towards Real-World Blind Face Restoration with Generative Facial Prior", Computer Vision Foundation CVPR 2021, pp 9168-9178.

[2] Chaofeng Chen,Xiaoming,Lingbo Yang,Xianhui Lin,Lei Zhang,Kwan-Yee K. Wong, "Progressive Semantic-Aware Style Transformation for Blind Face Restoration", Computer Vision Foundation CVPR 2021, pp 11896-11905.

[3] Jinjin Gu, Yujun Shen, Bolei Zhou1, "Image Processing Using Multi-Code GAN Prior", Computer Vision Foundation CVPR 2020, pp 3012-3021.

[4] Orest Kupyn,Tetiana Martyniuk, Junru Wu, Zhangyang Wang, "DeblurGAN-v2: Deblurring (Orders-of-Magnitude) Faster and Better", Computer Vision Foundation ICCV, pp 8878-8897.

[5] Xiaoming Li1,Chaofeng Chen,Shangchen Zhou,Xianhui Lin,Wangmeng Zuo,Lei Zhang, "Blind Face Restoration via Deep Multi-scale, Component Dictionaries", Computer Vision and Pattern Recognition, Aug 2021, pp 1-16.

[6] Sachit Menon, Alexandru Damian, Shijia Hu, Nikhil Ravi, Cynthia Rudin, "PULSE: Self-Supervised Photo Upsampling via Latent Space Exploration of Generative Models", Computer Vision Foundation CVPR 2020, pp 2437-2445.

[7] Ziyu Wan Bo Zhang, Dongdong Chen, Pan Zhang, Dong Chen, Jing Liao,Fang Wen, "Bringing Old Photos Back to Life", Computer Vision Foundation CVPR 2020, pp 2747-2757.

[8] Yu Chen,Ying Tai2,Xiaoming Liu,Chunhua Shen,Jian Yang, "FSRNet: End-to-End Learning Face Super-Resolution with Facial Priors", CVPR 2020, pp 2492-2501.

[9] Xiaomeng Guo, Li Yi, Hang Zou and Yining Gao, "Generative Facial Prior for Large-Factor Blind Face Super- Resolution", ICAITA 2021, pp 1-11.

[10] [Yotam Nitzan,Kfir Aberman,Qiurui He,Orly Liba,Michal Yarom, "MyStyle: A Personalized Generative Prior", ARXIV 2022, pp 1-19.

[11] Tongxin Wei,Qingbao Li,Zhifeng Chen and Jinjin Liu, "FRGAN: A Blind Face Restoration with Generative Adversarial Networks", HindawiMathematical Problems in Engineering 2021, pp 1-14.

[12] Arthur Conmy, Subhadip Mukherjee, and Carola-Bibiane Schönlieb, "STYLEGAN-Induced Data-Driven Regularization For Inverse Problems", IEEE explore 2022, pp 1-5.

[13] Weihao Xia, Yulun Zhang, Yujiu Yang, Jing-Hao Xue, Bolei Zhou, Ming-Hsuan Yang, "GAN Inversion: A Survey", ARXIV 2021, pp 1-17.

[14] Zhaoqing Pan, Weijie Yu, Xiaokai Yi, Asifullah Khan, Feng Yuan, And Yuhui Zheng, "Recent Progress on Generative Adversarial Networks (GANs): A Survey", IEEE Access 2019, pp 36322- 36333.

[15] Kunfeng Wang, Member, Chao Gou, Yanjie Duan, Yilun Lin, Xinhu Zheng, and Fei-Yue Wang, "Generative Adversarial Networks: Introduction and Outlook", IEEE/CAA Journal Of

Automatica Sinica, Vol. 4, No. 4, October 2017, pp 588-598.

[16] Shilpa Rani, Sonika Jindal, Bhavneet Kaur, “A Brief Review on Image Restoration Techniques”, International Journal of Computer Applications 2016, pp 30-34.

[17] Abdul Jabbar, Xi Li, And Bourahla Omar, “A Survey on Generative Adversarial Networks: Variants, Applications, and Training”, ACM Computing Surveys, Vol. 54, No. 8, Article 157. Publication date: October 2021, pp 1-49.

[18] Xin Yia, Ekta Waliaa, Paul Babyna, “Generative Adversarial Network in Medical Imaging: A Review”, Elsevier 2019, pp 1-24.

[19] Antonia Creswellx, Tom White, “Generative Adversarial Networks: An Overview”, IEEE-SPM, APRIL 2017, pp 1-14.

[20] Aziz Makandar, Anita Patrot, “Computation Pre-Processing Techniques for Image Restoration”, International Journal of Computer Applications 2015, pp 11-17.

[21] Prabhishek Singh, Raj Shree, “Comparative Study to Noise Models and Image Restoration Techniques”, International Journal of Computer Applications 2016, pp 18-28.

[22] M. Hassaballah, Saleh Aly, “Face recognition: challenges, achievements and future directions”, IET Comput. Vis., 2015, Vol. 9, Iss. 4, pp. 614–626.

[23] Murat Taskirana, Nihan Kahramana and Cigdem Eroglu Erdemb, “Face Recognition: Past, Present and Future (A Review)”, Digital Signal Processing 2020, pp 1-44.

[24] Shilpi Singha,S.V.A.V.Prasad, “Techniques and Challenges of Face Recognition: A Critical Review”, Elsevier 2018, pp 536-543.

[25] Himanshu Joshi, Dr. Jitendra Sheetlani, “Image Restoration Techniques in Image Processing: An Illustrative Review”, IJARSE 2017, pp 145-158.