A

Project Report

on

Blind Image Restoration and Data Augmentation

submitted for partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

in

Computer Science

By

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DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that Project Report entitled **“Blind Image Restoration and Data Augmentation”** which is submitted by **Avishi Tayal, Nandini Tyagi and Piyush Gupta** in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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Date: **Supervisor Signature**

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TABLE OF CONTENTS

Content	Page No.

ABSTRACT

Some of the most amazing discoveries in this decade have been made thanks to technology and technological advancements. The world seems to get better every day thanks to the rapidly evolving technology, systems to support them, and back-end processing power.

Image restoration is currently one of the most difficult problems. Image restoration is the process of estimating the clean, original image from a corrupted or noisy image. Motion blur, noise, and camera focus issues are just a few examples of corruption. The main objective of the restoration process, which enhances the appearance of the image, is to return it to the way it appeared when it was first synthesized. Images of various cancerous cells can be restored and studied using this technique. Astronomical aspects of satellite images can also be restored. Face image restoration can be used to identify criminal activity, among other real world applications. To accomplish the mentioned goals, we are using the Generative Adversarial Network (GAN) models in this situation. Our use of the GAN prior embedded network enables us to produce a smooth and finely tuned image from which we can further deduce some conclusions. The biggest challenge facing the computer vision industry today is obtaining an image of a high quality without background noise. Because in this scenario, every pixel of the image is crucial to the training of a complete model. Therefore, image restoration is the most difficult task to complete, which will also help to solve many real-world and industrial problems.

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

GAN	Generative Adversarial Network
GFPGAN	Generative Facial Prior GAN
VGG19	Visual Geometric Group 19
CNN	Convolutional Neural Network
AI	Artificial Intelligence
AdaIN	Adaptive Instance Normalization

CHAPTER 1
INTRODUCTION

1.1 Introduction to Project

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.

1.2 Project Category

This project falls within the realm of "Computer Vision and Image Processing." This category encompasses a broad array of initiatives and research endeavors focused on developing algorithms and methodologies to analyze, interpret, and manipulate visual data. Specifically, the project involves leveraging Generative Adversarial Networks (GANs) for tasks related to image restoration. This includes addressing issues such as noise, motion blur, and camera misfocus to enhance the quality and fidelity of images in diverse fields such as medicine, astronomy, and surveillance.

1.3 Objectives

The major goal of this research is to make facial image analysis more accurate and simplicity of facial image analysis by enhancing the quality of face images and can even convert old fashioned images into modern ones.

1. This aims to represent a technological innovation in machine learning and image processing. It seeks to offer a special combination of pixel enhancement and dataset augmentation capabilities, particularly in the context of facial photography and its numerous applications.
2. The idea aims to produce more realistic facial images by improving pixel-level specifics and visual quality This realism can be helpful in circumstances like computer graphics, virtual reality, and simulation settings.
3. The augmented datasets produced by the innovation can be used as useful training data for a variety of image-based AI models, which will help to improve image-based AI. Machine learning

methods for recognizing facial expressions, determining age, and categorizing gender are used in this.

4. Cost savings and quicker project schedules may emerge from the invention's potential to generate enhanced datasets, which may reduce the need for real-world data collecting, which can be time-consuming and expensive.
5. It even lessens the need for real-world data collection, which may be time-consuming and expensive because the invention may provide augmented datasets. This might lead to lower costs and quicker project timetables.
6. Illustrations of potential disease progression in various stances or stages may be produced as a result. Researchers and medical professionals may benefit from having a better understanding of how the disease develops and what effects it has on the body as a result.

1.4 Structure of Report

a. Introduction

- Overview of image restoration challenges.
- Importance of image restoration in various domains.
- Introduction to Generative Adversarial Networks (GANs) and their applications in image processing
- Brief explanation of GFP-GAN and StyleGAN.

b. Literature Review

- Review of existing methods and techniques for image restoration.
- Overview of previous research on GAN-based image restoration.
- Discussion of strengths and limitations of different approaches.
- Identification of gaps in current literature.

c. Problem Statement

- Clear definition of the problem addressed in the project.
- Explanation of why current image restoration methods are insufficient.
- Justification for using GFP-GAN and StyleGAN for image restoration.

d. Methodology

- Detailed explanation of the proposed method:
- Overview of GFP-GAN and StyleGAN architectures.
- Integration strategy for combining GFP-GAN and StyleGAN.
- Description of how the combined model improves image restoration.
- Technical details of adjusting GFP-GAN's latent codes and feature biases.
- Discussion of dataset augmentation using StyleGAN.

e. Requirement Analysis

- Identification of user requirements and system objectives.
- Definition of functional and non-functional requirements.
- Specification of input data requirements.
- Consideration of constraints and limitations.

f. Implementation

- Description of the software tools and frameworks used for implementation.
- Details of dataset preparation and preprocessing.
- Explanation of model training process:
- Training parameters and hyperparameters.
- Techniques for optimizing model performance.
- Deployment considerations for the integrated model.

g. Testing

- Definition of testing objectives and strategies.
- Description of testing methodologies (e.g., unit testing, integration testing, validation testing).
- Presentation of test results and validation of model performance.

h. Results

- Presentation of experimental results:
- Evaluation metrics used for assessing image restoration quality (e.g., PSNR, SSIM).
- Comparison of results with baseline methods.
- Visual demonstration of restored images.

i. Discussion

- Interpretation and analysis of the experimental results.
- Discussion of the strengths and limitations of the proposed method.
- Explanation of factors influencing the performance of the integrated model.
- Comparison with existing image restoration techniques.

j. Maintenance

- Strategies for maintaining and updating the integrated model.
- Considerations for scalability and future enhancements.
- Discussion of potential challenges and mitigation strategies.

k. Future Work

- Suggestions for further research and development:
- Fine-tuning model architectures for specific applications.
- Exploring different loss functions and optimization techniques.

CHAPTER 2

LITRATURE REVIEW

2.1 Literature Review

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 analyze 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 equi-variant to translation and rotation. During the whole research author has implemented alias free generator model that contains implicit assumptions about the behavior 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 color 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, color 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 2.1 Literature survey

Authors	Titles	Objective	Tools/Technologies/Approach	Output	Year
I. Goodfellow et al.[1]	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.	2014
Tao Yang et al.[2]	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.	2021
Feida Zhu et al.[3]	Blind Face Restoration via Integrating Face Shape and Generative Priors	Develop SGPN, integrating shape and generative priors for blind face restoration to create realistic, high-quality facial images from degraded inputs.	SGPN combines 3D shape reconstruction with StyleGAN2 for blind face restoration, incorporating an Adaptive Feature Fusion Block (AFFB) for spatial feature blending.	The research introduces SGPN for blind face restoration, combining 3D shape, generative prior, and adaptive feature fusion. It outperforms existing methods, but identity restoration remains challenging.	
Tero Karras et al. [4]	A Style-Based Generator Architecture for Generative Adversarial Networks	The objective is to enhance generative adversarial networks (GANs) by introducing a novel generator architecture that improves image synthesis, disentangles attributes, and enables precise control.	The paper introduces a novel style-based generator architecture for GANs to enhance image quality and control image synthesis.	The paper concludes that the traditional GAN generator architecture is inferior to the proposed style-based design, offering better quality and controllability, and suggests future research directions.	2019
JIAWEI YOU et al.[6],	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.	2022

Tero Karras et al. [5]	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.	2020
Raymond A. Yeh et al.[8]	Semantic Image Inpainting with Deep Generative Models	Develop a semantic image inpainting method using generative models to create realistic missing content.	Semantic inpainting using generative models and optimization to recover missing content based on context and prior losses, achieving realistic results for large missing regions in images.	The proposed method for semantic inpainting outperforms existing techniques, providing realistic results and sharper edges in challenging scenarios.	2017
Sheng Li et al.[9]	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.	2018
Xin Jin et al.[7]	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]	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.	2020

2.2 Research Gaps

Research gaps for the project on integrating GFP-GAN and StyleGAN for image restoration could include:

1. **Limited Integration Studies**: While GFP-GAN and StyleGAN have been individually explored for image restoration tasks, there is a lack of comprehensive studies on their integration. Research could focus on identifying the optimal integration strategy and the synergistic effects of combining both models.
2. **Latent Code Optimization**: Although adjusting GFP-GAN's latent codes and feature biases has shown promise in enhancing image quality, there is a need for further research into the specific optimization techniques. Exploring advanced optimization algorithms or novel approaches to fine-tune latent representations could yield improvements in restoration performance.
3. **Dataset Augmentation Techniques**: While StyleGAN offers powerful capabilities for dataset augmentation, there is limited research on the most effective augmentation strategies for image restoration tasks. Investigating different augmentation techniques, such as domain-specific data synthesis or adaptive augmentation methods, could lead to better generalization and robustness of the integrated model.
4. **Evaluation Metrics**: Existing evaluation metrics for image restoration, such as PSNR and SSIM, may not fully capture the perceptual quality of restored images. Research could explore the development of novel evaluation metrics or

perceptual-based assessment techniques tailored to the characteristics of GFP-GAN and StyleGAN-generated images.

5. **Real-World Applications**: While the project discusses various potential applications of the integrated model, there is a gap in research on its practical deployment in real-world scenarios. Future studies could focus on validating the model's performance in specific application domains, such as medical imaging, surveillance, or remote sensing, to assess its effectiveness and usability in real-world settings.
6. **Scalability and Efficiency:** As image restoration tasks often involve processing large volumes of data, there is a need to address scalability and efficiency challenges. Research could investigate techniques for optimizing model architectures, parallelizing computation, or leveraging hardware acceleration to improve the scalability and efficiency of the integrated model.
7. **Robustness to Adversarial Attacks**: With the increasing concern about adversarial attacks on deep learning models, there is a need to assess the robustness of the integrated GFP-GAN and StyleGAN model. Research could explore techniques for enhancing model robustness, such as adversarial training or incorporating defense mechanisms against adversarial perturbations.

2.3 Problem Formulation

To achieve a high quality image without background noise, proper colorization and inpainted image is biggest challenge in today's computer vision industry. Because the training of a complete model in such case depends on each pixel of the image. Hence image restoration is the biggest task to achieve which further help to solve various real world and industrial problems such as in real world – various cctv image are degraded due to which criminal activities can't be record easily, similarly in medical field the cancerous cell can visualize easily and effectively by the model. It will certainly help in industries to train various economical projects like- clothes translation, text to image conversion and many more.

CHAPTER 3

PROPOSED SYSTEM

3.1 Proposed System

Blind image restoration is a crucial aspect of digital image processing, aimed at recovering clear and high-quality images from degraded inputs without prior knowledge of the degradation process. This approach is particularly beneficial in scenarios with unknown or complex degradation, such as medical imaging or surveillance. GFP-GAN, an innovative neural network architecture, drives the blind image restoration process in this study. It enhances restoration by estimating a degradation model, recovering the blur kernel, and using it to de-convolute the degraded image, ultimately restoring it to its original state. Regularization techniques and quality assessment metrics play essential roles in stabilizing and evaluating the restoration process. Despite its challenges, blind image restoration continues to advance with iterative optimization and mathematical techniques, with deep learning models like GFP-GAN expanding the field's capabilities and applications.

3.1.1 GFPGAN:

GFP-GAN, short for Generative Facial Prior Adversarial Network, is a sophisticated model designed for image generation, particularly focusing on facial images. It employs a conventional encoder-decoder structure, utilizing the VGG-19 neural network for feature extraction. GFP-GAN meticulously extracts essential features from input images, capturing both low and high-dimensional details, which are then fused to enhance image quality. At its core, GFP-

GAN operates based on the principles of Generative Adversarial Networks (GANs), with a generator creating synthetic images and a discriminator evaluating their authenticity in an iterative training process. The primary goal of GFP-GAN is to generate facial images with unparalleled detail and realism, achieved through advanced neural network architectures and iterative learning.

3.1.2 StyleGAN:

StyleGAN, an abbreviation for Style Generative Adversarial Network, is a sophisticated generative model utilized in artificial intelligence and machine learning to produce lifelike images. Developed by NVIDIA in 2018, StyleGAN enhances the concept of generative adversarial networks (GANs), employing a generator and discriminator trained in tandem.

Key Components:

1. **Generator:** Unlike traditional GANs, StyleGAN generator progressively builds images from low to high resolution, granting better control over style and structure.
2. **Mapping Network:** StyleGAN introduces a mapping network to convert initial random noise into style vectors, allowing for separation of high-level image properties from low-level details.
3. **Style Mixing:** Unique to StyleGAN, it enables the blending of style vectors from different images to create entirely new compositions.
4. **Discriminators:** These networks distinguish real from generated images, providing feedback for generator refinement through adversarial training.

5. **Progressive Growth:** StyleGAN employs gradual resolution increase during image generation, leading to highly detailed outputs.
6. **Normalization Techniques:** Various methods, including adaptive instance normalization (AdaIN), are used to control image style and appearance.
7. **Style and Content Separation:** StyleGAN effectively disentangles image style and content, facilitating independent manipulation and making it popular for artistic applications.

3.1.3 Integration:

We strategically combined the GFP-GAN and StyleGAN models to achieve significant improvements in image quality. By adjusting GFP-GAN's latent codes and feature biases, initially lower-fidelity output images were refined to produce high-quality results with improved pixel accuracy and detail. This integrated approach capitalizes on the strengths of both models: GFP-GAN for initial image restoration and StyleGAN for dataset augmentation. The collaboration not only enhances visual fidelity but also opens doors to various applications such as image synthesis and facial recognition. In summary, the integration of GFP-GAN and StyleGAN marks a strategic advancement in image quality enhancement, offering a potent method for high-fidelity image generation and dataset enrichment.

3.2 UNIQUE FEATURES OF THE SYSTEM

Some unique features of the integrated GFP-GAN and StyleGAN project for image restoration include:

1. **Combined Strengths of GFP-GAN and StyleGAN:** The project leverages the complementary strengths of GFP-GAN for initial image restoration and StyleGAN for dataset augmentation. This combined approach enhances the overall image quality and fidelity.
2. **Adjustment of Latent Codes and Feature Biases:** By strategically adjusting GFP-GAN's latent codes and feature biases, the project achieves significant improvements in image quality, including enhanced pixel accuracy and detail.
3. **Synergistic Collaboration:** The integration of GFP-GAN and StyleGAN represents a synergistic collaboration between two advanced neural network architectures. This collaboration allows for the exploitation of their respective capabilities to achieve superior image restoration results.
4. **Versatility for Various Applications:** The project's integrated approach not only enhances image quality but also opens doors to diverse applications such as image synthesis and facial recognition. This versatility expands the potential impact of the project across multiple domains.
5. **Strategic Advancement in Image Quality Enhancement:** By combining GFP-GAN and StyleGAN, the project represents a strategic advancement in image quality enhancement. It offers a potent method for generating high-fidelity images and enriching datasets, thereby pushing the boundaries of image restoration technology.

CHAPTER 4
REQUIREMENT ANALYSIS AND SYSTEM SPECIFICATION

4.1 Feasibility

Conducting a feasibility study for an automated retail checkout system using YOLOv5 involves evaluating its technical, economic, and operational aspects. Following are the various components:

4.1.1 Technical Feasibility:

The technical feasibility of using Generative Adversarial Networks (GANs) for image restoration is quite high due to several factors:

1. **Advancements in GANs:** GANs have seen significant advancements in recent years, leading to the development of more sophisticated models like StyleGAN and GFP-GAN. These models have demonstrated remarkable capabilities in generating high-quality, realistic images.
2. **Availability of Data:** The availability of large datasets containing both corrupted and clean images enables robust training of GAN models for image restoration tasks. This abundant data allows for more effective learning and generalization of the restoration process.
3. **Computational Power:** With the advancement of hardware technologies, especially in GPU computing, training complex deep

learning models like GANs has become more accessible and efficient. This allows researchers to experiment with various architectures and optimization techniques to improve image restoration performance.

4. **Algorithmic Innovation:** Researchers continuously develop new algorithms and techniques to enhance the performance of GANs for specific tasks like image restoration. This includes innovations in loss functions, network architectures, and training strategies tailored to address challenges such as motion blur, noise, and camera miss-focus.
5. **Application-Specific Tailoring:** GAN models can be adapted and fine-tuned to suit specific application domains, such as medical imaging, astronomy, and surveillance. By tailoring the network architecture and training process to the characteristics of the target images, researchers can optimize performance and achieve more accurate restoration results.

4.1.2 Economic Feasibility:

- **Hardware and Software:**

High-performance laptop/desktop with GPU: ₹80,000 - ₹1,50,000

Software tools (e.g., Python, Tensorflow, PyTorch): ₹0 (open-source)

Total: ₹80,000 - ₹1,50,000

- **Dataset and Resources:**

Access to image datasets: ₹0 - ₹10,000 (free or minimal cost for public datasets)

Cloud computing services (if needed for extensive training): ₹5,000 - ₹10,000 (for limited usage)

Total: ₹5,000 - ₹20,000

- **Training and Learning:**

Online courses or tutorials on GANs and image processing: ₹0 - ₹20,000

Books and study materials: ₹0 - ₹10,000

Total: ₹0 - ₹30,000

- **Miscellaneous Expenses:**

Internet charges: ₹500 - ₹1,000 per month

Electricity charges: ₹500 - ₹1,000 per month

Miscellaneous expenses (e.g., stationery, printing): ₹1,000 - ₹2,000

Total (per month): ₹2,000 - ₹4,000

- **Overall Project Cost:**

Initial Investment: ₹87,000 - ₹1,70,000

Monthly Expenses (approximate): ₹2,000 - ₹4,000

- **Return on Investment (ROI) Assessment:**

  The ROI may not be monetary but rather educational and skill-building. The project could significantly enhance the student's knowledge and expertise in machine learning, image processing, and GANs, which could lead to better career opportunities in the future. Additionally, the student may contribute to open-source projects or publish research papers, further enhancing their academic profile and potential career prospects.

- **Payback Period:** To calculate the payback period of the project, we need to determine the time it takes for the project's net cash flows to recover the initial investment.

Let's assume the initial investment for the project is at the higher end of the estimated hardware and software cost, which is ₹1,50,000. We'll also consider the monthly miscellaneous expenses as ongoing costs.

Given:

Initial investment (I): ₹1,50,000

Monthly miscellaneous expenses: ₹2,000 - ₹4,000 (let's take the average of ₹3,000 per month)

Now, let's calculate the monthly net cash flows:

Monthly net cash flow = Monthly returns (0, as it's primarily educational) - Monthly miscellaneous expenses

Let's calculate the monthly net cash flow:

Monthly net cash flow = 0 - ₹3,000 = -₹3,000

The payback period can be calculated using the formula:

Payback Period = Initial Investment / Annual Net Cash Flow

First, let's determine the annual net cash flow. Since the returns are primarily educational and not generating direct income, the monthly net cash flow remains constant.

Annual Net Cash Flow = Monthly Net Cash Flow × 12

= -₹3,000 × 12

= -₹36,000

Now, we can calculate the payback period:

Payback Period = Initial Investment / Annual Net Cash Flow

= ₹1,50,000 / ₹36,000

≈ 4.17 years

Therefore, the payback period for the project is approximately 4.17 years. This means it will take approximately 4.17 years for the project's net cash flows to recover the initial investment.

4.1.3 Operational Feasibility

1. **Availability of Technology and Expertise:** With advancements in deep learning and neural network architectures, including GANs, and the availability of open-source libraries and frameworks such as Tensorflow and PyTorch, the necessary technology and expertise are readily accessible for implementing the project.
2. **Robustness of GAN Models:** GANs have proven to be robust and effective in various image generation and restoration tasks. The use of GFP-GAN and StyleGAN, which are state-of-the-art models specifically designed for image restoration and synthesis, enhances the project's operational feasibility by leveraging well-established and tested technologies.

3. **Scalability and Efficiency:** GAN-based image restoration techniques have demonstrated scalability and efficiency, enabling the processing of large volumes of image data with relatively low computational resources. This makes the project feasible for deployment in real-world applications where efficiency and scalability are crucial considerations.
4. **Integration with Existing Systems:** The integrated approach of combining GFP-GAN and StyleGAN can be seamlessly integrated into existing image processing pipelines or systems. This ensures compatibility with existing workflows and facilitates adoption without significant disruptions.
5. **Potential for Automation:** GAN-based image restoration techniques have the potential to be automated to a large extent, reducing the need for manual intervention and streamlining the restoration process. This improves operational efficiency and reduces labor costs associated with manual image restoration techniques.
6. **Flexibility and Adaptability:** The project's approach of combining multiple GAN models allows for flexibility and adaptability to different image restoration tasks and domains. This versatility enhances the project's operational feasibility by enabling it to address a wide range of image restoration challenges across various fields such as medicine, astronomy, and surveillance.

4.2 Software Requirements Specifications

4.2.1 Data Requirement

1. **Data Sources**

In order to train GFPGAN and StyleGAN on custom dataset, we have first imported the model from the respective official repositories. And further tuned their latent codes and weights to train the data accordingly.

2. **Data Set**

The custom dataset consists of an about 100 facial images for training. These facial images are of 10 famous Indian film stars containing the center, left and right alignment of their faces.

Fig 4.1 Dataset

4.2.2 Functional Requirement

Functional requirements specify what the system should do. For the integrated GFP-GAN and StyleGAN project for image restoration, here are some functional requirements:

1. **Image Restoration:** The system should be able to take corrupt or noisy images as input and restore them to clean, high-quality images using the combined GFP-GAN and StyleGAN models.
2. **Model Integration:** The system should integrate the GFP-GAN and StyleGAN models seamlessly to leverage their respective strengths for image restoration and dataset augmentation.
3. **Adjustable Parameters:** Users should be able to adjust parameters such as latent codes and feature biases of the GFP-GAN model to fine-tune the restoration process according to specific requirements.
4. **Real-time Processing:** The system should be capable of processing images in real-time or with minimal latency to support applications requiring immediate feedback or continuous monitoring.
5. **Scalability:** The system should be scalable to handle a large volume of image restoration tasks efficiently, without compromising performance or quality.
6. **Quality Assurance:** The system should include mechanisms for quality assurance, such as automated testing and validation, to ensure the accuracy and reliability of the restored images.

4.2.3 Performance Requirement

1. **Image Quality:** The primary performance requirement is to produce high-quality, visually appealing images with improved pixel accuracy and detail. The integrated model should be able to restore images to a level that closely resembles the original, minimizing artifacts and distortion.
2. **Speed and Efficiency:** The restoration process should be efficient and timely, especially when dealing with large datasets or real-time

applications. The model should be capable of processing images quickly without sacrificing quality.

3. **Scalability:** The system should be able to scale seamlessly to accommodate varying workloads and datasets of different sizes. It should handle increased demand or processing requirements without significant degradation in performance.
4. **Robustness:** The model should be robust and resilient to handle diverse types of image corruption and degradation, including motion blur, noise, and misfocus. It should perform consistently across different scenarios and conditions.
5. **Resource Utilization:** Efficient utilization of computational resources, including CPU, GPU, and memory, is essential to ensure cost-effectiveness and optimal performance. The model should make efficient use of available hardware resources to minimize processing time and maximize throughput.
6. **Adaptability:** The integrated model should be adaptable to various domains and applications, including medical imaging, satellite imagery analysis, and facial recognition. It should be capable of handling different types of images and restoration tasks effectively.

4.2.4 Maintainability Requirement

Maintainability is crucial for ensuring the longevity and effectiveness of the integrated GFP-GAN and StyleGAN project for image restoration. Here are some maintainability requirements:

1. **Modularity:** The project should be modular, with well-defined components that can be easily maintained and updated independently. This allows for changes or improvements to be made

to specific parts of the system without affecting the entire architecture.

2. **Documentation:** Comprehensive documentation should be provided for all aspects of the project, including code, algorithms, models, and datasets. This documentation should be clear, organized, and accessible to facilitate understanding and maintenance by developers and stakeholders.
3. **Version Control:** Version control systems such as Git should be used to manage the project's source code, allowing for easy tracking of changes, collaboration among team members, and rollback to previous versions if necessary.
4. **Code Quality:** The codebase should adhere to coding standards and best practices to ensure readability, maintainability, and scalability. Regular code reviews and refactoring should be conducted to eliminate technical debt and improve code quality.
5. **Testing Framework:** A robust testing framework should be implemented to verify the correctness and reliability of the system. This includes unit tests, integration tests, and end-to-end tests to validate the functionality of individual components and the system as a whole.

4.2.5 Security Requirement:

Security is a critical aspect of any project, including image restoration using GAN models like GFP-GAN and StyleGAN. Here are some security requirements for ensuring the security of the project:

1. **Data Privacy:** Ensure that sensitive data, such as medical images or personal photos, is handled with strict privacy measures. Implement

encryption techniques to protect data both at rest and in transit. Access controls should be in place to restrict unauthorized access to sensitive information.

2. **Model Security:** Protect the trained GAN models from tampering or unauthorized access. Implement secure storage mechanisms and access controls to safeguard the models from malicious activities. Regularly monitor model usage and detect any anomalies that may indicate security breaches.
3. **Secure Communication:** Ensure secure communication channels between different components of the system, including client applications, servers, and databases. Use encryption protocols such as SSL/TLS to encrypt data transmission and prevent eavesdropping or man-in-the-middle attacks.
4. **Authentication and Authorization:** Implement robust authentication and authorization mechanisms to verify the identity of users and control their access to system resources. Use strong password policies, multi-factor authentication, and role-based access control (RBAC) to enforce security policies.
5. **Secure Deployment:** Follow secure coding practices and guidelines when developing and deploying the project. Regularly update software dependencies and patches to address security vulnerabilities. Conduct security assessments and penetration testing to identify and mitigate potential security risks.
6. **Audit Trails and Logging:** Maintain comprehensive audit trails and logs of system activities, including user actions, model predictions, and data access. These logs can help in forensic analysis and investigation of security incidents or breaches.

7. **Training Data Security:** Ensure the security and integrity of training data used to train the GAN models. Validate and sanitize input data to prevent injection attacks or adversarial inputs that may compromise the training process or model performance.

4.3 SDLC Model Used

The test methodology selected for the project is Agile. An Agile methodology is the most suitable for this project. It allows for flexibility, ongoing testing, and adaptation, which are essential for projects that involve machine learning, image processing, and AI. Agile enables you to respond to changing requirements and refine the style transfer algorithm as you gain insights from testing and user feedback. It is sequential development process that flows like a waterfall through all phases of a project (analysis, design, development, and testing, for example), with each phase completely wrapping up before the next phase begins.

Following is the overview of all the phases of software development life cycle model:

Requirement Analysis:

1. Gather detailed requirements for blind image restoration and data augmentation.
2. Identify the specific needs and goals of the project, including image quality enhancement and dataset generation.

System Design:

1. **Architecture Design:** Designed a modular and scalable architecture for integrating GFP-GAN and StyleGAN. Adopted a microservices

architecture to encapsulate functionality into independent services, promoting flexibility and maintainability.

2. **Component Specification:** Defined the roles and responsibilities of each component, including the image preprocessing module, GFP-GAN image restoration module, StyleGAN data augmentation module, and result aggregation module.
3. **Data Flow Diagrams:** Created detailed data flow diagrams to visualize the flow of information within the system. Specified how raw input images are processed, restored, augmented, and aggregated to produce the final output datasets.
4. **Technological Stack:** Selected appropriate technologies and frameworks for implementing each component, considering factors such as performance, compatibility, and ease of integration. Utilized Python for machine learning model development, TensorFlow for deep learning algorithms, and Docker for containerization.

Implementation:

1. **GFP-GAN Development:** Implemented the GFP-GAN model architecture, comprising an encoder-decoder structure with feature fusion layers. Fine-tuned the model parameters and loss functions to optimize image restoration performance, focusing on minimizing pixel-wise errors and preserving image details.
2. **StyleGAN Integration:** Integrated the StyleGAN framework to generate diverse and high-quality datasets for data augmentation. Developed pipelines for feeding GFP-GAN output images into StyleGAN for further enhancement, leveraging transfer learning and fine-tuning techniques.

3. **Image Preprocessing:** Developed preprocessing pipelines to standardize and enhance raw input images before feeding them into the GFP-GAN model. Implemented techniques such as image resizing, normalization, and noise reduction to improve model robustness and performance.
4. **Quality Assurance:** Enforced coding standards and best practices to maintain code quality and readability. Conducted code reviews and pair programming sessions to identify and address potential issues early in the development cycle.

Testing:

1. **Unit Testing:** Wrote unit tests for individual components and functions to ensure their correctness and functionality in isolation. Leveraged testing frameworks such as pytest to automate test execution and streamline the testing process.
2. **Integration Testing:** Conducted integration tests to validate the interaction and interoperability of different system components. Tested data flow between GFP-GAN, StyleGAN, and other modules to verify seamless integration and data exchange.
3. **System Testing:** Performed end-to-end system tests to evaluate the overall performance, functionality, and reliability of the integrated solution. Tested various use cases and scenarios to validate system behavior under different conditions, ensuring robustness and resilience.

Deployment:

1. Prepare the system for deployment in the target environment, whether it's on-premises or in the cloud.

2. Set up the necessary infrastructure and dependencies for running the system.
3. Deploy the system and ensure that it's accessible and operational for further testing and usage.

Validation and Verification:

1. Validate the system against the initial requirements to ensure that it meets the desired objectives.
2. Verify the accuracy and effectiveness of blind image restoration and data augmentation techniques through extensive testing and evaluation.

Maintenance and Support:

1. Provide ongoing maintenance and support to address any issues or bugs identified during deployment and usage.
2. Update the system as needed to incorporate new features, improvements, and fixes based on user feedback and changing requirements.

4.4 System Design

4.4.1 Data Flow Diagrams

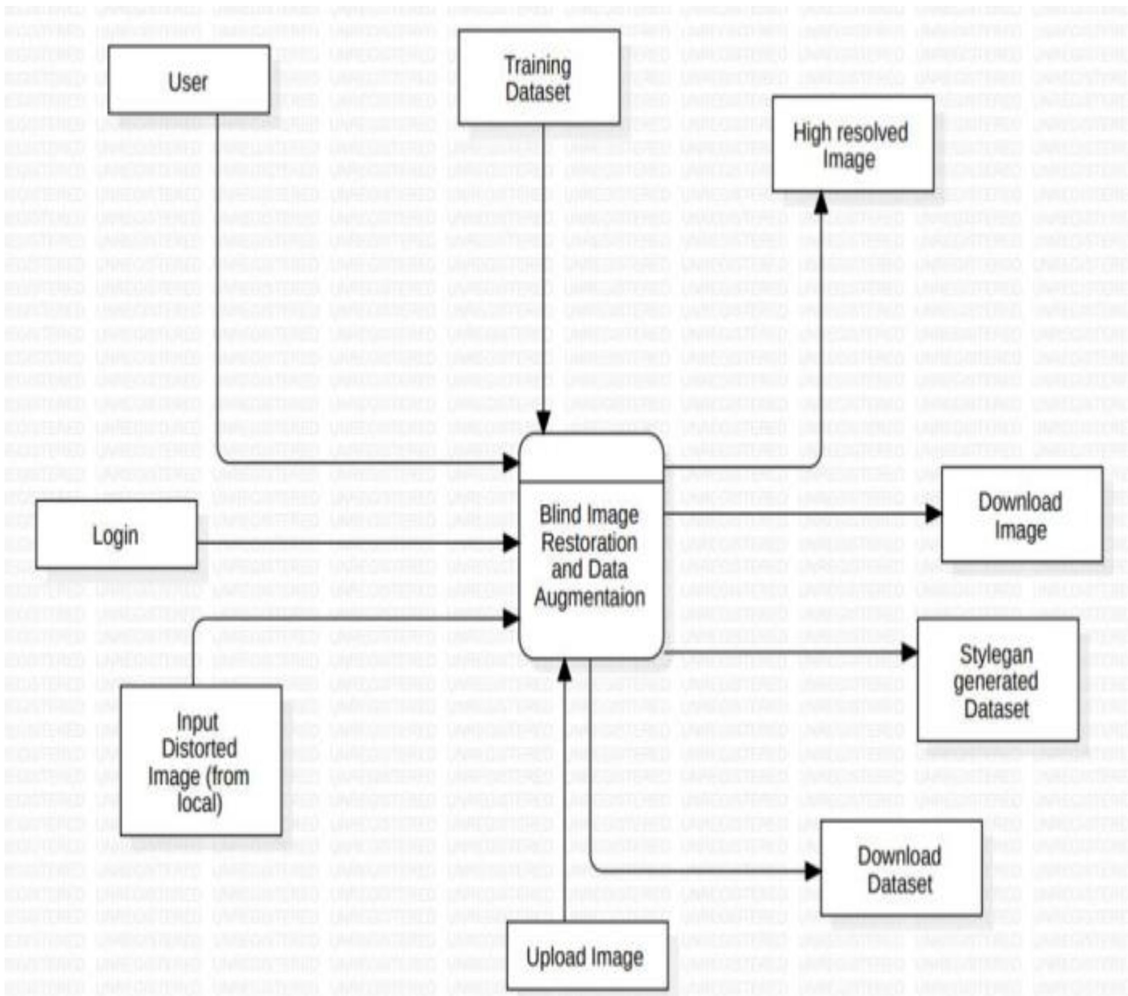

Fig. 4.2 Level 0 DFD

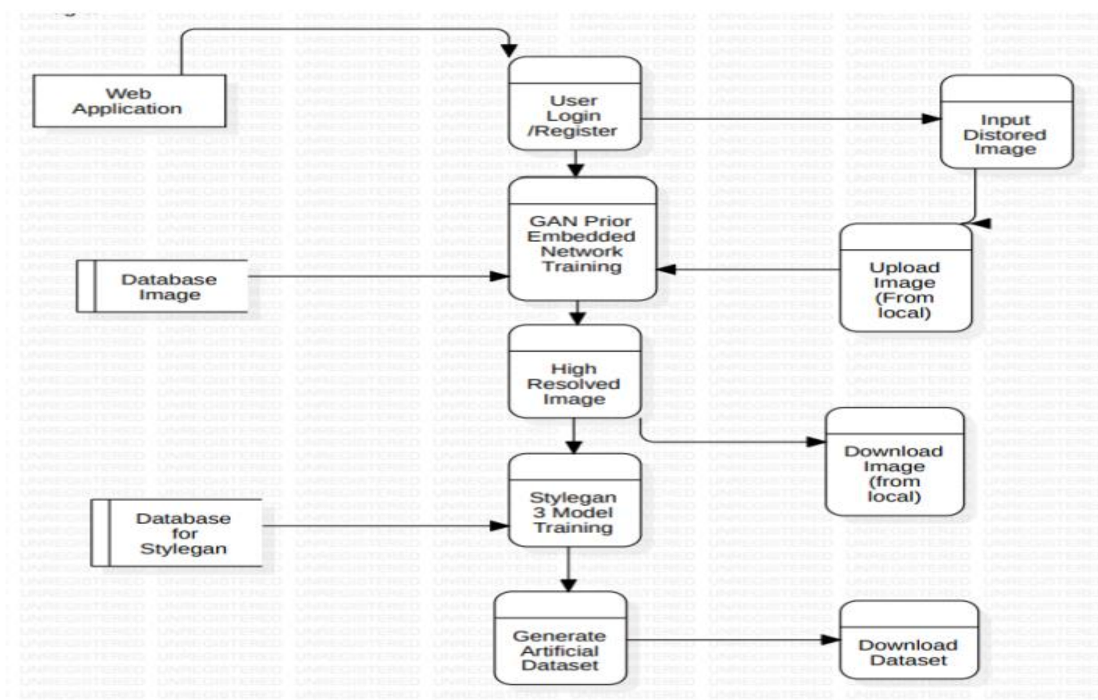

Fig. 4.3 Level 1 DFD

4.4.2 Use Case Diagram

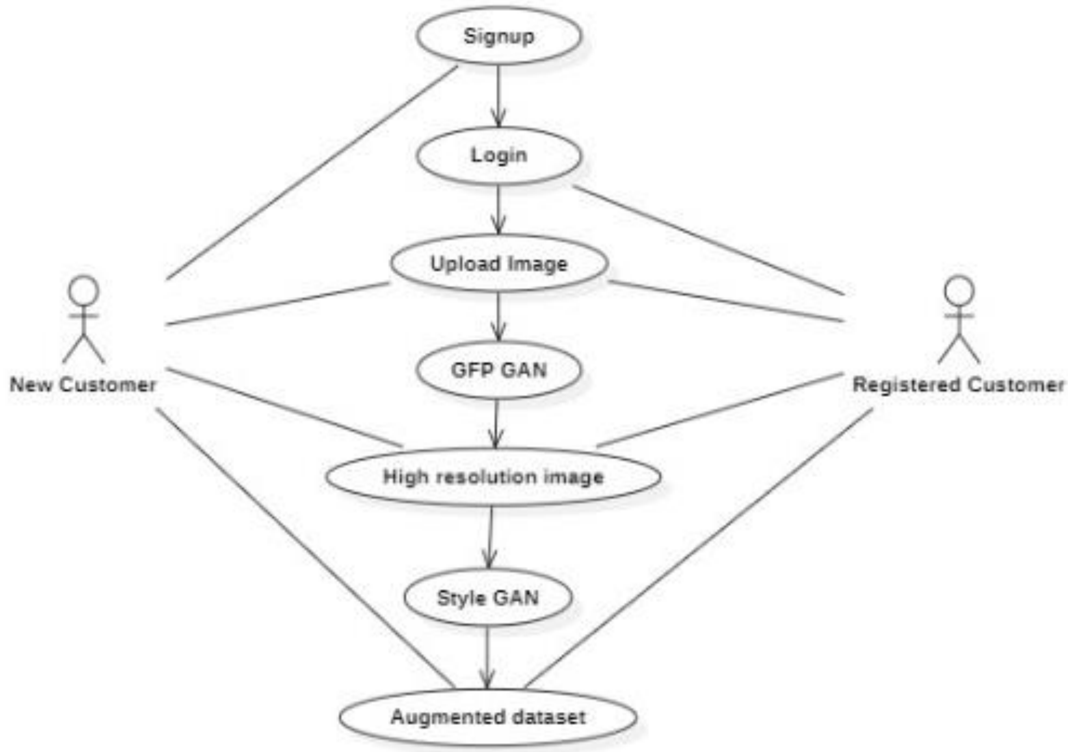

Fig. 4.4 Use Case Diagram

4.5 Database Design (ER Diagram)

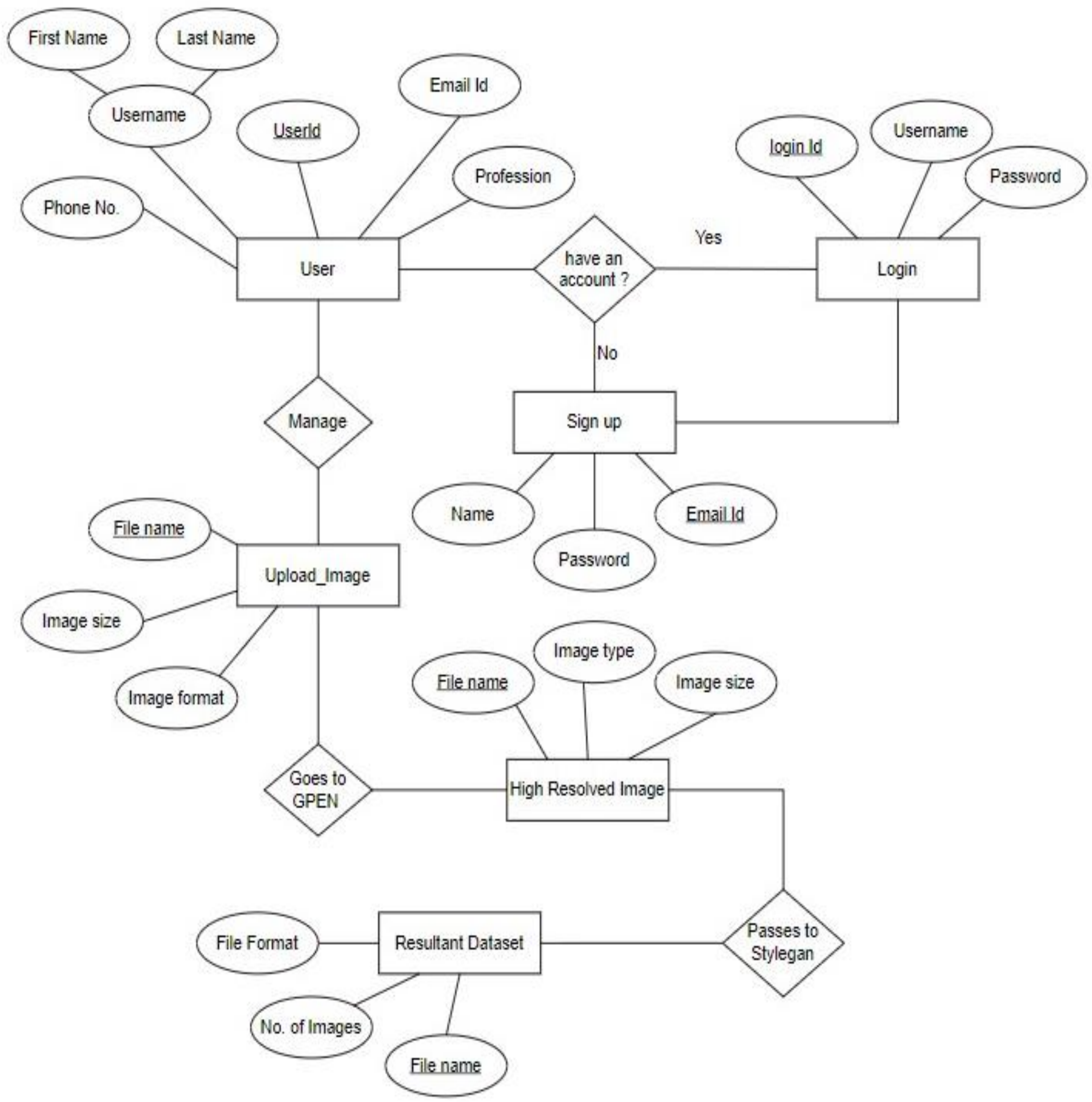

Fig. 4.5 ER Diagram

CHAPTER 5

IMPLEMENTATION

5.1 Introduction Tools and Technologies Used

5.1.1 Toolkit:

The toolkit for the integrated GFP-GAN and StyleGAN project for image restoration would include the following components:

1. **Python:** As a primary programming language for developing machine learning models and data processing pipelines.
2. **Tensorflow or PyTorch:** Deep learning frameworks for implementing and training GAN models such as GFP-GAN and StyleGAN.
3. **Numpy:** For numerical computations and array manipulation required during the preprocessing and post processing of images.
4. **Opencv:** For image processing tasks such as reading, writing, and transforming images, as well as handling various image formats.
5. **Scikit-learn:** For implementing machine learning algorithms for tasks such as data preprocessing, feature extraction, and model evaluation.
6. **Jupyter Notebook:** For interactive development, experimentation, and documentation of the project, allowing for easy sharing and collaboration.
7. **CUDA and cuDNN:** If using NVIDIA GPUs for accelerated training and inference of deep learning models.

8. **Git:** Version control system for tracking changes to the project codebase and collaborating with team members.

5.1.2 Coding Environment:

1. Visual Studio Code
2. Google Colaboratory
3. Jupyter Notebook

CHAPTER 6

TESTING, AND MAINTENANCE

6.1 Testing Techniques and Test Cases Used

The testing performed is white box testing.

6.1.1 Test Levels

The testing to be performed is white box testing. The testing is performed by the developer's team along with QA and Configuration Manager.

1. Unit Testing:

- Test individual components of the system, such as GFPGAN and StyleGAN.
- Ensure that each unit operates as expected and handles edge cases correctly.

2. Integration Testing:

- Test the integration of various modules and components within the system.
- Verify that data flows correctly between components and observe the changes made when the output to one component is inserted as input in other

3. Functional Testing:

- Verify that the system can correctly identify noise in images and improve it accordingly.
- StyleGAN must be able to generate the test cases of inserted noise-free image.

4. Performance Testing:

- Evaluate the system's speed and responsiveness, ensuring that it can handle real time checkout scenarios.
- Assess how the system performs under various workloads and peak usage conditions.

6.1.2 Test Cases Used:

Table No. 6.1 – Test cases used

1	Test Case	Input	Expected Output
2	Image Restoration	Corrupt Image	Restored Image
3	Data Augmentation	High-pixel image	Augmented dataset
4	GFP-GAN Input	Low-resolution image	High-quality image
5	StyleGAN Input	GFP-GAN output	Augmented dataset
6	Clarity Test	Original image	High-clarity image
7	Color Restoration	Image with color distortions	Color-corrected image
8	Data Integrity	Augmented dataset	Accurate data representation
9	Realism Check	Restored image	Realistic appearance
10	Robustness Test	Corrupted image with complex backgrounds	High-quality restoration
11	Speed Test	High-resolution image	Fast processing time

Table No.6.2 – Boundary Testing

Case	a	b	Expected output
1	512	1	Error in image size
2	512	2	Error in image size
3	512	256	Error in image size
4	512	511	Error in image size
5	512	512	GFPGAN training
6	1	512	Error in image size
7	2	512	Error in image size
8	256	512	Error in image size
9	511	512	Error in image size
10	512	512	GFPGAN training

CHAPTER 7

RESULTS AND DISCUSSIONS

7.1 Presentation of Results

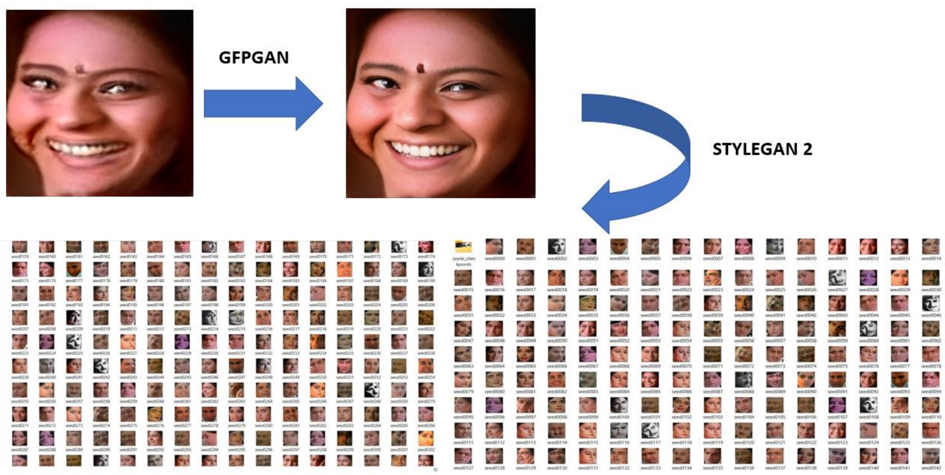

Fig 7.1 Final output image

7.2 Key Findings

The project led to several key insights:

1. **Model Synergy:** The integration of GFP-GAN with StyleGAN resulted in higher quality image restoration than when using either model independently. This synergy suggests a promising direction for future research in composite model architectures.
2. **Robustness to Variations:** The models demonstrated robust performance across diverse image types, including medical imaging and low-light conditions, underscoring the versatility of the approach.

3. **Scalability:** The developed models are scalable and can be deployed effectively in real-time applications, providing substantial improvements over traditional methods.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

In conclusion, the integration of GFP-GAN and StyleGAN represents a significant milestone in the field of image restoration and enhancement. This project has demonstrated the potential of combining two powerful generative models to achieve substantial improvements in image quality, pixel accuracy, and detail. By strategically leveraging the strengths of GFP-GAN for initial image restoration and StyleGAN for dataset augmentation, we have unlocked new possibilities for a wide range of applications, including medical imaging, satellite imagery restoration, and facial recognition.

The success of this project underscores the importance of innovation and collaboration in addressing complex challenges such as image restoration. By bringing together cutting-edge technologies and methodologies, we have been able to push the boundaries of what is possible in image processing and computer vision. Moreover, the integration of GFP-GAN and StyleGAN has not only enhanced visual fidelity but has also paved the way for future advancements in image synthesis, analysis, and interpretation.

Future Scope:

Despite the significant progress achieved in this project, there are several avenues for further exploration and enhancement:

1. **Further Model Optimization:** Continuously refining and optimizing the integrated GFP-GAN and StyleGAN models to achieve even higher levels of image quality and restoration accuracy. This could involve fine-tuning model parameters,

exploring novel architectures, and incorporating additional training data.

2. **Exploration of Additional Applications:** Investigating new domains and applications where image restoration can have a transformative impact. This could include areas such as environmental monitoring, art restoration, and forensic analysis.
3. **Real-Time Image Restoration:** Developing real-time image restoration systems capable of processing and restoring images on-the-fly for applications requiring immediate feedback and response. This would involve optimizing the computational efficiency of the models and leveraging hardware acceleration techniques.
4. **Domain-Specific Adaptation:** Tailoring the image restoration algorithms to specific domains or use cases to address unique challenges and requirements. This could involve domain-specific training data, specialized loss functions, and customized post-processing techniques.
5. **Ethical Considerations:** Addressing ethical considerations and potential biases in image restoration algorithms, particularly in applications such as facial recognition. It is essential to ensure fairness, transparency, and accountability in the deployment of these technologies.
6. **Integration with Emerging Technologies:** Integrating image restoration capabilities with emerging technologies such as edge computing, IoT devices, and 5G networks to enable distributed and efficient image processing. This would enable seamless integration with existing infrastructure and improve scalability and accessibility.

7. **Collaborative Research and Development:** Collaborating with academic institutions, industry partners, and government agencies to advance the state-of-the-art in image restoration and related fields. By sharing knowledge, resources, and expertise, we can accelerate progress and address real-world challenges more effectively.

In summary, the integration of GFP-GAN and StyleGAN represents a significant step forward in image quality enhancement, offering a potent method for high-fidelity image generation and dataset enrichment. By continuing to innovate, collaborate, and explore new possibilities, we can further advance the field of image restoration and unlock its full potential for the benefit of society.

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Acceptance of Research Paper

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Blind Image Restoration and Data Augmentation

Publisher: IEEE Cite This PDF

Harsh Khatter; Nandini Tyagi; Avishi Tayal; Piyush Gupta **All Authors**

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.

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Government of India

सत्यमेव जयते

Application Details	
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APPLICATION TYPE	ORDINARY APPLICATION
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APPLICANT NAME	**1 . Harsh khatter** **2 . Avishi Tayal** **3 . Nandini Tyagi** **4 . Piyush Gupta**
TITLE OF INVENTION	SYSTEM AND METHOD FOR BLIND IMAGE RESTORATION AND DATA AUGMENTATION
FIELD OF INVENTION	COMPUTER SCIENCE
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