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Filling Large Missing Area of Images by Using Hybrid Deep Learning Model

by

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7
*Capstone project report (CSE 4098C) submitted in partial fulfillment of the
requirements for the degree of*

Bachelor of Science in Computer Science and Engineering

Under the supervision of

Md. Aktaruzzaman Pramanik



**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
UNIVERSITY OF LIBERAL ARTS BANGLADESH**

SPRING 2025

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DECLARATION

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⁷ We declare that this capstone project report entitled *Filling Large Missing Area of Images by Using Hybrid Deep Learning Model* is the result of our own work except as cited in the references. The capstone project report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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We are greatly indebted to our honorable teachers of the Department of Computer Science and Engineering at the University of Liberal Arts Bangladesh who taught us during the course of our study. Without any doubt, their teaching and guidance have completely transformed us to the persons that we are today.

We are extremely thankful to our parents for their unconditional love, endless prayers and caring, and immense sacrifices for educating and preparing us for our future. We would like to say thanks to our friends and relatives for their kind support and care.

Finally, we would like to thank all the people who have supported us to complete the project work directly or indirectly.

Sakibul Hasan Rafi, Md. Nayamat Immam, Khan Adnan Rohan, Abidur Rahman, and Zannatul Ferdous

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Date: May 12, 2025

7

To my beloved parents
The source of my inspiration.

– Sakibul Hasan Rafi

Dedicated to
My loving parents

– Md. Nayamat Immam

Dedicated to my
Late paternal uncle.

– Khan Adnan Rohan

Dedicated to
My beloved parents
Forever grateful.

– Abidur Rahman

Dedicated to
My beloved parents.

– Zannatul Ferdous

ABSTRACT

This project presents a novel approach to filling large gaps in high-resolution images using a hybrid model consisting of U-Net as the generator and Generative Adversarial Networks (GANs) as the discriminator. The U-Net model is used to restore missing portions of the image, ensuring that important details are preserved, while the GAN is employed to generate realistic textures that seamlessly blend with the existing parts of the image. By training these models together, we aim to address the challenge of inpainting large gaps in broken or damaged images, producing natural and high-quality results. Additionally, to facilitate real-world applications, we have developed a web application that integrates this hybrid model, allowing users to upload and process images for practical use. The web application provides an intuitive interface for image inpainting, making it accessible for real-life scenarios such as restoring old photographs or repairing damaged images. We will compare the performance of our proposed model with existing inpainting techniques to assess its effectiveness across various image types. Our goal is to provide a reliable and efficient solution for image restoration that can be used in a variety of applications, from digital media repair to cultural heritage preservation.

Keywords: Image Inpainting, U-Net, Generative Adversarial Networks (GANs), Image Restoration, Hybrid Model, Web Application, High-Resolution Images, Realistic Texture Generation.

Contents

1	Introduction	1
1.1	Background Literature	1
1.2	Problem statement	1
1.3	Aims, objectives and Motivation	2
1.3.1	Aims	2
1.3.2	Objective	2
1.3.3	Motivation	3
1.4	Project Specification	3
2	Literature Review	4
3	Methodology	15
3.1	U-Net Architecture	15
3.2	GAN Architecture	16
3.3	Dataset Description	17
3.4	Our Implemented Architecture	18
3.5	Implementation Workflow	20
3.5.1	Data Loading and Preprocessing:	21
3.5.2	Training Process:	22
3.5.3	Model Optimization:	23
3.5.4	Testing Process:	23
4	Design and Development	24
4.1	System Development	24
4.1.1	Web Application	24
4.1.1.1	Web Interface Overview	25
4.1.1.2	Image Input Demonstration	26

4.1.1.3	Processed Output Demonstration	27
4.1.2	Key Features	28
4.1.3	System Workflow	29
4.2	Necessary Adopted Tools	30
4.2.1	Model Creation Tools	30
4.2.2	Design Tools	30
4.2.3	Web Development Tools	31
4.2.4	Communication Tools	31
4.3	Project Cost Analysis	32
4.4	Timeline	33
5	Result Analysis	35
5.1	Generator and Discriminator Losses	35
5.1.1	Generator Loss	35
5.1.2	Discriminator Loss	36
5.2	Training Performance Evaluation	37
5.2.1	Training Matrix Analysis	37
5.2.2	Training Loss Analysis	39
5.3	Confusion Matrix Evaluation	40
5.3.1	Confusion Matrix Analysis of GAN Model	41
5.3.2	Confusion Matrix Analysis of Our Hybrid Model	42
5.4	Quantitative Performance Comparison	43
5.4.1	Training Result Analysis	43
5.4.2	Testing Result Analysis	43
5.5	Visual Outputs Comparison	44
6	Conclusions	46
6.1	Social, Legal, Ethical, and Environmental Issues	46
6.1.1	Social Aspects	46
6.1.2	Legal Aspects	46
6.1.3	Environmental Aspects	47
6.2	Ethical and Professional Principles	47
6.2.1	Data Privacy and Security	47
6.2.2	Accuracy and Reliability	47
6.2.3	Ethical Use of Technology	48

6.2.4	Transparency and Consent	48
6.3	Brief Summary	48
6.4	Future works	49
References		50

List of Figures

3.1	U-Net Architecture (Adapted from Ronneberger et al. (2021))	16
3.2	GAN Architecture (Adapted from Little et al. (2021))	17
3.3	CelebA-HQ ⁴⁹ Dataset Samples	18
3.4	Place365 Dataset Samples	18
3.5	Implemented Architecture	19
3.6	Our Implementation Workflow	21
4.1	HomePage ⁵⁰ Interface	25
4.2	Input Interface	26
4.3	Output Interface	27
4.4	Key Features	28
4.5	System Workflow	29
4.6	Google Colab and Kaggle	30
4.7	Canva Lucid Chart and Draw-Io	31
4.8	VS Code and Google Chrome	31
4.9	Discord, Whatsapp and Google Meet	32
4.10	Cost Breakdown Chart	32
4.11	Project Timeline	34
5.1	GAN Training Metrics	38
5.2	Our Hybrid Model Training Metrics	38
5.3	GAN Training Loss	39
5.4	Our Hybrid Model Training Loss	40
5.5	GAN Confusion Matrix	41
5.6	Our Hybrid Model Confusion Matrix	42
5.7	Visual Outputs Comparison	45

List of Tables

2.1	Literature Review Analysis	14
3.1	Dataset Description	17
3.2	Dataset Train and Test	22
4.1	Estimated Project Cost Breakdown	33
5.1	Comparison Table of Training Phase	42
5.2	Comparison Table of Testing Phase	44

Chapter 1

Introduction

1.1 Background Literature

51
Image inpainting, the process of filling in missing or damaged parts of an image, is essential in fields like photo restoration, video editing, and computer vision Hou et al. (2024). However, traditional methods often struggle with large missing areas, leading to blurry or unrealistic results that fail to blend naturally, especially in high-resolution images where maintaining fine details and textures is crucial. This project proposes an innovative method that combines Generative Adversarial Networks (GANs) Hong et al. (2024) and U-Net architectures to address these challenges. GANs excel at generating realistic textures, while U-Net preserves spatial details through its encoder-decoder structure and skip connections Zuo & Tiddeman (2024). By integrating these methods, the proposed model aims to restore large missing areas in high-resolution images, ensuring that inpainted sections look natural and blend seamlessly with their surroundings. The model is designed to overcome the limitations of existing inpainting techniques, with a focus on handling complex, high-detail images. It will be tested on diverse datasets and evaluated for its ability to deliver strong, high-quality results in various real-world applications, such as restoring old or damaged photos.

1.2 Problem statement

6
Traditional inpainting methods are conducted by using pixel expansion or texture matching, and the inpainting effect is better in small defect areas and pure color areas. When the defect area is large, there will be problems such as blur and poor

structural connectivity with the method. To solve this limitation of traditional image inpainting methods, we have used deep learning technology in the field of image inpainting techniques to achieve significant results.

1.3 Aims, objectives and Motivation

1.3.1 Aims

The aim of this project is to develop an advanced image inpainting technique capable of accurately filling large missing areas in high-resolution images. The primary goal is to ensure that the inpainted sections not only retain realistic textures but also blend seamlessly with the surrounding content, addressing the common issue of blurry or unrealistic restorations seen in existing methods Yang & Ruhaiyem (2024). This will be achieved through a hybrid approach that combines the strengths of Generative Adversarial Networks (GAN) and U-Net architectures. By leveraging these techniques, the project seeks to overcome the limitations of current inpainting models, particularly in complex and high-detail images Maitin et al. (2024).

1.3.2 Objective

- Implement a method that combines GANs and U-Net to leverage their strengths in generating high-quality and coherent image content.
- Focus on enhancing the model's ability to process high-resolution images with detailed textures, ensuring the inpainted sections maintain the original visual integrity.
- Aim to enhance the overall accuracy of the inpainting process, particularly for large missing areas, by testing and refining the model against existing benchmarks.
- Evaluate the model's performance using various metrics to ensure naturalness and seamless blending of inpainted images.
- Validate the model's robustness on a diverse dataset of images to demonstrate its effectiveness across a range of complex scenarios, ensuring it can handle various real-world applications.

1.3.3 Motivation

82
Image inpainting techniques have made significant progress in the past few years, but they still struggle when it comes to filling in large gaps, especially in high-resolution images with detailed textures Yang & Ruhaiyem (2024). The result is often blurry and unrealistic, also making it hard for the restored image to blend naturally with its surroundings Xu et al. (2023). This issue is particularly important because accurate inpainting has many real-world applications, from photo editing to medical imaging. Motivated by these challenges, our project aims to develop a more effective inpainting approach that can handle these difficult cases better Maitin et al. (2024). By improving both the accuracy and efficiency of the inpainting process, our goal is to create a solution that delivers more realistic and seamless restorations, even when dealing with complex textures and large missing areas. This research could help improve the quality of image restoration across various fields, making it a valuable contribution to the growing need for advanced image processing technologies.

1.4 Project Specification

Develop a hybrid deep learning model that uses U-NET as a generator and GAN as a discriminator to restore images with large missing areas. The system aims to produce realistic, high-quality reconstructions that are contextually consistent with the original content.

- **Accuracy Target:** Achieve a Structural Similarity Index Measure (SSIM) of $\geq 85\%$ for visual similarity between original and restored images.
- **Dataset Compliance:** Use only publicly available datasets (e.g., CelebA-HQ, Places365).
- **Deployment:** Develop a functional web application that allows users to upload and restore images.
- **Success Criteria:** Successfully restore 256×256 images within a working web-based prototype, ensuring accurate, fast, and realistic image restoration.

Chapter 2

Literature Review

Boli Fang et. al. published a paper on "Deep Generative Inpainting with Comparative Sample Augmentation" in 2022. The research aims to improve image inpainting by developing a model that uses comparative sample augmentation to fill in missing or corrupted image areas more effectively. The results show that this approach significantly enhances both the visual quality and performance metrics compared to existing methods. The experiments demonstrate that using additional contextual information from similar samples helps the model learn better, resulting in more coherent and realistic image completions Fang et al. (2022) .

Omar Elharroussa et al. published a paper in 2024 titled "Transformer-based Image and Video Inpainting: Current Challenges and Future Directions." The paper reviews recent advancements in image and video inpainting using transformer techniques, emphasizing how transformers enhance inpainting quality by capturing long-range dependencies and understanding global context, which traditional CNNs often overlook. The findings indicate that transformer-based methods outperform conventional approaches in key metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), providing better reconstruction of textures and details. This paper serves as a valuable guide for new researchers, categorizing various approaches and discussing challenges and future research opportunities in the field Elharrouss et al. (2024) .

Enes Demirağ et al. published a paper titled "Image Inpainting with Deep Learning" in 2021. The paper explores various methods for replacing undesirable regions in images, such as those caused by aging or unwanted objects. It compares

traditional techniques like Navier-Stokes and fast marching with deep learning methods like EdgeConnect and Generative Multi-column Convolutional Neural Networks. The study finds that deep learning approaches, particularly GANs and CNNs, generally produce more realistic results, especially in complex situations with larger missing areas. It also introduces two novel inpainting methods inspired by these techniques to enhance visual realism [Demirağ & Bengü \(2021\)](#).

⁴⁵
Shuyi Qu published a paper on "Towards Theoretical and Practical Image Inpainting with Deep Neural Networks" in 2022. The aim of the paper is to find and address problems in current image inpainting methods, like not modeling image details well and the need for better user interaction. The author suggests new models and methods, tested through experiments. The findings include a model that uses attention to improve image completion and a two-step process that uses edge information to guide the inpainting [Qu \(2022\)](#).

²
Xin Li et. al. published a paper on "SemID: Blind Image Inpainting with Semantic Inconsistency Detection" in 2024. The aim of the paper is to propose a two-stage blind image inpainting network that detects semantically inconsistent regions and generates plausible content for restoration, especially for unknown damaged areas in realistic images. Researchers used a novel blind inpainting model for this study. The findings show that the proposed method produces visually and structurally complete results, outperforming previous approaches in handling diverse degradations with high accuracy [X. Li et al. \(2024\)](#).

¹²
Puranam Revanth Kumar et al. published a paper on "Inpainting Non-Anatomical Objects in Brain Imaging Using Enhanced Deep Convolutional Autoencoder Network." The study focuses on improving medical imaging, particularly MRI and CT scans, by using a deep convolutional autoencoder to fill in missing areas and remove irrelevant objects. This technique enhances diagnostic accuracy by producing sharper and more realistic images. The results showed that this approach outperformed traditional methods, achieving a PSNR of 52.44, SSIM of 0.95, and UQI of 0.96, while maintaining high quality in both low- and high-resolution images [Kumar et al. \(2024\)](#).

David Josué Barrientos Rojas et al. published a paper titled "A Review on Image Inpainting Techniques and Datasets" in 2020. The paper reviews both traditional and deep learning-based image inpainting methods, outlining their evolution and categorizing them. It emphasizes that deep learning techniques, especially GANs and context encoders, have significantly improved image inpainting, producing more consistent and realistic results. However, it also notes that challenges remain, such as reducing computation costs and managing complex image masks Rojas et al. (2020) .

Jing Yang et. al. published a paper on "Review of Deep Learning-Based Image Inpainting Techniques" in 2024. The aim of this paper is to provide a thorough review of deep learning methods for image inpainting by identifying gaps in previous reviews and categorizing these models. It classifies techniques into four types and analyzes key loss functions and evaluation metrics, helping researchers improve the models. The study offers insights into how these methods can be applied across different fields, including natural, detection, and artistic images Yang & Ruhaiyem (2024) .

Pedro Orii Antonacio published a paper titled "Completing Face Pictures: A Study on Image and Facial Inpainting Methods" in 2021. The research aims to improve facial inpainting techniques by training the DeepFillv2 model on a more diverse dataset called FFHQ, rather than the biased CelebA-HQ. The modified model showed better performance, producing more realistic and contextually appropriate results across various facial features and demographics. Quantitative evaluations using metrics like PSNR and SSIM confirmed significant improvements, highlighting the benefits of using a more representative dataset for training Antonacio (2021) .

Cheng Li et. al. published a paper titled "Multi-stage Image Inpainting Using Improved Partial Convolutions" in 2024. The research aims to improve image inpainting by introducing a multi-stage approach that uses enhanced partial convolutions to better handle large missing areas. The results show that this method significantly outperforms existing techniques on datasets like CelebA and Places2,

effectively restoring fine textures and reducing blurriness in images. Both quantitative and qualitative evaluations indicate that the use of improved partial convolutions leads to more photorealistic outputs, showcasing substantial improvements in image quality [C. Li et al. \(2024\)](#).

²⁴
Qingyu Liu et al. published a paper in 2023 titled "Mask Face Inpainting Based on Improved Generative Adversarial Network." The research develops an advanced model to restore facial images obscured by masks, a relevant issue due to the COVID-19 pandemic. The study introduces an improved generative adversarial network (GAN) that incorporates attention mechanisms and enhanced residual modules for high-quality inpainting results. The findings demonstrate that this model significantly outperforms existing methods like pix2pix and SRGAN in image quality, as shown by better evaluation metrics such as SSIM and PSNR, effectively restoring masked faces while preserving realistic facial features [Liu & Juanatas \(2023\)](#).

³⁹
Mehrshad Momen Tayefeh et. al. published a paper on "Image inpainting for corrupted images by using the semi-super resolution GAN" in 2024. The aim of the paper is to restore missing image segments and remove unwanted elements while preserving the background. Researchers used a modified SRGAN, which enhanced image quality and detail. Their approach involved a unique discriminator network, improving the assessment of image quality [Momen-Tayefeh et al. \(2024\)](#).

²⁰
Zhao Ruixia et al. published a paper on "Image Inpainting Research Based on Deep Learning" in 2020. The aim of the research is to enhance image repair quality using deep learning, particularly GANs. The study used a dual-path network and tested it on the Places2 dataset, outperforming existing models. Their method achieved a PSNR of 24.06 and an SSIM of 0.857, showing notable improvements in texture and structure [Z. Li & Ruixia \(2020\)](#).

⁹⁶
Dr. Hansaraj Wankhede et. al. published a paper on "Image Restoration using Deep Learning" in 2023. The paper aims to develop a deep learning system to restore images by reducing noise, deblurring, and improving resolution. The proposed U-Net architecture achieved an 85-90% accuracy in restoring images with

various issues, outperforming traditional methods in both quality and performance. It effectively addresses tasks like denoising, deblurring, and enhancing image resolution [Wankhede et al. \(2023\)](#) .

Surbhi Sarode et al. published a paper on "Image Restoration and Enhancement Using Deep Learning" in 2020. The aim of the research is to develop deep learning techniques for tasks like noise removal, inpainting, haze removal, and low-light enhancement using CNNs and other methods. The study achieved strong results: 80% accuracy for noise removal, 87% for inpainting, 96% for haze removal, and 89% for enhancing low-light images, significantly improving image quality [Sarode et al. \(2020\)](#) .

Haritha L et. al. published a paper on "Image Inpainting Using Deep Learning Techniques: A Review" in 2023. The paper aims to provide an overview of the advancements in image inpainting, focusing on how deep learning methods like CNNs and GANs have improved the quality and realism of inpainted images. The review highlights the effectiveness of models like U-Net and Context Encoders in handling complex image details and preserving fine structures. It shows how these approaches have outperformed traditional methods, achieving better results on datasets like CelebA and Paris StreetView [Haritha & Prajith \(2023\)](#) .

Xuan Ju et. al. published a paper on "Image Inpainting Models are Effective Tools for Instruction-guided Image Editing" in 2024. The paper aims to introduce a new solution for image editing that combines image inpainting models with large language models (LLMs) and diffusion models to improve editing accuracy and visual quality. The proposed method, IIIE, outperformed previous approaches in terms of instruction-following and content preservation, ranking first in the MAGIC benchmark. This approach demonstrates that using both LLMs and diffusion models leads to better and more faithful image editing results [Ju et al. \(2024\)](#) .

Thomas Bapaume et. al. published a paper on "Image Inpainting and Deep Learning to Forecast Short-Term Train Loads" in 2021. The paper aims to introduce a new method for predicting train loads by converting metro traffic into images

and using a U-net deep learning model for forecasting. The U-net framework outperformed traditional methods, showing strong accuracy even during disruptions like strikes. The model was validated with real data from the Paris metro, demonstrating its effectiveness in forecasting short-term train loads [Bapaume et al. \(2021\)](#).

⁵⁴
Zhen Qin et. al. published a paper on "Image inpainting based on deep learning: A review" in 2021. The aim of the paper is to restore damaged areas in images and create high-quality reconstructions using deep learning. To conduct this study, the researchers reviewed various methods, noting that while techniques work well with small areas of damage, they struggle when more than half of the image is missing. The findings indicate that inpainting works better for faces, while natural scenes still need improvement [Qin et al. \(2021\)](#).

¹¹
Bellaj K et al. published a paper titled "Enhancing Image Inpainting through Image Decomposition and Deep Neural Networks" in 2023. The paper proposes a method that combines Domain Decomposition Methods (DDM) with Deep Neural Networks (DNN) to improve image inpainting for high-resolution images with complex textures. This approach enhances image quality and reduces computational costs compared to traditional techniques. It shows better accuracy in reconstructing images with paint stains, particularly in preserving edges and textures during the inpainting process [Bellaj et al. \(2023\)](#).

²
Minda Yao et al. published a paper in 2023 titled "A Review of Image Inpainting Methods Based on Deep Learning." The research provides a comprehensive overview of the evolution of image inpainting techniques, particularly those using deep learning. It categorizes various methods by optimization strategies, network designs, and training approaches, highlighting their strengths and weaknesses. The findings indicate that deep learning methods are now preferred due to their superior ability to extract semantic features and generate images compared to traditional techniques. However, the paper also notes ongoing challenges in the field that need to be addressed for further advancement [Xu et al. \(2023\)](#).

²
Ana M. Maitin et. al. published a paper on "Evaluating Activation Functions in

GAN Models for Virtual Inpainting: A Path to Architectural Heritage Restoration” in 2024. The paper aims to test different activation functions for filling in missing parts of images of Greek temples. The researchers used math and expert opinions to compare them and found that ReLU worked best, while Mish and Leaky ReLU did not perform well Maitin et al. (2024) .

Ayoub Charef et. al. published a paper on “Improving Image Inpainting through Contextual Attention in Deep Learning” in 2024. The aim of the paper is to make image inpainting better by using a mix of techniques to fill in missing parts of images more effectively. The researchers created a new method that performed better than older techniques. Their results show that this approach keeps images looking realistic, even when large areas are missing Charef & Ouqour (2024) .

Eiffel Aqila Amarendra et al. published a paper on “Object Removal System for Urban Imagery Using Image Segmentation and Inpainting with a Deep Learning Approach” in 2024. The aim of the paper is to create a system that automatically detects, removes, and reconstructs areas with unwanted objects in urban images. They used the DeepLabv3+ model for image segmentation and an inpainting module. The system was evaluated using PSNR, SSIM, FID, and a human perception survey, showing strong performance in both objective and subjective assessments Amarendra & Munir (2024) .

Jennyfer Susan et al. published a paper titled “Deep Learning Inpainting Model on Digital and Medical Images-A Review” in 2023. The paper examines the effectiveness of deep learning methods, such as CNNs and GANs, for image inpainting in digital and medical images. It highlights how these methods surpass traditional techniques by reconstructing missing pixels more accurately, particularly in complex textures. The review demonstrates that deep learning models enhance image quality, reflected in higher PSNR and SSIM scores, making them valuable for both digital restoration and medical imaging tasks Susan & Subashini (2023) .

Frederic Madesta et. al. published a paper on “Deep learning-based conditional inpainting for restoration of artifact-affected 4D CT images” in 2024. The aim of the paper is to develop a deep learning method to repair damaged areas in

4D CT images used in radiotherapy. Researchers used patient-specific data and partial convolutions for the restoration. The findings show a significant reduction in artifacts, with improvements of 52% for interpolation artifacts and 59% for double structure artifacts, effectively removing 72% of noticeable issues in heavily affected images [Madesta et al. \(2024\)](#).

Ciprian Corneanu et al. published a paper titled "Latent Paint: Image Inpainting in Latent Space with Diffusion Models" in 2024. The paper introduces LatentPaint, a method for image inpainting in the latent space of diffusion models that reduces computational costs and inference time while maintaining high image quality. LatentPaint outperforms models like RePaint and GAN-based approaches in both efficiency and image quality, achieving superior results on datasets like CelebA-HQ and LSUN-Bedrooms. It generates coherent and semantically consistent images across various scenes, including human faces and indoor environments [Corneanu et al. \(2024\)](#).

Nermin Mohamed Fawzy Salem PhD published a paper on "A Survey on Various Image Inpainting Techniques" in 2021. The aim of the paper is to provide an overview of image inpainting methods, categorizing them into traditional and deep learning approaches. The study evaluates these techniques, highlighting their strengths and weaknesses. The findings show that traditional methods are effective for small areas but struggle with larger ones, while deep learning techniques achieve more realistic results in complex tasks [Salem \(2021\)](#).

Weize Quan et al. published a paper on "Deep Learning-based Image and Video Inpainting: A Survey" in 2024. The aim of the paper is to review deep learning techniques for image and video inpainting. The study covers various methods, including CNNs, VAEs, GANs, and diffusion models, categorizing them by their inpainting approach. The researchers found that techniques like FGVC and FGT are good at recovering textures using neighboring frames, while transformer-based models, such as STTN and FuseFormer, perform well in restoring object structure [Quan et al. \(2024\)](#).

Ziqi Sheng et al. published a paper on "Deep Generative Network for Image

Inpainting with Gradient Semantics and Spatial-Smooth Attention” in 2024. The paper aims to enhance image inpainting by introducing a two-stage generative network along with a new spatial-smooth attention mechanism. This method improves the restoration of missing image structures while ensuring consistency and reducing artifacts. The results show that the GS-SSA method outperforms existing techniques in key metrics like SSIM and PSNR, producing more realistic and coherent images, particularly in handling textures and structural integrity Sheng et al. (2024) .

Edgar Schönfeld et al. published a paper on “A U-Net Based Discriminator for Generative Adversarial Networks” in 2020. This research addresses the challenge of generating coherent images with realistic object shapes and textures using Generative Adversarial Networks (GANs). The authors propose a novel U-Net based discriminator architecture that enhances the generator’s ability to produce high-quality images by providing detailed per-pixel feedback while maintaining global coherence. The study reveals that the U-Net discriminator significantly improves the training of GANs by allowing for both global and local image assessments. Additionally, the authors introduce a per-pixel consistency regularization technique based on CutMix data augmentation. This method fosters a more robust learning process by penalizing inconsistencies in pixel-level predictions, thereby enhancing the discriminator’s ability to distinguish between real and fake images Schonfeld et al. (2020) .

Hancheng Zuo et al. published a paper on “A U-Net Architecture for Inpainting Lightstage Normal Maps” in 2023. The aim of this research is to restoring missing parts of facial normal maps generated from light stage data. The methodology used in there is a U-Net-based GAN model with skip connections to improve reconstruction quality, particularly for complex surface details. The model combines cosine similarity and adversarial losses to ensure accurate and realistic inpainting but it struggles with large occlusions, complex masks, and requires high computational resources. Future improvements are needed to enhance the model’s ability to handle challenging scenarios, improve evaluation methods, and explore more efficient architectures Zuo & Tiddeman (2024) .

Tzung-Pei Hong et al. published a paper on “Conditional-GAN-based Face Inpainting Approaches with Symmetry and View-degree Utilization” in 2024. The aim of this research is to address challenges such as geometric and symmetric variations in face inpainting. The methodology used in there is a combined hybrid model of Conditional Generative Adversarial Networks (CGAN) and face landmark predictions, where facial landmark prediction provides key points about facial structure, and using these landmarks, Conditional Generative Adversarial Networks guide the inpainting process and restore missing areas. But the following method struggles with very large occlusions and extreme side views, where landmark predictions become less accurate and improvement is needed in restoration for these challenging cases, extracting detailed features like makeup or gaze direction, and enhancing noise reduction techniques [Hong et al. \(2024\)](#) .

Chuangchuang Dong et al. published a paper on “Image Inpainting Method Based on AU-GAN” in 2024. The aim of the paper is to improve the quality of image inpainting, particularly for large missing regions, by proposing a dual-stream AU-Net network that integrates attention mechanisms and position coding into a GAN framework. To conduct this study, researchers used a dual-stream U-Net structure with attention modules and position coding, and incorporated the least squares GAN (LSGAN) loss, alongside CelebA and Paris datasets for evaluation. The findings of this paper are that their proposed method achieved superior performance in terms of PSNR and SSIM metrics, enhancing the texture and structural details of repaired images while reducing network convergence time [Dong et al. \(2024\)](#) .

Yanyang Hou et al. published a paper on “Symmetric Connected U-Net with Multi-Head Self-Attention (MHSA) and WGAN for Image Inpainting” in 2024. The aim of the paper is to develop an improved image inpainting model that utilizes Symmetric Connected U-Net (SC-Unet) architecture, Multi-Head Self-Attention (MHSA), and Wasserstein GAN (WGAN) to enhance the reconstruction of large missing areas in images. To conduct this study, researchers used a combination of U-Net with skip connections, dilated convolutional neural networks, MHSA layers, and WGAN loss, tested on CelebA-HQ and ImageNet datasets. The findings of this paper are that the proposed model significantly improved PSNR and SSIM metrics

by 10% and 2.94%, respectively, compared to state-of-the-art methods, achieving smoother reconstructions and better semantic consistency Hou et al. (2024).

In summary, the literature review reveals significant image inpainting advancements, focusing on traditional and deep learning techniques. Recent studies emphasize the superiority of deep learning methods like GANs, CNNs, and transformers, outperforming older approaches in handling complex textures and large missing areas. Techniques such as comparative sample augmentation, transformer-based models, and attention mechanisms have enhanced visual quality, structural integrity, and computational efficiency. Additionally, these methods have extended beyond natural images to applications in medical imaging and video inpainting, demonstrating their versatility across various fields. Table 2.1 summarizes the methods used by different authors, categorizing their research into three main types: GAN, U-NET, and GAN & U-NET. The table shows which authors employed each method, providing an overview of the prevalent techniques in image inpainting. In our proposed model, we are using both GAN and U-NET on the same model.

Author	GAN	U-NET	GAN & U-NET
Elharrouss et al. (2024)	✓	×	×
Momen-Tayefeh et al. (2024)	✓	×	×
Kumar et al. (2024)	✓	×	×
Yang & Ruhaiyem (2024)	✓	×	×
Maitin et al. (2024)	✓	×	×
Charef & Ouqour (2024)	✓	×	×
Amarendra & Munir (2024)	✓	×	×
Corneanu et al. (2024)	×	✓	×
Liu & Juan (2023)	✓	×	×
Wankhede et al. (2023)	×	✓	×
Haritha & Prajith (2023)	×	✓	×
Xu et al. (2023)	✓	×	×
Bapaume et al. (2021)	×	✓	×
Salem (2021)	✓	×	×
Our Proposed Model	✓	✓	✓

Table 2.1: Literature Review Analysis

Chapter 3

Methodology

In this section, we present the methodology used to achieve image inpainting through our proposed architecture Figure 3.5, which integrates Generative Adversarial Networks (GANs) Figure 3.2 with the U-Net model Figure 3.1. This hybrid approach addresses both the structural consistency and high visual fidelity of the inpainted images. We describe the workflow, including the generator and discriminator setup, the training process, the data preprocessing steps, and the evaluation metrics. The methodology also includes a detailed exploration of the adversarial and pixel-wise loss functions that guide the generator to produce realistic images while maintaining fine details.

3.1 U-Net Architecture

The U-Net architecture, as depicted in the diagram Figure 3.1, is a fully convolutional network designed for image segmentation tasks. It consists of a symmetric encoder-decoder structure, where the encoder compresses spatial information while capturing contextual features through a series of convolutional layers (3x3 kernels with ReLU activation) and 2x2 max-pooling operations for down-sampling.

The decoder mirrors the encoder, progressively up-sampling the compressed feature maps using 2x2 transposed convolutions (up-conv) and reconstructing spatial details. Skip connections between corresponding layers of the encoder and decoder play a critical role in transferring fine-grained spatial features, enabling precise localization during segmentation. The final layer applies a 1x1 convolution to produce a segmentation map with pixel-wise class probabilities. This architecture is particularly effective for biomedical and other dense prediction tasks due to

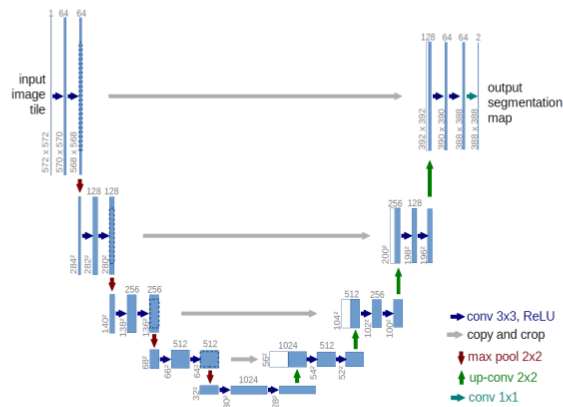


Figure 3.1: U-Net Architecture (Adapted from [Ronneberger et al. \(2021\)](#))

its ability to integrate multi-scale information while preserving high-resolution outputs.

37

3.2 GAN Architecture

The GAN architecture consists of two main components: the generator and the discriminator [Figure 3.2](#). The generator produces new data based on random noise or input data, aiming to create outputs indistinguishable from real data. The discriminator, a multilayer neural network, evaluates the outputs by comparing them with real samples, determining whether the generated content is real or fake.

Both components engage in an adversarial process, where the generator improves its outputs to fool the discriminator, while the discriminator becomes better at identifying fake data. This adversarial training ensures the generator produces highly realistic and coherent inpainted images. By leveraging the GAN's discriminator, our approach effectively restores large missing areas with seamless integration into the original image.

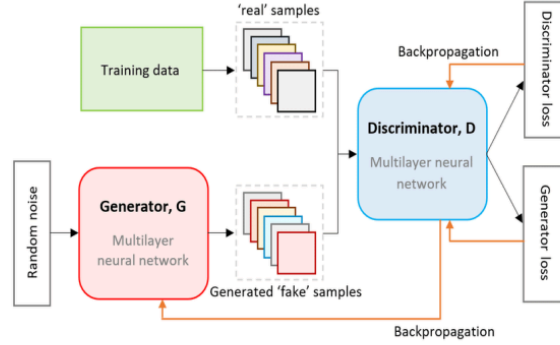


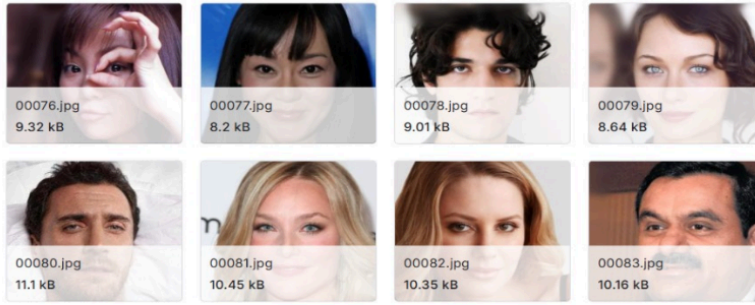
Figure 3.2: GAN Architecture (Adapted from [Little et al. \(2021\)](#))

3.3 Dataset Description

In this project, we utilized two publicly available datasets, CelebA-HQ and Places365, to train and evaluate our hybrid deep learning model. CelebA-HQ provided high-quality facial images for focused restoration tasks, while Places365 offered diverse scene images to ensure broader generalization. The Table 3.1 below provides a detailed description of each dataset.

Dataset Name	Description	Size & Resolution	Purpose
CelebA-HQ Figure 3.3	High-quality facial image dataset featuring diverse attributes like age, gender, lighting, and expression variations.	30,000 images at 1024×1024 pixels	Training and testing model performance on facial structure restoration.
Places365 Figure 3.4	Large-scale scene-centric dataset with a wide variety of natural and man-made environments across 365 categories.	Over 1.8 million images	Training and testing model performance on complex background and scene restoration.

Table 3.1: Dataset Description



49
Figure 3.3: CelebA-HQ Dataset Samples

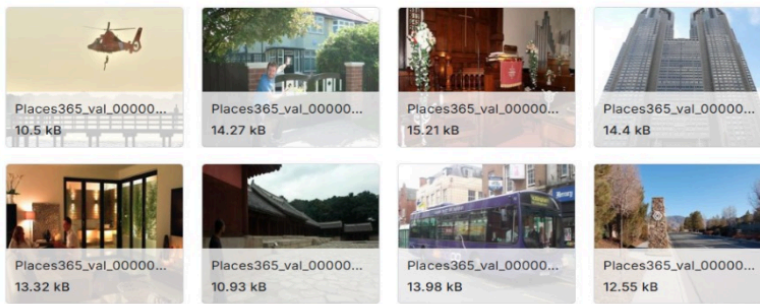


Figure 3.4: Place365 Dataset Samples

3.4 Our Implemented Architecture

The architecture Figure 3.5 implemented in this research integrates a hybrid deep learning approach combining the strengths of a U-NET-based generator and a multilayer GAN discriminator to address the challenge of large-area image restoration. The process initiates with random noise input into the Generator (G), constructed upon the U-NET architecture. U-NET's encoder-decoder structure, with its skip connections, enables the model to effectively capture both high-level semantic information and low-level spatial details essential for accurate image reconstruction.

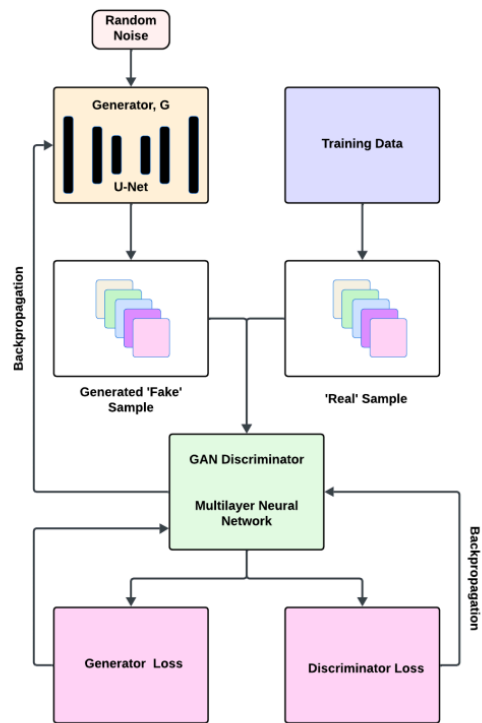


Figure 3.5: Implemented Architecture

In parallel, authentic training data samples drawn from the CelebA-HQ and Places365 datasets are introduced. The generator produces a synthetic ('fake') sample, attempting to restore the missing regions, while the training data provides the corresponding real samples for comparative evaluation.

Both real and generated samples are subsequently fed into the Discriminator, implemented as a multilayer neural network. The discriminator's role is to distinguish between authentic and synthetic images, providing adversarial feedback essential for refining the generator's outputs.

The optimization process is guided by two primary loss functions:

- **Adversarial Loss:** Calculated using Binary Cross-Entropy Loss (BCE), it compels the generator to produce outputs that are indistinguishable from real images while enabling the discriminator to correctly classify real and synthetic samples.
- **Pixelwise Loss:** Computed using L1 Loss, it ensures that the generated image closely matches the real image at the pixel level, promoting fine-grained detail preservation.

The Generator Loss is a combination of adversarial loss and pixel-wise reconstruction loss, driving the generator to both fool the discriminator and minimize pixel-level differences.

The Discriminator Loss is based on adversarial loss, encouraging accurate discrimination between real and fake samples.

Training is conducted through backpropagation, with loss signals propagated to update the parameters of both the generator and the discriminator. This adversarial learning process fosters progressive improvement in the realism and contextual coherence of the restored images.

Through the integration of U-NET's representational capacity and GAN's adversarial learning mechanism, the proposed architecture effectively addresses the complexities associated with filling large missing regions in images.

3.5 Implementation Workflow

The workflow of our implemented hybrid model Figure 3.6 follows a structured and modular process, ensuring efficient training and testing of the hybrid deep

learning model for large-area image restoration. The major stages are outlined as follows:

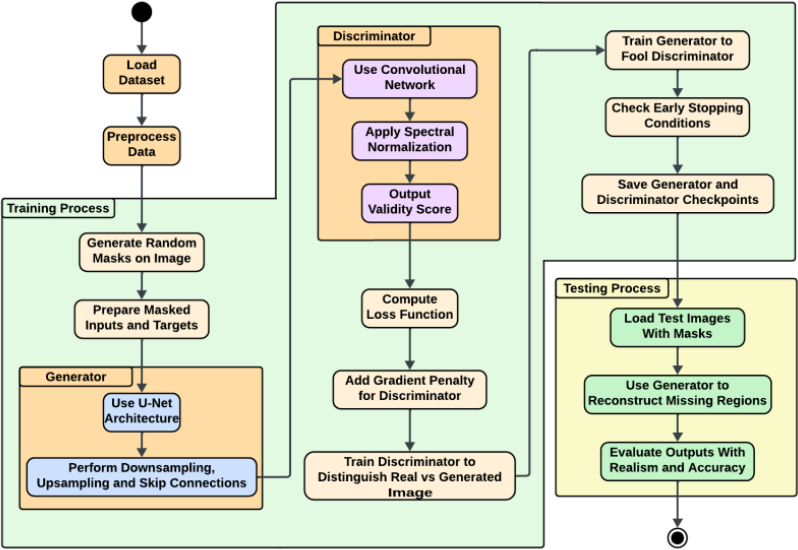


Figure 3.6: Our Implementation Workflow

3.5.1 Data Loading and Preprocessing:

The dataset is initially loaded and undergoes several preprocessing operations essential for optimizing model performance. Each image is resized to a fixed resolution of 256×256 pixels and normalized to a pixel intensity range of [-1, 1] to stabilize training. A random square mask is applied to the images to simulate missing regions, creating paired inputs for the supervised learning framework, where the masked images serve as inputs and the corresponding original images serve as ground truth targets. Following preprocessing, the dataset is partitioned into an 80:20 ratio, allocating 80% of the images for training and 20% for testing,

ensuring sufficient generalization capability while maintaining evaluation rigor. The following dataset preprocessing ratio is shown in Table 3.2

Dataset	Training	Testing	Total
CelebA-HQ	24000	6000	30000

Table 3.2: Dataset Train and Test

3.5.2 Training Process:

The training phase is designed around a two-network adversarial framework comprising a generator and a discriminator, each with specialized architectural features to optimize large-area image inpainting.

- Generator Module:** The generator employs a U-NET architecture, characterized by an encoder-decoder structure with symmetric skip connections. The encoder path performs successive downsampling operations through convolutional layers and max-pooling, enabling the extraction of high-level semantic features from the masked inputs. The decoder path performs upsampling operations via transposed convolutions, progressively reconstructing the spatial resolution while utilizing skip connections to retain low-level contextual details. This design ensures the generator can accurately infer and restore complex missing regions, maintaining structural and textural consistency with the unmasked areas.
- Discriminator Module:** The discriminator is constructed as a deep convolutional neural network (DCNN) integrated with spectral normalization layers to enforce Lipschitz continuity, promoting stable adversarial training. It processes both real and generated samples to output a validity score, indicating the probability of each sample being authentic. Through hierarchical feature extraction, the discriminator learns to distinguish fine-grained differences between real images and generated restorations. Its feedback drives the generator to progressively enhance the realism and fidelity of its outputs.

The adversarial interplay between the generator and discriminator is governed by a composite loss function consisting of adversarial loss (Binary Cross-Entropy) and pixelwise reconstruction loss (L1 Loss). The dataset is partitioned using an 80:20

training-to-testing ratio to ensure robust model generalization and to accurately evaluate performance under unseen data conditions. Training is conducted using mini-batch stochastic gradient descent with Adam optimizers and incorporates early stopping and model checkpointing strategies to prevent overfitting and ensure convergence.

3.5.3 Model Optimization:

The generator is trained to fool the discriminator, while the discriminator is trained to accurately distinguish between real and generated images. Early stopping criteria and model checkpoints are employed to ensure stable convergence and prevent overfitting.

3.5.4 Testing Process:

During testing, masked images are input into the trained generator. The generator reconstructs the missing regions, and the quality of the output is evaluated based on realism and pixel-level accuracy.

In summary, the implemented workflow systematically integrates data preprocessing, adversarial training of the generator and discriminator, and rigorous testing to restore large missing areas in images. The use of U-NET architecture, spectral normalization, and combined loss functions ensures that the restored outputs maintain both visual realism and structural accuracy.

Chapter 4

Design and Development

4.1 System Development

⁵⁵ This section provides an overview of the development process for the web application that we developed for the hands-on experience of our image inpainting system. It demonstrates the key features and functionalities of the application, including the seamless user interface for image upload and inpainting result display. Additionally, the section outlines the system workflow, from user input to the final output, ensuring a smooth and efficient process. We also present the costing and timeline associated with the development, highlighting the ⁸⁶resources allocated and the milestones achieved during the project. The goal of this section is to provide a comprehensive understanding of the technical and operational aspects of the developed system.

4.1.1 Web Application

To effectively deploy our image inpainting model in real-life scenarios, a user-friendly application is essential. To bridge the gap between our model and practical usage, we developed a web application that allows users to easily interact with the system. This application serves as the interface for uploading images, processing them through the model, and viewing the inpainted results. By integrating the model into a web application, we ensure that the system is accessible, scalable, and ready for real-world implementation, making it convenient for users to harness the power of our inpainting solution.

4.1.1.1 Web Interface Overview

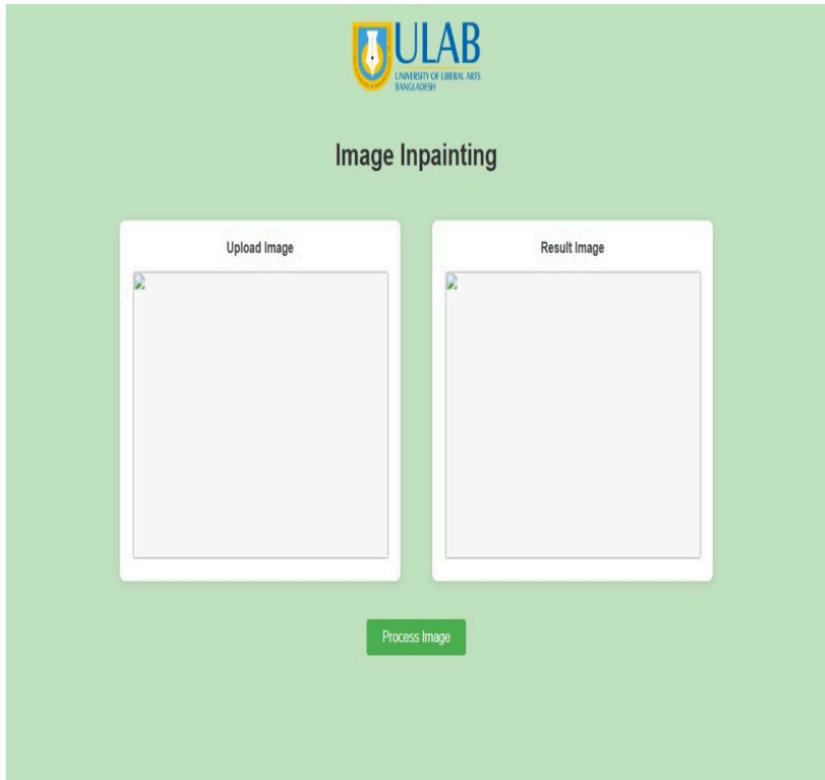


Figure 4.1: HomePage Interface

This is the web interface Figure 4.1 of our project that enables users to upload images and process them for image inpainting. The "Upload Image" section allows the user to select an image, and the "Result Image" section displays the processed output after applying the inpainting model. This interactive interface provides an intuitive user experience for image restoration tasks.

4.1.1.2 Image Input Demonstration

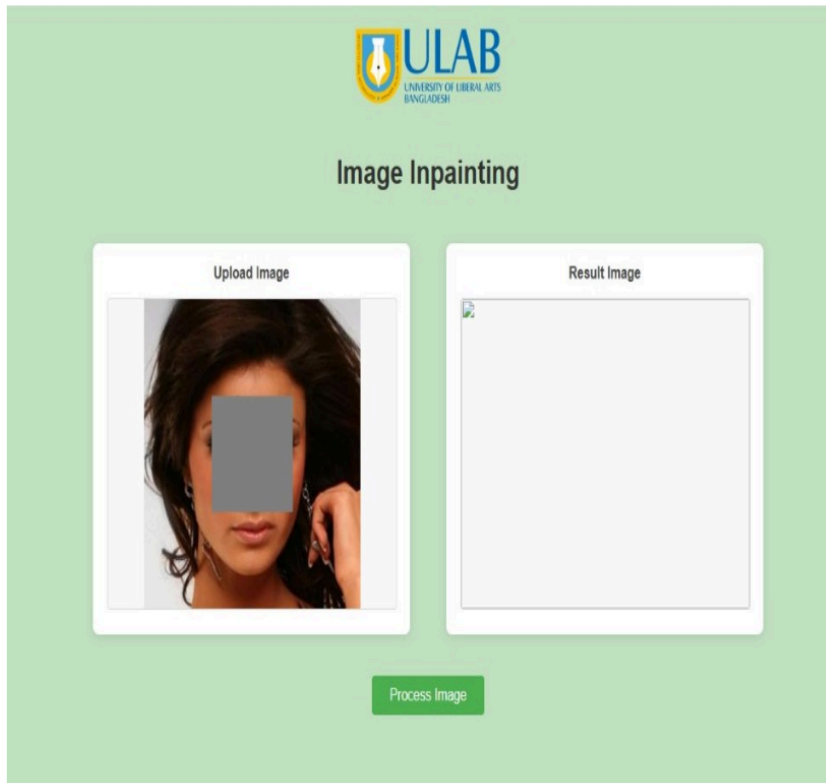


Figure 4.2: Input Interface

The image Figure 4.2 showcases the image input demonstration section of the web interface of our project, where users can upload their selected image. This input section allows the system to process the uploaded image for further inpainting or restoration tasks.

4.1.1.3 Processed Output Demonstration

The image Figure 4.3 shows the processed output demonstration section of the web interface of our project, where users can view the result after the image inpainting process is completed. The output image is displayed on the right, showing the areas that have been filled or restored based on the input image.

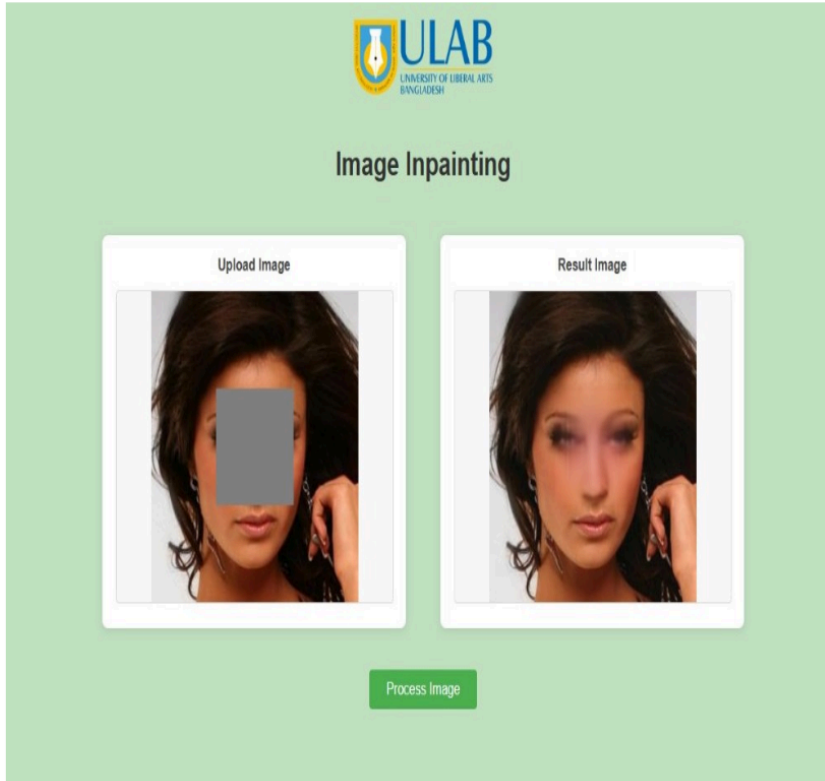


Figure 4.3: Output Interface

4.1.2 Key Features

The diagram Figure 4.4 illustrates the sequential workflow of the image restoration web application. The user uploads a damaged image, which is first handled by a preprocessing module that resizes and normalizes the input.

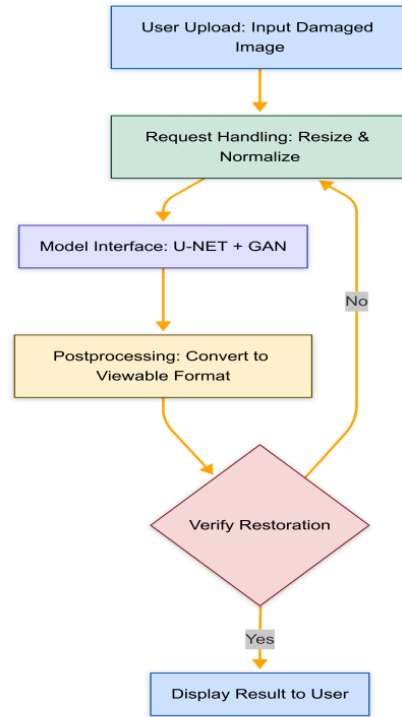


Figure 4.4: Key Features

The processed image is then passed to the hybrid deep learning model U-NET & GAN for restoration. Following inference, the image undergoes postprocessing to convert it into a viewable format. A verification step assesses the restoration quality. If the result meets the defined threshold, it is displayed to the user otherwise, the

process loops back for retrieval or reprocessing. This design ensures modularity, quality assurance, and real-time user interaction.

4.1.3 System Workflow

The system workflow diagram Figure 4.5 illustrates the end-to-end process of user interaction with the web application for image inpainting. The workflow begins with the user uploading a broken or masked image through the front-end interface. The server handles this request and forwards the input to the preprocessing module, where the image is resized and normalized to meet the input specifications of the hybrid deep learning model.

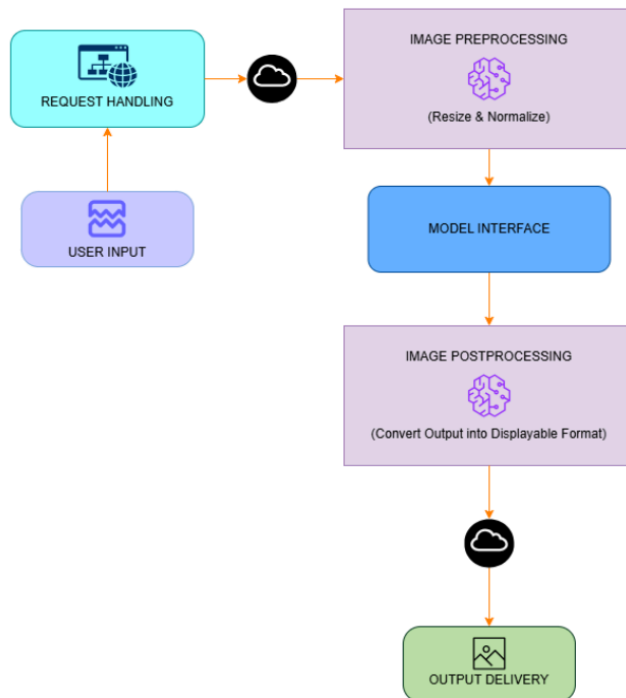


Figure 4.5: System Workflow

Next, the preprocessed image is passed into the model interface, which internally invokes the trained hybrid model comprising a U-NET generator and a GAN-based discriminator. The model processes the input and outputs a restored image. Following inference, the output undergoes postprocessing to convert it into a standard displayable format. Finally, the restored image is returned to the user through the front-end interface, completing the cycle of image restoration.

4.2 Necessary Adopted Tools

Throughout the development of our project, we utilized various tools across different stages to support model creation, design, development, and collaboration. These tools enhanced our productivity, efficiency, and communication during the research process.

4.2.1 Model Creation Tools

To build and train our hybrid deep learning model, we used Google Colab Pro and Kaggle. These cloud-based platforms provided the necessary computational resources, GPU acceleration, and a collaborative environment for efficient training, testing, and experimentation.



Figure 4.6: Google Colab and Kaggle

4.2.2 Design Tools

For designing diagrams and graphical representations included in our project, we used Canva, Lucidchart and Draw-IO. These tools helped us create clear, professional, and visually appealing figures that effectively convey the architecture and workflow of our model.



Figure 4.7: Canva Lucid Chart and Draw-Io

4.2.3 Web Development Tools

We developed our web application using Visual Studio Code as our primary code editor and Google Chrome for testing and debugging. These tools enabled a smooth front-end and back-end development process, ensuring the usability of our application.



Figure 4.8: VS Code and Google Chrome

4.2.4 Communication Tools

Effective collaboration was maintained using WhatsApp, Google Meet, and Discord. These platforms supported real-time discussions, meetings, and coordination, especially during different phases of our project.



Figure 4.9: Discord, Whatsapp and Google Meet

4.3 Project Cost Analysis

The following Table 4.1 outlines the estimated costs associated with the development and implementation of our project. These expenses include model training resources, web deployment, design tools, communication, and other project-related utilities. The following pie chart Figure 4.10 illustrate the graphical representation of the cost analysis of our project.

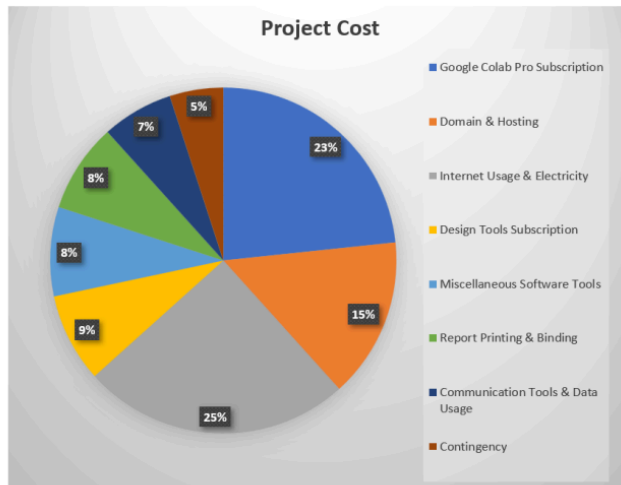


Figure 4.10: Cost Breakdown Chart

Item	Description	Estimated Cost (BDT)
Google Colab Pro Subscription	GPU-enabled cloud platform for model training/testing	2,800
Domain & Hosting	Web deployment and server hosting	1,800
Internet Usage & Electricity	Broadband and power for the project duration	3,000
Design Tools Subscription	Canva Pro, Lucidchart for diagram and UI design	1,000
Miscellaneous Software Tools	IDEs, browser tools, extensions	1,000
Report Printing & Binding	Final report copies for submission	1,000
Communication Tools & Data Usage	Google Meet, WhatsApp, Discord utilities	800
Contingency	Buffer for minor unforeseen costs	600
Total Estimated Cost		12,000 BDT

Table 4.1: Estimated Project Cost Breakdown

4.4 Timeline

The Gantt chart Figure 4.11 outlines the timeline and sequential flow of major tasks involved in the completion of our project. The timeline of our project are from August 2024 to May 2025. The project began with domain selection, literature review, and problem identification in August and September, followed by finalizing the problem statement and developing the implementation workflow in the subsequent months. The hybrid model design, dataset preparation, and training were conducted between November and March, with overlapping phases for testing, debugging, and web application development. Integration of the model with the

web interface and final documentation were completed by May. This structured timeline ensured an organized and parallel execution of research, development, and deployment phases.

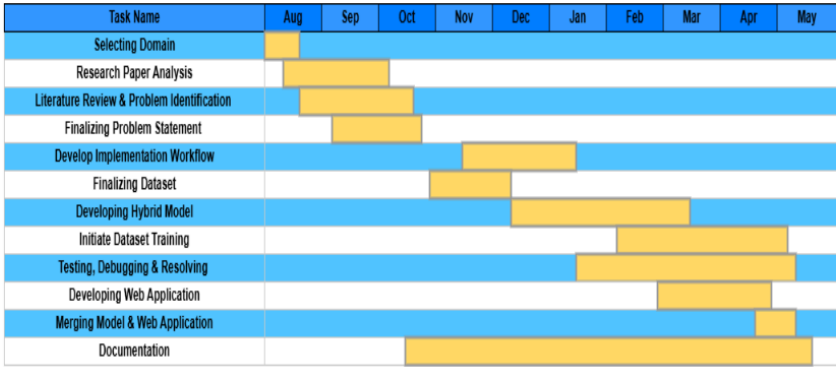


Figure 4.11: Project Timeline

Chapter 5

Result Analysis

5.1 Generator and Discriminator Losses

In our image inpainting project, the Generator and Discriminator networks are trained in opposition, following the standard framework of Generative Adversarial Networks (GANs). Below is a detailed explanation of the loss functions used for both the generator and the discriminator in this model.

5.1.1 Generator Loss

The Generator is responsible for producing realistic inpainted images. Its objective is to create images that can fool the Discriminator into classifying them as real. The generator's loss consists of two primary components:

- **Adversarial Loss:** The Adversarial Loss encourages the generator to produce images that are indistinguishable from real images. This loss is calculated using Binary Cross-Entropy Loss (BCE), where the generator's goal is to maximize the likelihood that the discriminator classifies the generated images as real.

$$\mathcal{L}_{D_{real}} = -\mathbb{E} [\log(D(x))]$$

Where $D(G(z))$ is the discriminator's prediction of whether the generated image $G(z)$ is real or fake. $G(z)$ is the image generated by the generator Maitin et al. (2024).

- **Pixel-wise Loss (L1 Loss):** The Pixel-wise Loss ensures that the generator not only produces realistic images but also generates images that closely match

the ground truth at the pixel level. This is done using L1 Loss, which calculates the absolute difference between the pixel values of the generated and real images.

$$\mathcal{L}_{G_{pixel}} = \frac{1}{N} \sum_{i=1}^N |x_i - \hat{x}_i|$$

Where x_i is the pixel value of the original image, $\hat{x}_i$ is the pixel value of the generated image, and N is the total number of pixels in the image Yang & Ruhaiyem (2024).

- **Total Generator Loss:** The total generator loss is the weighted sum of both the adversarial loss and pixel-wise loss, with the pixel-wise loss being given more importance by a factor λ .

$$\mathcal{L}_G = \mathcal{L}_{G_{adv}} + \lambda \mathcal{L}_{G_{pixel}}$$

Where λ is a hyperparameter that adjusts the relative importance of the pixel-wise loss in the overall generator loss Yang & Ruhaiyem (2024).

5.1.2 Discriminator Loss

The Discriminator is responsible for distinguishing between real and generated images. The discriminator's objective is to correctly classify real images as real and fake images as fake. The loss function for the discriminator consists of three components.

- **Real Loss:** The Real Loss measures how well the discriminator can classify real images as real.

$$\mathcal{L}_{D_{real}} = -\mathbb{E} [\log(D(x))]$$

Where $D(x)$ is the discriminator's prediction for the real image x Maitin et al. (2024).

- **Fake Loss:** The Fake Loss measures how well the discriminator can classify fake images that are generated by the generator as fake.

$$\mathcal{L}_{D_{fake}} = -\mathbb{E} [\log(1 - D(G(z)))]$$

Where $D(G(z))$ is the discriminator's prediction for the fake image generated by the generator Yang & Ruhaiyem (2024).

- **Gradient Penalty (GP):** To ensure stable training and prevent the discriminator from becoming too sharp, a Gradient Penalty is added. The gradient penalty encourages the discriminator to maintain a smooth decision boundary by penalizing large gradients in its decision function.

$$\mathcal{L}_{GP} = \mathbb{E} \left[(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2 \right]$$

Where $\hat{x}$ is an interpolated image between real and fake images, and $\nabla_{\hat{x}} D(\hat{x})$ is the gradient of the discriminator with respect to the interpolated image Maitin et al. (2024).

- **Total Discriminator Loss:** The total discriminator loss is the sum of the real loss, fake loss, and the gradient penalty, with the gradient penalty weighted by a factor λ_{GP} .

$$\mathcal{L}_D = \frac{1}{2} (\mathcal{L}_{D_{real}} + \mathcal{L}_{D_{fake}}) + \lambda_{GP} \mathcal{L}_{GP}$$

Where λ_{GP} is a hyperparameter that controls the weight of the gradient penalty Yang & Ruhaiyem (2024).

5.2 Training Performance Evaluation

This section presents the training performance of both the existing GAN model and our proposed Hybrid Model (U-Net + GAN). The evaluation is illustrated through visual representations of training metrics, highlighting the models' learning behavior and performance progression over epochs.

5.2.1 Training Matrix Analysis

Figure 5.1 illustrates the training performance of the existing GAN-based model across multiple epochs. The graph shows a steady improvement in all four metrics—Precision, Recall, Accuracy, and F1 Score—as training progresses. Accuracy starts high and continues to increase, reaching close to 0.98, indicating strong overall classification capability. Precision and recall gradually converge toward 0.93, showing balanced improvement in detecting relevant features and minimizing false predictions. The F1 Score also consistently rises, reflecting a healthy balance

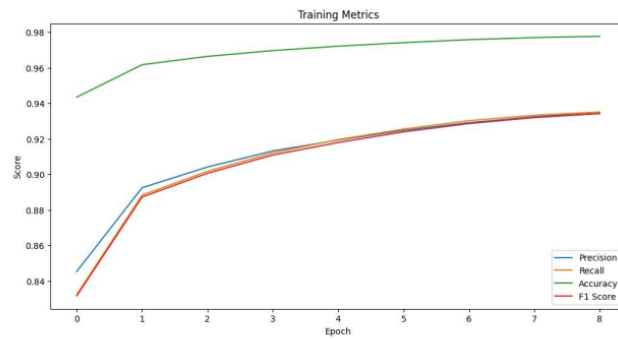


Figure 5.1: GAN Training Metrics

between precision and recall. This upward trend confirms that the GAN model effectively learns image inpainting features with increased training iterations.

Figure 5.2 shows the training metrics of our Hybrid Model (U-Net + GAN) over successive epochs. All four evaluation metrics—Precision, Recall, Accuracy, and F1 Score—demonstrate consistent and strong improvement throughout the training.

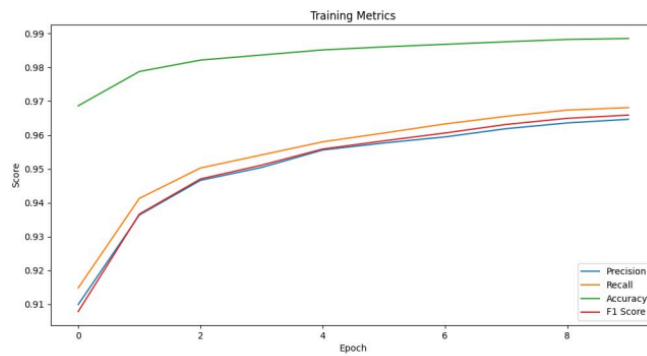


Figure 5.2: Our Hybrid Model Training Metrics

The model achieves high accuracy (approaching 0.99) early in training and continues to refine precision and recall, both exceeding 0.96 by the final epoch.

Compared to the existing GAN-only model, our hybrid model shows faster convergence and higher final metric values, particularly in recall and F1 score, indicating better balance and fewer misclassifications. This reflects the effectiveness of integrating U-Net with GAN for robust image inpainting performance.

5.2.2 Training Loss Analysis

Figure 5.3 illustrates the training loss trends of the GAN-based model over several epochs. The Generator Total Loss and Discriminator Loss show a consistent decline, indicating stable learning and improved performance over time.

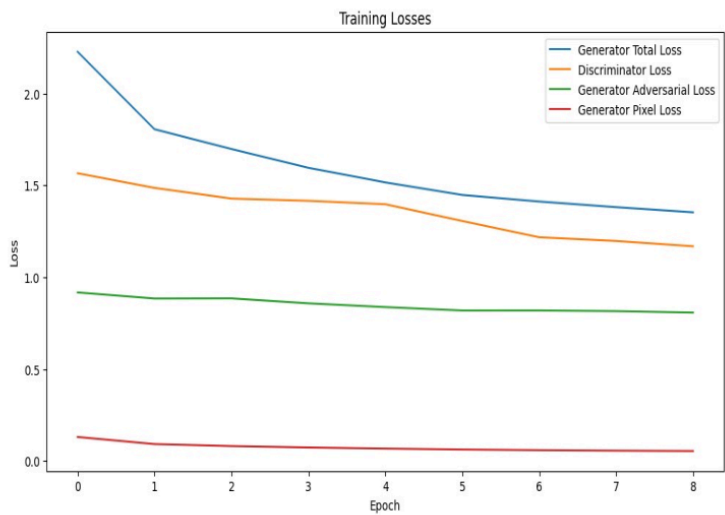


Figure 5.3: GAN Training Loss

The Generator Adversarial Loss decreases moderately, reflecting the generator's increasing ability to fool the discriminator. Meanwhile, the Generator Pixel Loss remains low and steadily declines, demonstrating the model's improving accuracy in reconstructing fine-grained image details. Overall, the decreasing loss values across all components validate the effectiveness of the training process for image inpainting tasks.

Figure 5.4 presents the training loss curves of our Hybrid Model (U-Net + GAN) across epochs. The Generator Total Loss and Discriminator Loss both show a steady decrease in the early stages, reflecting effective model learning.

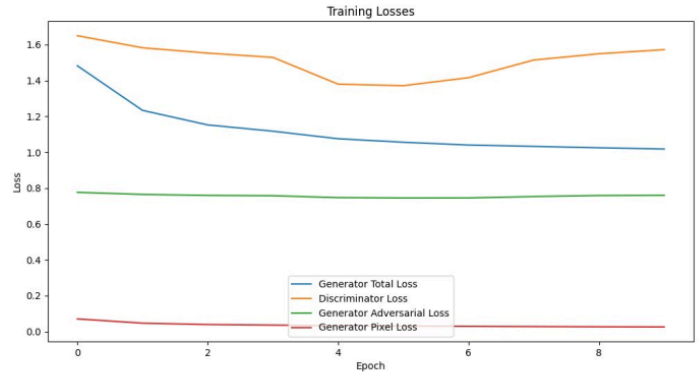


Figure 5.4: Our Hybrid Model Training Loss

The Generator Adversarial Loss and Pixel Loss remain consistently low, indicating stable adversarial training and accurate pixel-level reconstruction. Compared to the GAN-only model, our hybrid approach achieves lower total generator loss and better stability in pixel loss. Although the discriminator loss slightly fluctuates after the midpoint, the overall trend confirms the hybrid model’s stronger learning capacity and more refined image restoration capabilities.

5.3 Confusion Matrix Evaluation

This section presents the confusion matrix evaluation of both the existing GAN model and our proposed Hybrid Model (U-Net + GAN). By comparing classification outcomes, we analyze each model’s ability to correctly distinguish between relevant and irrelevant image regions.

5.3.1 Confusion Matrix Analysis of GAN Model

The confusion matrix of the existing GAN model in Figure 5.5 shows the model's classification performance during the testing phase. It correctly identified 165,441 true negatives (Actual 0, Predicted 0) and 26,381 true positives (Actual 1, Predicted 1).

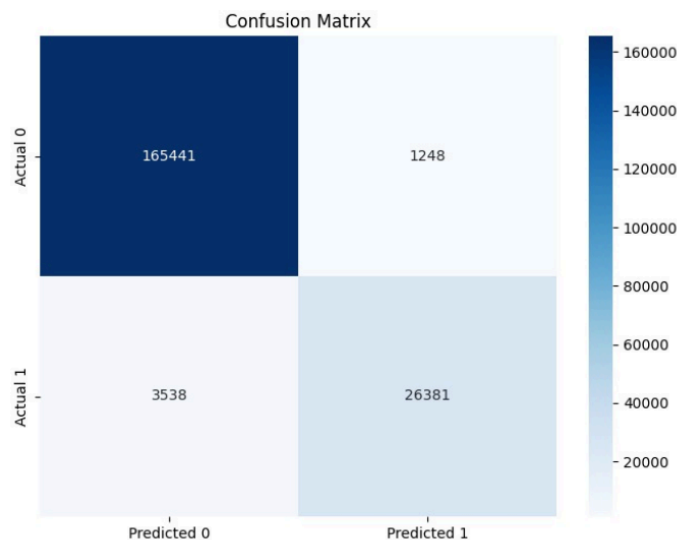


Figure 5.5: GAN Confusion Matrix

However, it also produced 1,248 false positives (Actual 0, Predicted 1) and 3,538 false negatives (Actual 1, Predicted 0). These results indicate that while the GAN model performs well in identifying both classes, there is still a notable number of misclassifications, particularly in detecting positive cases. This reinforces the need for a more robust architecture, as addressed in our proposed hybrid model.

5.3.2 Confusion Matrix Analysis of Our Hybrid Model

The confusion matrix of our proposed Hybrid Model (U-Net + GAN) demonstrates in Figure 5.6 a significant improvement over the existing GAN-based model. The hybrid model correctly classified 155,981 true negatives and 36,979 true positives.

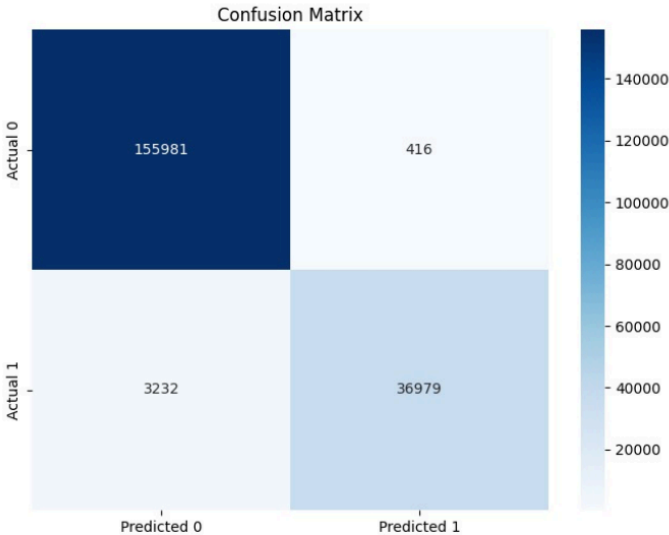


Figure 5.6: Our Hybrid Model Confusion Matrix

It reduced false positives to 416, compared to 1,248 in the GAN model, and slightly decreased false negatives to 3,232, from 3,538. These results indicate better precision and recall in the hybrid model, as it more accurately identifies both classes. The reduced number of misclassifications reflects the hybrid model’s superior ability to restore large missing regions in images while maintaining structural and contextual accuracy.

5.4 Quantitative Performance Comparison

This section provides a quantitative performance comparison between the existing GAN model and our proposed Hybrid Model (U-Net + GAN). Training and testing phase metrics, Precision, Recall, Accuracy, and F1 Score are presented in tabular form to highlight the improvements achieved by the hybrid approach.

5.4.1 Training Result Analysis

Table 5.1 presents a performance comparison between the existing image inpainting model based solely on Generative Adversarial Networks (GAN) and our proposed hybrid model combining U-Net and GAN, evaluated during the training phase.

Metric Name	GAN	Our Model (U-NET + GAN)
Precision	0.9350	0.9646
Recall	0.9351	0.9681
Accuracy	0.9778	0.9885
F1 Score	0.9342	0.9659

Table 5.1: Comparison Table of Training Phase

The results demonstrate that the hybrid model significantly outperforms the standalone GAN across all key performance metrics. In terms of precision, the hybrid model achieved 0.9646, compared to 0.9350 from the existing model, indicating a more accurate identification of relevant pixels. Recall improved from 0.9351 to 0.9681, reflecting the model's enhanced sensitivity to true positive detections. Overall accuracy increased from 0.9778 to 0.9885, confirming the higher general correctness of our model's predictions. Furthermore, the F1 score, which harmonizes precision and recall, rose from 0.9342 to 0.9659, validating the hybrid model's balanced performance. These training phase results substantiate the effectiveness of using U-Net as a generator in conjunction with a GAN-based discriminator to produce structurally consistent and visually realistic inpainting outcomes.

5.4.2 Testing Result Analysis

Table 5.2 illustrates the comparative performance of the existing GAN-based model and the proposed Hybrid model (U-Net + GAN) during the testing phase.

Metric Name	GAN	Our Model (U-NET + GAN)
Precision	0.9548	0.9889
Recall	0.8817	0.9196
Accuracy	0.9757	0.9814
F1 Score	0.9168	0.9530

Table 5.2: Comparison Table of Testing Phase

The hybrid model demonstrates clear improvements across all evaluation metrics. Precision increased from 0.9548 to 0.9889, indicating a more accurate detection of relevant image features. Recall also improved significantly from 0.8817 to 0.9196, reflecting the model's enhanced capability in identifying all relevant pixels, even in complex missing regions. The accuracy of the hybrid model rose from 0.9757 to 0.9814, confirming its higher overall correctness in image reconstruction tasks. Additionally, the F1 score, which balances both precision and recall, improved from 0.9168 to 0.9530, underscoring the hybrid model's robust and reliable performance. These results affirm that integrating U-Net as a generator with a GAN discriminator provides a more effective solution for high-quality image inpainting in real-world scenarios.

5.5 Visual Outputs Comparison

Figure 5.7 compares the output of our Hybrid Model with the existing GAN-only model for image inpainting. The top-left image shows the Original Image, followed by the Masked Image in the top-right, where a portion of the face is removed for inpainting. The GAN Output on the bottom left demonstrates the result from the GAN-only model, which shows noticeable texture distortion and lacks structural coherence in the missing region. In contrast, our Model Output on the bottom-right produced by our Hybrid Model restores the missing area with improved realism, preserving finer details and enhancing overall visual quality. This comparison highlights the superior performance of our hybrid approach in maintaining structural integrity and generating visually coherent results.

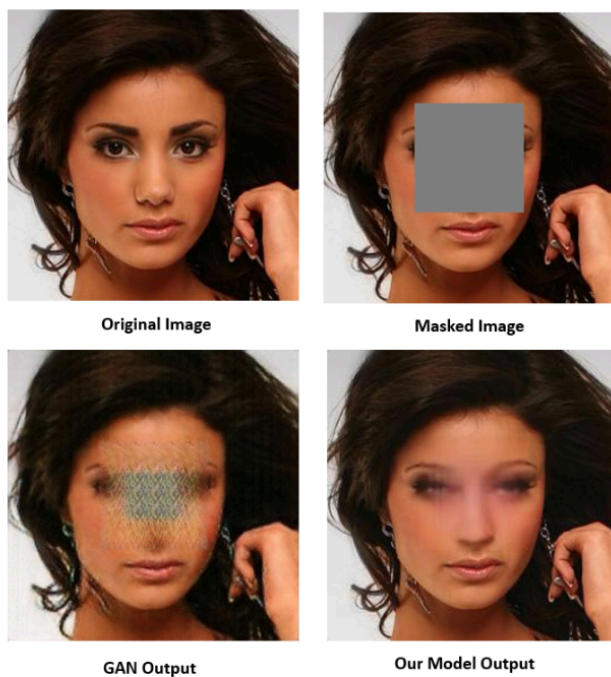


Figure 5.7: Visual Outputs Comparison

¹ Chapter 6

Conclusions

6.1 Social, Legal, Ethical, and Environmental Issues

6.1.1 Social Aspects

Our proposed hybrid deep learning model for filling large missing areas of images offers substantial benefits to society. It can restore damaged images with large missing areas, which could be invaluable in fields like digital heritage preservation, healthcare imaging, law enforcement, and even space exploration. By enabling seamless image reconstruction, this technology supports the revitalization of cultural archives, improves medical diagnostics, and aids in interpreting low-quality satellite imagery in the future.

Moreover, this model contributes to inclusivity and accessibility. It allows underserved communities to gain access to high-quality restored visuals for education and communication, thereby narrowing the digital divide. The technology also supports creativity and innovation in digital content creation, empowering artists, designers, and educators with advanced tools for image restoration.

6.1.2 Legal Aspects

Our research strictly adheres to ethical and legal standards, ensuring responsible use and implementation of artificial intelligence. We utilize publicly available datasets that comply with open-source licenses and data protection regulations, including the National Cyber Security Act 2023 of Bangladesh. Our project aligns with

national and global legal frameworks that prioritize transparency, accountability, and privacy.

Furthermore, by maintaining academic integrity and following best practices in AI development, our work reinforces the importance of lawful innovation. The model’s design encourages responsible use by ensuring ethical and legal clarity.

6.1.3 Environmental Aspects

Sustainability is at the heart of our research. While training deep learning models is often energy-intensive, our approach incorporates environmentally conscious strategies to minimize impact. By using a hybrid model, we optimize performance while reducing computational load and ensuring efficient resource usage and lower energy consumption.

Our project exemplifies how cutting-edge innovation can align with green computing principles, paving the way for eco-friendly AI development. It proves that powerful technological advancement and environmental stewardship can go hand in hand. No animals or natural environments were harmed in the course of this research.

6.2 Ethical and Professional Principles

6.2.1 Data Privacy and Security

Since our research uses only publicly available and open-source datasets such as CelebA-HQ and Places365, we fully uphold data privacy standards. No personal or proprietary data has been used or exposed during the development of our hybrid deep learning model. This approach ensures compliance with ethical research practices and reduces the risk of privacy breaches, while also reinforcing our commitment to transparent and secure data handling.

6.2.2 Accuracy and Reliability

Our model emphasizes high accuracy and consistent performance across diverse image datasets. Through rigorous testing and validation, we ensure the output is

reliable and robust. This focus on dependability enhances the model’s practical applicability in real-world use cases, ranging from medical imaging to digital restoration.

6.2.3 Ethical Use of Technology

We are committed to promoting the ethical use of AI. Our research is developed with a clear focus on positive applications such as education, preservation, and accessibility. We discourage and actively prevent misuse by advocating for responsible deployment, clear usage policies, and ethical training materials that raise awareness about the potential consequences of misusing image generation technologies.

6.2.4 Transparency and Consent

Transparency is a core value in our project. We clearly document our processes, models, and data sources to allow replication and careful review. Although our dataset does not include personal or sensitive content, we advocate for user consent and informed participation when working with datasets that do. This ensures ethical accountability and supports trust in AI-driven research.

6.3 Brief Summary

Our project focuses on implementing a hybrid deep learning model that combines U-NET and Generative Adversarial Networks (GANs) to effectively fill and restore large missing areas in images. In our approach, U-NET functions as the generator, producing inpainted image regions, while GAN serves as the discriminator, evaluating the realism of the generated content to improve overall quality. This combined setup enables the model to generate visually coherent and contextually accurate restorations. We have conducted our experiments using the CelebA-HQ and Places365 datasets to validate the performance of our model on both facial and scene images. The ultimate goal is to provide a reliable, scalable solution for image inpainting that can be applied in real-world scenarios such as photo restoration, content generation, etc.

To enhance the accessibility and usability of our work, we developed a web application where users can upload a broken image, and the application will provide a restored image as output. This hands-on tool enables anyone to interact with our model and experience its image restoration capabilities firsthand.

6.4 Future works

⁵⁸ In the future, we plan to develop a mobile application that integrates our model, ²⁹ allowing users to restore images conveniently from their devices. To improve the model's performance and versatility, we aim to train it with larger and more diverse datasets such as COCO [Schonfeld et al. \(2020\)](#) and ImageNet [Rojas et al. \(2020\)](#).

We also see potential in adapting our model for medical imaging [Kumar et al. \(2024\)](#), where it could help enhance or restore diagnostic images like X-rays or MRIs. Lastly, we will continue refining the model to achieve greater accuracy and more flawless results, making it more effective across various real-world applications.

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