ARTI-FUSE: INTELLIGENT IMAGE INPAINTING WITH DEEP LEARNING

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INTRODUCTION

Introduction to image inpainting:-

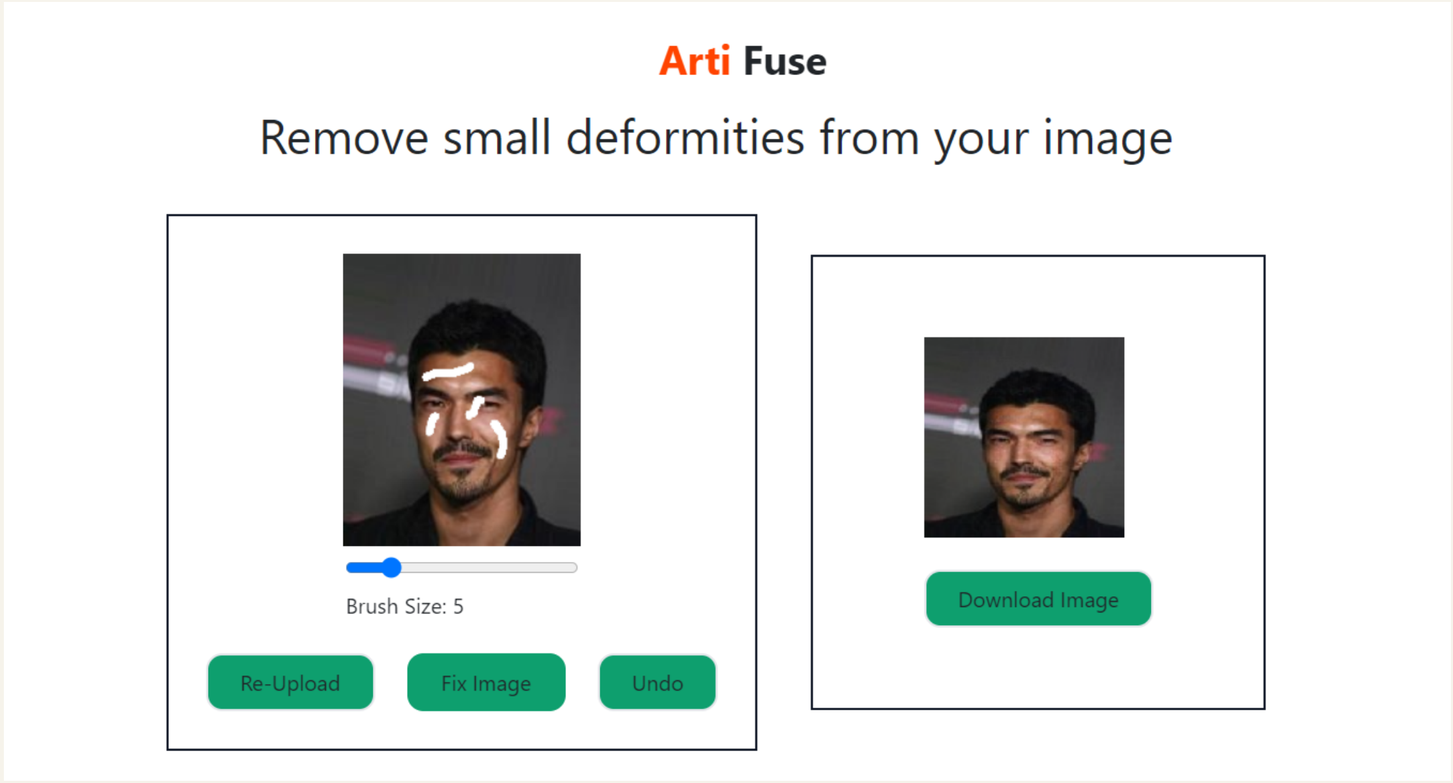
- **Restoring/reconstructing missing parts in an image.**

Introduction to GAN:-

- **Neural network for generating realistic data.**

PROJECT OVERVIEW

Restoring the small damaged, missing or corrupted part of facial features in an image for enhanced visual quality.



OBJECTIVE

- **Create GAN model for facial image inpainting with diverse dataset, integrate into user-friendly web app for interactive custom mask inpainting.**

LITERATURE REVIEW

1 Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1125–1134, 2017

2 Sangharsha Bidari and Bal krishna Nyaupane. An approach for damaged facial image restoration using gan. 2021

3 Omar Elharrouss, Noor Almaadeed, Somaya Al-Maadeed, and Younes Akbari. Image inpainting: A review. Neural Processing Letters, 51:2007–2028, 2020.

METHODOLOGY

Data Collection

- Diverse Dataset Compilation: Ensuring dataset diversity
- CelebA Dataset Utilization: utilizing 34,000 facial images.
- Additional Dataset: 500 old photographs
- Additional Dataset: 500 primary data collected across social media

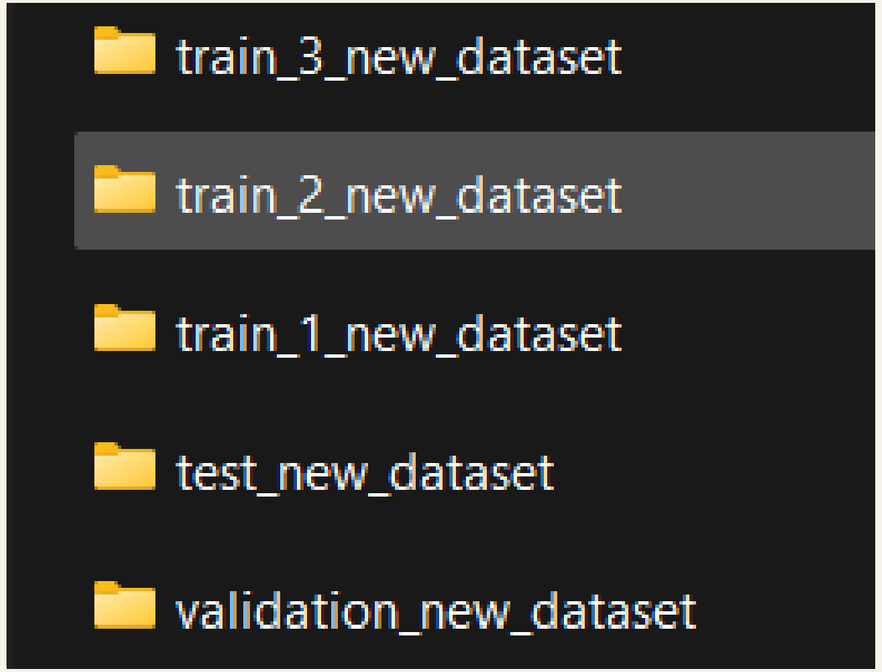
Figure 4.1: Celeb-A Dataset

METHODOLOGY

Data Preprocessing

- **Facial Region Focus: Raw images resized to emphasize facial regions for preprocessing.**

- **Subset Division: Dataset segmented into training, testing, and validation subsets for model development.**



METHODOLOGY

Data Preprocessing..

- Mask Generation: Python scripts employed to generate masks, aiding in the training process.

- Mask type: random patches of circle or squares, lines with different length and thickness.

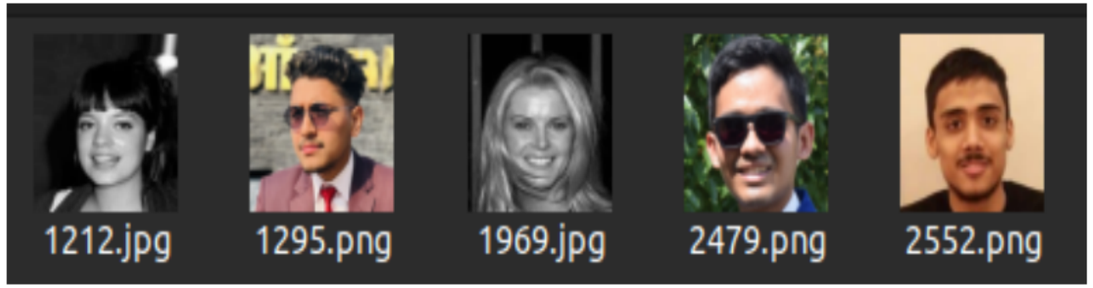


Figure 4.3: Original Images

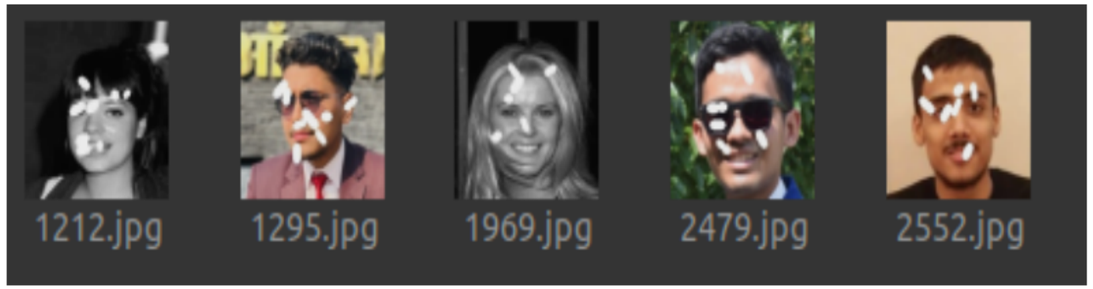


Figure 4.4: Maked Images

SYSTEM DESIGN

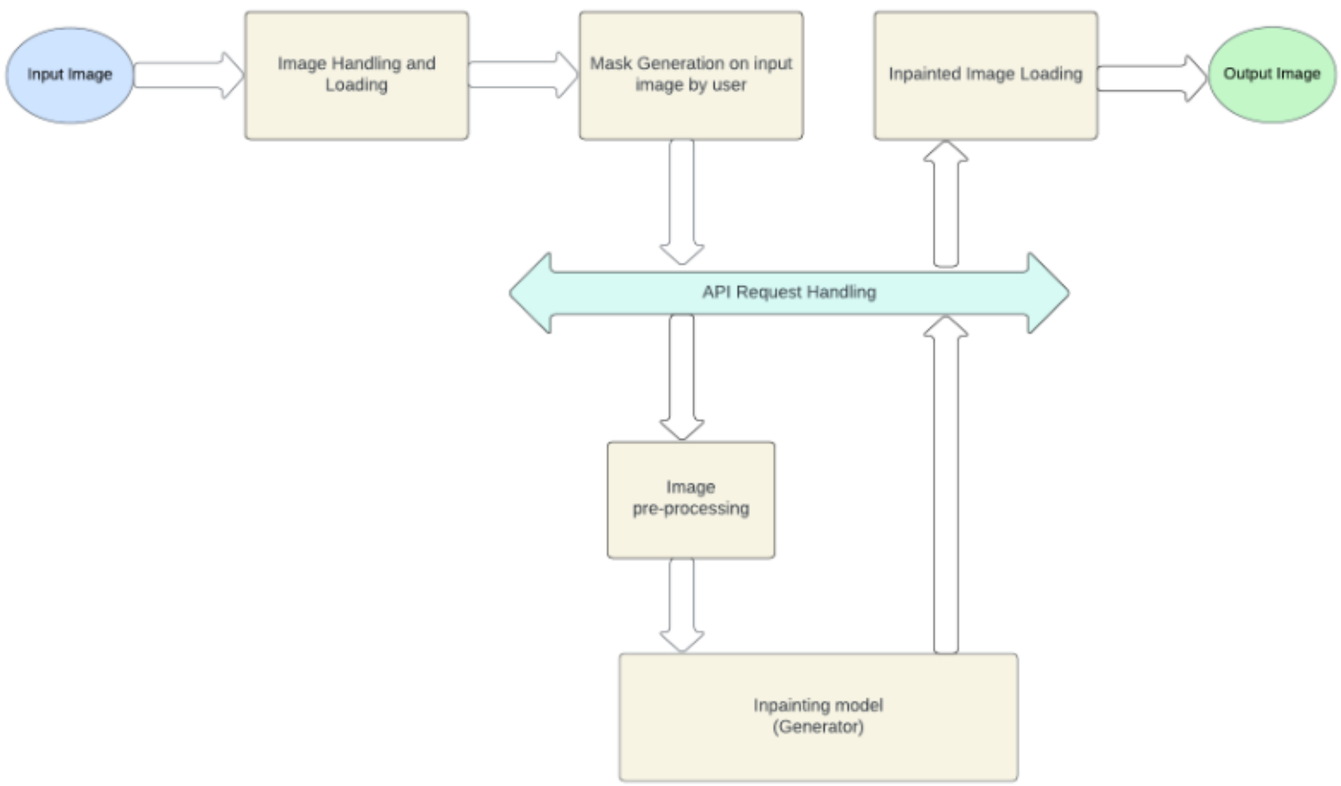
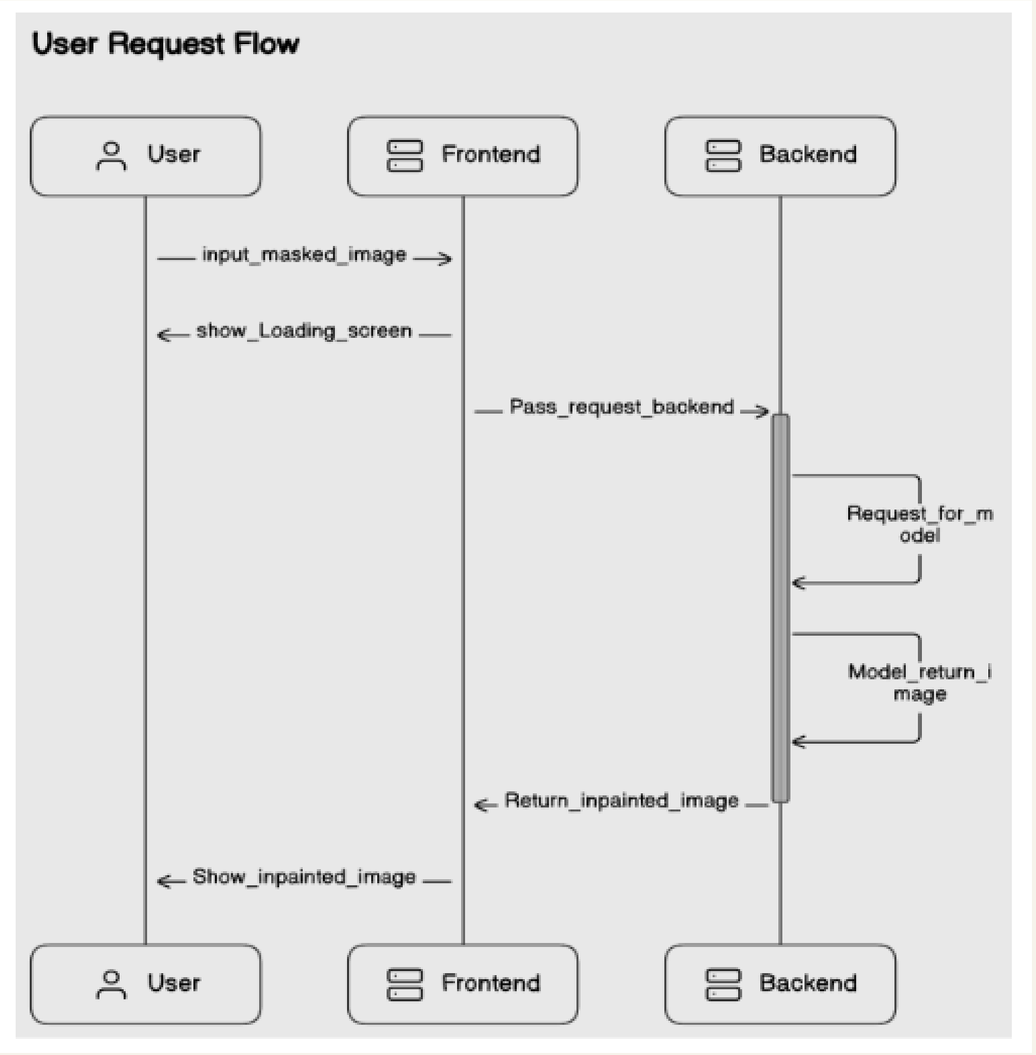


Figure 5.1: Abstract System Diagram

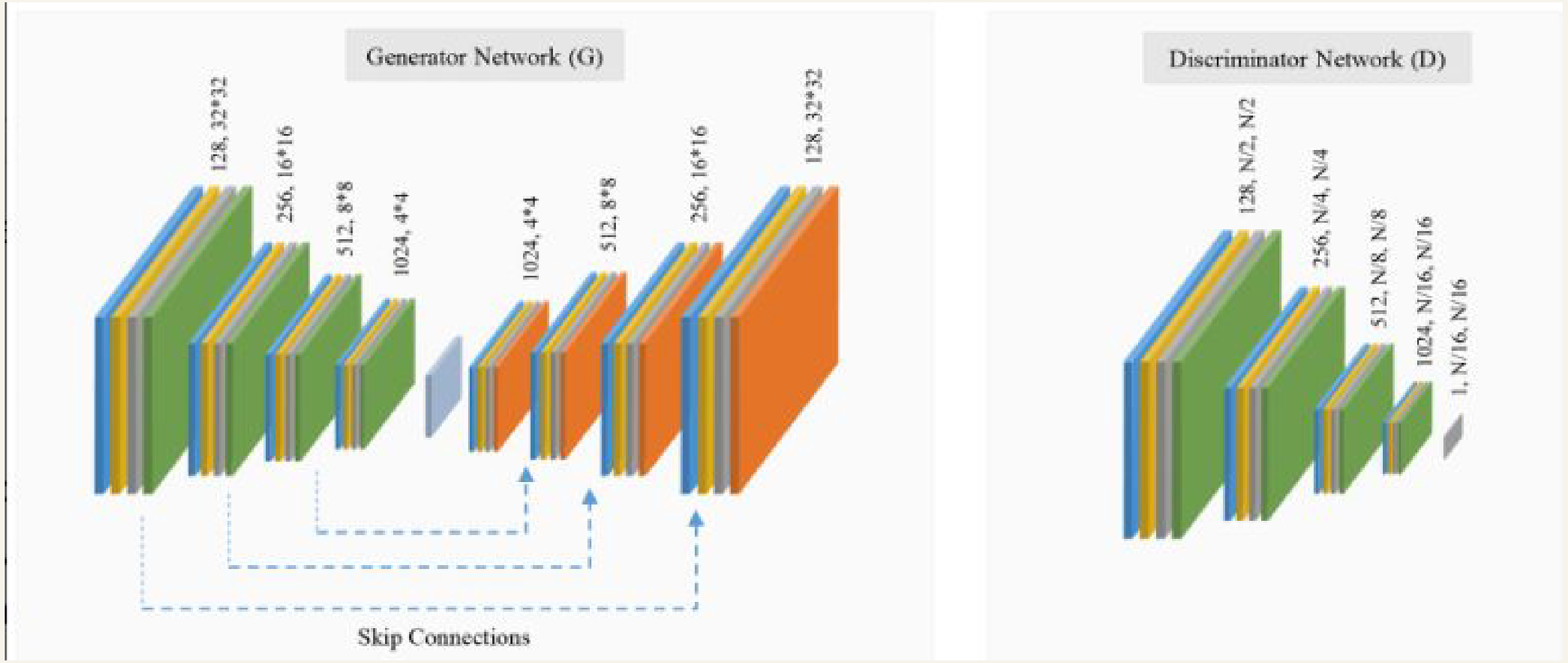
SYSTEM DESIGN

Sequence Diagram



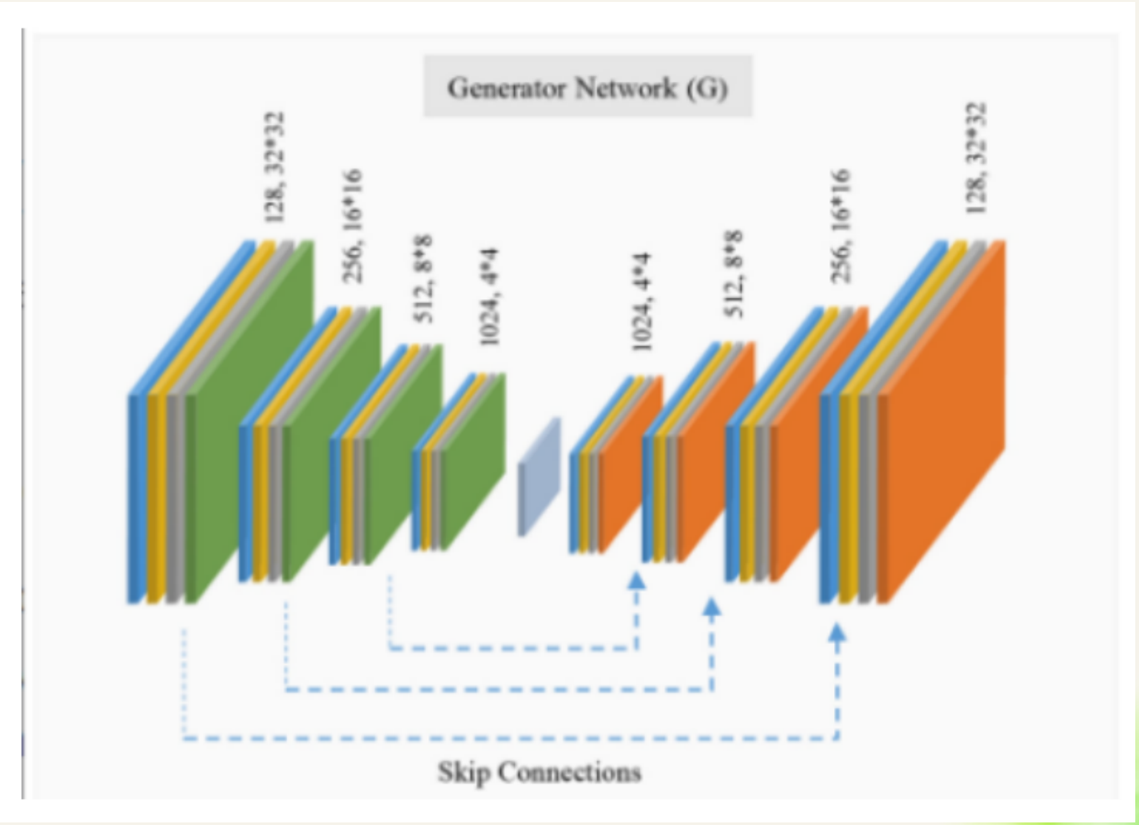
MODEL ARCHITECTURE

- **PIX2PIX GAN, a varient of c-gan**



GENERATOR

- U-NET architecture
- Encoder, bottleneck and decoder sections.
- Output: 128*128
- a total of 41,841,283 parameters.



GENERATOR

Two types of losses:

- **Adversarial loss:- Distinguish between real and generated images.**

$$\mathcal{L}_{adv} = -E_{x,y}[\log D(x, y)]$$

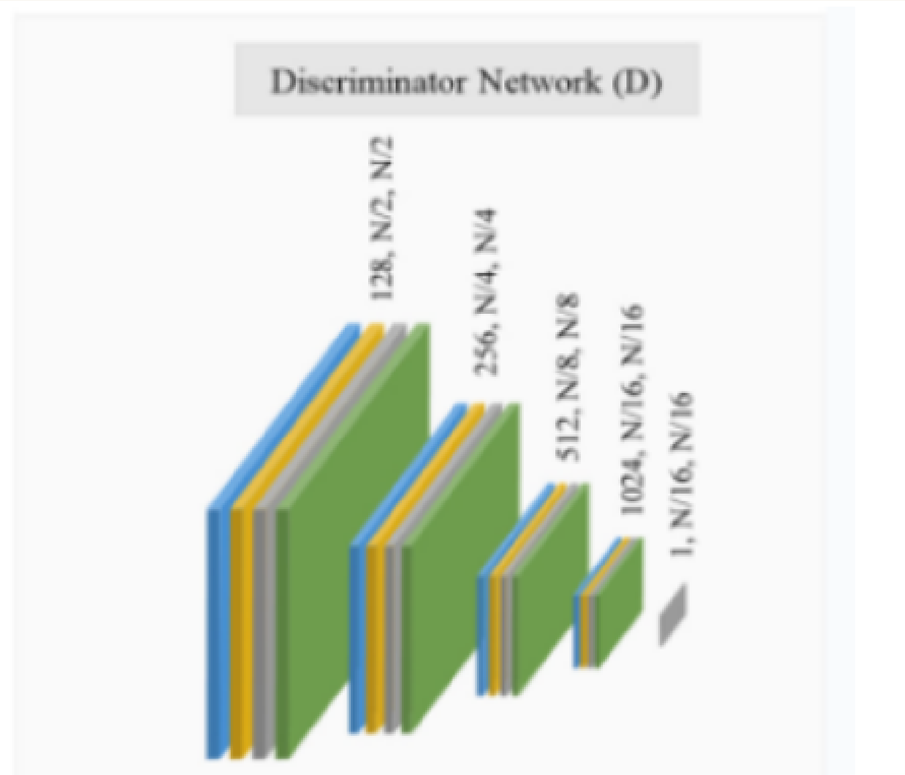
- **Regularization loss:- Also known as Mean Absolute Error(MAE), enforce pixel-wise similarities between inpainted and original image.**

$$\mathcal{L}_{reg} = \frac{1}{N}\sum_{i=1}^{N}|G(x_i) - y_i|$$

DISCRIMINATOR

- Global discriminator
- Binary classification
- a total of 6,968,257 parameters
- Binary cross entropy:

$$\mathcal{L}_{\text{binary}} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

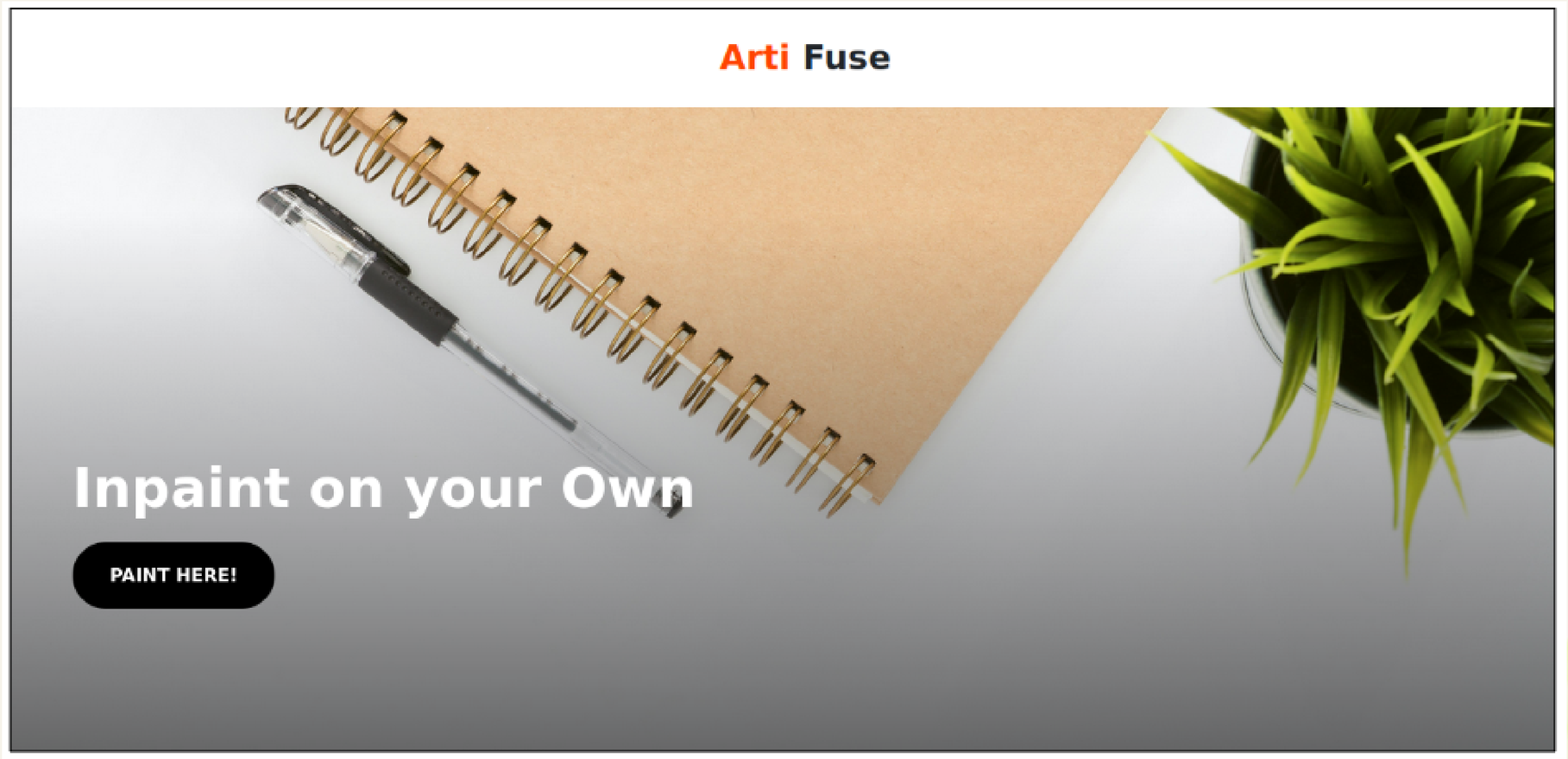


TECH STACKS AND LIBRARIES

- Backend: fastAPI
- frontend: React
- cv2, PIL python library for mask generation
- Trained on Goggle Collab on T4 GPUs
- keras library for training the model

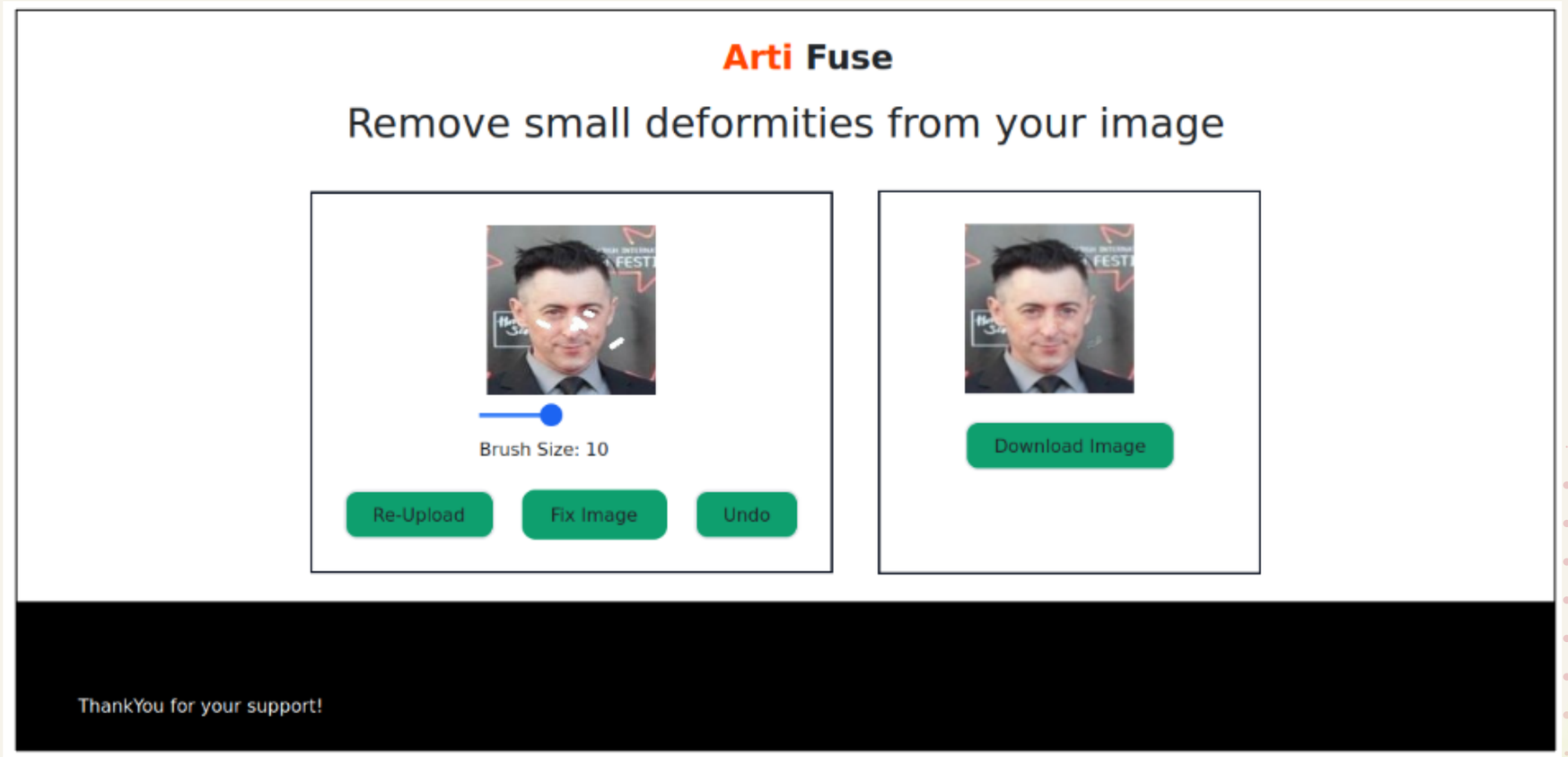
WEB DESIGN

Landing Page

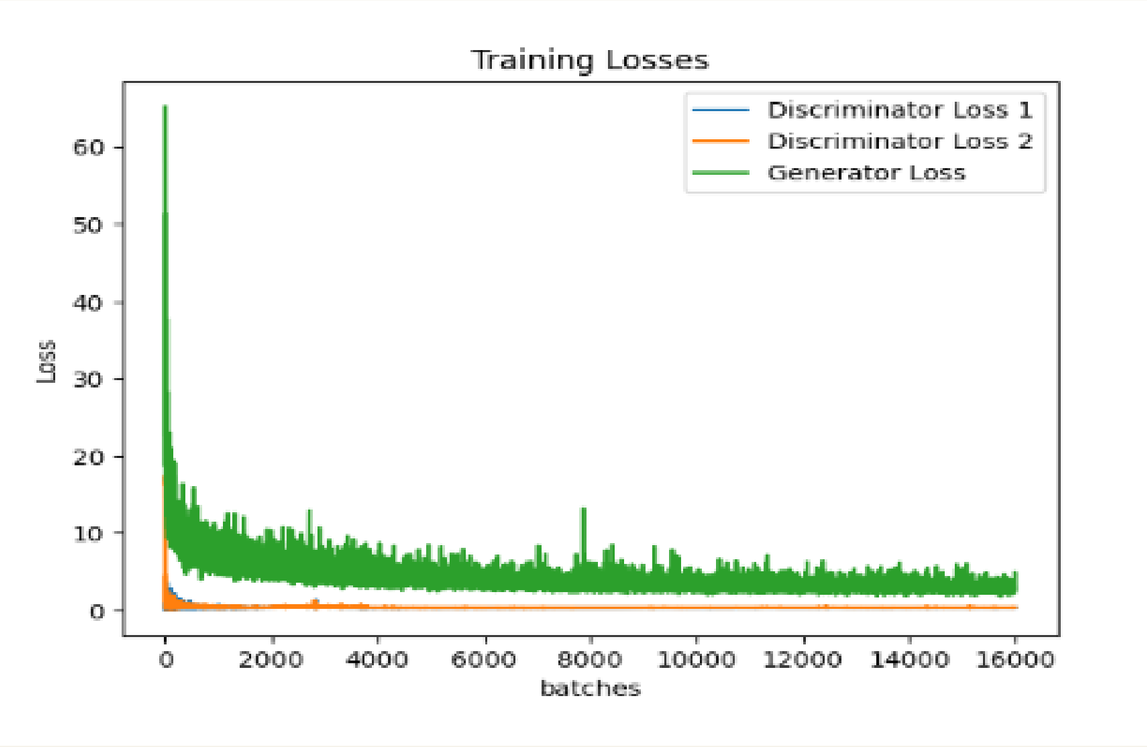


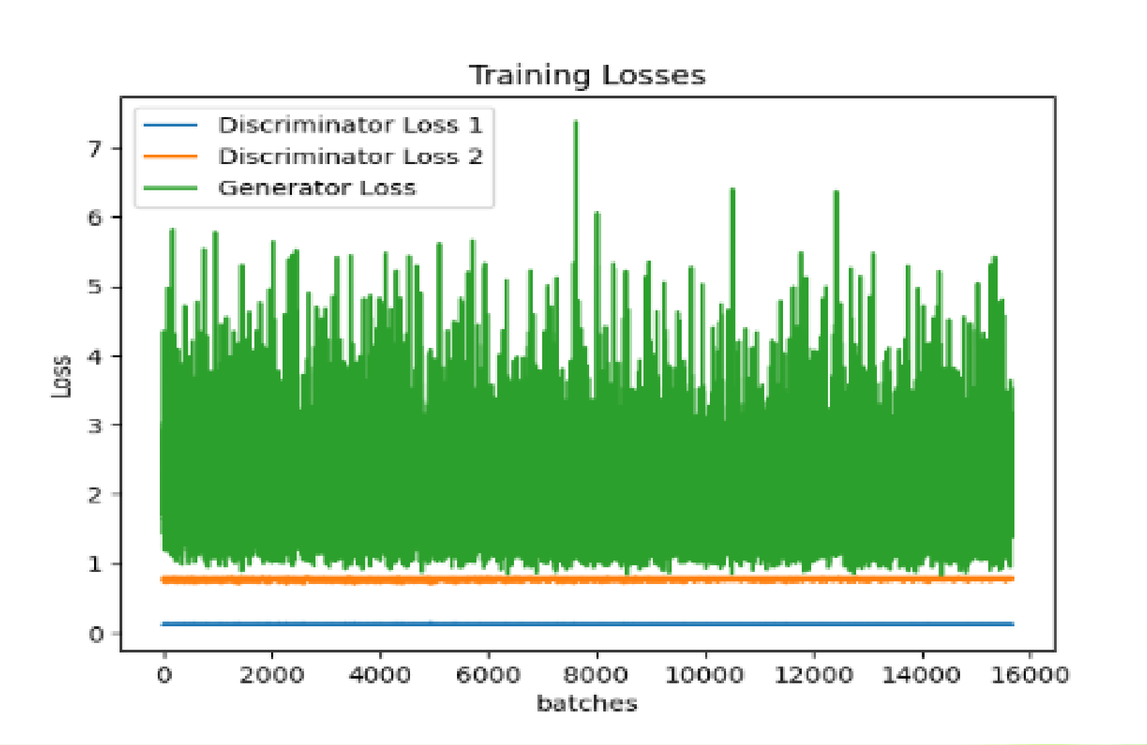
WEB DESIGN

Inpainting Page



PERFORMANCE





PERFORMANCE

Figure 6.4: Training and Testing Losses EPOCH-2

Figure 6.6: Training and Testing Losses EPOCH-20

RESULTS

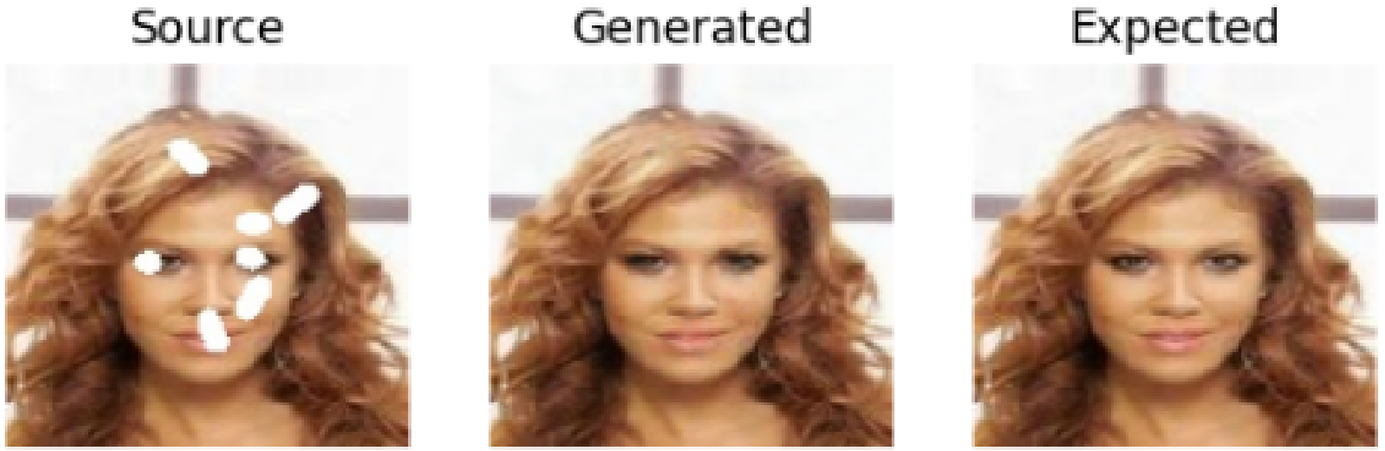


Figure 6.7: Model Performance on Training Data

RESULTS

Figure 6.8: Model Performance on Testing Data

RESULTS

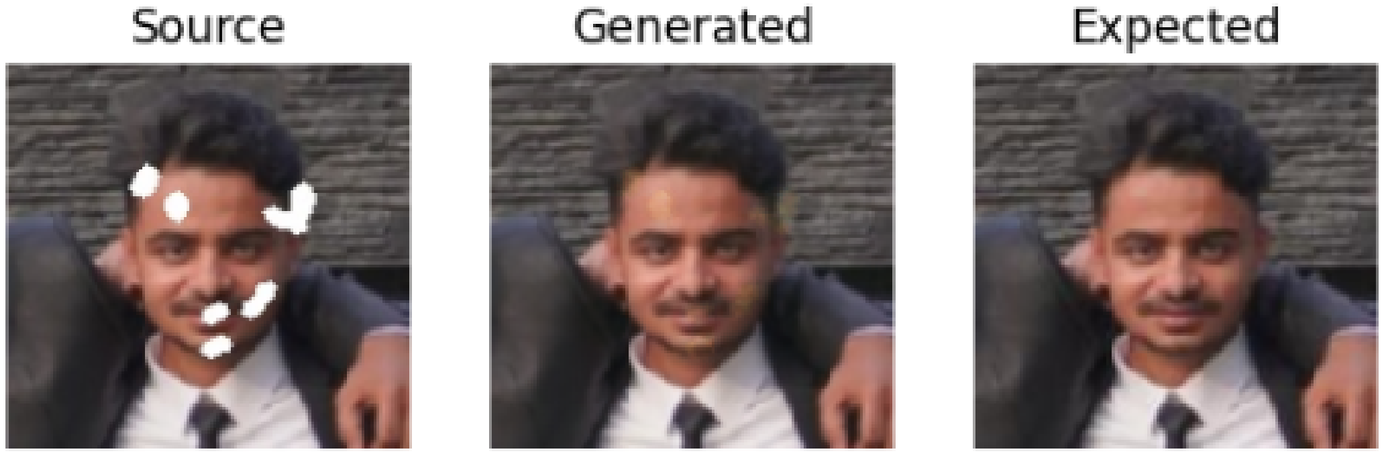


Figure 6.9: Model Performance on Primary Data

RESULTS

Figure 6.10: Model Performance on Old Photographs

RESULTS

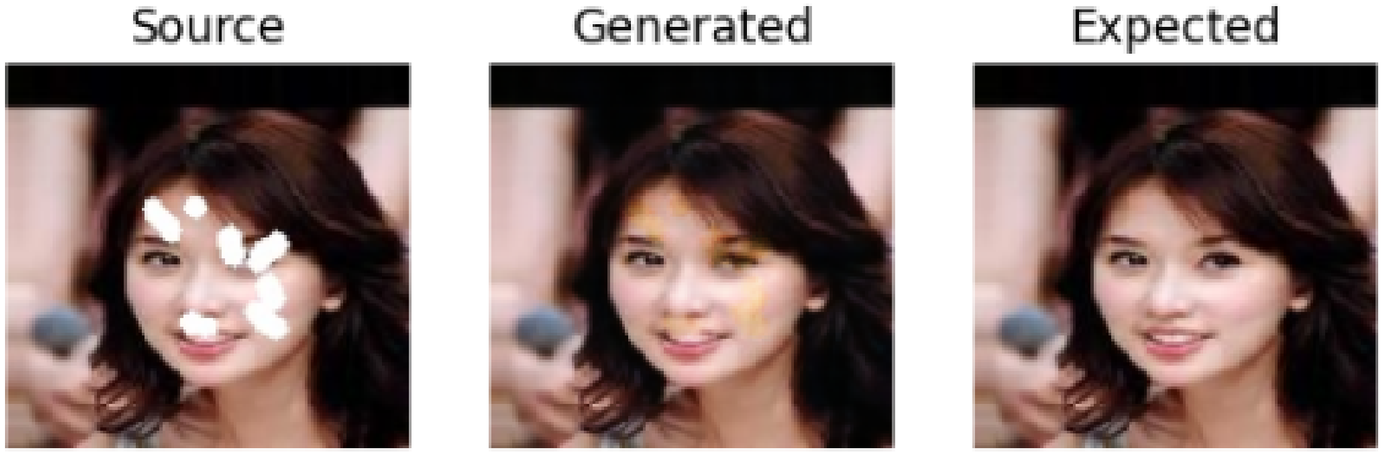


Figure 6.11: Model Performance on Dense Masking

LIMITATIONS

- Not promising result for large masks.
- Skin tone matching may be inaccurate.
- Output resolution restricted to 128x128 pixels.
- Model trained primarily on facial images

FUTURE ENHANCEMENT

- Train at higher resolutions for better quality.
- Explore advanced techniques for diverse masks.
- Add more CelebA data for improved facial inpainting.
- Diverse images from Places Dataset to inpaint wider scenes and objects.


DEMO

THANK YOU

ANY QUERIES