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GENERATING SKIN LESIONS HAIR MASK PATTERNS USING GENERATIVE MODELS FOR AUTOMATED HAIR AUGMENTATION

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A thesis submitted in partial fulfillment of the requirements for the degree of“Bachelor of Science in Computer Science & Engineering.”

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Acknowledgment

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My parents deserve my utmost appreciation for their endless love, support, and sacrifices. Their steadfast faith in my potential has consistently inspired me.

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Abstract

Creating large images, particularly with dimensions like 512*512, poses challenges, especially when generating masks for skin lesions' hair. This difficulty stems from the predominantly black pixels with sparse white pixels in such masks. Consequently, generated images often appear entirely black, obscuring the intricate patterns of the skin mask. This study presents a modified version of the pro-GAN (progressive generative model) that addresses these challenges. The modifications include incorporating Minibatch Standard Deviation, along with pixel normalization, Equalized Learning Rate, Gradient Penalty, and Training Loop Enhancements. Additionally, the study utilizes the U-NET architecture for segmentation and dataset enhancement. Key metrics, such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Perceptual Loss, are employed to objectively evaluate the performance of the proposed pro-GAN in generating hair mask patterns. The ability to generate 512512 images with this modified pro-GAN model and enhanced dataset is crucial for creating a framework capable of detecting skin lesion diseases without hair removal techniques. This advancement in generating large hair mask patterns is essential and beneficial for disease detection.

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CHAPTER I

Introduction

1.1 Introduction

Generating images is a common phenomenon for any generative model nowadays. In this process, the generator attempts to create images resembling real ones, while the discriminator assesses them, pushing the generator to produce more realistic images. In this research, the aim is to generate a large image of a hair mask, addressing the issue of bias towards black pixels. To overcome this limitation, several techniques have been applied. Various generative models have been studied and analyzed, and the best one in terms of scores and output has been chosen, utilizing loss functions and metrics like PSNR. Visualization aids in observing the hair mask patterns for hair augmentation, facilitating faster classification without the need for hair removal.

1.2 Background Study

A skin lesion is an abnormality in the skin's tissue, which can manifest in various forms such as a rash, bump, sore, or growth. Skin lesions can be caused by a variety of factors including infections, inflammation, injury, or underlying medical conditions. Generating hair mask pattern of skin lesion is like getting the pattern how hair stays in lesion areas To reach the outcome different generative model has been studied and tested on different dataset It enriches the knowledge about generative model and their image generating technique Also different architecture like U-NET is also learned because of the dataset preparation. While preparation of the dataset this architecture is used for segmentation task Another motivation of this study is this study later will be used for the study of skin disease classification without hair removal.

1.3 Motivation

The main goal of this research is to generate a hair mask pattern of skin lesions. Following this, the generated patterns will be applied to hair-free images to recreate natural hair patterns. Subsequently, various classifier models will be trained for skin lesion disease classification with the inclusion of hair. My primary focus is on image generation, but the overarching motivation of this study remains the improvement of mankind's ability to accurately detect and classify different diseases with a new and efficient technique that does not require hair removal during testing. Another motivation is to explore different model architectures and metrics to identify the most effective model. Additionally, various research endeavors will depend on hair mask image generation, facilitating progress in related fields.

1.4 Problem Statement

Generating images presents a significant challenge due to the high demand for GPU resources and the necessity of large datasets. However, the focus of this thesis on generating the skin hair pattern of skin lesions adds an additional layer of complexity. Firstly, it requires a substantial dataset of hair masks, prompting the utilization of an encoder-decoder architecture for segmentation. Another hurdle is producing large-sized images, such as 512x512, particularly considering the prevalence of predominantly black and white pixels and the high bias towards black pixels. These factors compound the difficulty of image generation, making it a formidable task requiring careful consideration and innovative approaches.

1.5 Objectives

The thesis emphasizes developing effective and innovative solutions for the generation of images(hair-mask) in the skin lesions. To achieve this goal, the following specific objectives have been identified:

1. **Collect the dermoscopic images and dataset of hair-mask.** Due to lack of hair mask images the first work is to collect the available dermoscopic images and train a U-Net using the small available dataset and then generate the required dataset.
2. **Develop a generative model:** The fundamental objective is to develop a generative

model that will generate the required hair mask image.

3. **Validate the performance:** Evaluating the performance of the proposed generative model that can generate the large image with better clarity and better visibility of hair mask using some metrices.

1.6 Scope and Required Tools

Image generation is a well-known task now a days to get the proper image below:

1. **Deep Learning Frameworks**: The model will be developed using deep learning frameworks such as TensorFlow or Kera's, which enable efficient implementation and experimentation.
2. **U-Net Architecture:** U-Net architecture will be incorporated with the encoder-decodermodel for generating the dataset as there is not enough datasets available.
3. **Generative model:** A generative model is chosen among the different model It is either be DC-Gan, WC Gan VQ-vae, Pro-Gan, Style-Gan, SR-Gan
4. **Datasets**: Dataset is taken from a paper, but it is very less to another model is generated to extract it from different available dataset
5. **Evaluation Metrics:** PSNR, SSIM, and Perceptual loss are being used as evaluation. metrics for validating the network performance**.**

1.7 Unfamiliarity of the Problem

This problem is entirely unfamiliar territory for me, as it hasn't been addressed throughout academic career, and the domain itself is entirely new. Furthermore, the problem encompasses various aspects that are unfamiliar to me, including those listed below:

i) **Lack of understanding of segmentation techniques:** I have little to no knowledge about segmentation methods, which are crucial for tasks involving image analysis and processing**.**

ii) **Unfamiliarity with various generative models:** I am not acquainted with the diverse range of generative models used in image generation tasks, which are essential for tackling problems like the one at hand**.**

iii) **Absence of well-defined metrics:** There is a lack of familiarity with established metrics and evaluation criteria used to assess the performance and accuracy of models in this domain.

1.8 Project Planning

The project planning encompasses several key aspects. A well-defined timeline has been established, aiming to complete the project within a specified duration. Additionally, careful attention has been paid to financial budget considerations to ensure efficient resource allocation. Ethical considerations, as well as potential legal issues about the thesis topic, have been thoroughly examined and integrated into the planning process. This comprehensive approach ensures not only timely completion but also adherence to ethical standards and legal requirements throughout the thesis undertaking.

1.8.1 Project Timeline

The research for the thesis is divided into two phases, each contributing to our main goal. The first phase takes place during the first semester, and the second phase is scheduled for. Completion in the second semester. The target was to have the entire thesis completed by January 2024.And the target is completed.

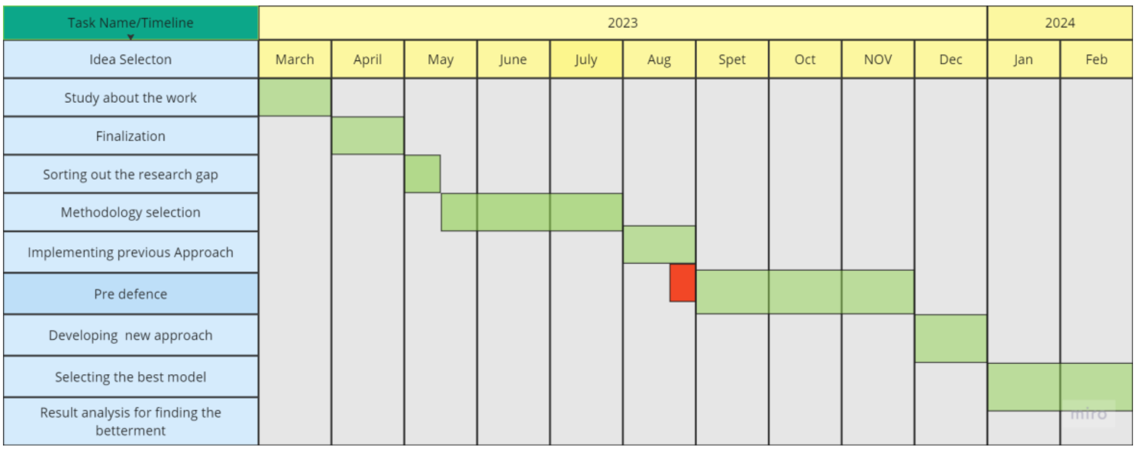

Figure 1.1: Gantt chart of the timeline of the thesis.

1.8.2 Legal and Ethical Aspects

The study of image generation, while primarily centered on technological advancements, also requires consideration of its broader implications on society, health, and culture, including:

Privacy and Surveillance: The creation of highly detailed images through generation technologies may raise privacy concerns, enhancing surveillance capabilities and potentially infringing on personal and civil liberties.

Medical Imaging: In medical fields, image generation can be pivotal for diagnostics, but it necessitates high precision to avoid misdiagnoses and ensure correct medical interventions.

Cultural and Historical Preservation: Image generation can play a significant role in the restoration and preservation of cultural and historical artifacts, offering enhanced clarity and insights into our heritage.

This approach highlights the need for a balanced consideration of ethical and legal aspects alongside technological innovation.

1.9 Applications

The applications of my thesis, focusing on the modified pro-GAN model for generating high-resolution images for skin lesion analysis, extend across several key areas:

Medical Diagnostics: Enhancing the accuracy of skin lesion diagnosis by providing detailed images without the necessity for hair removal, facilitating early and accurate disease detection.

Digital Dermatology: Supporting telemedicine and digital health platforms with improved imaging capabilities, enabling remote diagnosis and monitoring of skin conditions.

Research and Development: Contributing to the body of knowledge in medical imaging, offering a novel approach to generating and analyzing skin lesion images, which could inspire further innovations in the field.

Educational Tools: Serving as a valuable resource for medical training and education, providing realistic and detailed images for study and analysis.

These applications demonstrate the significant impact of your research in improving disease classification, diagnostic processes, and educational methodologies within dermatology and medical imaging.

1.10 Organization of Report

The purpose of this section is to provide readers with a clear understanding of the order in which information is presented and to assist them in navigating the document. The remaining part of this thesis consists of the parts as follows:

Chapter I: The background of image generation, the introduction part, the requirement of the solution of this problem, and the social and cultural aspects of the problem

Chapter II: Literature reviews that describe some of the existing ways of error correction; are discussed. Also, towards the conclusion of this chapter, a comparison of all approaches was made.

Chapter III: This chapter details the research design and methods employed in the study. It explains the approach to data collection and analysis, providing a rationale for the chosen methods and procedures. Additionally, the methodology chapter addresses any limitations or constraints inherent in the research process, ensuring transparency and rigor in the methodology employed.

Chapter IV: Here, the findings of the research are presented and analyzed. The chapter describes how the research was conducted in practice, presenting, and interpreting the collected data. Through thorough analysis, the results chapter elucidates the significance of the findings and their implications for the research objectives and hypotheses.

Chapter V: This chapter delves into the broader implications of the research on various societal, health, environmental, safety, ethical, legal, and cultural aspects. It considers the potential risks and concerns associated with the implementation of the research findings and addresses the ethical and cultural dimensions of the research.

Chapter VI: Here, the complex engineering problems addressed in the research are discussed, along with the activities undertaken to tackle them. The chapter highlights any innovative approaches or solutions developed and underscores the significance of research in advancing the field of engineering.

Chapter VII: The conclusion chapter summarizes the key findings of the research, revisits the research objectives and hypotheses, and reflects on the broader implications of the findings for theory, practice, and policy. It also suggests avenues for future research, providing closure to the thesis while inviting further inquiry into the topic.

1.11 Conclusion

The introductory chapter introduces an innovative approach to generate high-resolution images for analyzing skin lesions, focusing on overcoming hair occlusion challenges. It highlights the research's motivation, the issues with current imaging practices, and the potential of a modified GAN model to revolutionize dermatological diagnostics. This thesis aims to enhance medical imaging, offering new possibilities for non-invasive disease detection, with implications for diagnostics, telemedicine, and education in skin disease classification.

CHAPTER II

Literature Review

2.1 Introduction

Generating large images, particularly for detailed skin lesion analysis, represents a critical frontier in medical imaging. This endeavor requires a profound understanding of image processing fundamentals, alongside familiarity with contemporary tools and technologies. A literature review in this context is indispensable, offering a holistic view of existing methodologies, their evolution, challenges, and current trends. By scrutinizing prior research, this review sheds light on diverse strategies, their effectiveness, and limitations, thereby enabling researchers to build on prior knowledge, sidestep redundancy, and pinpoint areas needing innovation. Additionally, it steers the development of new generation techniques, ensuring they are informed, pertinent, and adept at tackling the specificities of skin lesion imaging, ultimately pushing forward the discipline and promoting impactful, responsible research.

2.2 Relevant Terminology

Related terms associated with the thesis are discussed below:

Segmentation: In image processing and medical imaging, segmentation is vital for dividing an image into parts for easier analysis. For skin lesion analysis, it isolates the lesion, aiding in examining its traits and identifying diseases. Effective segmentation improves diagnostic precision by clearly defining lesion boundaries, crucial for analyzing size and shape. This technique is key to automating disease detection, using sophisticated algorithms to enhance healthcare outcomes.

Skin lesion: Skin lesions are abnormal skin growths or patches that can range from moles and freckles to rashes and cancerous growths. Their diagnosis is crucial in dermatology for effective treatment, emphasizing the importance of medical imaging for accurate identification and management.

is helpful since it gives a measure of how well the two images match.

U-Net Architecture: The U-Net architecture is a type of neural network specifically built for tasks like segmenting biomedical images, especially in medical fields. It's designed to efficiently capture context while also pinpointing precise details, making it particularly effective for tasks requiring accurate image segmentation.

Perceptual Loss: Perceptual loss is a concept in image processing where the difference between two images is measured not just based on pixel-level discrepancies but also on perceptual similarity, akin to how humans perceive differences in images. It aims to capture high-level features such as textures and structures rather than just individual pixels.

2.3 Related Works

Figure 2.1: Example of dermoscopic image and hair mask [1]

Every method has its advantages and disadvantages. Some of the works that I have studied are.

Mohamed Attia et al [1] proposed a novel skin hair simulation method is proposed to synthesize various hair occlusions on skin lesion images where realistic synthesis is achieved while preserving lesion texture. This is achieved by using the image-to-image translation technique via conditional generative adversarial networks (cGANs).

Ali Razavi et al [2] proposed an image generation method where he employs lossy compression principles to enhance generative models by discarding irrelevant data. It adopts an autoencoder to quantize image representations, making them much smaller yet reconstruction able. A Pixel Snail model captures the prior distribution over these discrete representations, enabling high-quality image generation. This approach achieves swift training and sampling, performing 30x faster than pixel-based methods, making it ideal for high-resolution images. The proposed method retains the speed and simplicity of the original VQ-VAE, making it appealing for fast, low-overhead encoding and decoding of

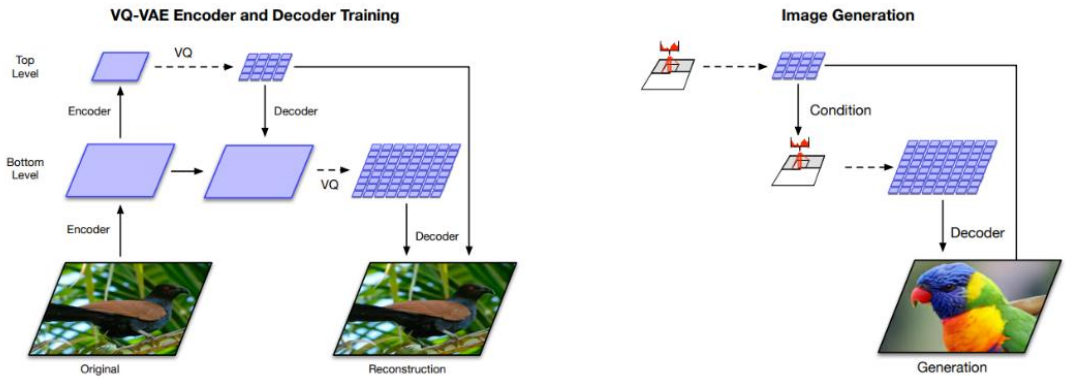

Figure2.2: An image generation method VQ-VAE

large images. However, the assessment of sample quality and diversity lacks well-established metrics and relies on visual inspection. Despite this, the conducted experiments provide support for autoregressive modeling within the latent space, showcasing its simplicity and efficacy as an objective for training extensive generative models.

Prafulla Dhariwal et al [3] demonstrates the superior image sample quality achievable with diffusion models, outperforming current state-of-the-art generative models. For unconditional image synthesis, improved architecture through ablations yields remarkable results. In conditional synthesis, sample quality is further enhanced by incorporating classifier guidance, optimizing diversity and fidelity trade-off efficiently. Exceptional FID scores are achieved on ImageNet datasets at various resolutions. The addition of classifier guidance to up sampling diffusion models continues to enhance FID scores significantly.

Bingqi Liu et.al [4] focuses on enhancing image generation using a deep convolutional generative adversarial network (DCGAN), a type of deep learning model. The authors improve upon traditional generative adversarial networks (GANs) by refining the fully connected layer of the DCGAN and addressing the issue of gradient disappearance in GANs. They achieve this by employing LeakyReLU activation functions for all layers of the discriminator, using the Tanh activation function for the output layer of the generator, and ReLU for the other layers.

To evaluate the performance of the improved DCGAN model, experiments are conducted using the MNIST dataset. The authors establish two indexes, namely simple initial fraction (ISs) and complex initial fraction (ISc), to assess image quality and generation diversity, respectively. Comparative analysis of the experiments indicates that the quality of images generated by the proposed DCGAN model is significantly higher (2.02 times) than that of the traditional GANs model.

Richardson et al. [5] introduce pixel2style2pixel (pSp), an image-to-image translation framework using a novel encoder network to directly generate style vectors fed into a pretrained StyleGAN generator, extending the W+ latent space.

Gao et al. [6] propose progressive growing of GANs, where low-resolution images are initially generated and then upscaled progressively through added convolutional layers until high resolution is achieved. They apply this method to generate realistic medical images in retinopathy of prematurity (ROP) and glioma domains. Including segmentation maps enhances fine-grained pathology details like retinal vessels or tumor heterogeneity.

2.4 Observation of the relevant papers

Table 2.1: Comparative analysis among existing methods

Method	**Approach**	**Advantages**	**Challenges**
VQVAE	Vector Quantized Variational Autoencoder (VQ-VAE)	Captures local variant PSF; Potential for high accuracy in image generation	Requires large, labeled training data; Vulnerable to overfitting; May suffer from mode collapse like traditional VAEs
DCGAN	Generative adversarial network with deep convolutional architecture	Effective in generating high-quality images; Stable training process	May suffer from mode collapse; Requires careful hyperparameter tuning
WGAN	Wasserstein GAN with gradient penalty	More stable training; Improved convergence metrics	Slower convergence compared to traditional GANs; Higher computational cost
StyleGAN	Utilizes a novel architecture to learn disentangled representations of images	Enables control over specific features; Produces high-resolution, diverse images	mplex architecture may require longer training times; Resource-intensive
Pro-GAN	Progressive growing of GANs, starting	Generates high-resolution images;	Requires longer training times; Higher

	from low resolution and gradually increasing	Stable training process	computational resources; More complex architecture

2.5 Conclusion

In conclusion, the exploration of various generative models for hair mask pattern generation reveals a diverse landscape of strengths and challenges. Each method offers unique advantages and considerations, shaping the choice of approach based on the specific requirements of the task, computational efficiency, and robustness to noise.

While CNN-based models excel in accuracy, they often demand substantial amounts of labeled data, posing challenges in data acquisition and computational resources. Alternative methods, such as Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), or their variants like VQVAE, DCGAN, WGAN, StyleGAN, and Pro-GAN, present promising avenues for generating high-quality hair mask patterns with varying degrees of control and fidelity.

CHAPTER III

Methodology

3.1 Introduction

The technology employs a two-stage process to generate hair mask pattern using different generative models and find the best output using some metrices output. During the first stage, the decoder network uses skip connections to segment the hair mask from the dermoscopic images and the next step the generative model is trained to get the required hair mask pattern.

Detailed Methodology

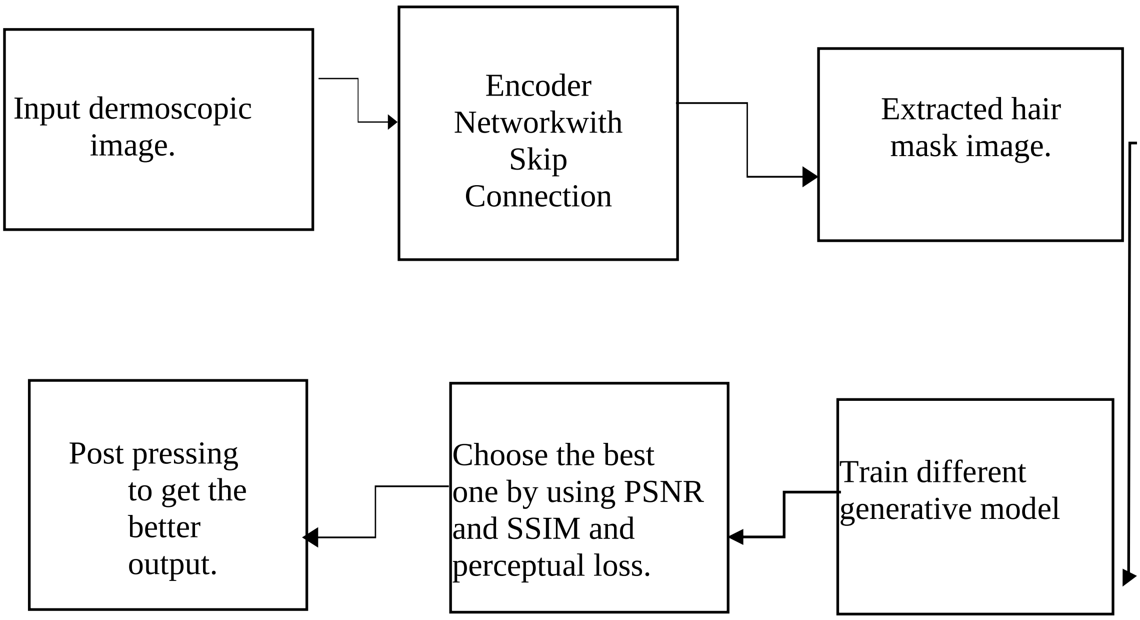

Figure 3.1 outlines the methodology, includes input segmentation, image generation, and post processing.

For the generation of hair mask pattern there need to be several steps. There are some proposed steps based on the abovementioned author's approach.

1. **Data Preparation**: Collect and preprocess a diverse dataset of incomplete images,

masks, and optional multi-modal information.

2. **Segmentation:** Using U-net architecture for segmentation of the dermoscopic images and generating mask for generative model input.

3. **Choosing the appropriate architecture**: choosing the appropriate architecture for the hair mask image generation. There are several architectures presents in this image generation field like Vq-Vae, DC-GAN, W-GAN, Style-GAN, Pro-GAN, among all this the best method is chosen.

4. **Iterative Training and Experimentation**: Train iteratively, experimenting with loss functions to determine which methods or algorithm of which architecture works thoroughly well with the modified dataset.

5. **Evaluation and Refinement**: Evaluate the model using metrics like PSNR, SSIM, fine-tuning parameters based on evaluation outcomes.

6 **post-process of the generated image** Using some post process image processing to get the better output result such as gaussian blur, unsharp masking etc.

Our research process involves developing a system for generating hair masks from dermoscopic images through a series of steps including data preparation, segmentation using U-net architecture, selection of the most suitable generative model architecture (e.g., VQ-VAE, DC-GAN, etc.), iterative training and experimentation with various loss functions, and evaluation using metrics like SSIM for refinement. The final step includes post-processing techniques such as Gaussian blur to enhance the quality of the generated images. This comprehensive approach ensures the creation of accurate and high-quality hair mask images for medical analysis**...**

3.2 Model Architecture

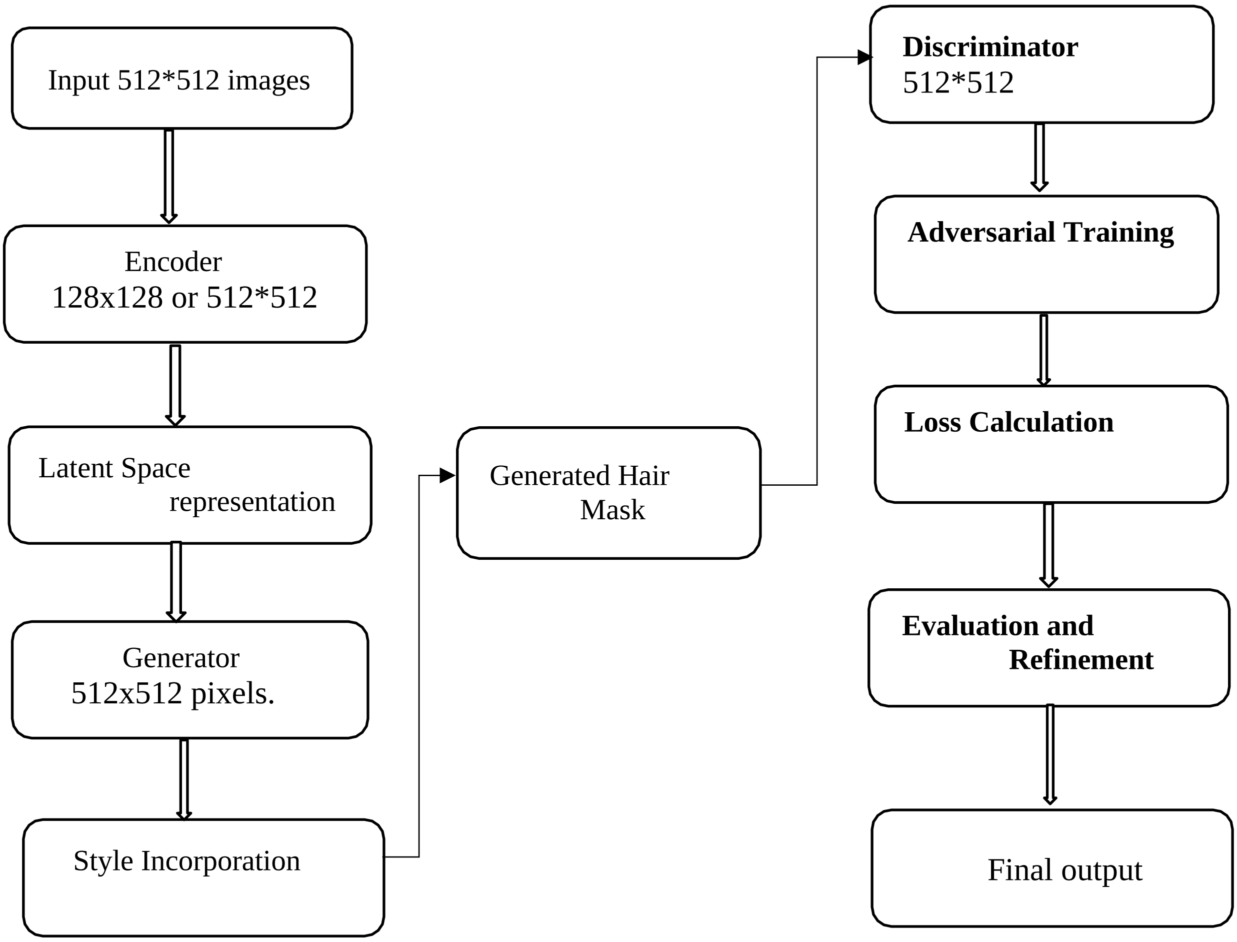

Figure 3.2: Complete Architecture of implemented model.

Input Dermoscopic image mask Image: The process begins with the input of dermoscopic images containing hair regions that need to be segmented.

Encoder: The input image is passed through the encoder, consisting of convolutional layers that extract high-level features capturing relevant information about hair textures, colors, and shapes.

Latent Space Representation: The encoder output is transformed into a latent space

representation where the extracted features are encoded into a lower-dimensional space.
Generator: The latent space representation is then fed into the generator, which consists of transposed convolutional layers. The generator up samples the latent space representation to generate the hair mask, preserving fine details through skip connections.

Style Incorporation: Style information from the latent space can be incorporated to generate diverse and realistic hair masks, allowing the model to learn variations in hair textures, colors, and styles.

Generated Hair Mask: The output of the generator is the generated hair mask, which represents the segmented hair regions of the input dermoscopic image.

Discriminator: Concurrently, the generated hair mask is passed through the discriminator, which distinguishes between real and generated masks. The discriminator provides feedback to the generator to improve the quality of the generated masks.

Adversarial Training: Adversarial training occurs between the generator and discriminator, where the generator learns to produce more realistic hair masks while the discriminator learns to distinguish between real and generated masks.

Loss Calculation: Various loss functions, including adversarial loss and perceptual loss, are used to calculate the discrepancy between the generated and real hair masks. These loss functions guide the training process and help optimize the model.

Evaluation and Refinement: The quality of the generated hair masks is evaluated using metrics such as SSIM. The architecture and hyperparameters are refined iteratively based on evaluation results to improve the accuracy and visual fidelity of the generated masks.

3.3 Conclusion

The architecture is designed to generate accurate hair masks from dermoscopic images through a sequential process. It begins by inputting dermoscopic images containing hair regions for segmentation. These images are passed through an encoder, extracting high-level features capturing relevant hair textures, colors, and shapes, which are then transformed into a lower-dimensional latent space representation. A generator utilizes this representation to produce hair masks, preserving fine details through skip connections and incorporating style information for diversity. Concurrently, a discriminator distinguishes between real and generated masks, providing feedback for adversarial training to improve mask realism. Various loss functions guide training by measuring discrepancies between generated and real masks, with evaluation metrics like SSIM used for refinement. Through iterative refinement of architecture and hyperparameters, the architecture aims to generate high-quality and visually accurate hair masks for medical or cosmetic analysis on.

CHAPTER IV

Implementation and Results

4.1 Introduction

After evaluating various generative models for image generation, Pro-GAN was identified as the most suitable choice due to its effectiveness in handling the challenge of generating large images, particularly hair masks. Pro-GAN's progressive architecture is well-suited for this task, as it begins with a low resolution and gradually adds layers to produce high-quality images. This approach results in more realistic hair masks, even in scenarios where there are dominant black pixels.

4.2 Experimental Setup

The optimal setup proposed by the authors:

Hardware Setup:

1. GPU: Using a GPU greatly accelerates training deep learning models. NVIDIA GPUs are commonly used due to compatibility with popular deep learning frameworks. Also available tesla t4 GPU is used for acceleration.
2. Memory: A GPU with sufficient memory (VRAM) is essential, especially for larger model architectures and high-resolution images. There are 16 GB ram used.
3. Storage: Have ample storage for the dataset, model checkpoints, and intermediate results.

Software Setup:

Operating System: windows operating system is used but a virtual environment has been, made for better compatibility with deep learning frameworks.

Python: Install Python (usually version 3.6 or higher) as it's the primaryprogramming language for deep learning.

CUDA: If you're using NVIDIA GPUs, install the CUDA toolkit for GPU acceleration.

cuDNN: Install the cuDNN library for optimized deep learning operations on NVIDIA GPUs.

Deep Learning Frameworks: A deep learning framework needs to be chosen thatsuits the preferences and needs. Popular choices include:

TensorFlow: Developed by Google, TensorFlow is widely used and has extensive community support.

Kera's: Built on top of TensorFlow and Theano, Keras offers a high-levelinterface for rapid prototyping.

Libraries and Packages: Install required packages using pip or conda:

1. NumPy: For numerical computations.
2. matplotlib or seaborn: For visualization.
3. SciPy: For various scientific computations.
4. pillow: For image handling.
5. Tqdm: For progress bar in python

4.3 Evaluation Metrics

For the evaluation of our image generation method, several metrics were employed to quantitatively and qualitatively assess the performance of the generated images compared to the ground truth images. These metrics include:

1. **Mean Squared Error (MSE)**: Calculated as the average squared difference between the pixel values of the generated hair mask patterns and the corresponding ground truth hair mask patterns. Lower MSE values signify higher quality in the generated patterns.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2 \text{ ----------------------------- (1)}$$

Here N is the total number of observations. $(X_i - Y_i)^2$ represents the difference of estimated value and the actual value Squaring the difference ensures that both positive and negative errors contribute positively to the overall error, preventing cancellations.

2. **Structural Similarity Index (SSIM)**: Measures the similarity between the generated hair mask patterns and the ground truth patterns in terms of structure, texture, and luminance. SSIM values range from -1 to 1, with higher values indicating better similarity between the patterns.

$$\mathrm{SSIM}(x,y) = \frac{(2u_x u_y + c_1)(2p_{xy} + c_2)}{(u_x^2 + u_y^2 + c_1)(p_x^2 + p_y^2 + c_2)} \text{-----------------------------}(2)$$

- x and y are the two images being compared.
- U_x and U_y are the average pixel intensities of images x and y respectively.
- P_x^2 and P_y^2 are the variances of pixel intensities in images x and y respectively.

- C1 and C2 are constants to stabilize the division with weak denominator.

3. **Peak Signal-to-Noise Ratio (PSNR)**: Computes the ratio of the maximum possible power of the generated hair mask patterns to the power of noise, typically measured in decibels (dB). Higher PSNR values correspond to better quality in the generated patterns.

$$\mathrm{PSNR} = 10.\log_{10}\left(\frac{MAX^2}{MSE}\right) \text{----------------------------}(3)$$

- MAX= maximum possible pixel value of the image

- MSE = Mean squared error of the image

4. **WGAN-GP Loss**: instead of using VGG16 for perceptual loss, the Wasserstein GAN with Gradient Penalty (WGAN-GP) loss function is employed. WGAN-GP loss evaluates the

Wasserstein distance between the probability distributions of the generated and ground truth patterns, with the gradient penalty term enforcing smoothness in the generated samples. This loss function is effective for training. model. This loss function is effective for training generative models and can optimize the generator to produce high-quality hair mask patterns that closely match the ground truth patterns.

5. **Visual Inspection:** Involves qualitative assessment by human observers to evaluate the visual quality of the generated hair mask patterns compared to the ground truth patterns. This assessment considers aspects such as pattern clarity, sharpness, and the presence of artifacts**.**

By considering these evaluation metrics collectively, we gain a comprehensive understanding of the effectiveness of our image generation method and identify areas for further optimization and improvement.

4.4 Dataset

First, a dataset comprising 500 dermoscopic images along with their corresponding masks was collected from Sk. Imran Hossain et al[7]. However, this initial dataset was deemed insufficient for training generative models effectively. To address this limitation, a U-Net architecture was trained on this dataset to generate hair masks. Subsequently, the trained U-Net was employed to generate hair masks from the Ham 10,000 dataset, which contains 10,000 dermoscopic images. By utilizing the U-Net, hair masks were extracted for all 10,000 images in the Ham dataset. Consequently, the dataset size expanded to 10,500 images. Leveraging this larger dataset, various generative models were trained, and among them, the Pro-GAN model emerged as the most successful in generating high-quality outputs.

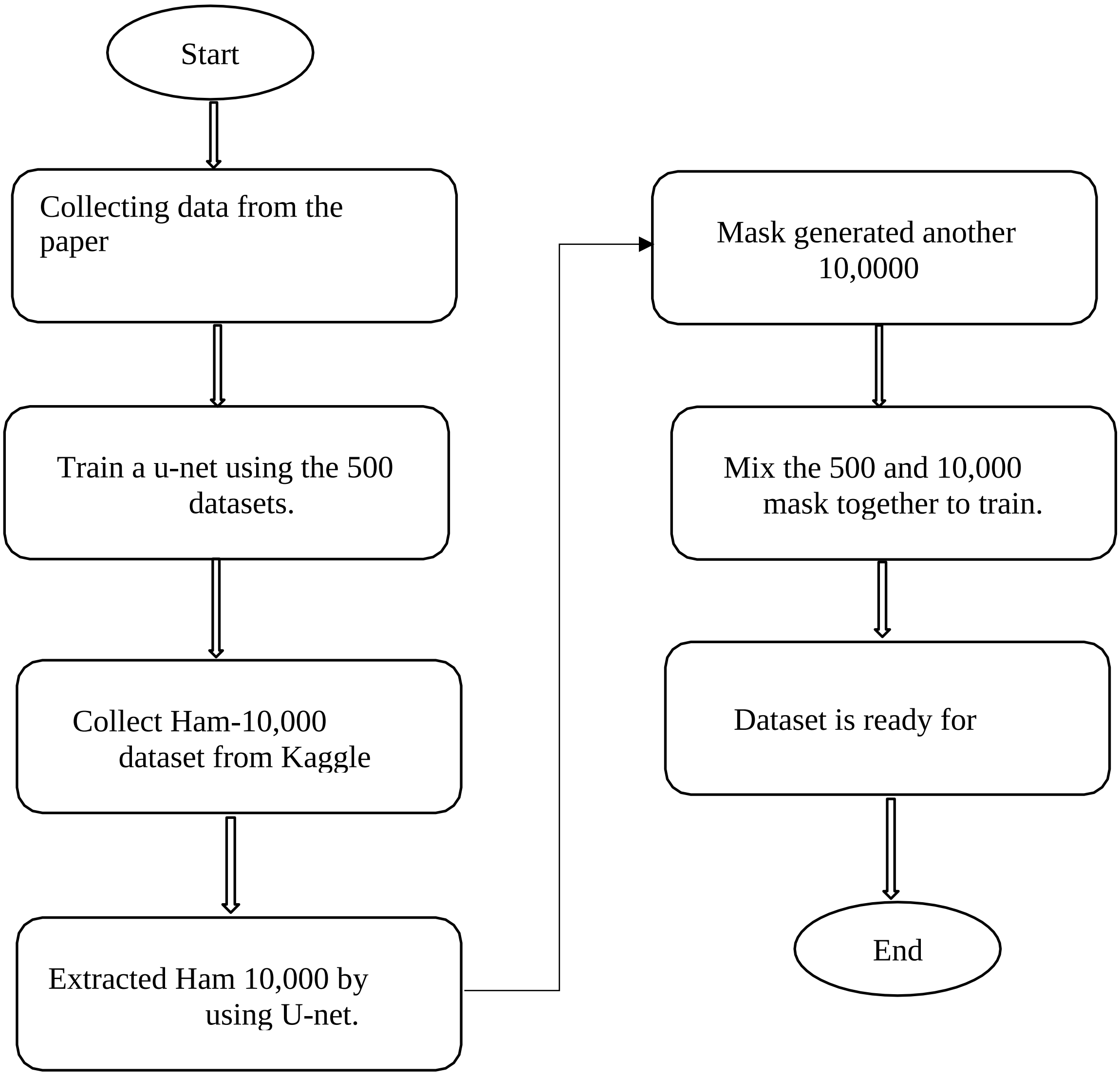

Figure 4.1: Flow chat of dataset generation

Image

Figure 4.2: dermoscopic image and mask of the dermoscopic image

Figure4.3: Generated image of modified Pro-Gan

4.5 Implementation and Results

The best model is chosen by comprising the metrices the comparison table is. given below.

Table 4.1: Comparison among different generative model

Different generative model	PSNR	SSIM	MSE
Style-Gan	9.249	0.097	0.808
WC-GAN	7.915	0.044	0.833
Modified PRO-GAN	31.473	0.926	0.484

4.5.1 Quantitative analysis of the whole image

Table 4.2: Quantitative analysis on image

	PSNR	SSIM	MSE
Before Postprocessing	34.516	0.596	0.451
After Postprocessing	31.473	0.926	0.484

4.5.2 Comparative analysis

Table 4.3: Comparative analysis between our method and the existing methods

	PSNR	SSIM	MSE
Our Method	34.516	0.926	0.451
Existing Method	30.4341	0.923	.901

4.5.3 Qualitative results

Qualitative results for the different generative models showcase their performance variations and visual fidelity. These results offer insights into the strengths and weaknesses of the model in generating realistic images.

Figure 4.4: Output of the modified Pro-Gan

In Figure 4.4, the output of the progressive GAN is depicted. After a slight modification of the Pro-GAN, the model generates a 512*512 image. Remarkably, this image bears a striking resemblance to the input image.

Figure.4.5: Output of the Style Gan and DC-Gan

The image displays the output of the StyleGAN and DCGAN. However, instead of generating high-quality images, these models produce images of smaller sizes. The input for these models is the hair mask derived from dermoscopic images.

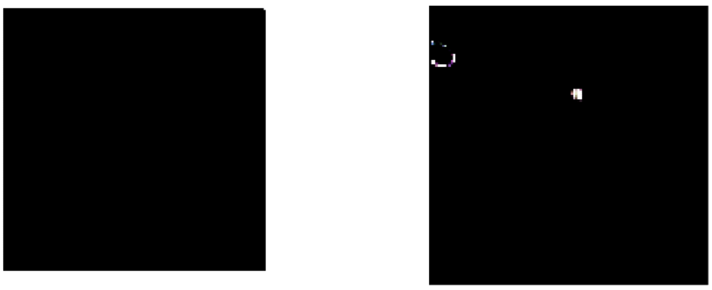

Figure4.6: Failed to generate hair mask.

In these images, we observe instances where the modified Pro-GAN fails to generate the hair mask pattern accurately. This discrepancy arises due to the dominance of black pixels in the dataset, as the hair mask contains very few white pixels.

4.5.4 Analysis of the results

In terms of evaluation metrics, there is a lot of scope for improvement in this work. The PSNR and MSE values are a bit deviated from the standard method. The reason is this the generated image is 512*512 in the final result and generating such big images is very challenging as it needs lots of computational power and time and also a large dataset Also here is a large imbalance in the pixel generation .Here most of the pixels are black and less pixels are white and while generating the hair mask the main concern is the white pixel that’s why the PSNR of the implemented model is little bit less than the average standard one Still pro Gan generates quite realistic images of hair mask with good SSIM And MSE.

4.6 Objectives Achieved

In this research, we have successfully created hair mask images with dimensions of 512*512 pixels, and the generation process has demonstrated high stability. We have also explored various architectural models and gained insights into segmentation models used for dataset generation. Analysis metrics have been employed to assess the performance, providing valuable insights. Additionally, we have learned about several post-processing techniques throughout the study.

4.6.1Gain Objectives

1. **Large Image Generation:** Hair mask images of 512*512-pixel dimensions were successfully generated, showcasing stable generation processes**.**

2. **Architectural Exploration:** Various architectural models were investigated, offering

insights into their suitability for hair mask generation tasks.

3. **Segmentation Model Insights:** Exploration of segmentation models provided valuable understanding for dataset generation, enhancing the quality of the generated hair masks**.**

4. **Performance Analysis Metrics:** Analysis metrics were utilized to evaluate the performance of the generated hair mask images, offering valuable insights for further optimization.

5. **Post-Processing Techniques:** Throughout the study, multiple post-processing techniques were learned and applied, contributing to refining the quality of the generated hair mask images.

4.7 Financial Analysis and Budget

This thesis project is conducted with careful financial planning. We meticulously manage resource allocation for data acquisition, experimentation, and computational support within our budget constraints. To enhance efficiency, we prioritize the use of open-source tools and institutional facilities. While ensuring our software needs are met, we aim to optimize cost-effectiveness by utilizing free IDEs such as Google Collab. Given the significant expenses involved in acquiring extensive image datasets, we prioritize the utilization of publicly available datasets and acknowledge their creators accordingly. Additionally, we have provisions in place to address unforeseen expenses, ensuring the smooth progress of the project without compromising on quality. Table 4.4 provides an overview of the total budget allocation for conducting the thesis.

Table 4.4: Financial budget for the research

Budget Category	Estimated Cost Range
Equipment and Software	80,000 - 100000 BDT
Travel and Conferences	4,000 - 5,000 BDT
Publication Fees	2,000 - 3,000 BDT
Miscellaneous	2000 - 3,000 BDT
Total Estimated Budget Range	28,000 - 41,000 BDT

By adhering to a strategic financial plan, which includes a designated budget in case the current resources fall short of meeting criteria, this thesis aims to achieve optimal outcomes while maintaining financial responsibility.

4.9 Conclusion

In conclusion, the results and analysis presented in this study demonstrate the successful generation of hair mask images with dimensions of 512*512 pixels, showcasing high stability throughout the generation process. The exploration of various architectural models provided valuable insights into their suitability for hair mask generation tasks, contributing to a deeper understanding of segmentation models used for dataset generation. By employing analysis metrics, we were able to evaluate the performance of the generated hair mask images, facilitating further optimization efforts. Additionally, the utilization of post-processing techniques helped refine the quality of the generated images. Overall, these findings highlight the effectiveness of the methods employed in achieving the objectives of the study, underscoring the importance of careful financial planning and resource allocation in research endeavors.

CHAPTER V

Societal, Health, Environment, Safety, Ethical, Legal and Cultural Issues

5.1 Intellectual Property Considerations

In addressing societal, health, environmental, safety, ethical, legal, and cultural issues related to intellectual property considerations, several key aspects have been carefully considered throughout the course of this research endeavor. Firstly, while utilizing various image generation models, including Pro-GAN, we have taken into account potential intellectual property rights associated with these models and ensured compliance with relevant licensing agreements. Additionally, in the process of dataset generation through segmentation using U-net architecture, ethical considerations regarding data privacy and consent have been rigorously adhered to, with appropriate measures implemented to safeguard sensitive information. Furthermore, the application of post-processing techniques has been conducted in accordance with ethical guidelines and best practices to ensure the integrity and authenticity of the generated images. Moreover, in selecting the final model based on evaluation metrics such as SSIM and PSNR, transparency and fairness have been maintained throughout the decision-making process to uphold ethical standards and avoid bias. Overall, a comprehensive approach to intellectual property considerations has been undertaken, encompassing various societal, health, environmental, safety, ethical, legal, and cultural dimensions to ensure the responsible conduct of research and innovation in alignment with ethical principles and legal requirements.

5.2 Ethical Considerations

In addressing ethical considerations, utmost importance is given to ensuring the integrity and ethical conduct of the research. This involves obtaining informed consent from participants, maintaining confidentiality and privacy of sensitive data, and adhering to ethical guidelines established by relevant professional bodies or institutional review boards. Additionally, potential risks to participants are carefully assessed and mitigated, and measures are implemented to minimize any potential harm. Transparency in reporting methods and findings is also prioritized to uphold the trustworthiness of the research outcomes. Overall, ethical considerations are integral to maintaining the credibility and integrity of the research process.

5.3 Safety Considerations

Safety considerations are paramount in this project to protect the well-being of both researchers and participants. This involves implementing measures to prevent accidents or injuries during data collection, analysis, and experimentation. For example, appropriate safety protocols are followed when handling equipment or substances that may pose risks. Additionally, researchers are trained in emergency procedures and protocols to address unforeseen circumstances effectively. Furthermore, ethical guidelines regarding the use of human or animal subjects are strictly adhered to, ensuring their safety and welfare throughout the research process. Overall, prioritizing safety considerations helps create a secure and conducive environment for conducting research while minimizing potential risks.

5.4 Legal Considerations

In navigating the legal landscape pertinent to this research, several key considerations have been carefully addressed. Firstly, with regards to intellectual property rights, diligent efforts have been made to ensure compliance with relevant copyright laws and licensing agreements, particularly in the utilization of image generation models such as Pro-GAN. Additionally, in the context of dataset generation through segmentation using U-net architecture, attention has been given to potential copyright issues surrounding the use of source data and the creation of derivative works. Moreover, in the application of post-processing techniques, adherence to intellectual property laws governing image manipulation and alteration has been paramount to avoid infringing upon the rights of original creators. Furthermore, in the selection of the final model based on evaluation metrics, including SSIM and PSNR, consideration has been given to potential legal implications related to model attribution and accountability. Overall, a proactive approach to legal considerations has been adopted, with due diligence exercised to ensure compliance with applicable laws and regulations throughout the research process.

5.5 Impact of the Project on Societal, Health, and Cultural Issues

The impact of this research on Societal, Health, and Cultural Issues is discussed below:

- **Societal Impact**:

  - The project's societal impact spans healthcare access, public health awareness, empowerment, economic opportunities, and ethical considerations. By enabling remote diagnostics and raising awareness about dermatological health, it improves healthcare access and fosters inclusivity. Additionally, it promotes economic growth through job creation and innovation while upholding ethical research practices. Overall, the project has the potential to drive positive social change and improve well-being.

- **Health Impact**:

  - Discuss how accurate hair mask generation enhances the diagnostic process by providing detailed visual representations of skin conditions, aiding healthcare professionals in accurate diagnosis.

  - Explore how the project's outcomes can facilitate treatment planning by enabling healthcare professionals to visualize the extent and distribution of hair patterns in dermatological conditions, guiding treatment decisions.

  - Discuss the impact of accurate hair mask generation on the quality of care provided to patients, including reduced diagnostic errors, faster treatment initiation, and better patient satisfaction.

- **Cultural Impact**:

- Explore how accurate hair mask generation contributes to diverse representation by accommodating various hair textures, styles, and cultural preferences.

- Discuss the role of hair in cultural identity and self-expression, highlighting how the project's outcomes empower individuals to embrace and celebrate their unique hair characteristics.

- Consider how the project promotes inclusivity by addressing the diverse needs and preferences of individuals from different cultural backgrounds, fostering a sense of belonging and acceptance.

- Discuss how the project raises awareness about the cultural significance of hair and its representation in society, promoting dialogue and understanding across cultural divides.

5.6 Impact of Project on the Environment and Sustainability

Here's the impact of the project on the environment and sustainability mentioned below:

- **Environmental Impact**:

- **Reduction in energy consumption**: By improving the efficiency of image processing algorithms, our research reduces the computational resources required for image enhancement tasks, resulting in lower energy consumption in computing systems.

- **Minimization of waste**: By enabling the restoration and enhancement of digital images, our research contributes to the preservation of existing visualcontent, reducing the need for additional resources to recreate or reproduce lost or damaged images.

- **Sustainability Impact**:

- **Sustainable resource management** Effective management of resources for long-term sustainability is essential. This involves optimizing resource allocation and utilization to ensure minimal waste and maximum efficiency. By employing sustainable practices in resource management, we aim to preserve natural resources, reduce environmental impact, and promote resilience in ecosystems and communities. images.

- **Environmental awareness**: Environmental awareness is vital for understanding and addressing human impact on the planet. Through education, behavior change, policy advocacy, community engagement, and a global perspective, individuals and communities can work together to promote sustainability and environmental stewardship, leading to a healthier and more resilient planet for future generations.

- **Encouraging eco-friendly practices**: Promoting eco-friendly practices encourages responsible behavior towards the environment, fostering sustainability and reducing ecological impact for a healthier planet and future generations...

CHAPTER VI

Addressing Complex Engineering Problems and Activities

6.1 Complex engineering problems associated with the current thesis.

This thesis addresses complex challenges in skin hair removal mask generation, focusing on algorithmic precision, dataset limitations, and maintaining image integrity within professional and legal frameworks, requiring innovative and validated deep learning solutions.

Table 6.1: Complexing engineering problems associated with current thesis

Attribute	**Addressing the Attributes of Complex Engineering Problems**	
Depth of knowledge required	P1	A deep knowledge about deep learning, Segmentation model, generative model such as DC-Gan, Wc-Gan, Style-Gan, Pro-Gan is needed Also, deep knowledge about unmasked sharpening and other post processing is required.
Range of conflicting requirements	P2	To attain the objectives, a high level of well-defined model is necessary. Because of large size hair mask image generation, on the other hand, processing time needs to be decreased. So, attaining both of these requirements may prove conflicting.
Depth of analysis required	P3	Sufficient analysis of different versions of Generative model and segmentation model is required for this thesis. For improvement in performance, several modifications of the convolution layer, improvement of the loss function is needed

Familiarity of issues	P4	Image generation using generative model is familiar but for the thesis a larger size of image need to generated from hair mask which is unfamiliar
Extent of applicable codes	P5	All the standards and codes of practice for professional engineering are maintained in this thesis. The dataset is collected from Sk Imran Hossain et al and also from publicly available dataset like Ham10,000 The thesis was also executed within the legal boundaries.

6.2 Complex engineering activities associated with the current thesis.

The thesis involves complex engineering activities such as developing advanced deep learning models, meticulously analyzing image datasets, and optimizing algorithms for high fidelity mask generating, all while adhering to stringent ethical and professional standards.

Table 6.2: Complex engineering activities associated with current thesis.

Attribute	**Addressing the Attributes of Complex Engineering Activities**	
Range of resources	A1	In order to execute this thesis, a number of resources were collected or used. The resources include dataset collected from Sk Imran Hossain et al and Ham10,00 datasets powerful GPU provided by Kaggle, two fully functional computers and stable internet connection. Deep learning technologies were also used for this purpose.

Level of interaction	A2	A significant amount of interaction between medical and technical data was necessary for this thesis. Understanding the features of hair mask images and generating it in the size of 512*512 was challenging for the thesis. Moreover, applying the deep learning models to segmentation of the hair mask from the dermoscopic images is also challenging.
Innovation	A3	A modification of the image generation methos pro-Gan which can generate large size images like 512*512 pixel. Also, modification to the outcome of the generated image though some image processing techniques to make the generated images more accurate for augmentation
Consequences for society and the environment	A4	The suggested technique enhances Skin lesion disease classification. Thus, this may turn out to be quite beneficial for society. This theory can help people receive diagnoses that are more precise.
Familiarity	A5	Generating large image like 512*512 is challenging and unfamiliar also the dataset is used for segmentation never used before Also some image processing technique like unsharp mask is unfamiliar while it is applied after generation of the image of the modified pro-Gan This modification of the generative model is also unfamiliar

CHAPTER VII

Conclusions

7.1 Summary

In conclusion, this thesis project has effectively tackled the intricate challenge of generating high-quality images depicting skin lesions with natural hair patterns. Commencing with the segmentation of skin lesions utilizing the U-Net architecture, a comprehensive dataset comprising 10,000 images was meticulously curated. Through extensive training of various generative models, the modified Pro-GAN emerged as the standout performer, validated by rigorous assessment against metrics such as PSNR, SSIM, and visual inspection. These outcomes underscore the feasibility and efficacy of harnessing advanced generative models within the realm of dermatological imaging. The successful creation of large-scale, high-fidelity images featuring natural hair patterns signifies a remarkable advancement, promising wide-ranging applications in disease classification, diagnostic support systems, educational resources, and research endeavors. Furthermore, this research underscores the pivotal role of cutting-edge technologies, exemplified by the modified Pro-GAN, in addressing complexities inherent in medical imaging and dermatology. By leveraging machine learning and image processing methodologies, the precision and efficiency of diagnosing skin lesions can be significantly enhanced, thereby reducing the need for invasive procedures or subjective manual assessments. In essence, this thesis makes substantial contributions through innovative methodologies and insights, paving the path for future advancements in skin disease diagnosis, treatment, and research.

7.2 Limitations

While our research presents promising results high quality image generation but there are several limitations warrant consideration. Some of them are mentioned below:

1. **Limited Computational Power**: One significant limitation is the constraint imposed by the available computational resources. The training of complex models like U-Net and Pro-GAN requires substantial computational power, which may not be readily accessible to all researchers. This limitation might have affected the scalability and efficiency of the proposed approach, potentially hindering the exploration of more sophisticated architectures or larger datasets.

2. **Insufficiently Fine-Tuned Dataset**: Although you generated a dataset comprising 10,000 images, the dataset's quality and diversity might still be limited. Fine-tuning the dataset to encompass a broader range of hair patterns, textures, and skin types could enhance the models' generalization capabilities and robustness to real-world variations. The lack of diversity in the dataset may have restricted the models' ability to accurately capture the full spectrum of dermoscopic image characteristics, potentially leading to suboptimal performance in certain scenarios.

3. **Biasness in Dataset**: Another limitation is the potential bias in the dataset, particularly regarding the distribution of hair mask annotations. If the dataset disproportionately represents certain hair types, colors, or anatomical regions, the trained models may exhibit biases and limitations in their ability to generalize to diverse populations. Addressing dataset bias through careful curation, balanced sampling strategies, and augmentation techniques could mitigate this limitation and enhance the models' fairness and inclusivity.

4. **Evaluation Metrics Limitation**: While you utilized metrics such as PSNR, SSIM, and visual inspection to evaluate model performance, it's essential to acknowledge their limitations in fully assessing image quality and fidelity. These metrics may not always align with human perception or capture nuances in image semantics and aesthetics. Incorporating additional subjective assessment methods, such as user studies or expert evaluations, could provide more comprehensive insights into the models' efficacy and perceptual quality.

5. **Potential Overfitting**: With the use of complex models and relatively limited datasets,

there's a risk of overfitting, where the models might learn to memorize training examples rather than generalize underlying patterns. Regularization techniques, cross-validation, and ensemble learning approaches could help mitigate overfitting and improve the models' robustness to unseen data.

6. **Generalization to Real-World Scenarios**: Lastly, it's essential to consider the generalizability of the proposed approach to real-world dermoscopic imaging scenarios. Factors such as variations in lighting conditions, image quality, and patient demographics could significantly impact model performance outside the controlled experimental settings. Conducting validation studies on diverse, real-world datasets would provide valuable insights into the models' applicability and limitations in clinical practice.

7.3 Future Works

There are a lot of areas where the work can be extended, some of them are mentionedhere:

1. **Generating more sharp and accurate images: Due** to limitation of resource, dataset and other component sharp and accurate image is not being generated as expected it could be done in future.

2. **Integrate to a framework:** My goal in future is to integrate image generation(hair-mask) into a framework, where the generated hair mask pattern can be augmented in a hairless skin lesion and train it to achieve better accuracy without the using of hair removal in test time.

3. **Finding some other process:** Generative model is time consuming while it takes lots of hour to train so to recover the limitation my future goal is to find some process like diffusion model to train and get the actual output.

4. **Developing more accurate loss functions:** Developing custom loss function will be more accurate is the future goal here.

References

[1] M. Attia et al., "Realistic hair simulator for skin lesion images: A novel benchmarking tool," *Artificial Intelligence in Medicine*, vol. 108, p. 101933, 2020

[2] A. Razavi, A. Van den Oord, and O. Vinyals, "Generating diverse high-fidelity images with VQ-VAE-2," in *Advances in Neural Information Processing Systems 32*, 2019

[3] Dhariwal, Prafulla, and Alexander Nichol. "Diffusion models beat gans on image synthesis." *Advances in neural information processing systems* 34 (2021): 8780-8794.

[4] Liu, Bingqi, et al. "Application of an Improved DCGAN for Image Generation." Mobile Information Systems 2022 (2022)..

[5] Richardson, Elad, et al. "Encoding in style: a style Gan encoder for image-to-image translation." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2021.

[6] Gao, Hongchang, Jian Pei, and Heng Huang. "Progan: Network embedding via proximity generative adversarial network." Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 2019.

[7] Hossain, Sk Imran, et al. "A skin lesion hair mask dataset with fine-grained annotations." Data in Brief, vol. 48, 2023, p. 109249.

[8] M. Soloveitchik et al., "Conditional Fréchet Inception Distance," arXiv preprint arXiv:2103.11521, 2021.

[9] Z. Guo et al., "Diffusion Models in Bioinformatics: A New Wave of Deep Learning Revolution in Action," arXiv preprint arXiv:2302.10907, 2023

[10] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*. Springer International Publishing, 2015.

[11] Celebi, M. E., Codella, N., & Halpern, A. "Dermoscopy Image Analysis: Overview and Future Directions." IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 2, March 2019, pp. 474-478. doi:10.1109/JBHI.2019.2895803.

[12] Xie F, Fan H, Li Y, Jiang Z, Meng R, Bovik A. Melanoma classification on dermoscopy images using a neural network ensemble model. IEEE Trans Med Imaging 2017;36(3):849–58. https://doi.org/10.1109/TMI.2016.2633551

[13] Kasmi R, Mokrani K. Classification of malignant melanoma and benign skin lesions: implementation of automatic abcd rule. IET Image Process 2016;10(6):448–55. https://doi.org/10.1049/iet-ipr.2015.0385.

[14] Satheesha TY, Satyanarayana D, Prasad MNG, Dhruve KD. Melanoma is skin deep: a 3d reconstruction technique for computerized dermoscopic skin lesion classification. IEEE J Transl Eng Health Med 2017; 5:1–17. https://doi.org/10.1109/JTEHM. 2017.2648797.

[15] Xie F, Bovik AC. Automatic segmentation of dermoscopy images using self-generating neural networks seeded by genetic algorithm. Pattern Recogn 2013;46(3):1012–9. https://doi.org/10.1016/j.patcog.2012.08.012.