
ISSN: 2321-2152
IJMECE
International Journal of modern electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

ISSN 2321-2152
www.ijmece.com
Vol 11, Issue 4, 2023

Controllable Image Synthesis Utilizing Attribute-Decomposed GAN

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Abstract

This paper presents a novel framework for controllable image synthesis using Attribute-Decomposed Generative Adversarial Networks (AD-GAN). The proposed model addresses the challenge of fine-grained control over image attributes by decomposing the latent space into distinct subspaces, each corresponding to specific attributes such as pose, expression, and identity. This decomposition allows for independent manipulation of individual features without affecting others, significantly enhancing the flexibility and accuracy of image generation. Through extensive experiments, we demonstrate that AD-GAN not only achieves superior attribute control but also maintains high image quality and diversity compared to existing methods. The robustness and scalability of the model across various datasets make it a valuable tool for applications requiring detailed attribute manipulation, such as photo editing, avatar creation, and virtual reality.

Keywords: Controllable Image Synthesis, Attribute-Decomposed GAN, Generative Adversarial Networks, Image Attributes, Fine-Grained Control, Image Generation.

1. Introduction

1.1 Introduction

Generative Adversarial Networks (GANs) have revolutionized the field of image synthesis, enabling the generation of high-quality, photorealistic images. However, a significant challenge remains in achieving precise control over specific attributes of generated images. Traditional GAN architectures often entangle various attributes, making it difficult to modify one without inadvertently altering others. This paper proposes a novel approach to controllable image synthesis using AD-GAN, which decomposes the latent space into subspaces corresponding to different attributes, facilitating independent control and enhancing the quality of generated images.

1.2 Objective

The primary objective of this project is to design and implement an advanced image synthesis system using Attribute-Decomposed Generative Adversarial Networks (AD-GAN) that enables fine-grained, independent control over multiple image attributes. The specific objectives are as follows:

Attribute Decomposition: Develop a method to decompose the latent space into distinct subspaces, each corresponding to a specific attribute (e.g., pose, expression, identity). This allows for precise control over individual attributes during the image synthesis process.

Independent Attribute Manipulation: Enable users to modify specific image attributes independently without causing unintended changes to other features. This capability is crucial for applications requiring detailed and customizable image outputs.

Multi-Attribute Conditioning: Incorporate multi-attribute conditioning into the AD-GAN framework, allowing simultaneous control over multiple attributes. This feature is essential for generating images with complex combinations of attributes.

High-Quality Image Generation: Ensure that the generated images maintain high quality and realism, even after attribute modifications. The system should produce photorealistic images that accurately reflect the desired changes.

Robustness and Scalability: Demonstrate the robustness of the AD-GAN model across various datasets and its scalability to handle a large number of attributes. The system should perform effectively in diverse scenarios and applications.

User -Friendly Interface: Design a user-friendly interface that allows users to easily interact with the system, upload images, and manipulate attributes intuitively.

Evaluation and Benchmarking: Establish comprehensive evaluation metrics to assess the quality and controllability of the generated images. This includes quantitative measures such as SSIM (Structural Similarity Index) and qualitative assessments through user studies.

2. Literature Review

The literature review examines existing methods for controllable image synthesis, including Conditional GANs (CGAN), InfoGAN, and StarGAN. While these methods provide some level of control, they often struggle with attribute entanglement and quality loss. AD-GAN addresses these limitations by introducing a decomposition strategy that allows for precise control over individual attributes.

3. Existing System

Existing systems for controllable image synthesis often face challenges related to attribute entanglement, limited control, and reduced image quality. Traditional GAN models generate images as holistic entities, making it difficult to modify specific attributes without affecting others. This section discusses the limitations of current approaches and sets the stage for the proposed AD-GAN framework.

3.1 EXISTING SYSTEM DISADVANTAGES:

- **Attribute Entanglement:**
  Changing one attribute (like smile) often unintentionally changes others (like face shape or background).

- **Limited Control:**
  Existing models struggle to modify multiple attributes independently and precisely.

- **Reduced Image Quality:**
  When trying to control attributes, image realism often drops, resulting in blurry or unnatural outputs.

- **Complex Training:**
  Many existing methods require complicated architectures and careful tuning but still don’t achieve full disentanglement.

- **Scalability Issues:**
  Difficult to handle many attributes at once; performance decreases as the number of attributes increases.

- **Artifacts in Generated Images:**
  Attribute manipulation often introduces noise, distortions, or unrealistic features in images.
- **Lack of Flexibility:**
  Users cannot smoothly control attribute strength (e.g., smiling a little vs. smiling broadly).
- **Dependency on Labels:**

ISSN 2321-2152
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Some models require exact attribute labels for training and testing, limiting flexibility in real-world applications.

4. Proposed System

The proposed AD-GAN framework decomposes image attributes into separate components, enabling precise control over each attribute. The system architecture includes a generator, discriminator, and attribute conditioning modules. The generator synthesizes images based on decomposed latent vectors, while the discriminator evaluates both the authenticity of images and the correctness of attribute representations. This section details the input and output design, the AD-GAN algorithm, and the system architecture.

4.1 System Architecture:

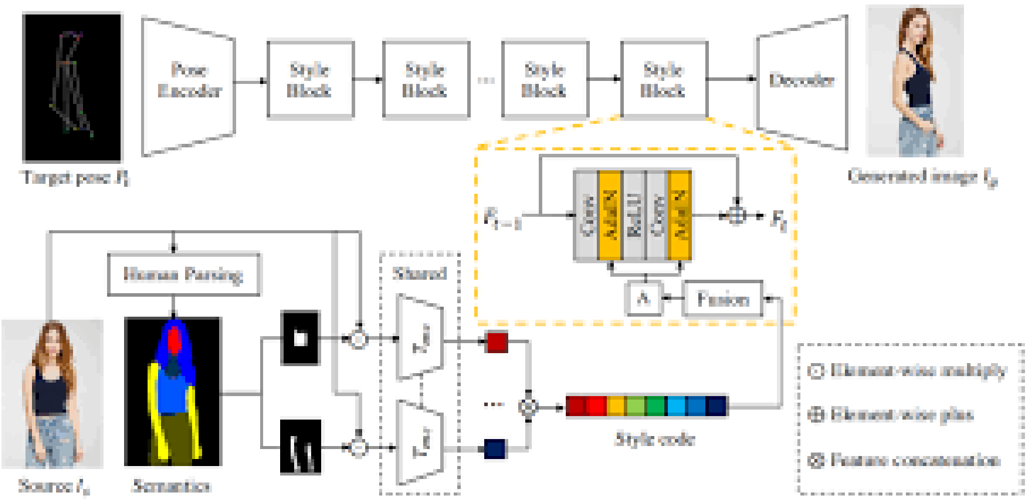

Fig 4.1: System architecture of Controllable image synthesis with attribute-Decomposed-GAN

the system architecture of AD-GAN consists of a Generator, a Discriminator, and Attribute Conditioning modules. The input image is preprocessed and mapped into a decomposed latent space, where each subspace controls a specific attribute like pose, expression, or identity. Attribute labels guide the generator to synthesize high-quality, realistic images based on the selected attributes. The discriminator judges both the authenticity of images and whether the requested attributes are correctly applied. Specialized loss functions, including adversarial, attribute, perceptual, and mutual information losses, optimize the training. This structured design ensures independent attribute control while preserving overall image realism and diversity.

4.5 System Analysis

The Attribute-Decomposed Generative Adversarial Network (AD-GAN) is an advanced approach to controllable image synthesis that overcomes the limitations of traditional GANs in managing specific image attributes. The key innovation of AD-GAN is its ability to decompose the latent space into separate subspaces, each representing a different attribute (e.g., pose, expression, identity). This allows for precise control over individual attributes, enabling targeted modifications without affecting other features of the generated images.

The architecture of AD-GAN consists of two main components: the generator and the discriminator. The generator creates images based on the decomposed latent vectors, ensuring that each attribute is accurately represented. The discriminator not only distinguishes between real and generated images but also checks if the attributes are correctly applied. This dual function helps maintain the realism of the generated images while ensuring they meet the desired attribute specifications.

A significant challenge that AD-GAN addresses is the entanglement of attributes, which is common in traditional GANs. In AD-GAN, each attribute is treated independently, allowing for more granular control. For example, users can change a person's age in a photo without altering their identity or modify the color of a car without affecting its shape.

The training process of AD-GAN uses a well-designed loss function that balances the need for realistic images and accurate attribute representation. The adversarial loss ensures that generated images look real, while attribute-specific losses enforce correct attribute representation. Additionally, a mutual information term helps keep attributes separate within the latent space, leading to high-quality image synthesis.

AD-GAN has been tested on various datasets, demonstrating its robustness and scalability. It performs well on both standard benchmarks and more complex datasets, showing its adaptability to different image synthesis tasks. The model can handle multiple attributes simultaneously, making it a versatile tool for various applications.

In summary, AD-GAN represents a significant advancement in controllable image synthesis, providing a powerful solution for generating high-quality images with precise control over attributes. Its innovative approach has the potential to transform applications in photo editing, creative content generation, and other areas where detailed attribute manipulation is essential.

4.6 Data Flow Model

The data flow model visually represents how data moves through the AD-GAN system. It uses standardized symbols to illustrate activities, decision points, and transitions. This model is useful for understanding the workflow of the system and is commonly used in both business process modeling and software engineering.

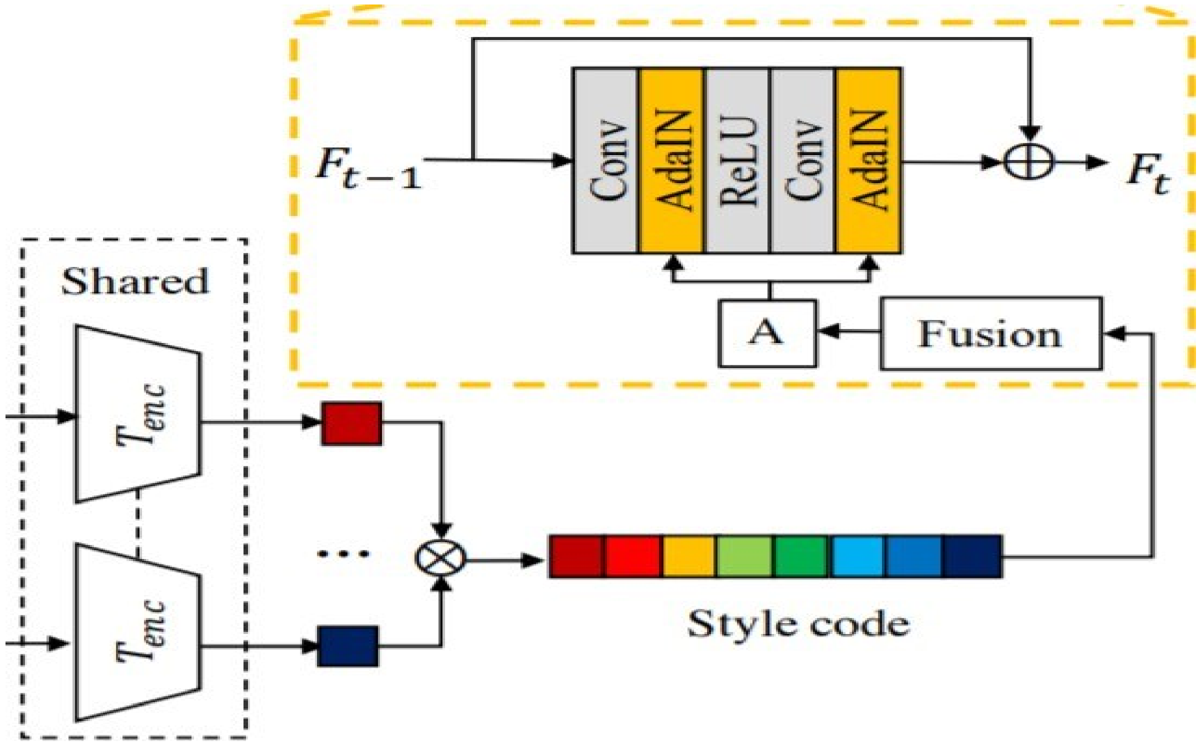

Fig 4.2: Data Flow Model For Controllable image synthesis with attribute-Decomposed - GAN

In the data flow model for AD-GAN:

Activities are represented by rectangles, indicating the steps involved in the process.

Decision points are shown as diamonds, where the flow can branch based on certain conditions.

Transitions are depicted with arrows, showing the direction of data movement.

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4.1 Data Flow Diagram:

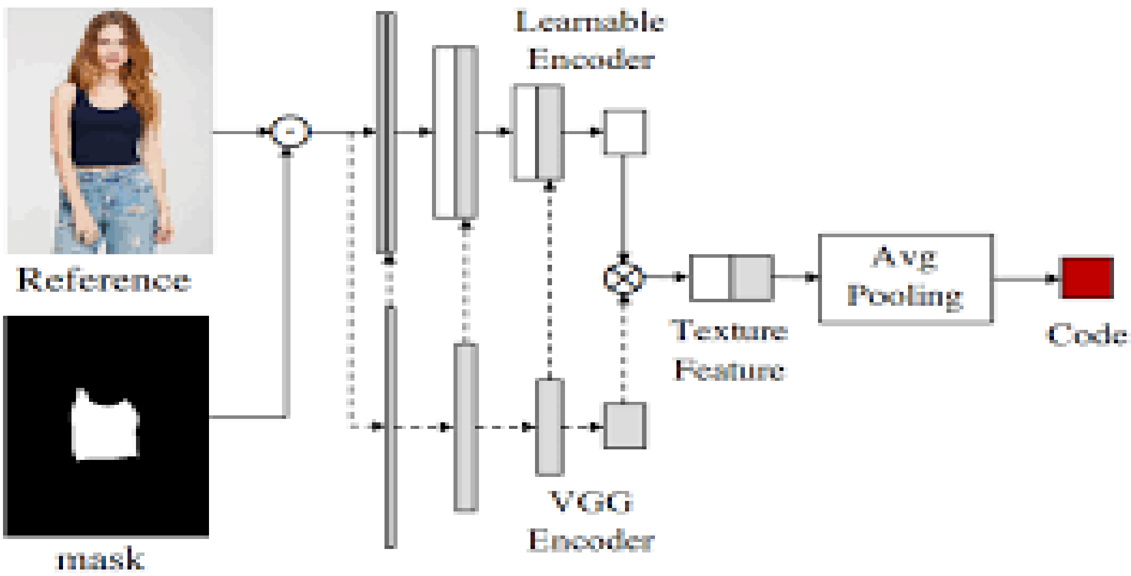

Fig 4.3: Data Flow Diagram For Controllable image synthesis with attribute-Decomposed - GAN

The Data Flow Diagram (DFD) for the AD-GAN system represents the movement and transformation of data throughout the controllable image synthesis process. It starts with the user uploading the dataset, followed by preprocessing steps like resizing and normalization. The system then decomposes the latent space into attribute-specific parts and applies attribute conditioning. The generator uses this processed data to create synthetic images, while the discriminator evaluates image realism and attribute accuracy. The system continuously optimizes using loss functions and provides users with editable, high-quality outputs. This structured data flow ensures precise attribute control and realistic image generation.

System Implementations

The implementation of the Attribute-Decomposed Generative Adversarial Network (AD-GAN) involves several key steps:

- Data Preprocessing: Prepare the input images by resizing and normalizing them. This step ensures that the images are in a suitable format for the model to process effectively.

ISSN 2321-2152
www.ijmece.com
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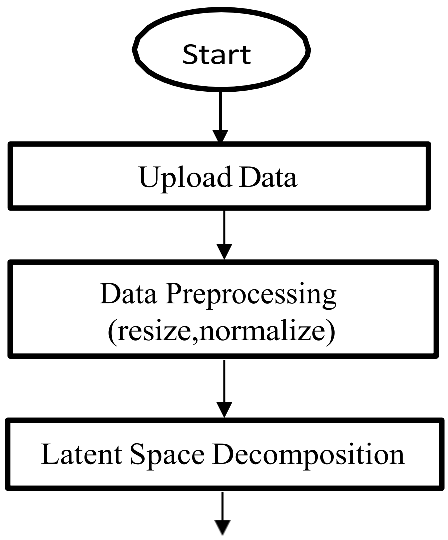
- Sentiment Analysis Model: Utilize pre-trained models to analyze the sentiment of the input data. This model detects whether the sentiment is positive, negative, or neutral, helping to inform the image generation process.
- Summarization Model: Implement a model that generates concise summaries of the input data. This model should consider the sentiment information to ensure that the summaries reflect the emotional context of the original content.
- Integration: Combine the sentiment analysis and summarization models to enhance the image generation process. This integration allows the system to adjust the generated images based on the sentiment of the input data.
- Evaluation: Assess the performance of the system using standard metrics. This includes measuring the quality of the generated images and the accuracy of sentiment analysis. Benchmark datasets should be used for thorough evaluation.
- Optimization: Improve the system's efficiency and scalability. Techniques such as parallel processing and model compression can be employed to enhance performance. Consider using hardware accelerators like GPUs for faster processing.
- User Interface: Create a user-friendly interface that allows users to easily input data and view the generated images and summaries. The interface should be intuitive and accessible on various devices.
- Deployment: Launch the system in a production environment, ensuring it is scalable, reliable, and secure. Implement monitoring and maintenance procedures to address any issues that arise.
- Feedback Loop: Establish a mechanism for gathering user feedback and monitoring system performance. Use this feedback to continuously improve the system's accuracy and usability.

4.2 Flow Chart Representation:



ISSN 2321-2152
www.ijmece.com
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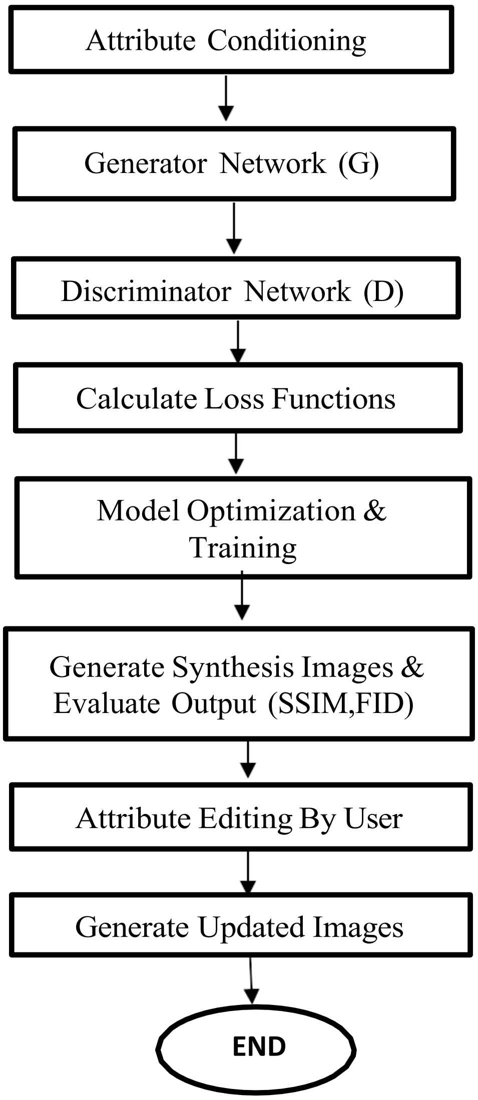

Fig 4.4: Flow chart Representation of Controllable image Synthesis with attribute – Decomposed GAN:

Chapter 5: System Requirements

This chapter outlines the hardware and software requirements for implementing the AD-GAN framework. It includes specifications for the operating system, coding language (Python), and essential libraries such as TensorFlow, NumPy, and Matplotlib.

Chapter 6: Results and Discussions

The Attribute-Decomposed GAN (ADGAN) demonstrates significant advancements in controllable image synthesis, showcasing both qualitative and quantitative improvements over existing methods. The results indicate that ADGAN and its enhanced version, ADGAN++, effectively generate realistic images while allowing for precise manipulation of attributes, outperforming state-of-the-art techniques in various tasks.

ISSN 2321-2152
www.ijmece.com
Vol 11, Issue 4, 2023

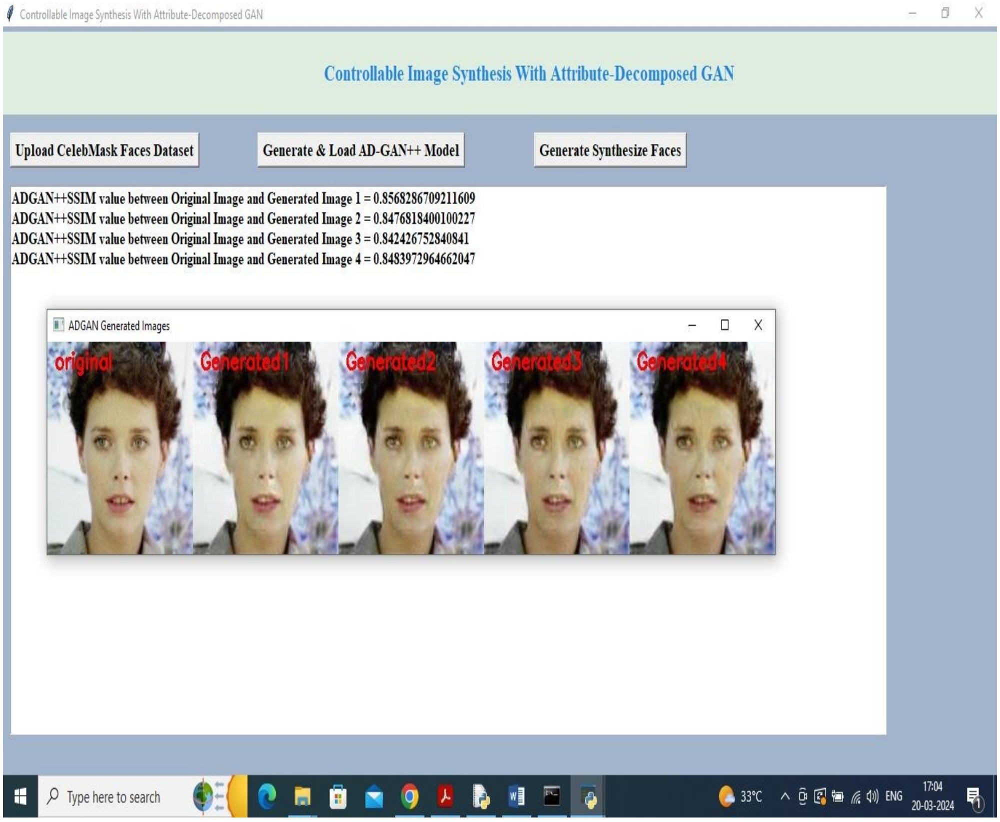

Fig 6.4: Image Generation Screen

In the above figure 6.6, The first image is the original uploaded image and remaining 4 are the generated images and can see some changes in the generated images and in text area can see SSIM similarity percentage between original and generated images.

Similarly we can upload and test other images.

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ISSN 2321-2152
www.ijmece.com
Vol 11, Issue 4, 2023

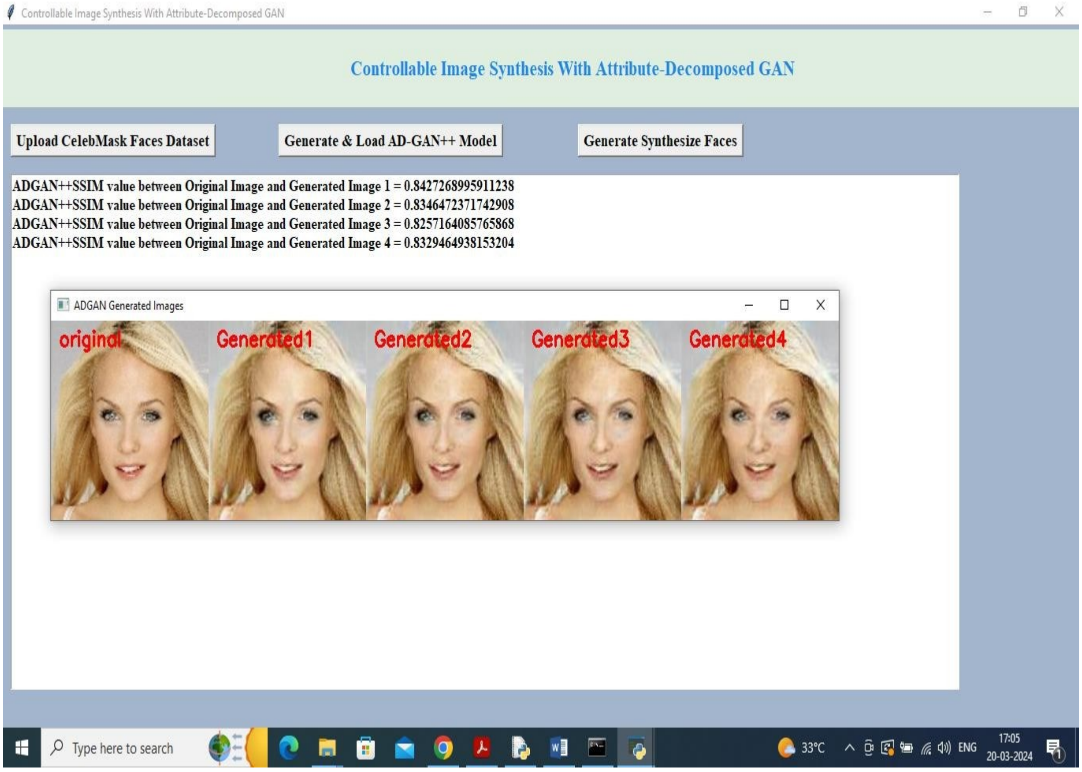

Fig 6.5: Image Generation Screen

In the above figure 6.5, we can see the output of other images

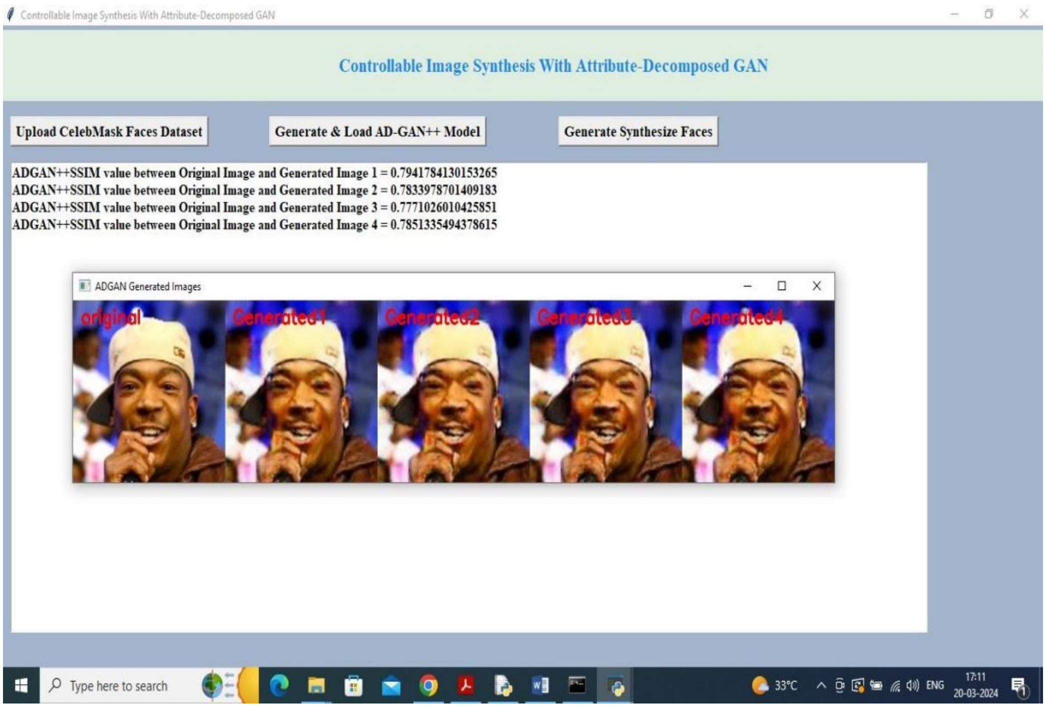

Fig 6.6: Image Generation Screen

In the above figure 6.6 we can see the output of other images.

7: Conclusion and Future Enhancement

The AD-GAN framework represents a significant advancement in controllable image synthesis, providing a powerful tool for generating high-quality images with precise attribute control. Future enhancements may include refining attribute decomposition methods, integrating more complex attributes, and improving the efficiency of the training process. The potential applications of AD-GAN span various fields, including creative industries, virtual reality, and data augmentation.

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This publication matter provides a comprehensive overview of the AD-GAN project, suitable for submission to a conference or journal in the field of computer vision and generative modeling.