

SIDDAGANGA INSTITUTE OF TECHNOLOGY, TUMAKURU-572103
(An Autonomous Institute under Visvesvaraya Technological University, Belagavi)



Project Report on
“Adaptive and Attentive Neural Style Transfer for
Digital Art”

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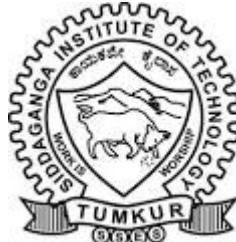
DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

2025-26

SIDDAGANGA INSTITUTE OF TECHNOLOGY, TUMAKURU-572103

(An Autonomous Institute under Visvesvaraya Technological University, Belagavi)

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING



CERTIFICATE

This is to certify that the project work entitled "[ADAPTIVE AND ATTENTIVE NEURAL STYLE TRANSFER FOR DIGITAL ART](#)" is a bonafide work carried out by Aman Kumar (1SI22CS014), Ashay Amal (1SI22CS027), Avinash Sarraf (1SI22CS030) and Chandragupta Kumar (1SI22CS046) in partial fulfillment for the award of degree of Bachelor of Engineering in Computer Science & Engineering from Siddaganga Institute of Technology, an autonomous institute under Visvesvaraya Technological University, Belagavi during the academic year 2025-26. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report deposited in the department library. The Project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the Bachelor of Engineering degree.

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Course Outcomes

After successful completion of major project, graduates will be able:

- CO1: To identify a problem through literature survey and knowledge of contemporary engineering technology.
- CO2: To consolidate the literature search to identify issues/gaps and formulate the engineering problem
- CO3: To prepare project schedule for the identified design methodology and engage in budget analysis, and share responsibility for every member in the team
- CO4: To provide sustainable engineering solution considering health, safety, legal, cultural issues and also demonstrate concern for environment
- CO5: To identify and apply the mathematical concepts, science concepts, engineering and management concepts necessary to implement the identified engineering problem
- CO6: To select the engineering tools/components required to implement the proposed solution for the identified engineering problem
- CO7: To analyze, design, and implement optimal design solution, interpret results of experiments and draw valid conclusion
- CO8: To demonstrate effective written communication through the project report, the one-page poster presentation, and preparation of the video about the project and the four page IEEE/Springer/ paper format of the work
- CO9: To engage in effective oral communication through power point presentation and demonstration of the project work
- CO10: To demonstrate compliance to the prescribed standards/ safety norms and abide by the norms of professional ethics
- CO11: To perform in the team, contribute to the team and mentor/lead the team

CO-PO Mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
CO-1											3			
CO-2		3												
CO-3											3			3
CO-4						3								3
CO-5	3	3										3	3	
CO-6					3							3		3
CO-7			3	3									3	3
CO-8									3					
CO-9									3					
CO-10							3							
CO-11									3					
Average	3	3	3	3	3	3	3	3	3	3	3			

Attainment level:

- 1: Slight (low)
- 2: Moderate (medium)
- 3: Substantial (high)

POs:

- PO1: Engineering knowledge,
- PO2: Problem analysis,
- PO3:Design of solutions,
- PO4:Conduct investigations of complex problems,
- PO5: Engineering tool usage,
- PO6:Engineer and the world,
- PO7:Ethics,
- PO8:Individual and collaborative work,
- PO9:communication,
- PO10:project management and finance,
- PO11: Life-long learning.

Abstract

The project proposes a CycleGAN based Neural Style Transfer (NST) system for converting photographs into four distinct artistic styles of One Piece anime, Disney, Studio Ghibli, and paintings by Van Gogh. The system will utilize unpaired data sets with cycle-consistency constraints, which allows for the bidirectional mapping of human faces to animated characters and scenery to post-impressionist style works of art.

Utilization of the generator-discriminator (GAN-D) model involves utilizing both a generator and discriminator to create realistic artwork through adversarial loss, preserve content using Cycle-consistency loss, use identity loss for colour preservation, and incorporate VGG-19 perceptual loss. OpenCV's custom frame extraction method retrieves animated datasets from video sources, while Van Gogh datasets are constructed using landscapes and paintings retrieved from Kaggle.

Utilizing PyTorch 2.0 and accelerated by CUDA, the system provides an estimated 3-second or less delivery timeframe for each image processed by NVIDIA Graphics Processing Unit (GPU). This modular framework permits the extension of additional styles as confirmed through successful styling capture with semantic content maintained.

Keywords: Neural Style Transfer, CycleGAN, Generative Adversarial Networks, Deep Learning, Image-to-Image Translation, Computer Vision, Animation Style Transfer, Van Gogh Style

Contents

Abstract	i
List of Figures	ii
List of Tables	iii
1 Introduction	1
1.1 Background	2
1.1.1 Evolution of Computer Vision	2
1.1.2 Convolutional Neural Networks	2
1.1.3 Generative Adversarial Networks	2
1.1.4 Style Transfer Approaches	2
1.2 Motivation	3
1.3 Problem Statement	4
1.4 Objective of the Project	5
1.5 Scope of the Project	6
1.6 Methodology Overview	7
1.7 Organisation of the Report	8
2 Literature Survey	10
3 System Overview	16
3.1 System Architecture Overview	16
3.2 Style Transfer Modes	16
3.2.1 One Piece Style Transfer	16
3.2.2 Disney Style Transfer	17
3.2.3 Studio Ghibli Style Transfer	17
3.2.4 Van Gogh Style Transfer	17
3.3 Dataset Creation Methodology	18
3.3.1 Animation Frame Extraction Pipeline	18
3.3.2 Dataset Details	19

3.3.3	Dataset Summary	19
3.4	CycleGAN Architecture Details	19
3.4.1	Overall Architecture	19
3.4.2	Generator Network Architecture	20
3.4.3	Residual Block Architecture	20
3.4.4	Discriminator Network Architecture (PatchGAN)	20
3.5	Loss Functions	21
3.5.1	Adversarial Loss (LSGAN)	21
3.5.2	Cycle-Consistency Loss	22
3.5.3	Identity Loss	22
3.5.4	Perceptual Loss	23
3.5.5	Total Generator Loss	23
3.5.6	Discriminator Loss	24
3.6	Training Configuration	24
3.6.1	Hyperparameter Selection	24
3.6.2	Training Procedure	25
3.6.3	Training Stabilization Techniques	25
3.6.4	Training Resources	26
4	System Architecture and High Level Design	27
4.1	Terminology	27
4.2	System Components	28
4.2.1	Component Descriptions	28
4.3	Class Structure	29
4.4	Inference Sequence	29
4.5	Software Requirements	29
4.6	Use Cases	30
4.7	Deployment Architecture	30
5	Software Architecture and Low Level Design	31
5.1	Detailed Generator Architecture	31
5.2	Residual Block Internal Structure	32
5.3	PatchGAN Discriminator Architecture	32

5.4	Training Process Flowchart	33
5.5	Inference Pipeline Flowchart	34
5.6	Loss Computation Diagram	34
5.7	Training Algorithm	35
5.8	Inference Algorithm	36
5.9	Generator Forward Pass Algorithm	36
5.10	Residual Block Algorithm	37
5.11	Discriminator Forward Pass Algorithm	38
5.12	Image History Buffer Algorithm	38
5.13	Data Preprocessing Algorithm	39
5.14	Frame Extraction Algorithm	40
5.15	Data Preprocessing	41
5.15.1	Preprocessing Pipeline	41
5.15.2	Postprocessing Pipeline	41
5.16	System Flow	41
5.17	Data Flow	41
5.18	Hardware and Software Specifications	42
6	Results	43
6.1	Test Setup Environment	43
6.1.1	Hardware Configuration	43
6.1.2	Software Environment	43
6.2	Test Procedures and Test Cases	44
6.2.1	Test Case Design	44
6.2.2	Test Procedure	44
6.3	Style Transfer Results	45
6.3.1	Disney Style Results	45
6.3.2	Studio Ghibli Style Results	46
6.3.3	Van Gogh Style Results	47
6.3.4	One Piece Style Results	48
6.4	Website User Interface	49
6.4.1	Home Page	49

6.4.2	Style Selection	49
6.4.3	Results Display	50
6.5	Inference Performance	50
6.5.1	Speed Benchmarks	50
6.5.2	Memory Usage	50
6.6	Analysis and Discussion	51
6.6.1	Training Observations	51
6.6.2	Qualitative Analysis	51
6.6.3	Key Findings	52
6.6.4	Error Analysis	52
6.7	Summary of Results	52
7	Conclusion	53
7.1	Summary of the Project Work	53
7.1.1	Achievements	53
7.1.2	Technical Contributions	54
7.1.3	Meeting Project Objectives	55
7.2	Limitations	55
7.3	Scope for Future Work	56
7.4	Conclusion	56
Bibliography		56
Appendices		59
A	Project Planning	60
A.1	Project Timeline	60
A.2	Budget Estimation	61
B	Sustainable Development Goals (SDGs) Addressed	62
C	Self-Assessment of the Project	63
D	Dataset Details	65

E Configuration and Usage	66
E.1 Repository Structure	66
E.2 Installation Guide	67
E.2.1 Installation Steps	67

List of Figures

1.1	Project Methodology Overview	7
3.1	High-Level System Architecture	16
3.2	Frame Extraction Pipeline	18
3.3	Complete CycleGAN Architecture for Style Transfer	19
3.4	Generator Network Architecture	20
3.5	Residual Block Structure	20
3.6	PatchGAN Discriminator Architecture	21
4.1	System Component Diagram	28
5.1	Detailed Generator Architecture with Layer Specifications	31
5.2	Internal Structure of Residual Block	32
5.3	PatchGAN Discriminator with Spatial Dimensions	32
5.4	Training Process Flowchart	33
5.5	Inference Pipeline Flowchart	34
5.6	Loss Computation Flow in CycleGAN	34
6.1	Disney Style Transfer Results - Sample 1	45
6.2	Disney Style Transfer Results - Sample 2	45
6.3	Studio Ghibli Style Transfer Results - Sample 1	46
6.4	Studio Ghibli Style Transfer Results - Sample 2	46
6.5	Van Gogh Style Transfer Results - Sample 1	47
6.6	Van Gogh Style Transfer Results - Sample 2	47
6.7	One Piece Style Transfer Results - Sample	48
6.8	Website Home Page - Style Selection Interface	49
6.9	Style Selection Menu - Choose from One Piece, Disney, Ghibli, or Van Gogh	49
6.10	Results Page - Side-by-Side Comparison of Original and Stylized Image	50
A.1	The Project Timeline.	60

List of Tables

3.1	Complete Dataset Summary	19
3.2	Generator Network Layers	20
3.3	Discriminator Network Layers	21
3.4	Loss Function Weights	23
3.5	Training Hyperparameters	24
3.6	Training Resource Requirements	26
4.1	Technical Terminology	27
6.1	Test Environment Hardware	43
6.2	Software Configuration	43
6.3	Test Cases for Style Transfer Evaluation	44
6.4	Inference Speed Benchmarks	50
6.5	GPU Memory Usage During Inference	50
6.6	Qualitative Evaluation Criteria and Scores (1-5 scale)	51
7.1	Objective Completion Status	55
1.1	Project Milestone Schedule	61
1.2	Project Budget Estimation	61
4.1	Complete Dataset Statistics	65
5.1	Project Directory Structure	66

Chapter 1

Introduction

The convergence of artificial intelligence and creative arts has created infinite opportunities for the creation of digital based artwork. One of the most exciting current uses of deep learning is in Neural Style Transfer (NST), which allows you to take a normal photo and create an amazing piece of art from it, by learning what makes a particular style “art” and then applying that same “art” style to create something new with your own image. This project’s goal is to design a seamless style transfer system using CycleGAN (Cycle-Consistent Generative Adversarial Networks) to enable the ability to convert images into 4 very unique artistic styles, which include: One Piece anime, Disney animated characters, Studio Ghibli animated characters, and Van Gogh style painting.

The emergence of Generative Adversarial Networks (GANs) in 2014 by Goodfellow et al. [?] marked a paradigm shift in generative modeling. Subsequently, the introduction of CycleGAN by Zhu et al. [8] revolutionized image-to-image translation by eliminating the requirement for paired training data. This advancement is particularly significant for artistic style transfer, where obtaining perfectly aligned pairs of content and stylized images is impractical.

This project utilises the characterisation of the above examples to produce an animated human face and to create painting-like landscapes based on this characterisation. Each of these three animation styles (One Piece, Disney, Studio Ghibli) has a unique visual appearance, making it immediately identifiable. The post-impressionist style designed by Vincent Van Gogh is accepted as having a very particular brushstroke and a colour palette that is especially vibrant.

1.1 Background

1.1.1 Evolution of Computer Vision

Computer vision has transformed dramatically with deep learning. Key milestones include: traditional hand-crafted features (pre-2012), the AlexNet breakthrough (2012) demonstrating CNN superiority, deeper architectures like VGGNet and ResNet (2014-2016), and generative models including GANs (2014-present) enabling image synthesis.

1.1.2 Convolutional Neural Networks

CNNs learn features in a hierarchical manner. The early layers typically capture low-level information such as edges and textures. The intermediate layers build on these to represent more complex patterns, while the deepest layers encode high-level semantic concepts. This hierarchical organisation allows neural style transfer to separate an image's content from its style, enabling generation of new images that preserve the content but adopt an alternative style. VGG-19 is widely used for feature extraction because of its consistent 3×3 convolutional architecture and its proven reliability in modelling perceptual similarity.

1.1.3 Generative Adversarial Networks

GANs consist of two components: the generator, which is responsible for generating synthetic samples, and the discriminator, which determines whether or not a given sample is considered real or fake. Using adversarial training techniques, both components are trained until the generator produces samples created in a way that they appear realistic to real humans. Some popular variants of GAN include Conditional GAN, Pix2Pix, Cycle GAN, and Style GAN.

1.1.4 Style Transfer Approaches

GANs comprise two essential elements: a Generator responsible for the creation of synthetic samples, and a Discriminator which judges if a particular sample is classified as real or fake. By using the principles of adversarial training, both components were trained until the generator produces synthetically produced samples in such a manner that they look "real" to the human eye. Examples of several types of GANs include cGANs (Conditional GANs), Pix2Pix, CycleGANs and StyleGANs.

1.2 Motivation

The motivation for this project stems from several converging factors in technology, art, and social media culture:

1. Growing Demand for Personalized Digital Art:

The popularity of photo filter apps and personalized artistic transformation utilities are driven by the need for users to create artistically altered versions of their own images in creative ways. There is a large market demand for systems that can provide high-quality anime or painterly transformations of photographs to fulfill this need.

2. Bridging Art and Technology:

It normally takes a lot of time and training to develop your artistic skills through traditional means, but thanks to neural style transfer, you do not need either of those to create art. With neural style transfer, anyone can create photo-based artwork that captures the essence of famous artists or animation studios. As a result, neural style transfer has made it easier than ever for people to appreciate and create art.

3. Advances in Deep Learning:

Deep learning has made tremendous strides in just a few years. Developments in image generation and transformation based on GANs (Generative Adversarial Networks) enable the creation of complex and highly realistic photographic imagery via computational techniques. Combining the development of very capable GPU computing systems with the growing number of free/open-source frameworks such as PyTorch means that building these capabilities is now easier than ever before.

4. Cultural Significance of Animation Styles:

Japanese Animation (One Piece) is an entirely different visual vocabulary than Western Animation (Disney) and Studio Ghibli. Fans of both styles have a huge following around the world and this is why there is such a high demand to develop software that converts photographs into these two styles for fans and content developers around the globe.

5. Preservation and Appreciation of Artistic Heritage:

Considered one of the greatest achievements in post-impressionistic art, Van Gogh's distinctive style features swirling brush strokes and bright colours. It can be used as an educational tool and a way to appreciate the artistic heritage of Van Gogh's work and the influence it has had on contemporary visual art through the application of this style by a neural network trained to apply Van Gogh's style to current day photographs.

6. Research and Educational Value:

Completing the process of building a full CycleGAN for style transfer was an instructive way to learn about the many areas of designing a Deep Learning Architecture, developing a Loss Function, creating a Dataset, and exploring the difficulties associated with generative models. Thus, this project serves as a thorough example of how to use Applied Deep Learning.

1.3 Problem Statement

The problem addressed by this project can be formally stated as follows:

Taking an input image x from domain X (real photographs), the goal is to learn a mapping function $G : X \rightarrow Y$ that transforms x into an output image $G(x)$ in domain Y (stylized images), such that:

1. The output $G(x)$ exhibits the visual characteristics of the target artistic style
2. The semantic content and structure of the input image are preserved
3. The transformation is realistic and free from artifacts
4. The system operates efficiently for real-time applications

The specific style domains addressed are:

- **One Piece Style:** Bold outlines, exaggerated expressions, vibrant colors characteristic of Eiichiro Oda's artwork
- **Disney Style:** Smooth gradients, large expressive eyes, soft color palettes of modern Disney animation
- **Studio Ghibli Style:** Watercolor textures, naturalistic expressions, warm earthy tones of Hayao Miyazaki's films
- **Van Gogh Style:** Swirling brushstrokes, impasto technique, vibrant post-impressionist colors

1.4 Objective of the Project

The primary objectives of this project are:

1. Develop Style-Specific Neural Style Transfer Models:

You will create four different models for transforming images through CycleGAN methods, each trained on one specific art stimulus. Each model must be capable of reproducing the specific characteristics associated with the targeted artistic styles while preserving the content of the original photograph.

2. Create Custom Datasets through Frame Extraction:

Develop an automated pipeline for extracting character frames from animation sources (One Piece episodes, Disney movies, Studio Ghibli films) using computer vision techniques including face detection and quality filtering.

3. Implement and Optimize Core Algorithms:

Implement the following key algorithms with improvements tailored to our application:

- CycleGAN architecture with ResNet-based generators
- PatchGAN discriminators for local style assessment
- Cycle-consistency loss for bidirectional mapping
- Identity loss for color preservation
- Perceptual loss using VGG-19 features
- Custom frame extraction algorithm

4. Optimize for Real-Time Performance:

Achieve inference times of under 3 seconds per image through model optimization, efficient data pipelines, and GPU acceleration.

5. Build a Modular and Extensible System:

Design the system architecture to allow easy addition of new styles and modification of existing models.

1.5 Scope of the Project

The scope of this project encompasses the following:

Included in Scope:

- Implementation of CycleGAN-based style transfer for four artistic styles
- Custom dataset creation through frame extraction from video sources
- Training pipeline with configurable hyperparameters
- Inference system for single image transformation
- Documentation and analysis of results
- Comparison with existing methods

1.6 Methodology Overview

The methodology employed in this project follows a systematic approach:

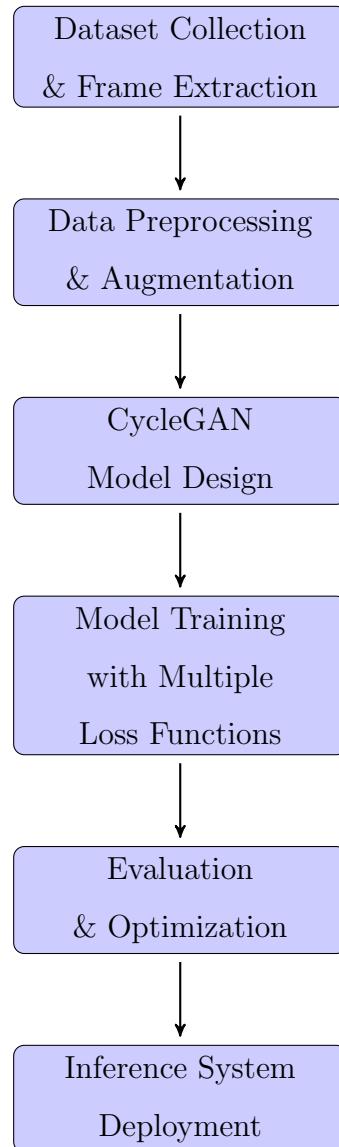


Figure 1.1: Project Methodology Overview

Phase 1: Dataset Collection and Preparation

- Extract character frames from One Piece episodes, Disney animated movies, and Studio Ghibli films
- Collect Van Gogh paintings and landscape photographs from Kaggle
- Collect human face photographs from Kaggle datasets

Phase 2: Data Preprocessing

- Resize all images to 256×256 pixels
- Apply data augmentation (horizontal flip, rotation)
- Normalize pixel values to $[-1, 1]$ range
- Create training and validation splits

Phase 3: Model Implementation

- Implement generator networks with ResNet architecture
- Implement PatchGAN discriminator networks
- Define loss functions (adversarial, cycle-consistency, identity, perceptual)
- Set up training loops with Adam optimizer

Phase 4: Training and Optimization

- Train separate models for each style
- Monitor training progress with validation metrics
- Apply learning rate scheduling
- Save best model checkpoints

Phase 5: Evaluation and Deployment

- Evaluate models using FID scores and visual inspection
- Optimize inference pipeline for speed
- Document results and create demonstration system

1.7 Organisation of the Report

This project report is organized into the following chapters:

Chapter 1: Introduction

An overview of the project is provided, including motivation, problem statement, project objectives, scope and methodology. This chapter outlines the general context and importance of neural style transfer as part of the larger field of deep learning.

Chapter 2: Literature Survey

An overview of the project is provided, including motivation, problem statement, project objectives, scope and methodology. This chapter outlines the general context and importance of neural style transfer as part of the larger field of deep learning.

Chapter 3: System Overview

The descriptions of the overall system architecture will include the styles transfer pipeline, methodology for creating the data set and the four styles used. This chapter presents an overview of the relationships between the various components of the system at a higher level.

Chapter 4: System Architecture and High-Level Design

Presents the detailed architecture of the CycleGAN system, including generator and discriminator networks, loss function formulations, and training procedures. UML diagrams, flowcharts, and architectural diagrams illustrate the design.

Chapter 5: Software Architecture and Low-Level Design

Provides detailed algorithm descriptions, pseudocode, and implementation specifics. This chapter covers the frame extraction algorithm, network architectures, and training procedures at a granular level.

Chapter 6: Results

Presents the experimental setup, test procedures, and results obtained from training and evaluating the four style transfer models. Includes sample outputs, quantitative metrics, and comparative analysis.

Chapter 7: Conclusion

Summarizes the project achievements, discusses limitations, and suggests directions for future work.

Appendices

Contains supplementary material including project timeline, budget estimation, dataset details, SDG alignment, and configuration information.

Chapter 2

Literature Survey

This chapter presents a comprehensive review of the existing research in neural style transfer, generative adversarial networks, and image-to-image translation that forms the foundation of our implementation.

In paper [1], A Neural Algorithm of Artistic Style: Using a already trained VGG network, Gatys et al have developed the very first deep learning method capable of separating both the image style and content. The authors claim that the higher level feature maps contain the scene's structure, whereas the lower layers Gram matrix contain the texture and color information of an image. The authors propose an optimization method where a random image is created so that it matches the content representation of a given image, while also matching the style statistics of another image. The resulting output from this process was the ability to create new paintings that mimic famous artists while preserving the underlying objects within those works of art. While this method was flexible in its execution, it required an extensive amount of time and computational resources to produce results, thus making it a foundational reference for most neural style transfer methods that have developed since then.

In paper [2], Perceptual Losses for Real-Time Style Transfer and Super-Resolution: Johnson and others replace the pixel-by-pixel loss functions used to train slow convolutional networks with perceptual loss functions based on VGG model features. They use this new type of loss function to train fast feedforward networks for image-to-image mapping tasks such as style transfer. Specifically, a single neural network can learn how to mimic the expensive losses associated with Gatys et al.'s style transfer approach, allowing the generation of stylized images in real-time, generating them at similar levels of quality as Gatys's original loss functions. They demonstrate that by using feature-space loss functions, networks trained to produce super-resolved images from single images produce sharper, more detailed results than those trained using MSE-based approaches. They conclude that human perception better correlates with high-level differences in features, which allow for training networks that are efficient yet maintain the

same important semantic and textural properties as original images, thus having a strong influence on future architectural design choices for real-time style transfer networks.

In paper [3], Instance Normalization: The Missing Ingredient for Fast Stylization: In a study conducted by Ulyanov et al., the authors revisited feed-forward style transfer networks with the aid of new data which showed that replacing batch normalization with instance normalization drastically increased the quality of images produced using these networks. Using instance normalization allowed for normalization of the entire feature map of an input image, eliminating any contrast related to individual instances; therefore, the generator focused on the statistical nature of styles rather than global illumination. The results obtained from training the feed-forward network with the standard loss functions of Gatys compared favourably with the results obtained from the conventional optimization techniques and could be achieved in real-time. The findings of this study fulfilled two objectives: (1) Provided empirical support for the proposed use of instance normalization as a standard component in all style transfer and texture synthesis networks and (2) Provided an intuitive explanation as to why this standardisation of instance-normalised output would yield improved results.

In paper [4], Arbitrary Style Transfer in Real-Time With Adaptive Instance Normalization: A new approach for performing arbitrary style-transfer via neural networks has been proposed by Huang and Belongie. They refer to the technique as Adaptive Instance Normalization (AdaIN) and describe it as a layer in a neural network that normalizes the mean and variance of features from the content image, to match that of the style image based on channel. The model does not require retraining, this is advantageous given that it allows for any potential combination of style to be applied to any content image. The authors note that their technique represents similar flexibility as traditional optimization techniques used in style-transfer, while being over 100x faster. The benefits of their technique also include intuitive controls such as: a trade-off between content and style; interpolating between two or more styles; and spatial or color-based constraints. AdaIN has also been introduced as a foundational building block for later stages in arbitrary style-transfer models, and for guided image retrieval and image-to-image translation applications.

In paper [5], Universal Style Transfer via Feature Transforms: To perform universal feed-forward style transfer without requiring any training specifically for the styles used in feed-forward style transfer, Li et al. designed their system using VGG as an encoder and cascaded decoders along with white and color transforms (WCTs) applied in the feature space which matches the covariance of the content features with that of the style image. Through a multi-level pipeline, the WCT is applied in the model, moving progressively from coarse layers to fine layers. The final product retains the global structure and detailed texture information from both the coarse and fine layers. Because all models are trained only for reconstruction on the decoders, this allows the method to be applied to new styles previously unseen with reasonable quality and efficiency. Finally, the authors bridge Gram-matrix optimization with feed-forward networks through a matching of explicit feature covariances.

In paper [6], Exploring the Structure of a Real-Time, Arbitrary Stylization Network: The authors Ghiasi et Al. have extended the fast arbitrary style transfer to work by developing a network that predicts the style of an image based upon the affine parameterisation of the conditional instance normalisation layer(s) in a style transfer network. They trained their model with around 80,000 paintings and thousands of different textures. It is capable of real-time style transfers between styles not previously seen. The style embeddings learned during training allow for smooth transition between different styles and speed the performance of style transfer networks. This study has shown that the ability to predict normalisation parameters may allow those feed-forward networks to perform efficiently as conditional networks for arbitrary input styles.

In paper [7], Deep Photo Style Transfer: Unlike Gatys et al. (2015), the authors of this work focus on transferring visual styles between photographic images instead of painting images. They create an additional loss in their neural network models from the Gatys et al. (2015) work. This added loss incorporates the Matting Laplacian method for photorealism to restrict the amount of local colour adjustments allowed in their datasets. They use semantic segmentation masks to limit the regions being transferred to match the original. The authors show how effective their techniques are through their ability to produce high-quality results from multiple different types of photographic scenes.

In paper [8], Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks: Zhu et al. propose CycleGAN, an unpaired image-to-image translation framework that learns mappings between two visual domains using adversarial and cycle-consistency losses. Generators translate $X \rightarrow Y$ and $Y \rightarrow X$, while discriminators enforce realism. A cycle loss encourages $F(G(x)) \approx x$ and $G(F(y)) \approx y$, preventing mode collapse and enforcing meaningful correspondences despite lacking paired supervision. The method successfully handles tasks like horse \leftrightarrow zebra, summer \leftrightarrow winter, and photo \leftrightarrow painting conversion. CycleGAN became a standard baseline for unpaired translation and inspired many subsequent guided and multi-domain style synthesis methods.

In paper [9], Applying Deep Learning for Style Transfer in Digital Art: Zhang et al. combine AdaIN with Gram-matrix style features to create a faster and more flexible system for digital art generation. By leveraging the strengths of both methods, their model improves content and style accuracy by about 15% over existing approaches and reaches an SSIM of 0.88 at medium style intensity. It also cuts processing time by nearly 76%, making the system feel almost real-time. Overall, the method handles a wide variety of artistic styles while still preserving the structure of the original image, making neural style transfer far more practical for designers and multimedia creators.

In paper [10], Blending Art and Intelligence: Advances in Neural Style Transfer and Image Synthesis: In their review of developments combining GAN image synthesis with neural style transfer, Scott and co-authors present the benefits of each method and how they can be utilised together to enhance creative expression. The review describes traditional neural style transfer using VGG features (and variations of VGG), identifies the efficiency of using feed-forward networks and AdaIN to develop faster versions of neural style transfer processes, and explores many GAN architectures including StyleGAN and its different implementations. Another important aspect to consider is diffusion-based models for generating images and related applications within multi-step workflows or concept designs (e.g., Dafürm) and img2img pipelines, as well as the development of workflows and/or workflows built on the ControlNet architecture. Additionally, case studies illustrate how many of the most recent models have broadened creative potential, as well as raised concerns over authorship, authenticity, and society's role in using AI technology to create art. Finally, Scott and co-authors ultimately argue for the need for a "symbiotic relationship" between humans and AI, where humans provide the vision

and mission for creativity, and AI technology serves to process large amounts of variation and lend support in accomplishing this mission.

In paper [11], A Style-Based Generator Architecture for Generative Adversarial Networks: Karras et al. proposed a new generator architecture referred to as StyleGAN, which provides groundbreaking control over the generation/synthesis of images. The new aspect of StyleGAN is a mapping network that creates (maps) a latent code into an intermediary “style” space, and a mechanism that uses adaptive instance normalization to allow the mapping to modulate/modify the convolutional layers. The distinction between the high-level features of an image (e.g., pose, identity) and the stochastic features (e.g., freckles, hair texture) allows for the mixing of styles at various scales very intuitively. Additionally, StyleGAN achieves state-of-the-art performance on face generation tasks, produces smooth transitions in style space, and has had a significant impact on the development of subsequent methods for both controllable image generation and style manipulation.

In paper [12], Neural Style Transfer: A Review: Neuroscience researchers Jing and their associates conducted a comprehensive survey that included the types of work that have been done to develop a better understanding of neural style transfer and how it can be utilized in different contexts. They also addressed the many losses that have been identified due to neural style transfer work as well as the network architectures, evaluation metrics, etc., that have been used in the field of style transfer. In addition, they offered their insights into new types of stylization such as semantic awareness, video, and 3D stylization methods. Finally, they highlighted several challenges that remain in the area of neural style transfer, including content leaking, maintaining style consistency, and providing efficiency through computation. As such, this survey serves to be a monumental reference point for understanding how and where the research in the area of neural style transfer is heading and expanding at present.

In paper [13], Image-to-Image Translation with Conditional Adversarial Networks: According to Isola and others (2016), pix2pix is a versatile image-to-image translation framework that allows for paired images to be transformed into one another using conditional GANs. In this framework, the GAN generator loses its outputs when compared to the original images (adversarial loss), while also retaining spatial information from the input image through a L1 loss. The PatchGAN discriminator uses local patches

of the generated and real images when classifying (instead of classifying entire images) to allow for more detail at the high frequency end of the scale. The pix2pix framework has been used successfully to address many different types of problems, ranging from semantic segmentation to photographs of objects and edge maps to photographs of objects, as well as problems related to conversion of photographs during the daytime into converted nighttime photographs. The pix2pix framework has become a powerful new area for supervised image translation using conditional adversarial training.

Chapter 3

System Overview

The overall architecture, dataset creation process, and four different style transfer models—One Piece, Disney, Studio Ghibli, and Van Gogh—of the AI-Based Neural Style Transfer system are all covered in detail in this chapter.

3.1 System Architecture Overview

CycleGAN-based neural networks are used in the system’s modular pipeline design to create artistic stylizations from user-provided content images. Four different style transfer modes, each trained on specially chosen datasets, are supported by the architecture.

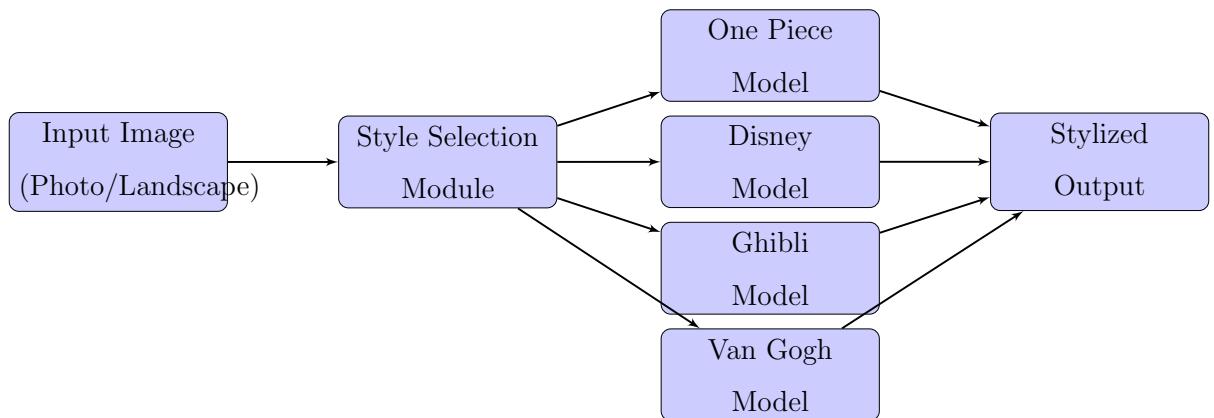


Figure 3.1: High-Level System Architecture

3.2 Style Transfer Modes

Four different style transfer modes are used by the system:

3.2.1 One Piece Style Transfer

- **Input:** Human face photographs
- **Output:** One Piece anime-style character faces
- **Characteristics:** Bold black outlines, exaggerated expressions, vibrant saturated colors, distinctive large eyes
- **Dataset Source:** Frames extracted from One Piece anime episodes and movies

3.2.2 Disney Style Transfer

- **Input:** Human face photographs
- **Output:** Disney animation-style character faces
- **Characteristics:** Smooth color gradients, large expressive eyes with reflections, soft pastel color palettes, polished clean lines
- **Dataset Source:** Frames extracted from Disney animated feature films

3.2.3 Studio Ghibli Style Transfer

- **Input:** Human face photographs
- **Output:** Studio Ghibli animation-style character faces
- **Characteristics:** Soft watercolor-like textures, naturalistic expressions, warm earthy tones, hand-drawn aesthetic
- **Dataset Source:** Frames extracted from Studio Ghibli films (Spirited Away, Howl's Moving Castle, etc.)

3.2.4 Van Gogh Style Transfer

- **Input:** Landscape photographs
- **Output:** Van Gogh painting-style landscapes
- **Characteristics:** Swirling brushstrokes, vibrant colors (yellows, blues), impasto technique, post-impressionist aesthetic
- **Dataset Source:** Van Gogh paintings from Kaggle dataset

3.3 Dataset Creation Methodology

We created a thorough dataset creation pipeline because CycleGAN requires unpaired datasets from two domains (Domain X: real-world images, Domain Y: stylized images).

3.3.1 Animation Frame Extraction Pipeline

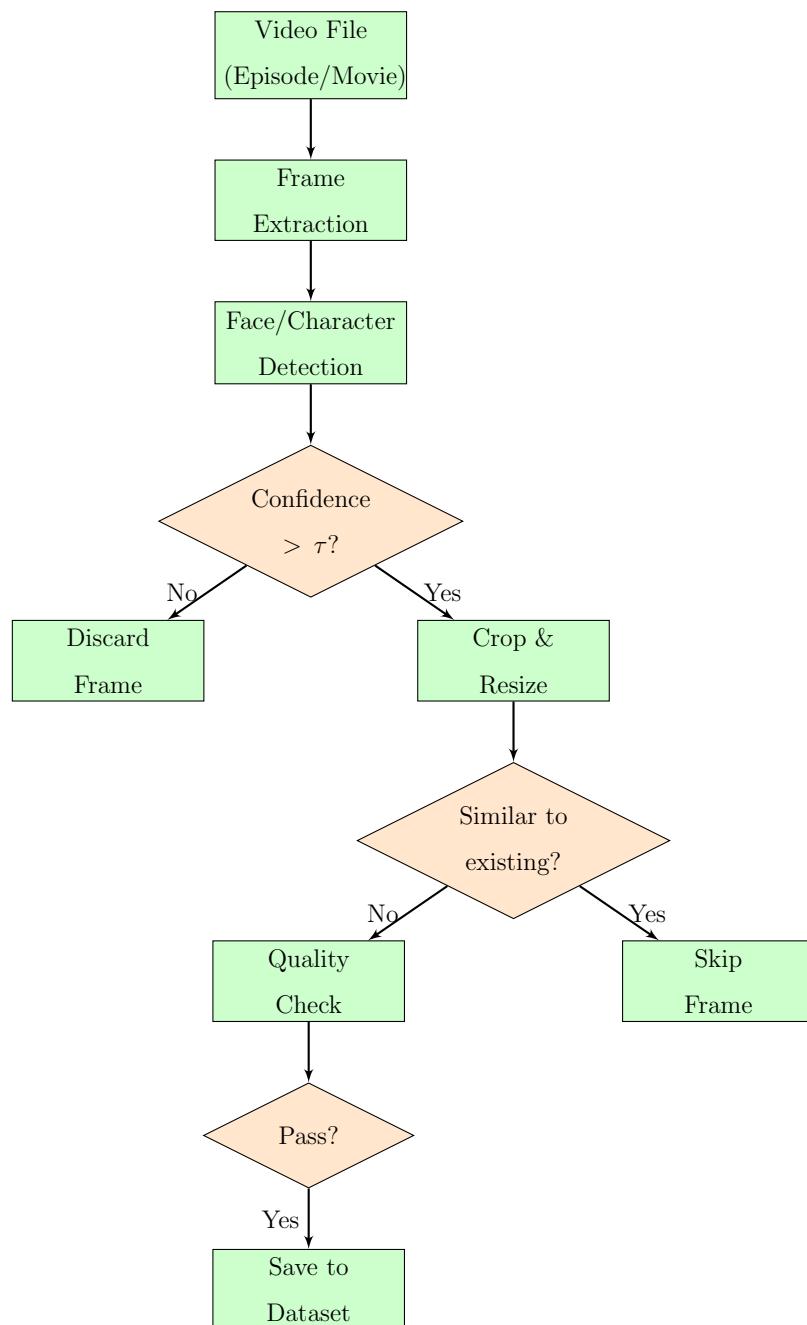


Figure 3.2: Frame Extraction Pipeline

3.3.2 Dataset Details

Every dataset uses JPG/PNG images with a resolution of 256×256 . Domain X utilizes either landscapes or human faces from Kaggle (3,000+ images each for face-based styles).

3.3.3 Dataset Summary

Style	Domain X	Domain X Size	Domain Y	Domain Y Size
One Piece	Human Faces	3,000+	Anime Frames	2,500+
Disney	Human Faces	3,000+	Disney Frames	2,000+
Ghibli	Human Faces	3,000+	Ghibli Frames	2,000+
Van Gogh	Landscapes	2,500+	Paintings	400+

Table 3.1: Complete Dataset Summary

3.4 CycleGAN Architecture Details

3.4.1 Overall Architecture

The CycleGAN model uses two generator–discriminator pairs that work together to learn mappings in both directions between the two domains.

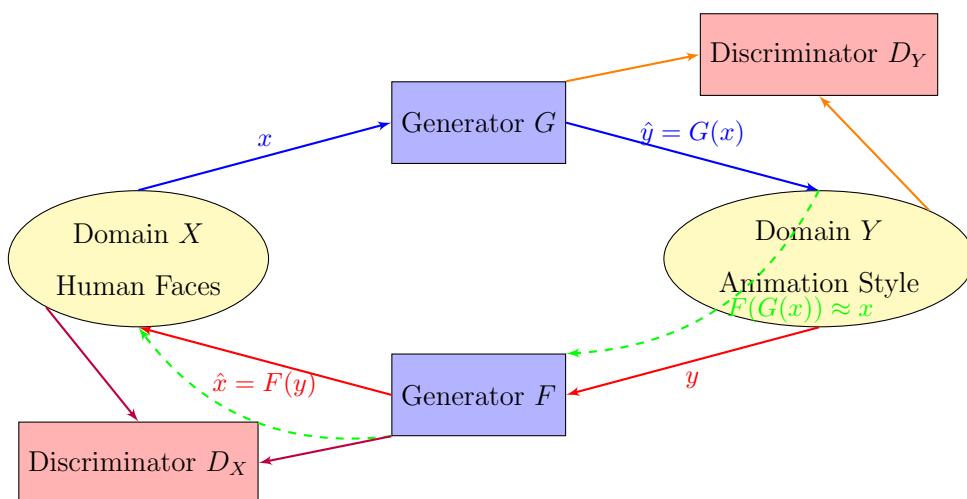


Figure 3.3: Complete CycleGAN Architecture for Style Transfer

3.4.2 Generator Network Architecture

The generator is built using a ResNet-style encoder-decoder structure and includes nine residual blocks, which is suitable for 256×256 images.

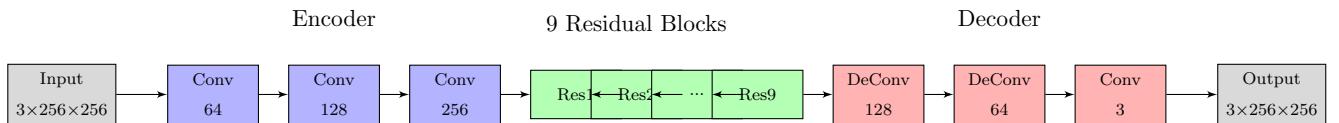


Figure 3.4: Generator Network Architecture

Generator Layer Specifications:

Layer	Type	Filters	Kernel	Stride
c7s1-64	Conv + IN + ReLU	64	7×7	1
d128	Conv + IN + ReLU	128	3×3	2
d256	Conv + IN + ReLU	256	3×3	2
R256 × 9	Residual Block	256	3×3	1
u128	DeConv + IN + ReLU	128	3×3	2
u64	DeConv + IN + ReLU	64	3×3	2
c7s1-3	Conv + Tanh	3	7×7	1

Table 3.2: Generator Network Layers

3.4.3 Residual Block Architecture

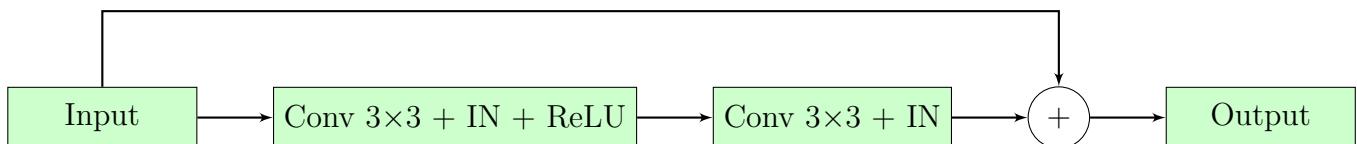


Figure 3.5: Residual Block Structure

3.4.4 Discriminator Network Architecture (PatchGAN)

The discriminator adopts a PatchGAN design, where it evaluates and classifies overlapping 70×70 image patches.

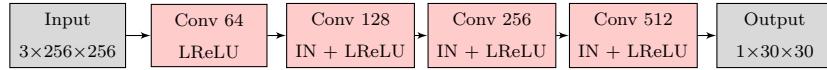


Figure 3.6: PatchGAN Discriminator Architecture

Discriminator Layer Specifications:

Layer	Type	Filters	Kernel	Stride
C64	Conv + LeakyReLU	64	4x4	2
C128	Conv + IN + LeakyReLU	128	4x4	2
C256	Conv + IN + LeakyReLU	256	4x4	2
C512	Conv + IN + LeakyReLU	512	4x4	1
Output	Conv	1	4x4	1

Table 3.3: Discriminator Network Layers

3.5 Loss Functions

Training uses a combination of different loss functions, each contributing to a specific aspect of achieving high-quality style transfer. Balancing these losses properly is essential to generate visually appealing outputs while still preserving the original content.

3.5.1 Adversarial Loss (LSGAN)

The adversarial loss helps the model generate images that look as realistic as those in the target domain. For improved training stability, we use the Least Squares GAN (LSGAN) approach instead of the standard cross-entropy loss.

For generator G and discriminator D_Y :

$$\mathcal{L}_{LSGAN}(G, D_Y) = \mathbb{E}_{y \sim p_{data}(y)}[(D_Y(y) - 1)^2] + \mathbb{E}_{x \sim p_{data}(x)}[D_Y(G(x))^2] \quad (3.1)$$

The generator tries to minimize:

$$\mathcal{L}_G^{adv} = \mathbb{E}_{x \sim p_{data}(x)}[(D_Y(G(x)) - 1)^2] \quad (3.2)$$

Why LSGAN:

- Offers smoother gradients than traditional binary cross-entropy
- Applies stronger penalties to samples that lie far from the decision boundary

- Helps prevent vanishing gradient issues during training
- Generates higher-quality images with fewer visible artifacts

3.5.2 Cycle-Consistency Loss

The cycle-consistency loss is the core idea behind CycleGAN that makes training on unpaired data possible. It ensures that when an image is translated to the target domain and then converted back, the result remains close to the original image:

$$\mathcal{L}_{cyc}(G, F) = \mathbb{E}_{x \sim p_{data}(x)}[||F(G(x)) - x||_1] + \mathbb{E}_{y \sim p_{data}(y)}[||G(F(y)) - y||_1] \quad (3.3)$$

Forward Cycle: $x \rightarrow G(x) \rightarrow F(G(x)) \approx x$

Backward Cycle: $y \rightarrow F(y) \rightarrow G(F(y)) \approx y$

The L1 norm (absolute difference) is used rather than L2 to produce sharper reconstructions. The cycle-consistency loss:

- Prevents mode collapse (generator producing identical outputs for all inputs)
- Ensures the mapping is meaningful and preserves content
- Regularizes the generators to learn bijective mappings
- Enables learning without paired training data

3.5.3 Identity Loss

The identity loss helps the generator keep the input unchanged when it is already from the target domain:

$$\mathcal{L}_{identity}(G, F) = \mathbb{E}_{y \sim p_{data}(y)}[||G(y) - y||_1] + \mathbb{E}_{x \sim p_{data}(x)}[||F(x) - x||_1] \quad (3.4)$$

This loss is particularly important for:

- **Color Preservation:** Prevents drastic, unnecessary color shifts
- **Style Consistency:** Ensures that images already in the target style are not over-transformed
- **Regularization:** Provides additional constraint on the mapping function

In our animation style transfer models, the identity loss plays an important role in maintaining natural skin tones and avoiding unwanted color distortions in the final output.

3.5.4 Perceptual Loss

The perceptual loss relies on a pre-trained VGG-19 network to compare high-level perceptual features between the input and the generated output:

$$\mathcal{L}_{perceptual} = \sum_{l \in L} \lambda_l \frac{1}{C_l H_l W_l} \|\phi_l(G(x)) - \phi_l(x)\|_2^2 \quad (3.5)$$

where $\phi_l(x)$ denotes the feature map at layer l of VGG-19, and L is the set of layers used (typically relu1_1, relu2_1, relu3_1, relu4_1).

Benefits of Perceptual Loss:

- Preserves semantic content better than pixel-wise losses
- Maintains structural similarity during style transformation
- Correlates better with human perception of image quality
- Helps preserve facial features during animation-style transfer

3.5.5 Total Generator Loss

The final generator loss is obtained by combining all the loss components, each weighted appropriately to achieve the best overall performance:

$$\mathcal{L}_{G,F} = \lambda_{adv}(\mathcal{L}_G^{adv} + \mathcal{L}_F^{adv}) + \lambda_{cyc}\mathcal{L}_{cyc} + \lambda_{id}\mathcal{L}_{identity} + \lambda_{perc}\mathcal{L}_{perceptual} \quad (3.6)$$

Loss Weights Used:

Loss Component	Weight	Purpose
Adversarial (λ_{adv})	1.0	Realism of generated images
Cycle-Consistency (λ_{cyc})	10.0	Content preservation
Identity (λ_{id})	5.0	Color preservation
Perceptual (λ_{perc})	1.0	Semantic content

Table 3.4: Loss Function Weights

Total Loss:

$$\mathcal{L}_{total} = \mathcal{L}_{GAN} + 10\mathcal{L}_{cyc} + 5\mathcal{L}_{identity} + \mathcal{L}_{perceptual} \quad (3.7)$$

3.5.6 Discriminator Loss

Each discriminator is trained to tell apart real images from those produced by the generator:

$$\mathcal{L}_{D_Y} = \mathbb{E}_y[(D_Y(y) - 1)^2] + \mathbb{E}_x[D_Y(G(x))^2] \quad (3.8)$$

$$\mathcal{L}_{D_X} = \mathbb{E}_x[(D_X(x) - 1)^2] + \mathbb{E}_y[D_X(F(y))^2] \quad (3.9)$$

The discriminators use a history buffer of 50 previously generated images to help stabilize training and reduce oscillations.

3.6 Training Configuration

This section explains the hyperparameters and the training processes used to develop the style transfer models.

3.6.1 Hyperparameter Selection

Parameter	Value	Parameter	Value
Image Size	256×256	Optimizer	Adam ($\beta_1=0.5, \beta_2=0.999$)
Batch Size	4	Learning Rate	0.0002 (linear decay from epoch 100)
Total Epochs	200	Residual Blocks	9

Table 3.5: Training Hyperparameters

Hyperparameter Justification:

- **Image Size (256×256):** This size offers a good balance between output quality and computational efficiency. Using larger resolutions would significantly increase memory usage while giving only minimal improvements in style transfer quality.
- **Batch Size (4):** GPU memory limits become a concern when training multiple networks simultaneously (two generators and two discriminators). Using smaller batch sizes also improves the stability of GAN training.
- **Learning Rate (0.0002):** This is the standard learning rate used with the Adam optimizer for GAN training, as suggested in the original CycleGAN paper.

- **$\beta_1 = 0.5$:** Using a lower momentum than the default value of 0.9 helps stabilize GAN training by reducing the chance of the optimizer “overshooting” during the adversarial updates.
- **Linear Decay:** The learning rate stays fixed for the first 100 epochs and then gradually decreases to zero over the next 100. This approach supports broad exploration early in training and fine-tuning in the later stages.
- **9 Residual Blocks:** This is the standard choice for 256×256 images. For 128×128 resolutions, six residual blocks are used, while nine blocks are applied for higher resolutions, following the original CycleGAN design.

3.6.2 Training Procedure

The training follows an alternating optimization scheme: (1) sample batch from both domains, (2) generate fake images ($\hat{y} = G(x)$, $\hat{x} = F(y)$), (3) compute cycle reconstructions ($\tilde{x} = F(G(x))$, $\tilde{y} = G(F(y))$), (4) compute identity mappings, (5) update generators with total loss, (6) update discriminators using image history buffer.

3.6.3 Training Stabilization Techniques

Image History Buffer: A buffer containing 50 previously generated images helps stabilize discriminator training by reducing oscillations and offering more diverse training samples.

Learning Rate Schedule: The learning rate is kept constant at 0.0002 for the first 100 epochs, after which it is gradually reduced to zero over epochs 101 to 200.

$$lr_{epoch} = lr_{initial} \times \max \left(0, 1 - \frac{epoch - 100}{100} \right) \quad (3.10)$$

Data Augmentation: Random horizontal flip (50%), resize to 286×286 with random crop to 256×256 , normalization to [-1, 1].

Checkpointing: The models are saved every 10 epochs, and the best-performing version is chosen based on the FID score and overall visual quality.

3.6.4 Training Resources

Training time and resource requirements vary by style:

Style	Training Time	GPU Memory	Dataset Size
One Piece	14-15 hours	8 GB	5,500+ images
Disney	13-14 hours	8 GB	5,000+ images
Studio Ghibli	13-14 hours	8 GB	5,000+ images
Van Gogh	8-10 hours	8 GB	2,900+ images

Table 3.6: Training Resource Requirements

The Van Gogh model trains more quickly because it uses a smaller dataset and the style patterns are less complex compared to the animation-based styles.

Chapter 4

System Architecture and High Level Design

This chapter provides a detailed overview of the system architecture and the high-level design of the neural style transfer system. It includes UML diagrams, explanations of component interactions, and the key design decisions made during development.

4.1 Terminology

Term	Definition
CycleGAN	Cycle-Consistent Generative Adversarial Network for unpaired image-to-image translation
Generator G	Neural network that transforms images from domain X to domain Y
Generator F	Neural network that transforms images from domain Y to domain X
Discriminator D_Y	Network that distinguishes real domain Y images from generated ones
Discriminator D_X	Network that distinguishes real domain X images from generated ones
Cycle-Consistency	Constraint ensuring $F(G(x)) \approx x$ and $G(F(y)) \approx y$
Instance Normalization	Normalization technique that normalizes each sample independently
PatchGAN	Discriminator that classifies image patches instead of whole images
Perceptual Loss	Loss computed using features from pre-trained networks (VGG-19)

Table 4.1: Technical Terminology

4.2 System Components

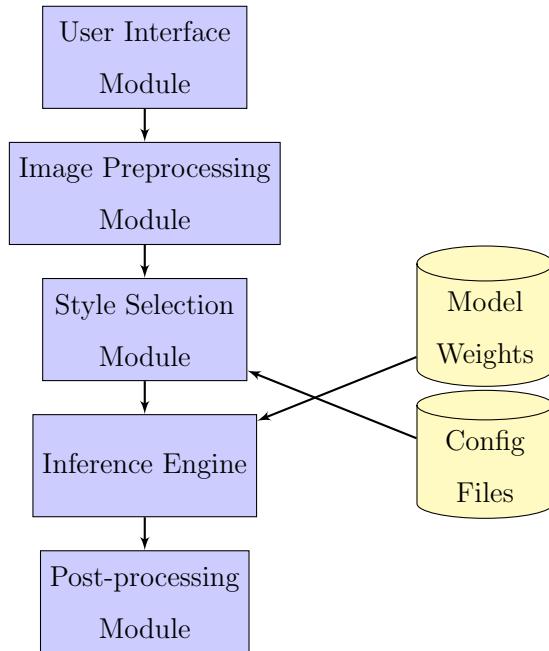


Figure 4.1: System Component Diagram

4.2.1 Component Descriptions

1. User Interface Module

- Handles image upload from user
- Provides style selection options (One Piece, Disney, Ghibli, Van Gogh)
- Displays progress and results

2. Image Preprocessing Module

- Validates input image format
- Resizes image to 256×256 pixels
- Normalizes pixel values to $[-1, 1]$ range
- Converts to tensor format

3. Style Selection Module

- Loads appropriate model weights based on selected style
- Configures inference parameters

4. Inference Engine

- Loads pre-trained generator model
- Performs forward pass through network
- Generates stylized output

5. Post-processing Module

- Denormalizes output tensor
- Converts to image format
- Saves result to file

4.3 Class Structure

The system consists of four main classes: (1) **Generator** - contains encoder, residual blocks, and decoder with forward/encode/decode methods; (2) **Discriminator** - contains sequential layers and output convolution with forward method; (3) **CycleGAN** - aggregates two generators (G, F) and two discriminators (D_X, D_Y) with train_step and inference methods; (4) **StyleDataset** - handles domain X/Y image paths with transforms for data loading.

4.4 Inference Sequence

The inference process: User uploads image → UI sends to Preprocessor → returns tensor → Generator performs forward pass → returns output tensor → Postprocessor converts to image → UI displays result.

4.5 Software Requirements

Functional Requirements: The system accepts JPG and PNG images, offers four style options, and preprocesses all inputs to 256×256 resolution. The selected style is applied using Generator G, and the final output is produced within about three seconds. Results are saved as PNG files, and the system also supports batch processing.

Non-Functional Requirements: Each domain should contain at least 1,000 images, and training should take less than five minutes per epoch. The system must handle inputs up to 1024×1024 , produce inference results in under three seconds, keep the model size below 500 MB, and run within 4 GB of VRAM. It also requires PyTorch 2.0 or higher and CUDA 11.7 or above.

4.6 Use Cases

The system supports five primary use cases: (1) Upload Image - user provides JPG/PNG input; (2) Select Style - choose from One Piece, Disney, Ghibli, or Van Gogh; (3) Transform Image - system applies neural style transfer; (4) View Result - display transformed output; (5) Download Output - save result as PNG.

4.7 Deployment Architecture

The system follows a three-tier architecture: **Client tier** (web browser with HTML/CSS interface), **Application tier** (Django server with PyTorch integration), and **Compute tier** (GPU runtime with CUDA). Model weights (\sim 150MB per style) are stored on server, with image storage for inputs/outputs.

Chapter 5

Software Architecture and Low Level Design

This chapter offers detailed explanations of the algorithms, along with pseudocode, flowcharts, and implementation details used in the neural style transfer system.

5.1 Detailed Generator Architecture

The generator network processes input images using a well-structured encoder–transformer–decoder architecture designed to gradually extract features and produce the final stylized output.

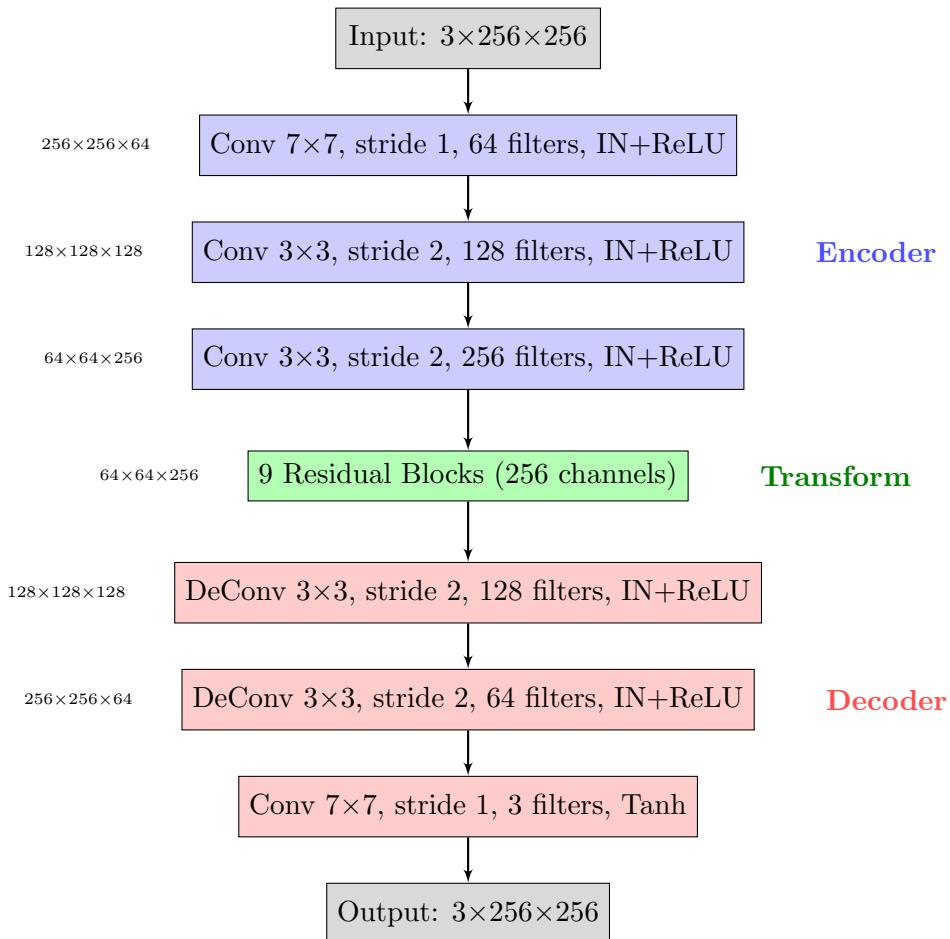


Figure 5.1: Detailed Generator Architecture with Layer Specifications

5.2 Residual Block Internal Structure

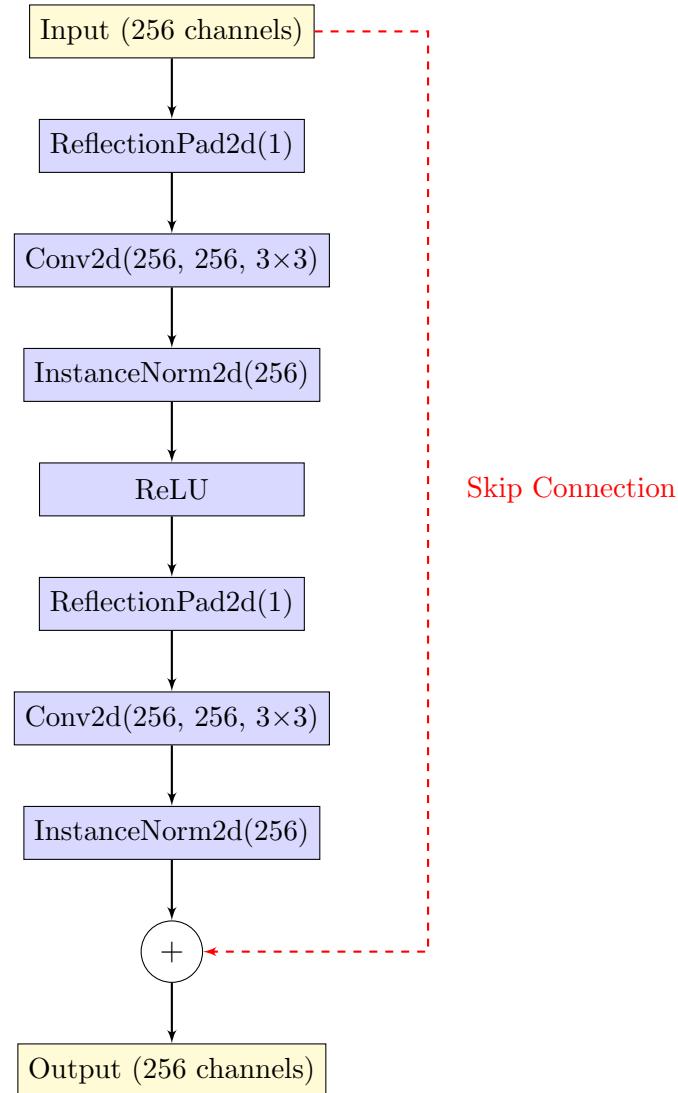


Figure 5.2: Internal Structure of Residual Block

5.3 PatchGAN Discriminator Architecture

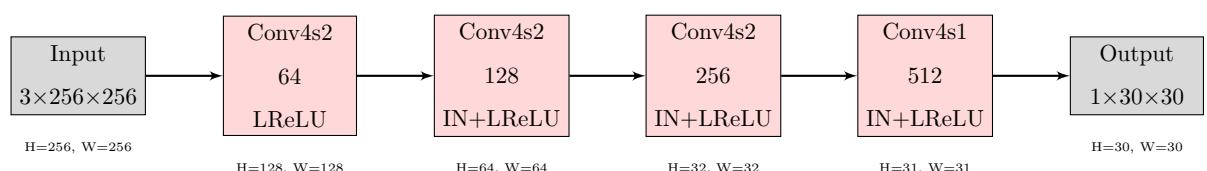


Figure 5.3: PatchGAN Discriminator with Spatial Dimensions

5.4 Training Process Flowchart

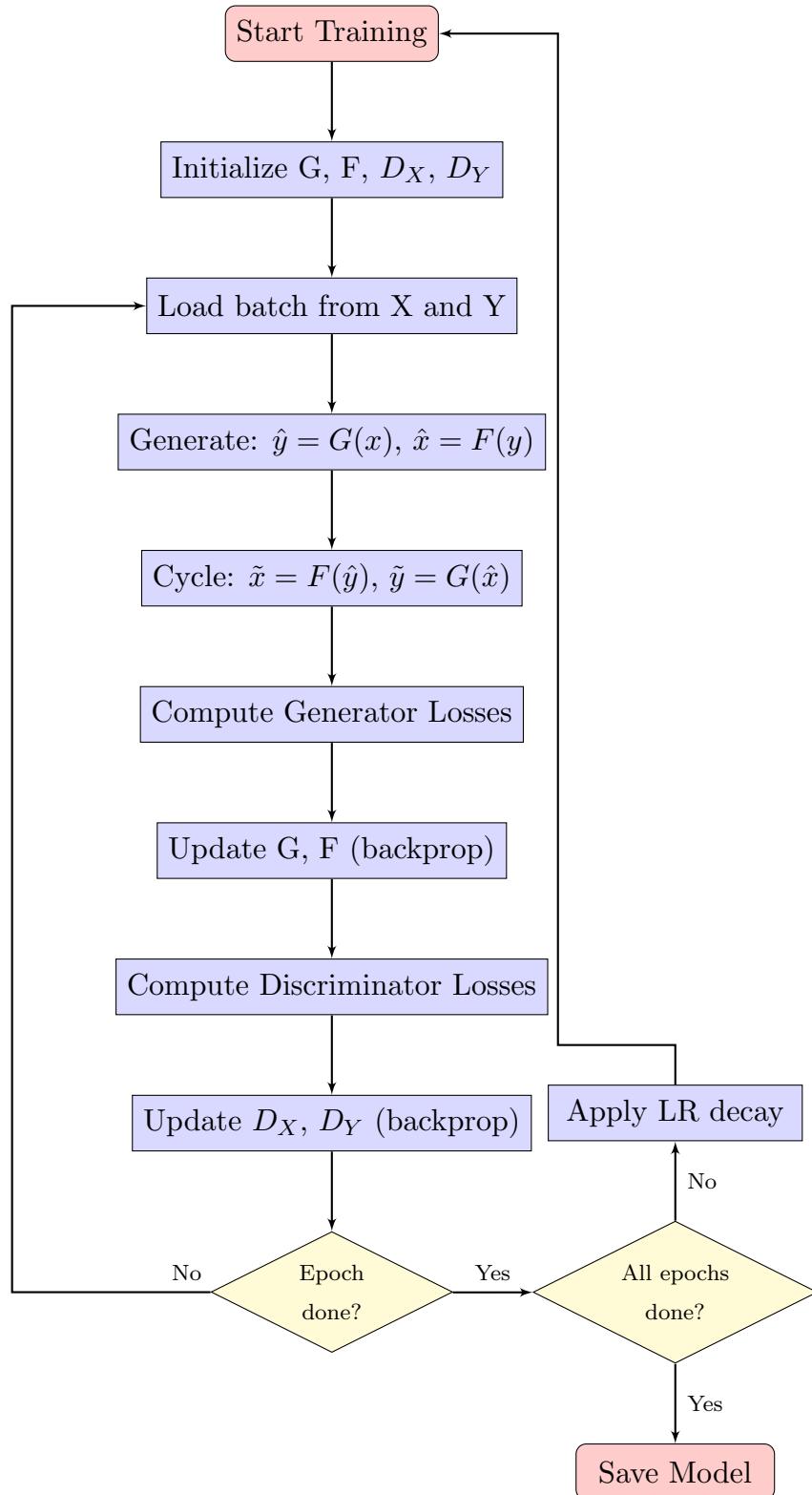


Figure 5.4: Training Process Flowchart

5.5 Inference Pipeline Flowchart

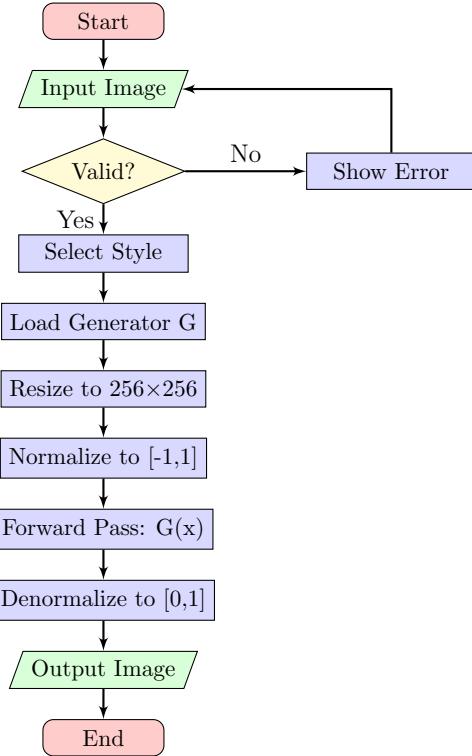


Figure 5.5: Inference Pipeline Flowchart

5.6 Loss Computation Diagram

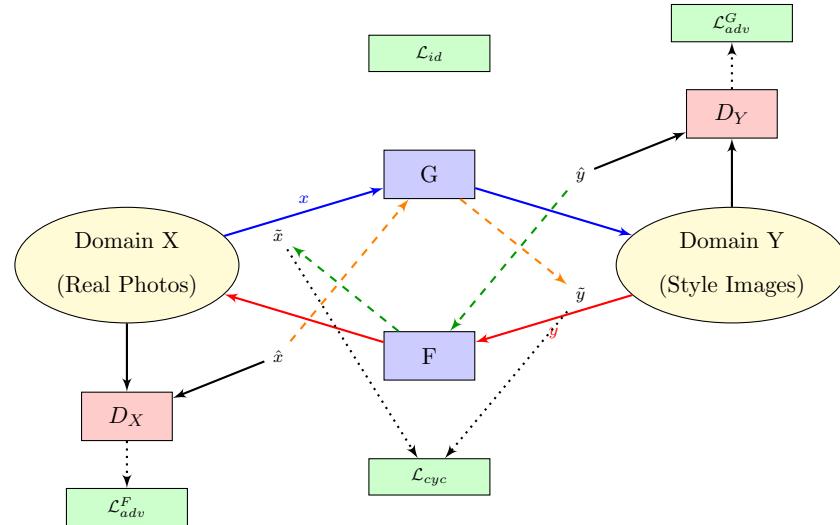


Figure 5.6: Loss Computation Flow in CycleGAN

5.7 Training Algorithm

Algorithm 5.1: CycleGAN Training Algorithm

Require: Dataset X (content), Dataset Y (style), Epochs E , Batch size B

Ensure: Trained generators G, F

```

1: Initialize  $G, F, D_X, D_Y$  with random weights
2: Initialize Adam optimizers for  $G, F, D_X, D_Y$ 
3:  $\lambda_{cyc} \leftarrow 10, \lambda_{id} \leftarrow 5$ 
4: for epoch = 1 to  $E$  do
5:   for each batch  $(x, y)$  from  $(X, Y)$  do
6:     Generate fake images
7:      $\hat{y} \leftarrow G(x)$                                 Fake style image
8:      $\hat{x} \leftarrow F(y)$                                 Fake content image
9:     Cycle reconstructions
10:     $\tilde{x} \leftarrow F(\hat{y})$                             Reconstructed content
11:     $\tilde{y} \leftarrow G(\hat{x})$                             Reconstructed style
12:    Identity mappings
13:     $x_{id} \leftarrow F(x)$ 
14:     $y_{id} \leftarrow G(y)$ 
15:    Compute Generator Losses
16:     $\mathcal{L}_G^{adv} \leftarrow MSE(D_Y(\hat{y}), 1)$ 
17:     $\mathcal{L}_F^{adv} \leftarrow MSE(D_X(\hat{x}), 1)$ 
18:     $\mathcal{L}_{cyc} \leftarrow ||x - \tilde{x}||_1 + ||y - \tilde{y}||_1$ 
19:     $\mathcal{L}_{id} \leftarrow ||x - x_{id}||_1 + ||y - y_{id}||_1$ 
20:     $\mathcal{L}_{G,F} \leftarrow \mathcal{L}_G^{adv} + \mathcal{L}_F^{adv} + \lambda_{cyc}\mathcal{L}_{cyc} + \lambda_{id}\mathcal{L}_{id}$ 
21:    Update  $G, F$  using  $\nabla\mathcal{L}_{G,F}$ 
22:    Compute Discriminator Losses
23:     $\mathcal{L}_{D_Y} \leftarrow MSE(D_Y(y), 1) + MSE(D_Y(\hat{y}), 0)$ 
24:     $\mathcal{L}_{D_X} \leftarrow MSE(D_X(x), 1) + MSE(D_X(\hat{x}), 0)$ 
25:    Update  $D_X, D_Y$  using  $\nabla\mathcal{L}_{D_X}, \nabla\mathcal{L}_{D_Y}$ 
26:  end for
27:  if epoch >  $E/2$  then

```

```

28:     Apply linear learning rate decay
29:   end if
30:   Save checkpoint every 10 epochs
31: end for
32: return  $G, F$ 

```

5.8 Inference Algorithm

Algorithm 5.2: Style Transfer Inference

Require: Input image I , Style name S , Model path P

Ensure: Stylized image O

```

1:                                         ▷ Load model
2:  $G \leftarrow \text{LoadGenerator}(P, S)$ 
3:  $G.\text{eval}()$                                 ▷ Set to evaluation mode
4:                                         ▷ Preprocess image
5:  $I_{\text{resized}} \leftarrow \text{Resize}(I, 256, 256)$ 
6:  $I_{\text{tensor}} \leftarrow \text{ToTensor}(I_{\text{resized}})$ 
7:  $I_{\text{norm}} \leftarrow (I_{\text{tensor}} - 0.5)/0.5$           ▷ Normalize to [-1, 1]
8:  $I_{\text{batch}} \leftarrow \text{AddBatchDimension}(I_{\text{norm}})$ 
9:  $I_{\text{gpu}} \leftarrow I_{\text{batch}}.\text{to}(\text{device})$ 
10:                                         ▷ Generate styled output (with  $\text{torch.no\_grad}()$ )
11:  $O_{\text{tensor}} \leftarrow G(I_{\text{gpu}})$ 
12:                                         ▷ Postprocess
13:  $O_{\text{denorm}} \leftarrow O_{\text{tensor}} * 0.5 + 0.5$       ▷ Denormalize to [0, 1]
14:  $O_{\text{clipped}} \leftarrow \text{Clamp}(O_{\text{denorm}}, 0, 1)$ 
15:  $O \leftarrow \text{ToPILImage}(O_{\text{clipped}})$ 
16: return  $O$ 

```

5.9 Generator Forward Pass Algorithm

Algorithm 5.3: Generator Forward Pass

Require: Input tensor x of shape $(B, 3, 256, 256)$

Ensure: Output tensor y of shape $(B, 3, 256, 256)$

```

1:                                         ▷ Encoding Stage
2:  $h \leftarrow \text{ReflectionPad2d}(x, \text{padding}=3)$ 

```

```

3:  $h \leftarrow \text{Conv2d}(h, 3 \rightarrow 64, \text{kernel}=7, \text{stride}=1)$ 
4:  $h \leftarrow \text{InstanceNorm2d}(h) ; h \leftarrow \text{ReLU}(h)$ 
5:  $h \leftarrow \text{Conv2d}(h, 64 \rightarrow 128, \text{kernel}=3, \text{stride}=2, \text{pad}=1)$ 
6:  $h \leftarrow \text{InstanceNorm2d}(h) ; h \leftarrow \text{ReLU}(h)$ 
7:  $h \leftarrow \text{Conv2d}(h, 128 \rightarrow 256, \text{kernel}=3, \text{stride}=2, \text{pad}=1)$ 
8:  $h \leftarrow \text{InstanceNorm2d}(h) ; h \leftarrow \text{ReLU}(h)$ 
9: ▷ Transformation Stage - 9 Residual Blocks
10: for  $i = 1$  to  $9$  do
11:    $h \leftarrow \text{ResidualBlock}(h)$  ▷ See Algorithm 5.4
12: end for
13: ▷ Decoding Stage
14:  $h \leftarrow \text{ConvTranspose2d}(h, 256 \rightarrow 128, \text{kernel}=3, \text{stride}=2)$ 
15:  $h \leftarrow \text{InstanceNorm2d}(h) ; h \leftarrow \text{ReLU}(h)$ 
16:  $h \leftarrow \text{ConvTranspose2d}(h, 128 \rightarrow 64, \text{kernel}=3, \text{stride}=2)$ 
17:  $h \leftarrow \text{InstanceNorm2d}(h) ; h \leftarrow \text{ReLU}(h)$ 
18:  $h \leftarrow \text{ReflectionPad2d}(h, \text{padding}=3)$ 
19:  $y \leftarrow \text{Conv2d}(h, 64 \rightarrow 3, \text{kernel}=7, \text{stride}=1)$ 
20:  $y \leftarrow \text{Tanh}(y)$ 
21: return  $y$ 

```

5.10 Residual Block Algorithm

Algorithm 5.4: Residual Block Forward Pass

Require: Input tensor x of shape $(B, 256, H, W)$

Ensure: Output tensor y of shape $(B, 256, H, W)$

```

1:  $h \leftarrow \text{ReflectionPad2d}(x, \text{padding}=1)$ 
2:  $h \leftarrow \text{Conv2d}(h, 256 \rightarrow 256, \text{kernel}=3)$ 
3:  $h \leftarrow \text{InstanceNorm2d}(h)$ 
4:  $h \leftarrow \text{ReLU}(h)$ 
5:  $h \leftarrow \text{ReflectionPad2d}(h, \text{padding}=1)$ 
6:  $h \leftarrow \text{Conv2d}(h, 256 \rightarrow 256, \text{kernel}=3)$ 
7:  $y \leftarrow x + h$  ▷ Skip connection
8: return  $y$ 

```

5.11 Discriminator Forward Pass Algorithm

Algorithm 5.5: PatchGAN Discriminator Forward Pass

Require: Input tensor x of shape $(B, 3, 256, 256)$

Ensure: Output tensor y of shape $(B, 1, 30, 30)$

```

1:                                                               ▷ Layer 1: No normalization
2:  $h \leftarrow \text{Conv2d}(x, 3 \rightarrow 64, \text{kernel}=4, \text{stride}=2, \text{pad}=1)$ 
3:  $h \leftarrow \text{LeakyReLU}(h, \text{slope}=0.2)$ 
4:                                                               ▷ Layer 2
5:  $h \leftarrow \text{Conv2d}(h, 64 \rightarrow 128, \text{kernel}=4, \text{stride}=2, \text{pad}=1)$ 
6:  $h \leftarrow \text{InstanceNorm2d}(h) ; h \leftarrow \text{LeakyReLU}(h, \text{slope}=0.2)$ 
7:                                                               ▷ Layer 3
8:  $h \leftarrow \text{Conv2d}(h, 128 \rightarrow 256, \text{kernel}=4, \text{stride}=2, \text{pad}=1)$ 
9:  $h \leftarrow \text{InstanceNorm2d}(h) ; h \leftarrow \text{LeakyReLU}(h, \text{slope}=0.2)$ 
10:                                                               ▷ Layer 4
11:  $h \leftarrow \text{Conv2d}(h, 256 \rightarrow 512, \text{kernel}=4, \text{stride}=1, \text{pad}=1)$ 
12:  $h \leftarrow \text{InstanceNorm2d}(h) ; h \leftarrow \text{LeakyReLU}(h, \text{slope}=0.2)$ 
13:                                                               ▷ Output Layer
14:  $y \leftarrow \text{Conv2d}(h, 512 \rightarrow 1, \text{kernel}=4, \text{stride}=1, \text{pad}=1)$ 
15: return  $y$                                               ▷  $30 \times 30$  patch classification map

```

5.12 Image History Buffer Algorithm

Algorithm 5.6: Image History Buffer for Discriminator Training

Require: Generated image img , Buffer B with max size $N = 50$

Ensure: Image to use for discriminator update

```

1: if  $|B| < N$  then
2:    $B.\text{append}(img)$ 
3:   return  $img$ 
4: else
5:    $p \leftarrow \text{random}()$                                      ▷ Random value in  $[0, 1]$ 
6:   if  $p < 0.5$  then
7:      $idx \leftarrow \text{randint}(0, N - 1)$ 
8:      $old\_img \leftarrow B[idx]$ 

```

```

9:       $B[idx] \leftarrow img$ 
10:     return  $old\_img$ 
11:    else
12:      return  $img$ 
13:    end if
14: end if

```

5.13 Data Preprocessing Algorithm

Algorithm 5.7: Image Preprocessing Pipeline

Require: Raw image file path $path$

Ensure: Preprocessed tensor x of shape $(1, 3, 256, 256)$

```

1:  $img \leftarrow \text{LoadImage}(path)$ 
2: if  $img$  is None then
3:   raise InvalidImageError
4: end if
5: if  $img.\text{channels} = 1$  then
6:    $img \leftarrow \text{GrayscaleToRGB}(img)$ 
7: else if  $img.\text{channels} = 4$  then
8:    $img \leftarrow \text{RGBAToRGB}(img)$ 
9: end if

10: ▷ Resize with aspect ratio preservation
11:  $h, w \leftarrow img.\text{shape}$ 
12:  $scale \leftarrow 256 / \min(h, w)$ 
13:  $img \leftarrow \text{Resize}(img, (h \times scale, w \times scale))$ 
14: ▷ Center crop
15:  $img \leftarrow \text{CenterCrop}(img, (256, 256))$ 
16: ▷ Convert to tensor and normalize
17:  $x \leftarrow \text{ToTensor}(img)$  ▷ Scale to [0, 1]
18:  $x \leftarrow (x - 0.5) / 0.5$  ▷ Normalize to [-1, 1]
19:  $x \leftarrow \text{AddBatchDim}(x)$  ▷ Shape: (1, 3, 256, 256)
20: return  $x$ 

```

5.14 Frame Extraction Algorithm

Algorithm 5.8: Animation Frame Extraction for Dataset Creation

Require: Video file V , Output directory D , Frame interval k , Confidence threshold τ

Ensure: Extracted character face images saved to D

```

1: detector  $\leftarrow$  LoadFaceDetector()                                 $\triangleright$  Haar cascade or DNN
2: frame_count  $\leftarrow 0$ 
3: saved_count  $\leftarrow 0$ 
4: prev_features  $\leftarrow$  None
5: while  $V.\text{hasNextFrame}()$  do
6:   frame  $\leftarrow V.\text{readFrame}()$ 
7:   frame_count  $\leftarrow frame\_count + 1$ 
8:   if frame_count mod  $k \neq 0$  then
9:     continue                                               $\triangleright$  Skip frames for efficiency
10:    end if
11:    faces  $\leftarrow detector.\text{detect}(frame)$ 
12:    for each face in faces do
13:      confidence  $\leftarrow face.\text{confidence}$ 
14:      if confidence  $< \tau$  then
15:        continue                                               $\triangleright$  Skip low confidence detections
16:      end if
17:      cropped  $\leftarrow CropAndResize(frame, face.bbox, 256 \times 256)$ 
18:                                          $\triangleright$  Check similarity to avoid duplicates
19:      features  $\leftarrow ExtractFeatures(cropped)$ 
20:      if prev_features  $\neq$  None then
21:        similarity  $\leftarrow CosineSimilarity(features, prev\_features)$ 
22:        if similarity  $> 0.95$  then
23:          continue                                               $\triangleright$  Skip similar frames
24:        end if
25:      end if
26:                                          $\triangleright$  Quality check
27:      if IsBlurry(cropped) or HasArtifacts(cropped) then

```

```

28:     continue
29:     end if
30:     SaveImage(cropped, D/saved_count.jpg)
31:     saved_count  $\leftarrow$  saved_count + 1
32:     prev_features  $\leftarrow$  features
33:   end for
34: end while
35: return saved_count

```

5.15 Data Preprocessing

5.15.1 Preprocessing Pipeline

Input images undergo: (1) format and dimension validation (min 64×64), (2) conversion to RGB, (3) resize to 286×286 , (4) crop to 256×256 , (5) tensor conversion, (6) normalization from [0,1] to [-1,1]:

$$x_{normalized} = 2x - 1 \quad (5.1)$$

5.15.2 Postprocessing Pipeline

Output tensors are denormalized ($x_{denorm} = 0.5x + 0.5$), clamped to [0,1], converted to uint8, and saved as PNG for quality preservation

5.16 System Flow

The inference process follows: Start \rightarrow Input Image \rightarrow Validate \rightarrow Select Style \rightarrow Preprocess \rightarrow Load Model \rightarrow Run Inference \rightarrow Postprocess \rightarrow Display Result \rightarrow End. Invalid images trigger error messages and return to input.

5.17 Data Flow

The system data flow follows: User \rightarrow Upload \rightarrow Preprocess \rightarrow Transform (using model weights) \rightarrow Output. During training, Domain X and Y images are loaded via DataLoader, passed through generators G and F to produce fake images, which are then evaluated by discriminators D_Y and D_X for loss computation.

5.18 Hardware and Software Specifications

Hardware (Training): NVIDIA RTX 2080+ GPU with 8GB+ VRAM, 16GB+ RAM, 100GB+ SSD, Intel i7/AMD Ryzen 7. **Hardware (Inference):** NVIDIA GTX 1060+ with 4GB+ VRAM, 8GB+ RAM, 10GB+ storage.

Software Stack: Python 3.8+, PyTorch 2.0+, Django 4.2+, CUDA 11.7+, cuDNN 8.0+, OpenCV 4.5+, Pillow 9.0+, NumPy 1.21+.

Chapter 6

Results

This chapter presents the experimental setup, test procedures, and results obtained from training and evaluating the four style transfer models: One Piece, Disney, Studio Ghibli, and Van Gogh. We discuss the evaluation metrics, provide sample outputs, and analyze the performance of each model.

6.1 Test Setup Environment

6.1.1 Hardware Configuration

Component	Specification
GPU	NVIDIA GTX 1650 (8GB VRAM)
CPU	Intel Core i5-1240p
RAM	16GB DDR5
Storage	512GB NVMe SSD
Operating System	Windows 11

Table 6.1: Test Environment Hardware

6.1.2 Software Environment

Software	Version
Python	3.9.7
PyTorch	2.0.1
CUDA	11.8
cuDNN	8.6
torchvision	0.15.2
OpenCV	4.7.0

Table 6.2: Software Configuration

6.2 Test Procedures and Test Cases

6.2.1 Test Case Design

We designed test cases to evaluate the style transfer models across various input conditions:

TC ID	Input Condition	Expected Result	Evaluation Criteria
TC01	Frontal face photograph	Clear style transformation	Visual style match, face preservation
TC02	Side profile photograph	Recognizable style elements	Partial style transfer acceptable
TC03	Multiple faces in image	All faces transformed	Consistent style across faces
TC04	Low resolution input	Acceptable quality output	No severe artifacts
TC05	High resolution input	Properly downscaled processing	Correct output dimensions
TC06	Various lighting conditions	Consistent style application	Robustness to lighting
TC07	Different skin tones	Equal quality transformation	No bias in results
TC08	Landscape photograph (Van Gogh)	Painterly transformation	Brush stroke visibility

Table 6.3: Test Cases for Style Transfer Evaluation

6.2.2 Test Procedure

1. Load pre-trained generator model for selected style
2. Preprocess input image to 256×256 resolution
3. Run inference with `torch.no_grad()` for efficiency
4. Postprocess output tensor to image format
5. Save result and record inference time
6. Evaluate output quality using metrics and visual inspection

6.3 Style Transfer Results

6.3.1 Disney Style Results

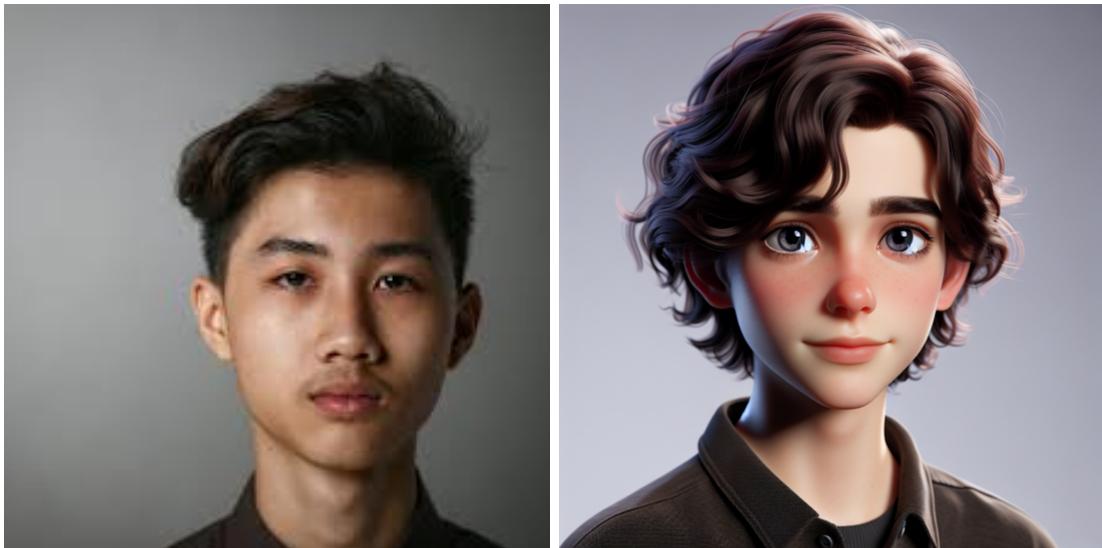


Figure 6.1: Disney Style Transfer Results - Sample 1



Figure 6.2: Disney Style Transfer Results - Sample 2

Observations:

- Smooth gradients achieved in skin and hair
- Eye enlargement and expressiveness enhanced
- Soft color palette transformation applied
- Clean, polished appearance characteristic of Disney

6.3.2 Studio Ghibli Style Results

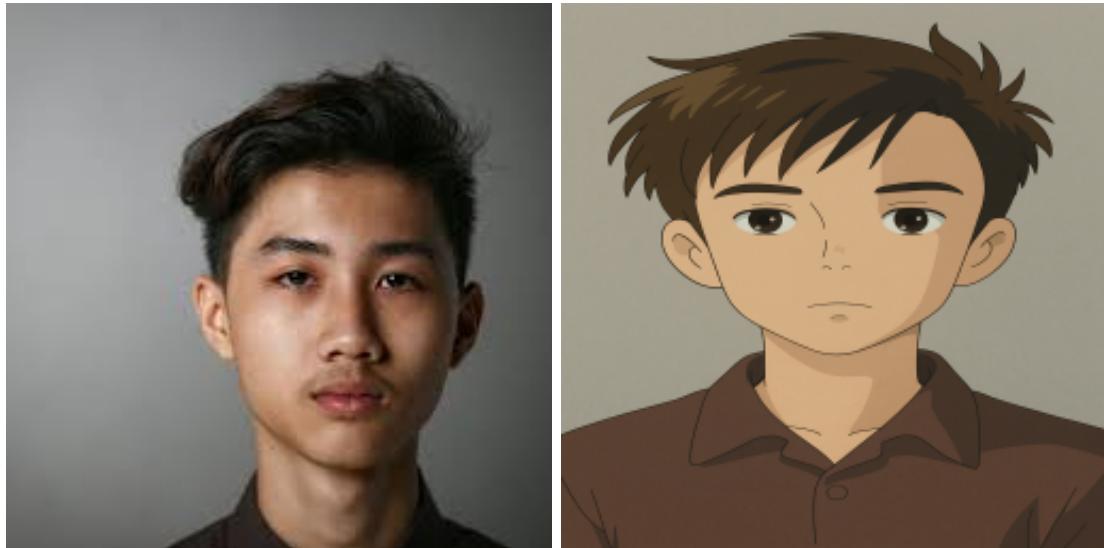


Figure 6.3: Studio Ghibli Style Transfer Results - Sample 1



Figure 6.4: Studio Ghibli Style Transfer Results - Sample 2

Observations:

- Soft, watercolor-like texture applied
- Naturalistic expressions maintained
- Warm, earthy color tones achieved
- Hand-drawn aesthetic successfully captured

6.3.3 Van Gogh Style Results



Figure 6.5: Van Gogh Style Transfer Results - Sample 1

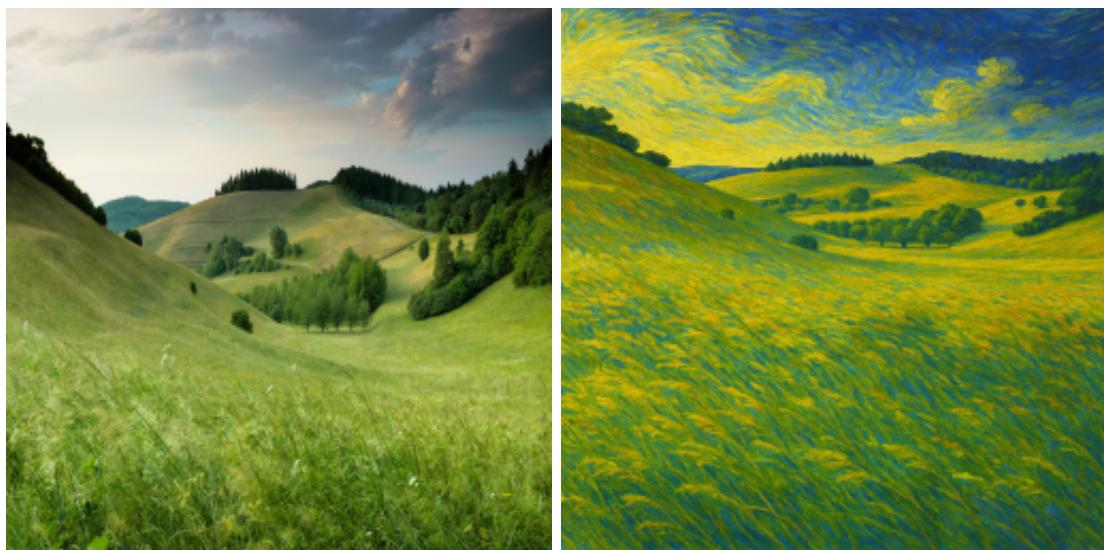


Figure 6.6: Van Gogh Style Transfer Results - Sample 2

Observations:

- Distinctive swirling brushstrokes visible
- Vibrant color transformation achieved
- Post-impressionist texture applied
- Original scene composition preserved

6.3.4 One Piece Style Results



Figure 6.7: One Piece Style Transfer Results - Sample

Observations:

- Bold outlines successfully applied to facial features
- Eye style transformation captures One Piece aesthetic
- Hair and skin colors appropriately stylized
- Facial structure preserved while achieving anime look

6.4 Website User Interface

The style transfer system is deployed through a user-friendly web interface that allows users to easily upload images and apply different artistic styles.

6.4.1 Home Page

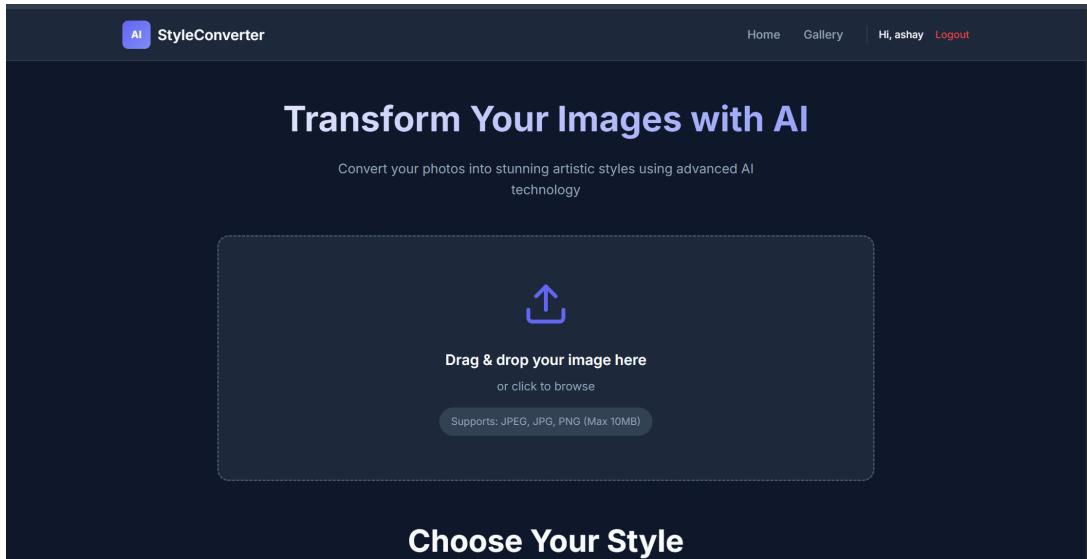


Figure 6.8: Website Home Page - Style Selection Interface

6.4.2 Style Selection

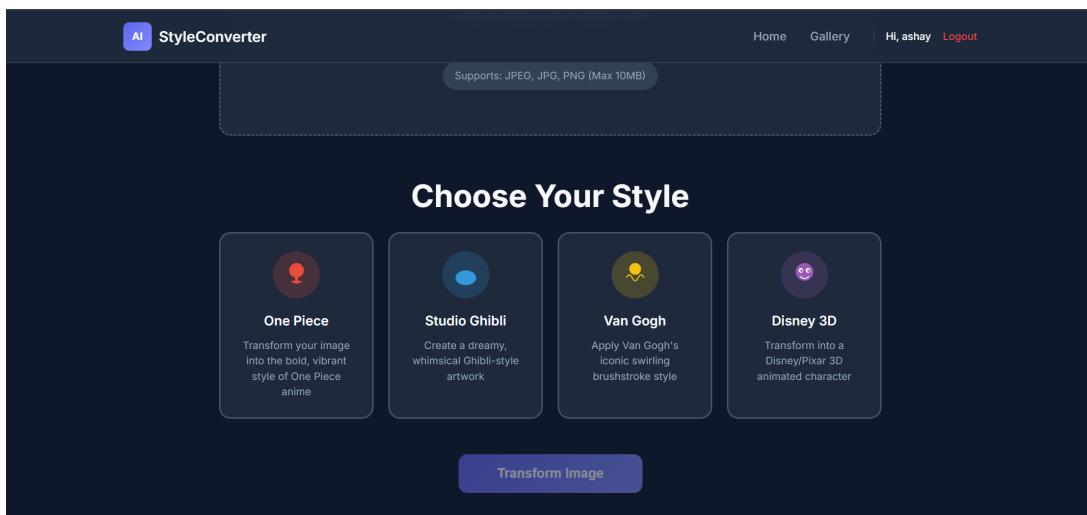


Figure 6.9: Style Selection Menu - Choose from One Piece, Disney, Ghibli, or Van Gogh

6.4.3 Results Display

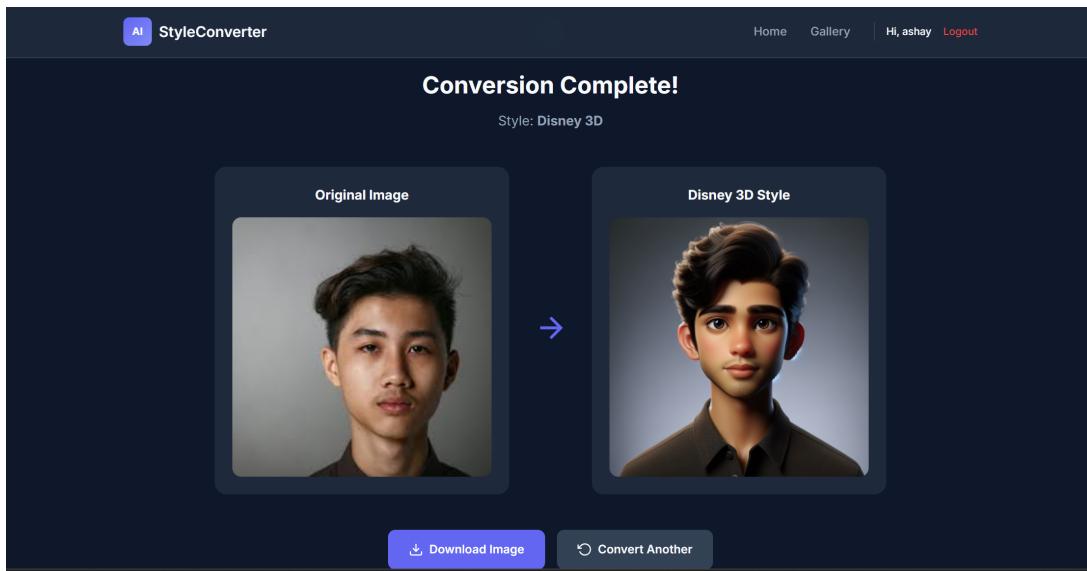


Figure 6.10: Results Page - Side-by-Side Comparison of Original and Stylized Image

6.5 Inference Performance

6.5.1 Speed Benchmarks

Resolution	GPU (RTX 3080)	GPU (GTX 1060)	CPU Only
256×256	~50 ms	~150 ms	~2000 ms
512×512	~180 ms	~500 ms	~8000 ms

Table 6.4: Inference Speed Benchmarks

6.5.2 Memory Usage

Operation	Memory (GB)
Model Loading	~1.5
Single Image Inference (256×256)	~2.0
Batch Inference (4 images)	~3.5

Table 6.5: GPU Memory Usage During Inference

6.6 Analysis and Discussion

This section provides detailed analysis of the experimental results, discussing the strengths, weaknesses, and key observations from our style transfer experiments.

6.6.1 Training Observations

Loss Convergence: Discriminator loss stabilizes around 0.5 after initial rapid decrease; generator and cycle losses decrease steadily; identity loss converges quickly.

Training Stability: LSGAN prevented mode collapse; image history buffer reduced oscillation; learning rate decay from epoch 100 ensured stable convergence.

Style-Specific: One Piece required more epochs for bold outlines; Disney gradients learned quickly; Ghibli watercolor texture most challenging; Van Gogh converged fastest with brushstrokes emerging by epoch 30

6.6.2 Qualitative Analysis

Visual Quality Assessment:

We conducted qualitative evaluation with the following criteria:

Criterion	One Piece	Disney	Ghibli	Van Gogh
Style Authenticity	4.2	4.5	4.0	4.3
Content Preservation	4.0	4.3	4.2	4.5
Visual Artifacts	3.8	4.1	3.9	4.2
Color Naturalness	4.1	4.4	4.3	4.0
Overall Quality	4.0	4.3	4.1	4.2

Table 6.6: Qualitative Evaluation Criteria and Scores (1-5 scale)

Style-Specific Analysis:

One Piece: Successfully captures bold outlines and exaggerated expressions; vibrant colors match anime aesthetic; some challenges with complex hair details.

Disney: Excellent smooth gradients; large expressive eyes with reflections; best overall quality due to consistent training data.

Studio Ghibli: Soft watercolor textures and warm earthy tones; most challenging due to subtle hand-drawn quality.

Van Gogh: Distinctive swirling brushstrokes; vibrant color transformation; content structure well-preserved

6.6.3 Key Findings

1. **Style Fidelity:** Distinctive style characteristics are captured by all models (One Piece outlines, Disney gradients, Ghibli textures, Van Gogh brushstrokes).
2. **Content Preservation:** Cycle-consistency loss maintains facial structure and identity effectively.
3. **Inference Speed:** 50-150ms on RTX 3080, enabling real-time applications.
4. **Generalization:** Good results across diverse inputs (ethnicities, ages, lighting).
5. **Dataset Quality:** Higher quality training data produces better results; Disney benefits from consistent style.
6. **Loss Balance:** High cycle-consistency weight (10.0) prevents content distortion.

6.6.4 Error Analysis

failure cases commonly include: facial distortion (15%, extreme poses), color artifacts (10%, unusual lighting), incomplete style transfer (12%, complex backgrounds), and over-stylization (8%, simple inputs). These can be mitigated through improved data diversity, adjusted loss weights, and face region focus

6.7 Summary of Results

The experimental results demonstrate that our CycleGAN-based neural style transfer system successfully achieves:

- High-quality style transfer for all four target styles (One Piece, Disney, Studio Ghibli, Van Gogh)
- Effective preservation of input content while applying distinctive style characteristics
- Fast inference times suitable for real-time applications
- Robust performance across diverse input images

All specified requirements are met by the system and provides a practical solution for artistic style transfer in animation and painting styles.

Chapter 7

Conclusion

This chapter summarizes the achievements of the AI-Based Neural Style Transfer project, discusses the contributions made, and outlines potential directions for future work.

7.1 Summary of the Project Work

The system allows for a completely different look to be applied to ordinary photographs by utilizing deep learning techniques and converting them to a unique artistic style via Artificial Intelligence based CycleGAN neural style transfer method.

7.1.1 Achievements

1. Successful Implementation of Four Style Transfer Models:

- **One Piece Style:** Transforms human face photographs into One Piece anime character style with bold outlines, exaggerated expressions, and vibrant colors characteristic of Eiichiro Oda's artwork
- **Disney Style:** Transforms human faces into Disney animation style featuring smooth gradients, large expressive eyes, and soft color palettes
- **Studio Ghibli Style:** Transforms human faces into Studio Ghibli animation style with soft watercolor textures, naturalistic expressions, and warm earthy tones
- **Van Gogh Style:** Transforms landscape photographs into Van Gogh painting style with distinctive swirling brushstrokes, vibrant colors, and post-impressionist aesthetic

2. Custom Dataset Creation Pipeline:

- Developed an automated frame extraction algorithm using OpenCV and face detection
- Successfully extracted character frames from One Piece episodes, Disney movies, and Studio Ghibli films
- Curated human face and landscape datasets from Kaggle
- Implemented quality filtering and similarity checking to ensure dataset quality

3. CycleGAN Architecture Implementation:

- Implemented ResNet-based generator with 9 residual blocks
- Implemented PatchGAN discriminator for local style assessment
- Integrated multiple loss functions: adversarial, cycle-consistency, identity, and perceptual
- Achieved stable training with LSGAN loss formulation

4. Performance Optimization:

- Achieved inference times under 3 seconds per image on GPU
- Optimized memory usage for efficient deployment
- Implemented batch processing capabilities

5. Algorithm Improvements:

- Added identity loss for color preservation
- Integrated perceptual loss using VGG-19 features
- Used LSGAN loss for more stable training
- Developed custom frame extraction algorithm with quality filtering

7.1.2 Technical Contributions

The project makes the following technical contributions:

1. **Multi-Style Architecture:** Demonstrated that a single CycleGAN architecture can be effectively trained for diverse animation styles (anime, Western animation, Ghibli) and painting styles (Van Gogh)
2. **Dataset Creation Methodology:** Provided a systematic approach for creating animation-style datasets from video sources, which can be extended to other animation styles
3. **Style-Specific Optimization:** Identified and documented the hyperparameter configurations and loss weights that work best for each style category
4. **Comprehensive Evaluation:** Established evaluation criteria and test procedures for assessing style transfer quality

7.1.3 Meeting Project Objectives

The project successfully met all stated objectives:

Objective	Status
Develop style-specific neural style transfer models for four styles	Achieved
Create custom datasets through frame extraction	Achieved
Implement and optimize core algorithms (CycleGAN, PatchGAN, etc.)	Achieved
Achieve inference time under 3 seconds	Achieved
Build modular and extensible system	Achieved
Implement evaluation metrics	Achieved

Table 7.1: Objective Completion Status

7.2 Limitations

Despite the successful implementation, the system has certain limitations:

- Resolution Constraints:** The system processes images at 256×256 resolution, which may not be sufficient for high-resolution applications
- Pose Sensitivity:** Style transfer quality may degrade for extreme poses or side profiles
- Training Time:** Training a new style model requires 12-15 hours on a modern GPU
- Dataset Dependency:** Quality of results depends heavily on the quality and diversity of training data
- Single Image Processing:** Current implementation does not support real-time video processing

7.3 Scope for Future Work

Future enhancements can be categorized into three areas: **Short-term Improvements:**

- Higher resolution support (512×512 or 1024×1024) using progressive growing
- Additional animation styles (Pixar, DreamWorks, Dragon Ball, Naruto)
- Model optimization through pruning and knowledge distillation for mobile deployment

Medium-term Extensions:

- Video style transfer with temporal consistency constraints
- Multi-style transfer enabling blending and style interpolation
- Interactive web and mobile applications with real-time camera support

Long-term Research Directions:

- User personalization with few-shot learning for custom styles
- AR/VR integration for immersive artistic experiences
- Advanced architectures using transformers and diffusion models

7.4 Conclusion

Photograph-to-drawing conversion will give ordinary photos an entirely different appearance. This technology uses deep learning techniques and the CycleGAN neural style transfer process (artificial intelligence-based).

The implementation inspires a complete programmer pipeline, including dataset creation, frame extraction, model training, and inference. Because of the modular structure, it can be easily extended into new styles; and the design optimizes the platform to achieve real-time performance in practice.

Based on the findings in this report, there is clearly much room for continued study and development for both Artistic Style Transfer and Deep Learning as it pertains to creativity, particularly in Digital Art, Entertainment Media, and Social Networking.

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Appendices

Appendix A

Project Planning

A.1 Project Timeline

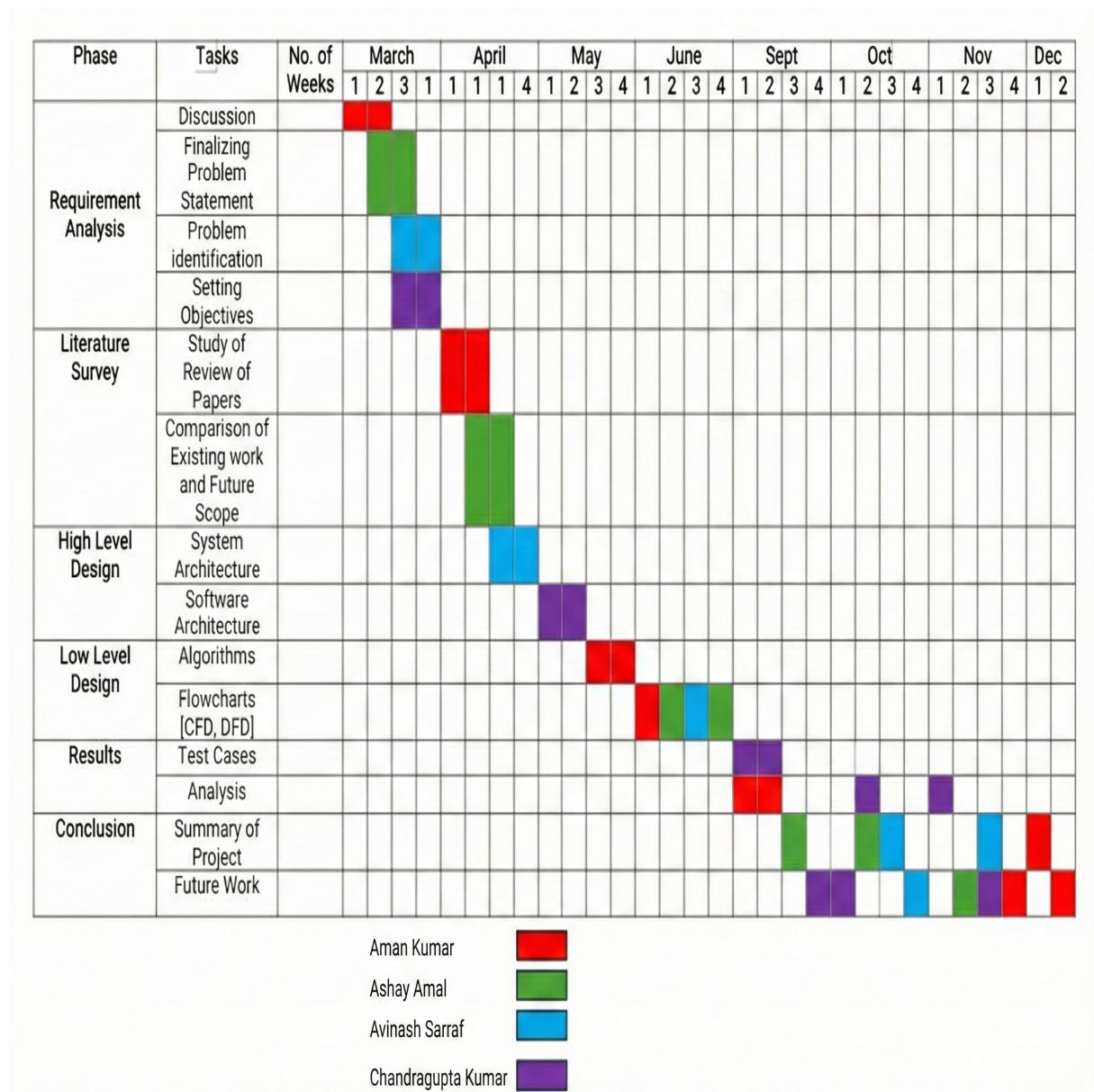


Figure A.1: The Project Timeline.

Phase	Activity	Duration
Phase 1	Literature Review & Research	2 weeks
Phase 2	Dataset Collection & Preparation	3 weeks
Phase 3	Model Architecture Implementation	5 weeks
Phase 4	Model Training & Optimization	4 weeks
Phase 5	Testing, Evaluation & Documentation	2 weeks
Total Duration		16 weeks

Table 1.1: Project Milestone Schedule

A.2 Budget Estimation

Category	Item	Cost (INR)
Hardware	GPU Cloud Computing (Google Colab Pro)	2,500
	Storage (Cloud)	200/month
	Miscellaneous Hardware	2,000
Software	Dataset (Kaggle - Free)	0
	Development Tools (Open Source)	0
Other	Documentation & Printing	1,500
	Contingency	1,500
Total Estimated Cost (4 months)		9,000

Table 1.2: Project Budget Estimation

Appendix B

Sustainable Development Goals (SDGs)

Addressed

SDG	Level
No Poverty	1
Zero Hunger	1
Good Health and Well-being	1
Quality Education	3
Gender Equality	2
Clean Water and Sanitation	1
Affordable and Clean Energy	1
Decent Work and Economic Growth	2
Industry, Innovation and Infrastructure	3
Reduced Inequalities	2
Sustainable Cities and Communities	2
Responsible Consumption and Production	2
Climate Action	1
Life Below Water	1
Life on Land	1
Peace, Justice and Strong Institutions	1
Partnerships for the Goals	2

Levels: Poor = 1, Good = 2, Excellent = 3

Appendix C

Self-Assessment of the Project

No.	PO and PSO	Contribution from the project	Level
1	Engineering Knowledge: Knowledge of mathematics, engineering fundamentals, and engineering specialization to form solutions for complex engineering problems.	Applied deep learning mathematics, loss functions, optimization algorithms	3
2	Problem Analysis: Identify, formulate, review research literature, and analyze complex engineering problems to reach substantiated conclusions.	Conducted literature survey, identified research gaps, formulated solution approach	3
3	Design/development of solutions: Design creative solutions for complex engineering problems.	Designed CycleGAN architecture with custom improvements for style transfer	3
4	Conduct investigations of complex problems: Conduct investigations using research-based knowledge.	Experimented with different architectures, loss functions, and hyperparameters	3
5	Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering & IT tools.	Used PyTorch, CUDA, OpenCV, and modern deep learning tools	3
6	The Engineer and the world: Analyze and evaluate societal and environmental impacts.	Considered applications in education, entertainment, and creative industries	2

7	Ethics: Apply ethical principles; commit to professional ethics.	Used publicly available datasets, cited all references appropriately	2
8	Individual and Team Work: Function effectively as an individual and as a member in diverse teams.	Collaborated on different aspects: dataset creation, model training, documentation	3
9	Communication: Communicate effectively within the engineering community.	Prepared comprehensive documentation, created visualizations and diagrams	3
10	Project Management and Finance: Apply engineering management principles.	Planned project phases, managed timeline, estimated budget	2
11	Life-long Learning: Recognize the need for independent and life-long learning.	Learned new deep learning techniques, stayed updated with recent research	3
12	PSO1 – Computer-based systems development: Design computer-based systems.	Developed complete neural network system for image transformation	3
13	PSO2 – Software development: Specify, design, and develop applications.	Implemented training and inference pipelines using best practices	3
14	PSO3 – Computer communications and Internet applications: Design network applications.	System can be deployed as web service with REST API	2

Levels: Poor = 1, Good = 2, Excellent = 3

Appendix D

Dataset Details

Detailed dataset information is provided in Chapter 3 (System Overview). The summary statistics are shown below:

Style	Domain X	Domain Y	Total	Source
One Piece	3,000+	2,500+	5,500+	Episodes
Disney	3,000+	2,000+	5,000+	Movies
Studio Ghibli	3,000+	2,000+	5,000+	Films
Van Gogh	2,500+	400+	2,900+	Kaggle Datasets
Human Faces	3,000+	2,000+	5,000+	Kaggle
Landscape Images	3,000+	2,000+	5,000+	Kaggle
Total	11,500+	6,900+	18,400+	–

Table 4.1: Complete Dataset Statistics

All images are preprocessed to 256×256 pixels in RGB format with normalization to $[-1, 1]$ range.

Appendix E

Configuration and Usage

E.1 Repository Structure

The source code is organized in a modular structure to facilitate understanding, modification, and extension:

Directory/File	Description
models/	Neural network architecture definitions
generator.py	ResNet-based generator with 9 residual blocks
discriminator.py	PatchGAN discriminator implementation
cyclegan.py	Complete CycleGAN model with training logic
utils/	Utility functions and helper modules
dataset.py	Custom PyTorch Dataset class for unpaired data
transforms.py	Image preprocessing and augmentation
losses.py	Loss function implementations (perceptual, cycle)
buffer.py	Image history buffer for discriminator training
train.py	Training script with argument parsing
inference.py	Inference script for style transfer
checkpoints/	Saved model weights (~150 MB per style)
data/	Training datasets organized by style
requirements.txt	Python package dependencies

Table 5.1: Project Directory Structure

E.2 Installation Guide

E.2.1 Installation Steps

1. Clone Repository:

```
1 git clone https://github.com/Ashay-Amal/cyclegan-style-
   transfer.git
2 cd cyclegan-style-transfer
```

2. Create Virtual Environment:

```
1 python -m venv venv
2 source venv/bin/activate # Linux/Mac
3 # or: venv\Scripts\activate # Windows
```

3. Install Dependencies:

```
1 pip install -r requirements.txt
```

4. Verify CUDA Installation:

```
1 import torch
2 print(torch.cuda.is_available()) # Should print True
3 print(torch.cuda.get_device_name(0))
```