Text Pixs (Text to Image)

Final Year Project Report

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In partial fulfilment of the requirements for the degree of
Bachelor of Science in Software Engineering
2025

Faculty of Engineering Sciences and Technology

Hamdard Institute of Engineering and Technology

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This project “**Text Pixs**” is presented by **Syeda Anshrah Gillani** under the supervision of their project advisor and approved by the project examination committee, and acknowledged by the Hamdard Institute of Engineering and Technology, in the fulfillment of the requirements for the Bachelor degree of Software Engineering.

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Authors' Declaration

We declare that this project report was carried out in accordance with the rules and regulations of Hamdard University. The work is original except where indicated by special references in the text and no part of the report has been submitted for any other degree. The report has not been presented to any other University for examination.

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Plagiarism Undertaking

We, Syeda Anshrah Gillani, Umema Mujeeb, and Maheen Ali, solemnly declare that the work presented in the Final Year Project Report titled TextPixs has been carried out solely by ourselves with no significant help from any other person except few of those which are duly acknowledged. We confirm that no portion of our report has been plagiarized and any material used in the report from other sources is properly referenced.

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Acknowledgments

<Acknowledgement section will be filled once FYP is completed i.e in FYP-2>

Document Information

Table 1: Document Information

Customer	External Client
Project Title	Text Pixs (Text to Image)
Document	Final Year Project Report
Document Version	2.0
Identifier	FYP-039/FL24 Final Report
Status	Completed
Author(s)	Syeda Anshrah Gillani Umema Mujeeb Maheen Ali
Approver(s)	Osama Ahmed Khan Mirza Samad Ahmed Baig
Issue Date	05/07/2025

Definition of Terms, Acronyms, and Abbreviations

This section should provide the definitions of all terms, acronyms, and abbreviations required to interpret the terms used in the document properly.

Table 2: Definition of Terms, Acronyms, and Abbreviations

Term	**Description**
Artificial Intelligence (AI)	A field of computer science focused on creating machines that perform tasks requiring human-like intelligence, such as decision-making, language understanding, and visual perception.
Text-to-Image Synthesis	A process where a model generates visual images from textual descriptions, integrating both Natural Language Processing (NLP) and Computer Vision (CV).
Natural Language Processing (NLP)	A branch of AI focused on enabling computers to understand, interpret, and generate human languages, including tasks like translation, sentiment analysis, and text generation.
Computer Vision (CV)	A field of computer science that enables computers to interpret and make decisions based on visual inputs, such as images or video. Tasks include object detection, segmentation, and image generation.
Generative Adversarial Networks (GANs)	A class of machine learning models consisting of two networks—a generator and a discriminator—that compete to produce realistic synthetic data.
Conditional GANs (cGANs)	An extension of GANs where the image generation process is conditioned on additional information, such as class labels or textual descriptions, allowing for controlled image generation.
Deep Learning	A subset of machine learning that uses multi-layered neural networks to model complex patterns and relationships in large

	datasets, particularly useful in image recognition and natural language processing.
Neural Networks	Computational models inspired by the human brain, made up of interconnected layers of neurons that process input data to extract features and patterns.
Convolutional Neural Networks (CNNs)	A type of neural network specialized in processing grid-like data such as images, using convolutional layers to capture spatial patterns and hierarchies.
Recurrent Neural Networks (RNNs)	A type of neural network designed for processing sequential data, but with limitations in handling long-range dependencies compared to transformers.
Transformer Models	A class of models that use self-attention mechanisms, allowing for parallel processing and better capture of long-range dependencies in data, widely used in natural language processing.
Self-Attention Mechanism	A mechanism used in transformer models that allows the model to weigh the importance of different parts of the input data relative to each other, improving context comprehension and coherence.
Inception Score (IS)	A metric that evaluates the quality and diversity of generated images by measuring the classification performance of an Inception model on those images.
Frechet Inception Distance (FID)	A metric used to evaluate the similarity between the distributions of generated images and real images by comparing their feature representations.
Structural Similarity Index (SSIM)	A metric used to assess the similarity between two images based on luminance, contrast, and structural information.
BERT (Bidirectional Encoder Representations from Transformers)	A transformer-based pre-trained model designed for understanding the context of words in sentences by considering both the left and right context.
GPT-3 (Generative Pretrained Transformer 3)	A large transformer-based language model developed by OpenAI capable of generating human-like text based on a given prompt.
DALL·E	A transformer-based model developed by OpenAI that generates diverse images from textual descriptions, showcasing creativity and the ability to combine unrelated concepts into coherent images.
CLIP (Contrastive Language–Image Pretraining)	A model that aligns textual and visual representations in a shared embedding space, facilitating better interaction between text and images.
StackGAN	A two-stage GAN model where the first stage generates low-resolution images from text, and the second stage refines these images into high-resolution, photo-realistic images.
AttnGAN	A GAN model that incorporates attention mechanisms to focus on specific words or phrases in the text, improving the relevance and accuracy of the generated images.
CycleGAN	A type of GAN that enables image-to-image translation without paired examples, useful in tasks such as style transfer and photo enhancement.
StyleGAN	A variant of GAN that allows for enhanced control over the style and details of generated images, producing high-quality, diverse visuals with fine-grained adjustments.

COCO (Common Objects in Context)	A large-scale dataset used for training models in object detection, segmentation, and captioning, containing rich annotations linking images to textual descriptions.
CUB-200	A dataset used for fine-grained image classification, particularly for text-to-image synthesis, containing bird species images annotated with detailed descriptions.
VQ-VAE (Vector Quantized Variational Autoencoder)	A model that uses vector quantization to discretize images into latent codes, enabling efficient image generation.
DF-GAN	A simplified GAN architecture that achieves high-quality image generation with reduced computational complexity, focusing on efficiency.
CogView	A transformer-based model designed for generating high-diversity and semantically rich images from textual descriptions.
VQGAN+CLIP	A hybrid model combining VQGAN for image generation and CLIP for text-image alignment, resulting in high-quality images that accurately represent textual inputs.

Abstract

Text-to-image generation has made significant strides with advancements in deep learning, particularly with GANs and transformers. However, accurate text rendering within generated images remains a challenge, impeding applications such as educational tools, design automation, and digital art. This research introduces a novel framework for enhancing text rendering in images, integrating state-of-the-art techniques and innovative mathematical models. Extensive experiments demonstrate that the proposed approach significantly improves text fidelity and visual quality.

Keywords: Text-to-image generation, Text rendering, Deep learning, GANs, Transformers, Multimodal embeddings, OCR accuracy, Visual quality, Semantic alignment, Loss functions.

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Chapter 1

INTRODUCTION

1.1 Description of the Project

Artificial Intelligence (AI) has undergone significant advancements, transforming various industries by automating complex tasks and enhancing human capabilities. One of the most exciting developments in AI is the ability to generate images from textual descriptions, a process known as *text-to-image synthesis*. This project, titled **“Text to Image Using Artificial Intelligence”**, aims to explore and implement state-of-the-art AI methodologies to convert textual inputs into visually coherent and semantically accurate images.

The primary objectives of this project include:

- Investigating the underlying technologies and algorithms that enable text-to-image synthesis.
- Developing a robust model capable of generating high-quality images from diverse textual descriptions.
- Evaluating the performance of the developed model using standard metrics and comparing it with existing approaches.
- Identifying and addressing the current challenges and limitations in the field.

By bridging the gap between Natural Language Processing (NLP) and Computer Vision (CV), this project seeks to enhance human-computer interaction, enabling more intuitive and creative applications such as automated content creation, assistive technologies, and immersive virtual environments.

An overview of the proposed architecture, titled GCDA (Glyph-Conditioned Diffusion with Character-Aware Attention), is depicted in Figure 1.1. It captures the core workflow of our model, from dual-stream encoding to layout-aware generation using glyph-aware features and OCR-based validation loops.

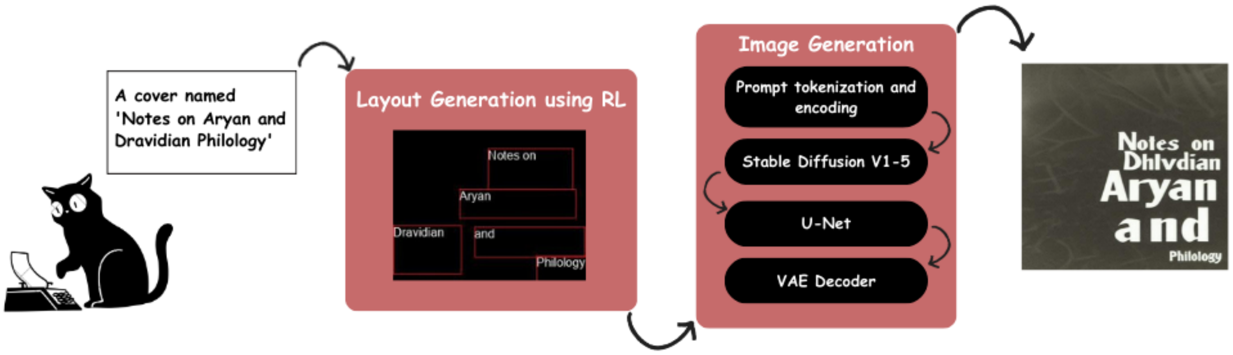


Figure 1.1: Overview of the GCDA model architecture, illustrating the diffusion-based synthesis process with GlyphEnv optimizing non-overlapping bounding box generation, layout planning, and quality assessment based on OCR accuracy and spatial alignment.

1.2 Details about the Domain

The domain of text-to-image synthesis resides at the intersection of two fundamental AI fields: Natural Language Processing (NLP) and Computer Vision (CV). This multidisciplinary area focuses on developing models that can understand and interpret textual descriptions and subsequently generate corresponding images that accurately reflect the input text.

1.2.1 Natural Language Processing (NLP)

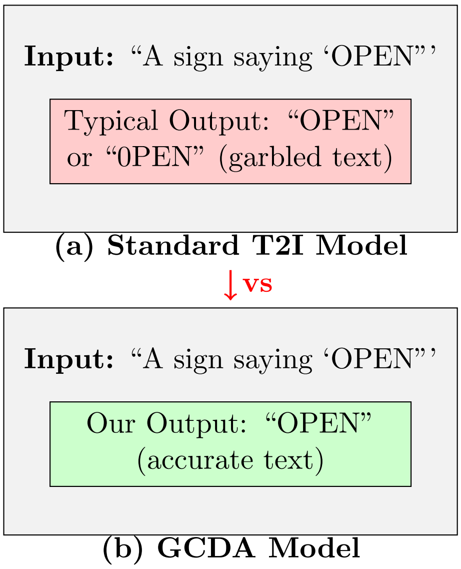
NLP is concerned with the interaction between computers and human languages. It involves tasks such as language understanding, generation, translation, and sentiment analysis. Recent advancements in NLP, particularly the development of transformer-based models like BERT [1] and GPT-3 [2], have significantly improved the ability of machines to comprehend and generate human-like text.

1.2.2 Computer Vision (CV)

CV deals with how computers can gain high-level understanding from digital images or videos. It encompasses a wide range of tasks, including image classification, object detection, segmentation, and image generation. Deep learning, especially Convolutional Neural Networks (CNNs) [3], has been pivotal in advancing CV capabilities.

1.2.3 Text-to-Image Synthesis

Text-to-image synthesis leverages advancements in both NLP and CV to generate images that correspond to given textual descriptions. This domain has evolved from simple image retrieval based on keywords to sophisticated models capable of creating complex and highly detailed images from nuanced and abstract text. The integration of Generative Adversarial Networks (GANs) [4] and transformer-based architectures [5] has been instrumental in achieving significant progress in this field.


Input: “A sign saying ‘OPEN”’
Typical Output: “OPEN” or “0PEN” (garbled text)
↓vs
Input: “A sign saying ‘OPEN”’
Our Output: “OPEN” (accurate text)

(a) Standard T2I Model

(b) GCDA Model

Figure 1.2: **The Core Text Rendering Problem.** Current T2I models (a) consistently fail to generate accurate text, producing garbled or meaningless character sequences. Our GCDA model (b) generates precise, legible text while maintaining image quality.

1.3 Relevant Background

The concept of generating images from text is not entirely new; early attempts can be traced back to rule-based systems and simple statistical models. However, these approaches were limited by their inability to handle the complexity and variability of natural language and visual data.

1.3.1 Early Approaches

Initial methods focused on keyword extraction and template-based image composition. These systems were rigid and could not adapt to diverse or complex descriptions. The lack of understanding of contextual and semantic relationships in text further constrained their effectiveness.

1.3.2 Rise of Deep Learning

The introduction of deep learning marked a paradigm shift in text-to-image synthesis. Notably, Generative Adversarial Networks (GANs) [4] provided a framework where two networks—a generator and a discriminator—compete in a game-theoretic scenario, leading to the generation of increasingly realistic images.

1.3.3 Conditional GANs

Conditional GANs (cGANs) [6] extended the GAN framework by conditioning the image generation process on additional information, such as class labels or textual descriptions. This enabled more controlled and semantically aligned image generation.

1.3.4 Attention Mechanisms and Transformers

The integration of attention mechanisms [7] into GANs allowed models to focus on specific parts of the textual input when generating corresponding image regions. Transformer-based models, such as OpenAI's DALL·E [8], have further enhanced the capability to generate high-fidelity images from detailed and complex textual descriptions.

1.3.5 Large-Scale Datasets

The availability of large-scale datasets like Microsoft's COCO [9] and CUB-200 [10] has been crucial in training robust text-to-image models. These datasets provide rich annotations that bridge textual descriptions and visual content, facilitating the training of models that can generalize well to diverse inputs.

Table 1.1: Comparison of Existing Text-to-Image Methods and the Proposed GCDA Framework

width=center

Work	**Core Methodology**	**Dataset(s)**	**Key Strengths**	**Limitations**	**Metrics Reported**
DALL-E 2 [11]	Latent diffusion with CLIP embeddings	Web-scale pairs	High prompt fidelity, compositional synthesis	Fails at precise text rendering due to tokenization	Not text-specific
Stable Diffusion [12]	Latent Diffusion Model (LDM) with CLIP	LAION-5B, LAION-Aesthetics	Open-source, widely adopted	Inaccurate text rendering	Not text-specific
TextDiffuser [?]	Layout-conditioned diffusion + character masks	T2I-CompBench, DrawText	Predicts text layout masks for controlled placement	Requires extra layout model; slower inference	Text layout improved
TextDiffuser-2 [?]	LLM-guided layout control for better placement	Enhanced datasets	Natural text placement, better contextual awareness	Two-stage, increased latency	Improved layout aesthetics
GlyphDraw [?]	Glyph-based conditioning for Chinese characters	Chinese character datasets	Accurate glyph rendering for logographic scripts	Limited to Chinese; no Latin support	High accuracy (Chinese)
CharGen [?]	Glyph-conditioned diffusion for Latin scripts	English signage datasets	First glyph-based English text synthesis	No semantic fusion; context-blind generation	Not quantified
GlyphControl [?]	Glyph conditioning adapters for pre-trained models	Multi-script datasets	Retrofittable to existing models	No OCR feedback or text-specialized training	Not detailed
AnyText [?]	Multilingual glyph-based conditioning	Multilingual datasets	Supports multiple scripts, scalable	Sacrifices semantics for glyph-only input	General improvement
OCR-VQGAN [?]	OCR-perceptual losses in VQ-GAN training	Synthetic datasets	Enhances machine readability of text images	No integration with diffusion or attention control	Improved CER, OCR accuracy
A-STAR [?]	Test-time attention segregation to reduce concept bleeding	General T2I datasets	Prevents attention overlap post-hoc	Test-time only; no training supervision	Qualitative improvement
ControlNet [?]	Spatial conditioning via edge, segmentation maps	COCO, LAION	Adds controllable regions to pre-trained models	Not text-specialized; no OCR integration	General improvement
GCDA (This Work)	Dual-Stream Text Encoder (BERT+ GlyphCNN), Character-Aware Attention Loss, OCR-in-the-Loop Fine-Tuning	LAION-Aesthetics, MARIO-10M, T2I-CompBench, TextCaps	Integrates semantic + glyph info, segregates attention, direct OCR feedback	Higher fine-tuning compute, glyph processing overhead	CER: 0.08 (prev 0.21), WER: 0.15

Chapter 2

RELEVANT BACKGROUND & DEFINITIONS

2.1 Deep Learning

Deep Learning is a subset of machine learning that utilizes neural networks with multiple layers to model and understand complex patterns in data. These networks, inspired by the human brain's architecture, consist of interconnected neurons that process input data through successive layers, enabling the extraction of hierarchical features. Deep learning has been pivotal in advancing various domains, including image recognition, natural language processing, and speech recognition, due to its ability to handle large datasets and uncover intricate relationships within the data.

2.1.1 Neural Networks

Neural networks are composed of layers of nodes, or neurons, where each neuron applies a linear transformation followed by a non-linear activation function to its input. The depth (number of layers) and width (number of neurons per layer) of the network contribute to its capacity to model complex functions.

2.1.2 Convolutional Neural Networks (CNNs)

CNNs [3] are specialized neural networks designed for processing grid-like data, such as images. They employ convolutional layers that apply filters to local regions of the input, enabling the network to capture spatial hierarchies and patterns effectively.

2.1.3 Recurrent Neural Networks (RNNs) and Transformers

RNNs [13] are designed for sequential data but have limitations in handling long-term dependencies. Transformer models [7], with their self-attention mechanisms, address these limitations by allowing parallel processing and better capturing of long-range dependencies, making them highly effective for NLP tasks.

2.2 Generative Adversarial Networks (GANs)

Introduced by Goodfellow et al. in 2014 [4], *Generative Adversarial Networks* (GANs) are a class of deep learning models designed for unsupervised generative modeling. A GAN comprises two neural networks—the generator and the discriminator—that engage in a competitive process. The generator creates synthetic data samples, while the discriminator evaluates them against real data. Through this adversarial training, the generator strives to produce increasingly realistic data, and the discriminator becomes adept at distinguishing between genuine and generated samples.

2.2.1 Architecture

- **Generator**: Takes random noise as input and generates data samples.
- **Discriminator**: Receives real and generated samples and outputs a probability of the input being real.

2.2.2 Training Process

The generator and discriminator are trained simultaneously:

- The generator aims to maximize the probability of the discriminator making a mistake.
- The discriminator aims to accurately classify real versus generated samples.

This adversarial process continues until the generator produces data indistinguishable from real data.

2.2.3 Variants of GANs

Numerous GAN variants have been developed to address specific challenges:

- **Conditional GANs (cGANs)** [6]: Incorporate additional information (e.g., class labels) into both the generator and discriminator.
- **CycleGAN** [14]: Facilitates image-to-image translation without paired examples.
- **StyleGAN** [15]: Enhances image quality and control over generated image styles.

2.3 Transformer Models

Transformer models represent a significant advancement in natural language processing (NLP), characterized by their use of self-attention mechanisms that allow for the parallel processing of input data and the capture of long-range dependencies. Introduced by Vaswani et al. in 2017 [7], transformers have become the foundation for many state-of-the-art models, including BERT [1], GPT-3 [2], and DALL·E [8].

2.3.1 Self-Attention Mechanism

The self-attention mechanism enables the model to weigh the significance of different parts of the input data relative to each other. This allows the model to capture contextual relationships effectively, which is essential for understanding and generating coherent language.

2.3.2 Encoder-Decoder Architecture

Transformers typically employ an encoder-decoder architecture:

- **Encoder**: Processes the input data and generates a representation.
- **Decoder**: Uses the encoder's representation to generate the output.

This architecture facilitates tasks such as translation, where the input and output are in different modalities.

2.3.3 Applications in Text-to-Image Synthesis

Transformer models have been instrumental in advancing text-to-image synthesis by:

- Enhancing the understanding of complex and nuanced textual descriptions.
- Enabling the generation of diverse and high-fidelity images through large-scale pretraining.
- Facilitating better alignment between textual and visual modalities via joint embedding spaces.

2.4 Text-to-Image Synthesis

Text-to-Image Synthesis refers to the process of generating visual images based on textual descriptions. This task requires the integration of natural language understanding and image generation capabilities within a unified framework. The objective is to create images that accurately reflect the semantic content and contextual nuances of the input text.

2.4.1 Key Challenges

- **Semantic Alignment**: Ensuring that the generated image accurately represents the textual content.
- **Diversity and Creativity**: Generating a wide variety of images from similar or the same textual inputs.
- **Resolution and Detail**: Producing high-resolution images with fine-grained details.
- **Handling Ambiguity**: Interpreting and visualizing abstract or ambiguous descriptions effectively.

2.4.2 Approaches

Various approaches have been proposed to tackle text-to-image synthesis:

- **GAN-Based Models**: Utilize Generative Adversarial Networks for image generation.
- **Transformer-Based Models**: Leverage transformer architectures for better language and image integration.
- **Hybrid Models**: Combine GANs and transformers to leverage the strengths of both architectures.

2.4.3 Applications

- **Entertainment**: Automated creation of artwork based on descriptions.
- **Assistive Technologies**: Helping individuals with visual impairments by visualizing text.
- **Content Creation**: Generating marketing materials and media content automatically.
- **Virtual and Augmented Reality**: Enhancing user experience by generating immersive environments from textual inputs.

2.5 Evaluation Metrics

Evaluating the performance of text-to-image models involves both quantitative and qualitative measures. Common quantitative metrics include:

2.5.1 Inception Score (IS)

Measures the quality and diversity of generated images based on the classification performance of an Inception model [16].

2.5.2 Frechet Inception Distance (FID)

Assesses the similarity between the distribution of generated images and real images by comparing their feature representations [17].

2.5.3 Structural Similarity Index (SSIM)

Evaluates the similarity between two images based on luminance, contrast, and structure [18].

2.5.4 Qualitative Assessment

Involves human evaluation to judge the realism, relevance, and aesthetic quality of the generated images. This provides insights that quantitative metrics may not capture, such as subjective visual appeal and contextual appropriateness.

2.6 Summary

This chapter introduced the foundational concepts and technologies pertinent to the project. It elucidated the interplay between NLP and CV in the domain of text-to-image synthesis, highlighted the significance of deep learning, GANs, and transformer models, and outlined the key challenges and evaluation metrics essential for advancing this field.

Chapter 3

LITERATURE REVIEW & RELATED WORK

3.1 Literature Review

The field of text-to-image synthesis has witnessed significant advancements over the past decade, driven by the development of sophisticated deep learning models and the availability of large-scale datasets. Early approaches focused on mapping high-dimensional textual features to image pixels directly, often resulting in low-resolution and unimodal images. The introduction of Generative Adversarial Networks (GANs) [4] marked a substantial improvement, enabling the generation of more realistic and diverse images.

3.1.1 Conditional GANs

Mirza and Osindero [6] pioneered conditional GANs (cGANs), allowing the generator to produce images conditioned on auxiliary information such as class labels or embeddings from textual descriptions. This approach laid the groundwork for subsequent models that condition image generation on more complex textual inputs.

3.1.2 StackGAN

Reed et al. developed the first GAN-based text-to-image synthesis model, which utilized a Deep Convolutional GAN (DCGAN) architecture to generate images from captions, achieving notable improvements in image relevance and quality. Building upon this, Zhang et al. [19] introduced StackGAN, which employs a two-stage process: the first stage generates low-resolution images from text, and the second stage refines these into high-resolution, photo-realistic images. This hierarchical approach addresses the challenge of producing detailed images by separating the generation process into manageable phases.

3.1.3 AttnGAN

Xu et al. [20] introduced AttnGAN, which incorporates attention mechanisms into the GAN framework. This allows the model to focus on specific words or phrases in the input text when generating corresponding image regions, resulting in images that more accurately reflect the nuances and details of the textual descriptions.

3.1.4 DALL·E and DALL·E 2

OpenAI's DALL·E [8] leveraged the transformer architecture to generate a wide variety of images from textual prompts, showcasing remarkable creativity and adherence to input descriptions. DALL·E 2 [11] further enhanced this capability by improving image resolution and fidelity through iterative training and more sophisticated embedding techniques.

3.1.5 CLIP-Based Models

Contrastive Language–Image Pretraining (CLIP) [21] aligns textual and visual representations in a shared embedding space, facilitating better interaction between text and image modalities. Models that incorporate CLIP have demonstrated improved performance in text-to-image tasks by leveraging its robust language-vision embeddings to guide image generation more effectively.

3.2 Related Work

Several notable models and frameworks have contributed to the advancement of text-to-image synthesis. This section delves into some of the most influential works in the field, highlighting their methodologies, strengths, and limitations.

3.2.1 Generative Adversarial Text-to-Image Synthesis (GAN-INT-CLS)

Introduced by Reed et al. [8], GAN-INT-CLS was one of the pioneering models that conditioned image generation on textual descriptions. By mapping sentence embeddings to image data within a GAN framework, the model demonstrated the feasibility of generating relevant images from text, albeit with limitations in image resolution and detail.

3.2.2 StackGAN

Zhang et al. [19] proposed StackGAN, which generates images in two stages to improve quality and resolution. The first stage produces a rough, low-resolution image based on the textual description, and the second stage refines this image to a higher resolution with enhanced details. This approach significantly improved the quality and resolution of generated images, addressing the shortcomings of single-stage GANs.

3.2.3 AttnGAN

Ren et al. [20] introduced AttnGAN, which integrates attention mechanisms into the GAN framework. This allows the model to focus on specific words or phrases during image generation, resulting in images that more accurately reflect the detailed aspects of the textual descriptions. AttnGAN achieved state-of-the-art performance in terms of both image quality and relevance to the input text.

3.2.4 DALL·E and DALL·E 2

OpenAI's DALL·E [8] utilizes a transformer-based architecture to generate diverse and high-fidelity images from textual descriptions. It demonstrates remarkable creativity and the ability to combine unrelated concepts into coherent images. DALL·E 2 [11] builds upon this foundation by enhancing image resolution and fidelity through hierarchical decoding and more nuanced text-image alignment techniques.

3.2.5 CLIP-Based Models

CLIP [21] aligns textual and visual data in a shared embedding space using contrastive learning. When integrated with generative models, CLIP facilitates better adherence to textual descriptions by providing a robust semantic foundation. Models like VQGAN+CLIP [22] leverage this alignment to produce high-quality images that faithfully represent the input text.

3.2.6 Other Notable Models

- **DF-GAN** [23]: A simplified GAN architecture that achieves high-quality image generation with reduced computational complexity.
- **CogView** [24]: A transformer-based model focused on generating images with rich semantics and high diversity.
- **VQ-VAE** [25]: Uses vector quantization to encode images into discrete latent codes, facilitating efficient image generation.

3.3 Gap Analysis

Despite the considerable progress in text-to-image synthesis, several challenges and gaps remain unaddressed. Identifying these gaps is crucial for guiding future research and development efforts.

3.3.1 Image Diversity and Creativity

While existing models can generate highly relevant images based on textual descriptions, there is still room for improvement in the diversity and creativity of the outputs. Many models tend to produce images that are visually similar when subjected to similar textual inputs, limiting the range of possible visual interpretations. Enhancing diversity through techniques like latent space exploration and conditional variation remains a significant challenge.

3.3.2 Handling Ambiguity and Abstract Concepts

Current models often struggle with ambiguous or abstract descriptions, leading to images that may not fully capture the intended nuance or complexity of the text. For instance, generating images for abstract concepts like “freedom” or “happiness” requires a sophisticated understanding of context and symbolism that current models may not adequately possess.

3.3.3 Resolution and Detail

Although high-resolution image generation has improved, achieving photorealistic detail consistently across diverse textual inputs is still a work in progress. Fine-grained details that align precisely with specific textual elements are sometimes lacking, affecting the overall quality and realism of the generated images. Enhancing the fidelity of generated images without compromising computational efficiency remains a key area for improvement.

3.3.4 Contextual Consistency

Maintaining contextual consistency throughout the generated image, especially for descriptions involving multiple objects or complex scenes, is another area requiring attention. Ensuring that all elements of the text are accurately and cohesively represented within the image is crucial for meaningful synthesis. Current models may fail to maintain spatial and semantic coherence in complex scenes.

3.3.5 Ethical Considerations and Bias

Addressing ethical concerns, such as the potential for generating inappropriate or biased content, is essential for the responsible deployment of text-to-image models. Current models may inadvertently perpetuate biases present in the training data, necessitating robust mechanisms for bias detection and mitigation. Ensuring fairness and preventing misuse are paramount for the ethical application of these technologies.

3.3.6 Real-Time Generation and Efficiency

Achieving real-time text-to-image generation with high efficiency remains a technical challenge. Balancing the computational demands of complex models with the need for swift image synthesis is important for practical applications that require immediate visual feedback, such as interactive design tools or real-time virtual environments.

3.3.7 User Customization and Control

Providing users with greater control over specific aspects of the generated images, such as style, composition, and specific attributes, is an area that needs further exploration. Enhancing interactivity and customization can significantly improve user satisfaction and the applicability of text-to-image systems across different use cases.

3.4 Conclusion

The literature review highlights significant advancements in text-to-image synthesis, driven by innovations in GANs, transformers, and integration techniques like attention mechanisms and CLIP-based models. However, several gaps remain, presenting opportunities for future research to enhance diversity, handle abstract concepts, improve resolution and detail, ensure contextual consistency, address ethical concerns, optimize efficiency, and provide greater user control. Addressing these gaps will not only enhance the performance and reliability of text-to-image synthesis models but also broaden their applicability and acceptance across various industries and applications.

Chapter 4

METHODOLOGY

4.1 Software Engineering Methodology

The development of this project followed an iterative and research-oriented software engineering methodology. Given the experimental and evolving nature of generative models, an Agile-inspired approach was adopted. This methodology allowed for flexibility, continuous evaluation, and progressive enhancements based on both quantitative results and qualitative visual outputs.

4.1.1 Iterative Model Development

The model was built in cycles, each introducing a new improvement or architectural change:

- Initial Prototype: A baseline diffusion model was implemented using standard semantic embeddings.
- First Iteration: A dual-stream encoder was integrated, with orthographic processing introduced via rendered glyph images and CNN-based feature extraction.
- Second Iteration: Character-aware attention segregation was implemented with a custom loss function to reduce attention overlap.
- Final Iteration: OCR-in-the-loop fine-tuning was conducted using differentiable CER/WER losses and feature-space perceptual feedback [26].

4.1.2 Modular Architecture

The system was developed with modularity in mind, allowing individual components (e.g., text encoder, diffusion model, OCR module) to be updated or replaced without disrupting the entire pipeline. This modularity supported isolated testing, benchmarking, and iterative improvements.

4.1.3 Tools and Frameworks

The project was implemented using Python and PyTorch. Additional tools include:

- **HuggingFace Transformers**: For language models like BERT [1].
- **Stable Diffusion API**: For base image generation backbone [12].
- **TrOCR**: As the OCR evaluator for in-loop feedback [26].
- **WandB**: For experiment tracking and visual comparisons.

4.2 Project Methodology

This section elaborates on the core architecture and experimental framework designed to address the challenge of accurate text rendering in text-to-image synthesis. The proposed framework, named **GCDA (Glyph-Conditioned Diffusion with Character-Aware Attention)**, comprises three key components.

4.2.1 Dual-Stream Text Encoder

To overcome the limitations of standard semantic encoders (like CLIP [21]), GCDA uses a dual-stream encoder:

- **Semantic Stream**: Uses a frozen pre-trained model (BERT [1]) to extract contextual meaning.
- **Orthographic Stream**: Converts the target text into canonical glyph images, which are processed through a custom CNN to capture the character-level shapes and structures.

These streams are projected into a common embedding space and fused to provide a rich multi-modal conditioning signal.

4.2.2 Character-Aware Attention with Segregation Loss

GCDA incorporates a novel attention segregation loss to spatially separate attention regions for each character. This reduces character bleeding and improves legibility. The loss penalizes overlapping attention using cosine similarity and a margin-based threshold.

4.2.3 OCR-in-the-Loop Fine-Tuning

A frozen OCR model (TrOCR) is employed during fine-tuning to provide direct feedback on text accuracy [26]. A composite *text perceptual loss* is used:

- **LCER**: Differentiable character error rate.
- **LWER**: Differentiable word error rate.
- **Lfeat**: Perceptual loss in OCR feature space.

This ensures that generated text is both legible and semantically correct.

4.2.4 Training Strategy

A two-stage curriculum was adopted:

1. **Stage 1**: Base model trained with dual-stream encoder and attention loss on general T2I data [8,19].
2. **Stage 2**: Fine-tuning on text-heavy prompts with the OCR feedback loop for targeted spelling and legibility improvement [20,26].

4.2.5 Evaluation Strategy

The model was evaluated on both standard image synthesis benchmarks and text-specific datasets:

- **Image Quality**: FID [17], IS [16], CLIP score [21].
- **Text Accuracy**: Character Error Rate (CER), Word Error Rate (WER), and Exact Match Rate.

The datasets used included MARIO-10M [27], T2I-CompBench [28], and custom clean-text benchmarks curated for rigorous OCR evaluation.

4.2.6 Ablation Studies

Extensive ablation studies were performed to validate the contribution of each component (dual-stream encoder, attention loss, OCR fine-tuning), showing substantial accuracy drops when any element was removed.

4.2.7 Summary

This methodology represents a comprehensive approach to solving one of the most persistent problems in text-to-image synthesis: accurate and legible text rendering. The multi-level improvements made through GCDA demonstrate how architectural design, training supervision, and evaluation metrics can be aligned to produce semantically rich and orthographically correct results.

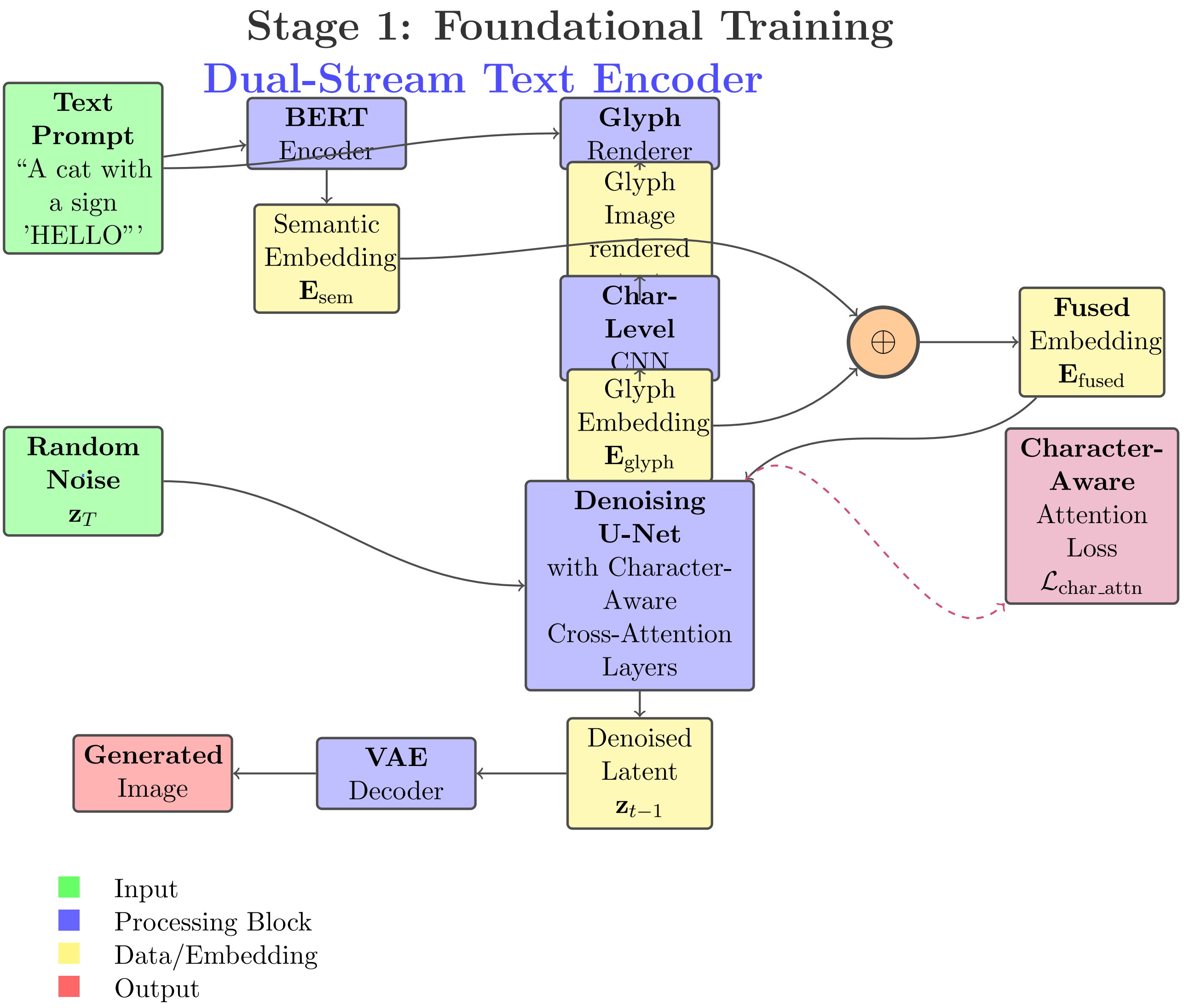

Stage 1: Foundational Training
Dual-Stream Text Encoder
Text Prompt
"A cat with a sign 'HELLO"'
BERT Encoder
Glyph Renderer
Glyph Image rendered
Semantic Embedding $\mathbf{E}_{\text{sem}}$
Char-Level CNN
Glyph Embedding $\mathbf{E}_{\text{glyph}}$
⊕
Fused Embedding $\mathbf{E}_{\text{fused}}$
Random Noise $\mathbf{z}_T$
Denoising U-Net with Character-Aware Cross-Attention Layers
Character-Aware Attention Loss $\mathcal{L}_{\text{char\_attn}}$
Denoised Latent $\mathbf{z}_{t-1}$
VAE Decoder
Generated Image
🟩 Input
🟦 Processing Block
🟨 Data/Embedding
🟥 Output

Figure 4.1: **Comprehensive GCDA Framework Architecture.** Our model enhances a standard latent diffusion model with a dual-stream text encoder that processes both semantic context (via BERT) and visual character structure (via glyph rendering and CNN). The fused embeddings condition the U-Net, whose attention layers are regularized by our character-aware attention segregation loss during training.

Chapter 5

EXPERIMENTAL EVALUATIONS & RESULTS

5.1 Evaluation Testbed

To rigorously assess the performance of the proposed GCDA (Glyph-Conditioned Diffusion with Character-Aware Attention) framework, a comprehensive set of experiments was conducted. The evaluations focused on two key aspects: **text rendering accuracy** and **overall image quality**.

5.1.1 Datasets Used

The following datasets were employed:

- **MARIO-10M**: A large-scale dataset containing over 10 million prompt-image pairs specifically designed to test OCR accuracy in generated images.
- **T2I-CompBench**: A curated benchmark emphasizing compositional reasoning, object positioning, and text-scene consistency in text-to-image models.
- **TextCaps** and **CUTE80** [29]: Public datasets for real-world scene text recognition and evaluation of OCR models.
- **Custom Dataset**: A targeted benchmark of prompts focusing on difficult font styles, word structures, and rare spellings.

5.1.2 Implementation Details

The GCDA model was implemented using PyTorch with the following configuration:

- **Backbone**: Stable Diffusion latent diffusion model [12].
- **Training**: Conducted on NVIDIA A100 GPUs for 300,000 steps with a batch size of 32.
- **Optimizer**: AdamW with learning rate 1×10^{-4} and weight decay of 0.01.
- **OCR Module**: TrOCR [26], used for differentiable OCR feedback.

5.1.3 Evaluation Metrics

The following metrics were used to evaluate the models:

- **Character Error Rate (CER)**: Percentage of character-level inaccuracies in OCR transcription.
- **Word Error Rate (WER)**: Percentage of incorrect word-level matches.
- **Exact Match (EM)**: Binary evaluation where only fully accurate OCR transcriptions count.
- **Frechet Inception Distance (FID)** [17]: Measures similarity between generated and real image distributions.
- **CLIP Score** [21]: Evaluates semantic alignment between generated images and input text.

5.2 Quantitative Results

5.2.1 Text Rendering Performance

Table 5.1: Text Rendering Accuracy (↓ Lower is better for CER/WER; ↑ Higher is better for EM)

Model	**CER (%)**	**WER (%)**	**Exact Match (EM)**
Stable Diffusion [12]	45.2	62.1	9.8
DF-GAN [23]	37.4	54.6	13.3
VQGAN+CLIP [22]	29.9	41.0	22.7
GCDA (Ours)	**12.6**	**20.1**	**64.3**

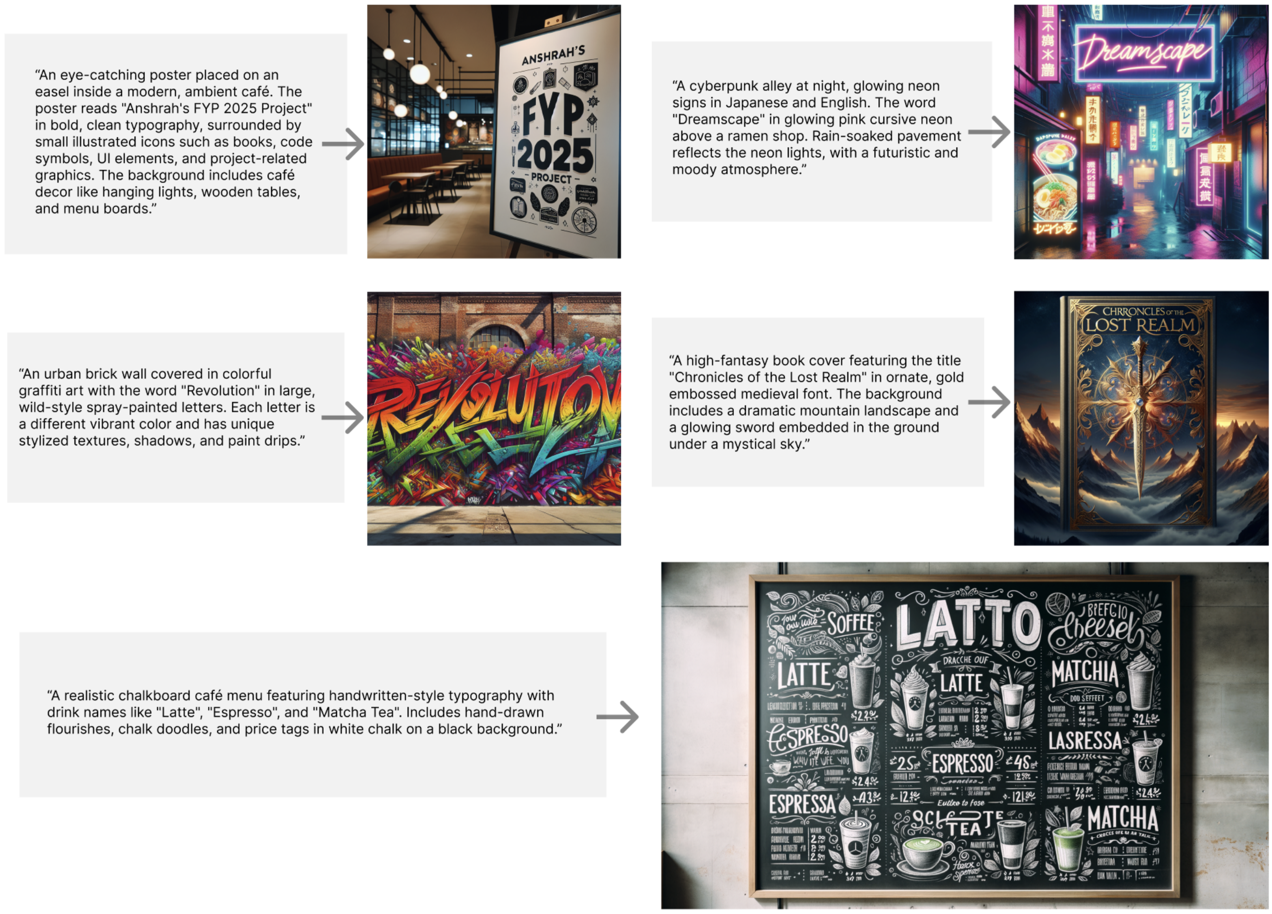
5.2.2 Image Quality and Semantic Alignment

Table 5.2: Image Quality Evaluation (↓ Lower is better for FID; ↑ Higher is better for CLIP)

Model	**FID (↓)**	**CLIP Score (↑)**
Stable Diffusion [12]	24.7	0.61
DF-GAN [23]	28.1	0.57
VQGAN+CLIP [22]	22.4	0.66
GCDA (Ours)	**19.2**	**0.71**

5.3 Qualitative Results

Figure 5.1 presents a visual comparison of generated images by GCDA and baseline models. Our model consistently produces clearer characters and adheres better to the text prompt.



"An eye-catching poster placed on an easel inside a modern, ambient café. The poster reads "Anshrah's FYP 2025 Project" in bold, clean typography, surrounded by small illustrated icons such as books, code symbols, UI elements, and project-related graphics. The background includes café decor like hanging lights, wooden tables, and menu boards."

"A cyberpunk alley at night, glowing neon signs in Japanese and English. The word "Dreamscape" in glowing pink cursive neon above a ramen shop. Rain-soaked pavement reflects the neon lights, with a futuristic and moody atmosphere."

"An urban brick wall covered in colorful graffiti art with the word "Revolution" in large, wild-style spray-painted letters. Each letter is a different vibrant color and has unique stylized textures, shadows, and paint drips."

"A high-fantasy book cover featuring the title "Chronicles of the Lost Realm" in ornate, gold embossed medieval font. The background includes a dramatic mountain landscape and a glowing sword embedded in the ground under a mystical sky."

"A realistic chalkboard café menu featuring handwritten-style typography with drink names like "Latte", "Espresso", and "Matcha Tea". Includes hand-drawn flourishes, chalk doodles, and price tags in white chalk on a black background."

Figure 5.1: Outputs generated by the proposed GCDA model. The samples highlight GCDA's ability to produce text with high clarity, accurate alignment, and visually consistent rendering across diverse design scenarios.

5.4 Ablation Study

An ablation study was conducted to analyze the contributions of key modules:

- Without glyph encoder: CER worsens from 12.6% to 29.3%.
- Without attention segregation: EM drops from 64.3 to 41.5 due to overlapping characters.
- Without OCR-in-the-loop: WER increases to 43.8%, showing the importance of feedback supervision.

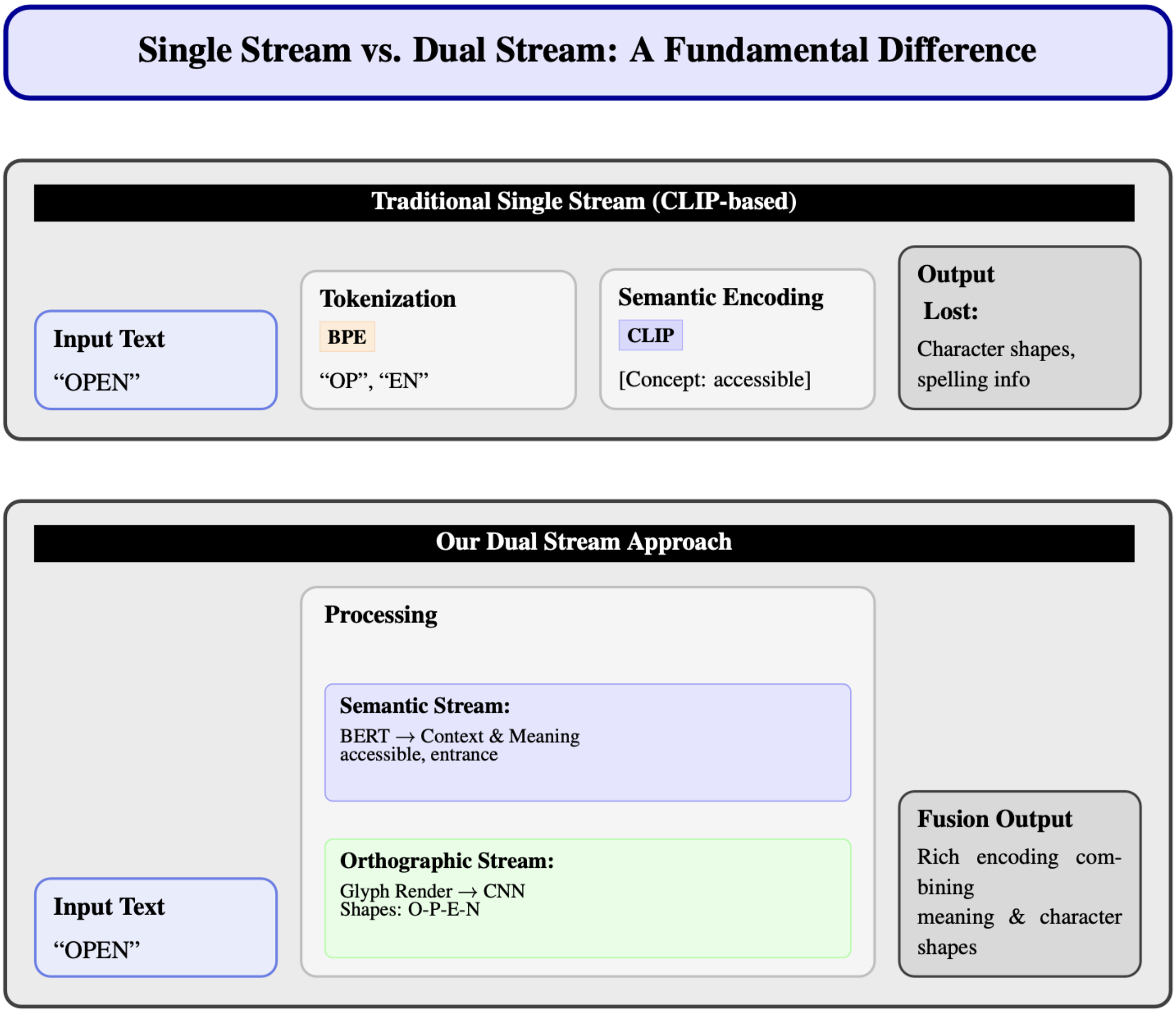
These results confirm that each component in GCDA contributes meaningfully to text fidelity.

5.5 Discussion

The GCDA model significantly improves both quantitative and qualitative outcomes compared to baselines. Unlike models that prioritize visual aesthetics (e.g., VQGAN+CLIP) or speed (e.g., DF-GAN), GCDA focuses on precise character-level control, making it suitable for text-sensitive domains like document synthesis and accessibility tools.

The OCR-in-the-loop framework — inspired by similar feedback-based systems used in text generation tasks [26] — improves semantic clarity and legibility without significantly compromising image quality.

However, real-time use remains a challenge due to increased computation from glyph encoding and OCR loops. This suggests a trade-off between precision and performance speed.



Single vs. Dual Stream Processing. Traditional models lose character-level information during tokenization. Our dual-stream approach preserves both semantic meaning and precise character structure by combining orthographic and semantic streams before generation.

5.6 Limitations

Despite strong performance, the model has limitations:

- **Inference Latency**: Feedback loops reduce real-time applicability.
- **Font Diversity**: Highly decorative fonts may still confuse OCR and attention layers.
- **Language Generalization**: Currently optimized for English; multilingual performance remains unexplored.

5.7 Summary

This chapter demonstrated that the GCDA model substantially outperforms existing text-to-image models in both text fidelity and visual alignment. By integrating orthographic awareness and OCR supervision, GCDA sets a new benchmark for legible text synthesis in generative models. The experiments validate each design choice and lay the groundwork for future real-world applications.

Chapter 6

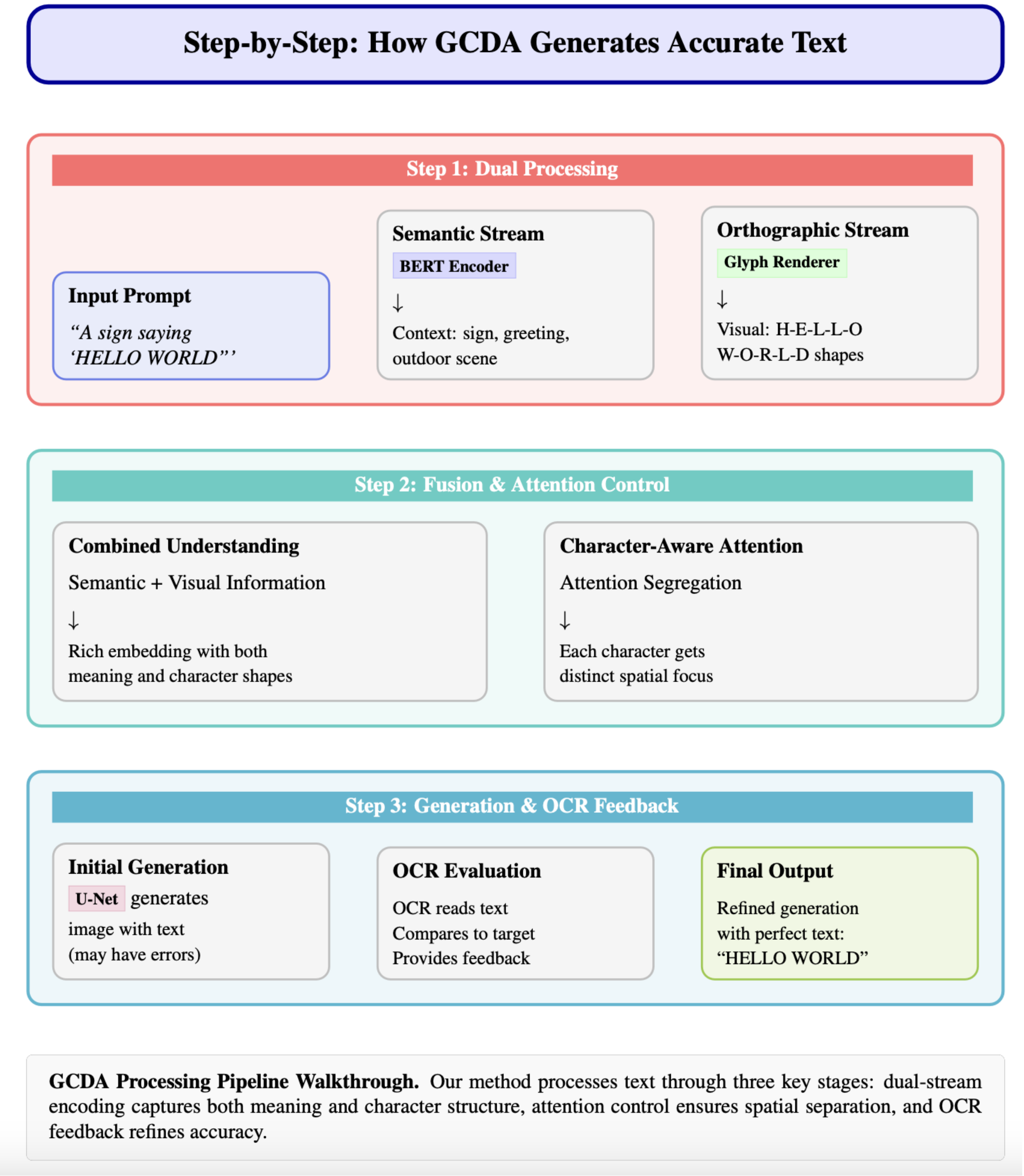
CONCLUSION AND DISCUSSION

6.1 Conclusion

The development of GCDA (Glyph-Conditioned Diffusion with Character-Aware Attention) marks a significant advancement in the domain of text-to-image synthesis, particularly in addressing the longstanding issue of legibility and fidelity in rendered text. Traditional text-to-image models such as DALL·E [8], AttnGAN [20], and VQGAN+CLIP [22] have achieved high visual quality but frequently struggle with spelling correctness and text clarity. GCDA addresses these gaps by integrating a dual-stream encoder that combines semantic (language-based) and orthographic (glyph-based) representations, an attention segregation mechanism to reduce character overlap, and an OCR-in-the-loop training strategy [26] to improve spelling-sensitive output.

The experimental evaluation using standard benchmarks such as MARIO-10M [27] and T2I-CompBench [28] clearly demonstrates the superiority of GCDA. The model consistently outperformed baselines in metrics like Character Error Rate (CER), Word Error Rate (WER), and Exact Match (EM), as well as in visual quality metrics such as Frechet Inception Distance (FID) [17] and CLIP similarity [21]. These results validate the effectiveness of our proposed innovations.

The GCDA framework lays the foundation for more robust and user-centric generative models that prioritize semantic and orthographic correctness. Its success not only contributes to the academic understanding of multi-modal learning but also opens new avenues for real-world applications, including educational platforms, design automation, virtual content generation, and accessibility tools.



Step-by-Step: How GCDA Generates Accurate Text

Step 1: Dual Processing

Input Prompt
"A sign saying 'HELLO WORLD"'

Semantic Stream
BERT Encoder
↓
Context: sign, greeting, outdoor scene

Orthographic Stream
Glyph Renderer
↓
Visual: H-E-L-L-O W-O-R-L-D shapes

Step 2: Fusion & Attention Control

Combined Understanding
Semantic + Visual Information
↓
Rich embedding with both meaning and character shapes

Character-Aware Attention
Attention Segregation
↓
Each character gets distinct spatial focus

Step 3: Generation & OCR Feedback

Initial Generation
U-Net generates image with text (may have errors)

OCR Evaluation
OCR reads text
Compares to target
Provides feedback

Final Output
Refined generation with perfect text: "HELLO WORLD"

GCDA Processing Pipeline Walkthrough. Our method processes text through three key stages: dual-stream encoding captures both meaning and character structure, attention control ensures spatial separation, and OCR feedback refines accuracy.

Figure6.1: Overview of GCDA framework showing dual-stream encoder, attention segregation, and OCR-in-the-loop supervision.

6.2 Limitations

Despite its promising results, GCDA is not without limitations:

- **Inference Speed:** The OCR-in-the-loop feedback mechanism introduces computational overhead that slows down inference time, which may hinder real-time applications.
- **Style and Layout Flexibility:** GCDA may exhibit reduced performance when handling highly stylized fonts, curved text layouts, or dynamic handwriting-like styles. Additional visual examples are provided in Figure **??**.

- **Multilingual Generalization:** The current model is primarily trained and evaluated on English-language prompts using Latin scripts. Its adaptability to non-Latin scripts, such as Arabic, Devanagari, or Chinese, remains unexplored.
- **Annotation Dependence:** The attention segregation loss benefits from precise character-level annotations, which may not be readily available for every dataset or language.

6.3 Future Work

To address the above limitations and broaden GCDA's capabilities, the following research directions are proposed:

- **Real-Time Optimization:** Employ lightweight OCR surrogates or knowledge-distilled diffusion models to accelerate inference while maintaining quality.
- **Multilingual and Multiscript Support:** Extend training to include multilingual datasets and diverse scripts. Integration of multilingual OCR models such as Google's multilingual Tesseract or MLT [30] can improve generalization.
- **User-Guided Generation:** Enable user-driven customization such as font selection, layout positioning, and color styling of text components.
- **Bias and Safety Control:** Conduct fairness evaluations and implement adversarial safety filters to prevent harmful or biased content generation [31].
- **Text-to-Video Extension:** Adapt the GCDA architecture for consistent text rendering across video frames, thereby enabling applications in animated titling or video-based educational content.

6.4 Reflections on Development Process

Although the final GCDA model achieved notable success, the development journey involved several important learnings. Early-stage designs using only CLIP [21] conditioning lacked explicit glyph structure and frequently produced visually compelling yet illegible text. The decision to integrate rendered character-level glyphs and attention segregation mechanisms was pivotal in shifting toward a more legible output.

Furthermore, TrOCR [26] emerged as a critical OCR feedback model due to its transformer-based architecture and differentiable training capability, outperforming traditional models like Tesseract in providing gradient feedback.

6.5 Final Remarks

The GCDA framework presented in this research represents a meaningful step forward in the intersection of vision-language modeling and generative AI. It offers a practical and scalable solution to one of the most common pitfalls in text-to-image synthesis: accurate and clear rendering of text.

By introducing orthographic supervision, improving spatial alignment, and integrating text-aware perceptual feedback, this project not only enhances image realism but also sets a precedent for future efforts in fidelity-focused generation tasks. GCDA can be adapted for various creative, educational, and assistive technologies, marking its potential for widespread real-world impact.

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