TEXT-TO-IMAGE GENERATION USING STABLE DIFFUSION

A Capstone Project report submitted

in partial fulfillment of requirement for the award of a degree

BACHELOR OF TECHNOLOGY

in

SCHOOL OF COMPUTER SCIENCE AND ARTIFICIAL INTELLIGENCE

by

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CERTIFICATE

This is to certify that this project entitled **"TEXT-TO-IMAGE GENERATION USING STABLE DIFFUSION"** is the bonafide work carried out by **P. Harshavardhan Reddy, D. Saketh Reddy, E. Sai Krishna Reddy, T. Deekshitha Rao** and **E.Swapna** as a Capstone Project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in **School of Computer Science and Artificial Intelligence** during the academic year 2024-2025 under our guidance and Supervision.

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ABSTRACT

Large text-to-image models are among the brightest leaps forward in ai, making it possible to produce high-quality and diversified syntheses of images based on a given text prompt. Still, these models cannot mimic subjects in a reference set or synthesize novel renditions of those subjects in other contexts.

In this work, we introduce a new means for "personalizing" text-to-image diffusion models, which can be considered as specializing them to a user's needs. Given only a few images of a subject, we fine-tune a pre-trained text-to-image model, imagen, though our method is not specific to any particular model, such that it learns to bind a unique identifier with that specific subject.

Now that the subject has been assimilated into the output domain of the model, this identifier can then be used to synthesize fully novel photorealistic images of the subject contextualized in different scenes. To utilize the semantic prior learned from the model by introducing a novel autogenous class-specific prior preservation loss, our method allows one to generate the subject in scenes, poses, views, and lighting not seen in the reference images.

We apply our method to several previously unattainable tasks, such as subject recontextualization, text-guided view synthesis, appearance modification, and artistic rendering-always preserving the subject's key features.

1.INTRODUCTION

Computer vision is combined with natural language processing in the use of text-to-image generation for realistic images from written descriptions. When models, such as Stable Diffusion, set standards in producing high-quality images in terms of variety, they have been short on providing personalization features that can be needed for tasks that require user-specific information or particular topics. This project will try to bridge that gap by producing a personalized text-to-image generation system using Stable Diffusion with some refinements to catch specific traits and adapt it to user-defined contexts.

There are various uses of the ability to make personalized visuals, ranging from marketing and education to the fine arts and digital design. Current models such as DALL·E and MidJourney can create decent generic images but have difficulties reproducing specific objects, people, or artistic styles. This project bridges these gaps by using specific fine-tuning methods such as DreamBooth and Low-Rank Adaptation (LoRA). These techniques enable a model that can merge subject-specific attributes with small data into outputs that meet user specifications but, at the same time, allow for generalization.

The novelty of the system was in integrating the personalized elements with contextual components drawn from textual prompts for enabling the automatic creation of unique and diversified scenes. Advanced text encoders, CLIP, ensured proper alignment of text inputs with images generated by the system, which further improved coherence and semi-correctness in the results. Considering computational efficiency as the first priority, this system was made to fit onto mediums of hardware, which gave it wider access to end-users, small businesses, and even to educational institutions.

Other safeguarding mechanisms, including watermarking and metadata embedding, discuss ethical considerations involving potential misuse in the design of deepfakes or copyright violation. These mechanisms promote responsible usage and ensure that the project does not violate ethical AI principles. The evaluation considers both quantitative measures, such as FID and CLIP similarity scores, and qualitative feedback from users in determining creativity, quality, and semantic coherence.

This comprehensive evaluation highlights the benefits that the system offers over existing models, especially its ability to generate personal and contextually relevant outputs. This initiative revolutionizes text-to-image generation as it brings in personalization, through which a whole range of applications can be made with efficiency, ethical considerations, and greater accessibility. Thus, this is a solid framework for creative and practical innovation that opens even wider possibilities for AI-driven content creation.

2.PROBLEM STATEMENT

Although the large text-to-image models have surprisingly revealed their aptitude for image generation concerning high-quality and diverse images from textual prompts, a limiting characteristic of such models is that they do not produce nearly exact renditions of specific subjects from a reference set while envisioning those subjects in different contexts. The actual models cannot quite get that visual essence of specific objects and have difficulties in synthesizing them with dramatic variations in scenes, poses, and lighting conditions, thereby resulting in large losses in fidelity.

3.EXISTING SYSTEM

1. Limitations:

- Current text-to-image models, such as DALL-E and Imagen, rely on semantic priors but cannot reconstruct specific subjects from reference images.
- Such models could output variations of the content of image representations but fail to produce high-fidelity representations of specific subjects in novel contexts.
- Language drift: models make associations between the class name and the instance itself too strong, making diversity in generated results weak.

2. Capabilities:

- Semantic priors are very strong and allow the model to generate diverse instances of general classes ("dog," "car") by textual description; though.
- They can synthesize visually good and coherent images, they are not personalized.

4.PROPOSED SYSTEM

4.1. Objective:

Stable Diffusion (v1-5):

- A pre-trained text-to-image diffusion model (runwayml/stable-diffusion-v1-5) known for its ability to generate visually appealing images from descriptive textual input.

Pre-trained on a large dataset (e.g., LAION-5B), the model understands diverse textual prompts and can render corresponding visuals with remarkable detail.

4.2. Key Innovations:

- Fine-tune pre-trained text-to-image models by using a unique identifier associated with the prompt.
- Utilize class-specific knowledge already encoded in the model to produce diverse and high-fidelity renditions.
- Prevents language drift by keeping the total class diversity while preserving the specificity of the topic.

- It ensures that the produced images are contextually diverse yet keep the core features of the subject under focus.

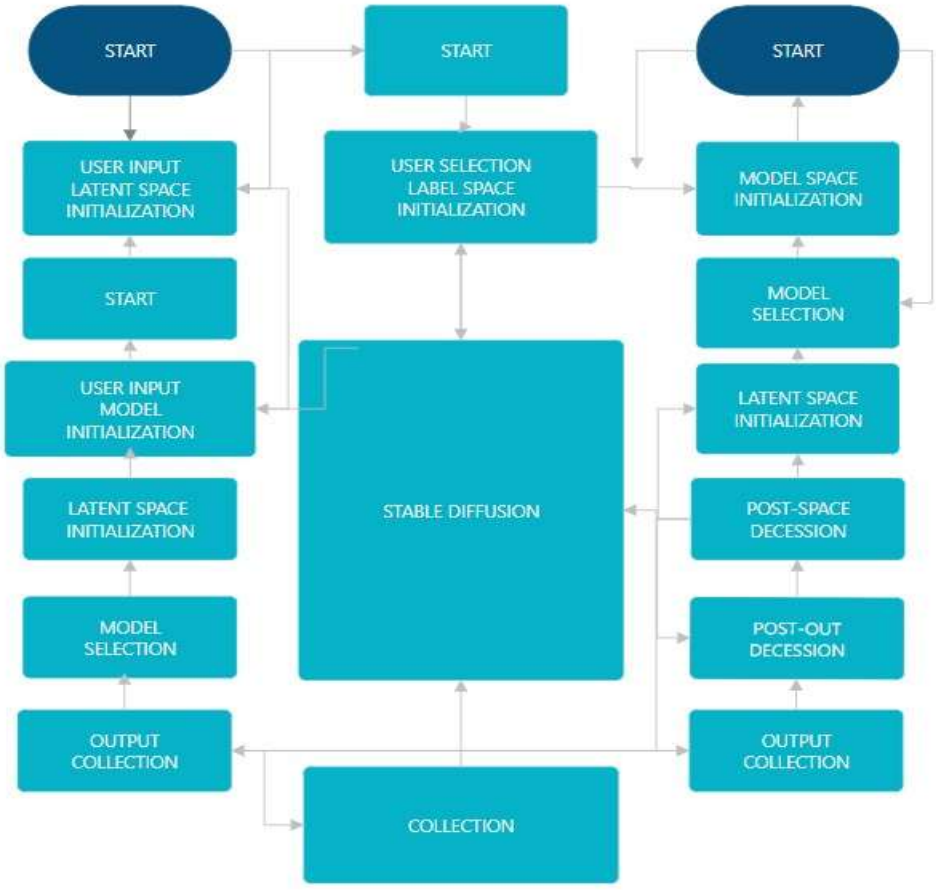
4.3 Applications:

- *Subject Recontextualization*: Align specific subjects with completely different contexts (for instance, a dog in space).
- *Artistic Rendering*: Generate artistic renderings of subjects but keeping their respective features intact.
- *Text-Guided View Synthesis:* Generate images of subjects in other views, poses, and lighting conditions.

4.4. Evaluation:

Construct a new dataset of varied subjects captured in different contexts. Propose a new protocol for evaluation that estimates: Subject Fidelity: How well the generated image matches the reference subject. Prompt Fidelity: How accurately does the image reflect the textual description given at input.

4.5. Workflow:



5. RISK ANALYSIS

Implementing a customized text-to-image generation application using Stable Diffusion will invite several risks technical, ethical, and operationswise. The following is a detailed risk analysis:

1. *TECHNICAL RISKS:*

- Model Overfitting:
  - Fine-tuning the Stable Diffusion model with a small dataset for personalization will lead to potential overfitting with less generalization and poor quality in outputs.
- Mitigation:
  - Regularize using LoRA or other regularization techniques to prevent overfit Computational Resource Limitations: Training and fine-tuning the stable diffusion model requires a lot of computational resources, which may be infeasible for smaller teams or users.

    This can be optimized by having to make usage of pre-trained models and low-resource fine-tuning Latency and Performance Issues:

  - Latency and performance issues are caused when high-resolution images are generated. This will, therefore, limit the usability of the system in time-sensitive applications.
  - Use efficient architectures like Latent Diffusion Models and optimize inference pipelines.

2. *DATA RISKS*

- Quality of Training Data:
  - This can lead to poor performance of the model or biased output in case of low-quality or biased datasets, impacting the personalization of images.
- Mitigation:
  - Curate datasets carefully, apply data augmentation techniques, and make sure that the dataset is diverse and of high quality.
  - Personalization often needs fine-tuning on a small dataset, which may not capture all the necessary variations of the subject.
  - Use advanced fine-tuning techniques that work well at low data regimes (such as DreamBooth).

3. *ETHICAL RISKS*

- Misuse of Technology:
  - Personalized picture generation can be abused for deep fakes, spreading of fake news, or violation of the rights of privacy.
- Mitigation:
  - Employ watermarking or traceability measures and establish transparent guidelines for responsible use.
- Copyright Infringement:
  - Ultra-specialization on niche subjects, such as celebrities or brands, could come across as involving intellectual property infringement.
- Mitigation:
  - Ensure the use of legally compliant datasets and seek permissions where necessary.
- Bias in Generated Images:
  - Propagation of existing biases in the training data may be a result, creating images that are less than ethical or culturally insensitive.
- Mitigation:
  - Audit training data for biases and use fairness-aware algorithms during training.

4. *OPERATIONAL RISKS*

- System Maintenance and Scalability:
  - Maintaining an evolving system to be robust and scalable with a rise in demand is challenging.
- Mitigation:
  - Modular designs and scalable infrastructure enable updates and expansions.
- User Misunderstanding:
  - Users may enter ambiguous or inappropriate prompts, which may result in undesirable output or system misuse.

5. *FINANCIAL AND BUSINESS RISKS*

- Very High Development Costs:
  - The development and maintenance of such a system would demand great investment in hardware, software, and human expertise.
- Mitigation:
  - Source funding and identify possible collaborations, optimize workflows to consume less cost.
- Market Competition:
  - There is always a risk of market acceptance as the software competes with well-established systems like DALL·E and MidJourney.

6. LITERATURE REVIEW

1. M. Ding, et al. (2021) developed a paper on:

   Cog View is a text-to-image generation 4 billion parameter transformer model that effectively makes use of VQ-VAE to bridge the gap between the two modality aspects of text and images. State-of-the-art improvements in style learning and super-resolution, achieved through advanced fine-tuning techniques, have led the performance of Cog View significantly ahead of those of GANs and DALL-E on the MS COCO benchmark. Deep learning has various applications in niche areas of design and creative arts. However, deploying deep learning is difficult here as it requires considerable computation, the need for superior quality of training data, and the chances of bias in the produced outputs.

2. T. Xu et al. 2018 authors proposed a paper on:

   AttnGAN is a state-of-the-art text-to-image synthesis model using attentional mechanisms to produce high-resolution images from text descriptions. It works in two stages: first, it produces a low-resolution image and then refines it by using word-region alignment to improve quality and reduce errors in the output. AttnGAN demonstrated superior performance over state-of-the-art methods, mainly over CUB and COCO datasets by garnering first place in most of the metrics and visual quality tests. This model shows how important it is to incorporate attention in interpreting semantic text descriptions and finally obtain high-quality images from a text prompt. Indeed, the state of the art brought about with this model brings out a noticeable advance in multimodal learning in text-to-image synthesis.

3. N. Ruiz, et al. (2023) developed a paper on:

   DreamBooth, a fine-tuning technique for text-to-image diffusion models that enables subject-driven image generation. By utilizing only a few images (typically 3-5) of a specific subject, DreamBooth effectively integrates a unique identifier with the subject, allowing for the generation of diverse and high-fidelity images based on text prompts. This model uses class-specific prior-preserving loss so as to limit language drift but further enhance the output diversity.

4. R. Dhariwal and A. Nichol (2021) introduced

   Diffusion Models have been known to supersede GANs in tasks of image synthesis. Their contribution thereby underlines the efficacy of diffusion processes for producing high-quality images by step-by-step denoising of random noises. Being able to present outputs that are extremely diverse yet with high fidelity, this method has drawn lots of attention. The work explores the possible creativity diffusion models can offer with application, even though the author acknowledges challenges including computation intensiveness and huge training sets.

5. K. Crowson, et al. (2022) presented VQGAN-CLIP;

   An open-domain model fusing Vector Quantized Generative Adversarial Networks with CLIP for image generation and editing. In this contribution, they integrate the best aspects of GANs and CLIP to produce images that are semantically aligned with their textual descriptions. Results for VQGAN-CLIP thus indicate that the model is capable of generating high-quality images and can further be made interactive and allow editing based on user input. However, it also draws some drawbacks in terms of the computational efficiency and potential biased output relative to the training data.

6. M. Ding et al. (2021)

   CogView: A 4-billion-parameter text-to-image generative model with VQ-VAE that effectively bridges the gap between the text and image modalities. The model achieves state-of-the-art performance in style learning and super-resolution through advanced fine-tuning techniques, outperforming the capabilities of GANs and DALL-E on the MS COCO benchmark. The challenge of deploying deep learning in creative fields is such that the authors have quite extensively pointed out the need for high-quality training data, extensive computational resources, and the likelihood of bias in the generated outputs.

7. A. Ramesh, et al. (2021) developed:

   The model DALL-E is a transformer-based model, enabling the synthesis of images from textual descriptions. The paper does an excellent job in showing the ability to create novel images combining many concepts, attributes, and styles such that large models in creative domains can have a real potential. The authors have also discussed the implications of such technology in art and design and relevant concerns regarding the use of AI-generated content and responsible deployment to minimize biases.

7. DESIGN

7.1 Software Requirements:

- Operating System: Windows 11, Linux, or macOS.
- Programming Language: Python 3.8 or later.
- Integrated Development Environment (IDE): Jupyter Notebook, Google Colab Pro, or VS Code.
- Libraries: PyTorch, Transformers, Hugging Face Diffusers, NumPy, Pillow, Matplotlib, Scikit-learn, Gradio (for Interface).

7.2 Hardware Requirements:

- Processor (CPU): 2 x 64-bit, 3.0 GHz quad-core CPUs or better.
- Graphics Processing Unit (GPU): NVIDIA GPU with CUDA support (e.g., NVIDIA RTX 2060 or better).
- Memory (RAM): Minimum 16 GB.
- Storage: Minimum 50 GB free (preferably SSD for faster access).
- Input Devices: Standard Windows or Mac Keyboard, Mouse.
- Display: Full HD Monitor or better.

8. RELATED WORK

Image Composition: This traditional technique tries to incorporate a subject into a novel background but lacks novelty in poses and often suffers from problems in integrating the scene, lighting, and shadows. The 3D reconstruction methods can handle some of the challenges, especially of rigid objects, but the approach requires multiple views, whereas our approach can generate subjects in novel poses and contexts.

Text-to-Image Editing and Synthesis: Most advanced text-driven image manipulation techniques are based on GANs and models like CLIP for realistic edits but fail with diverse datasets. Diffusion models establish new standards of quality and diversity, surpassing GANs' abilities. However, most remain in the global editing style, lacking both fine-grained control and preservation of subject identity across images. It leaves models like Imagen, DALL-E 2, and Stable Diffusion very good at semantic generation but incapable of representing the subject in an appropriately consistent manner.

*Controllable Generative model*s: Techniques such as diffusion-based image variations and mask-guided editing make possible some control while suffering from failure to preserve subject identity. Focused GAN-based approaches for real image editing, like Pivotal Tuning, are domain-specific, such as faces, and suffer from high data requirements. In parallel methods that involve embedding personalized tokens in frozen models allow limited degrees of customization but still are dependent on the expressiveness of the original model. Our fine-tune models to embed subjects and enable novelty-preserving identity-preserving image generation.

9. EXPERIMENTS

Our method enables diverse text-guided modifications to subject instances, including recontextualization, property changes (e.g., material, species), art renditions, and viewpoint adjustments, while preserving the subject's unique features. Recontextualization retains subject features, while stronger modifications, like cross-species transformations, maintain essential subject details.

9.1 DATASET

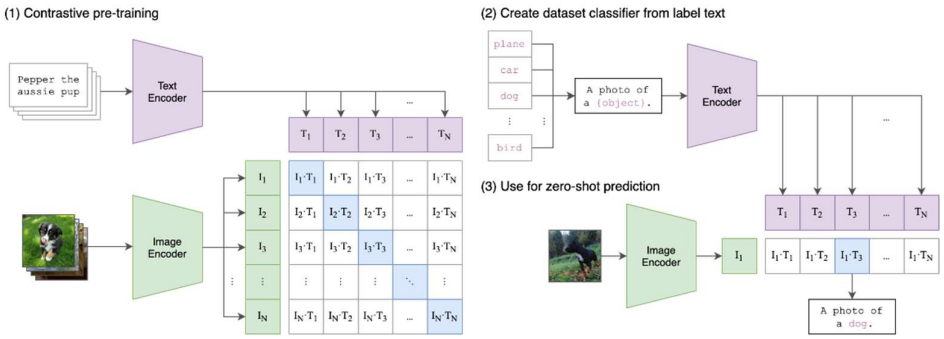


fig:1-LAION-5B

The Stable Diffusion model was trained using LAION-5B (*fig:1*), a publicly available large-scale dataset containing image-text pairs. It is one of the largest datasets designed for text-to-image and image-to-text model training. “LAION 5B" is also sometimes referred to as "LAION-5B", "Large-Scale Artificial Intelligence Open Network 5 Billion dataset", or simply "the LAION dataset" - essentially signifying a massive, open-source collection of 5.85 billion image-text pairs used for training AI models, particularly in the field of image generation; "LAION-2B-en" is sometimes used to refer to the English subset of LAION 5B which contains around 2.3 billion image-text pairs.

URL: The Image URL, millions of domains are covered.

TEXT: Captions, In English For, Other Languages For Multi And Nolan.

WIDTH: Picture Width

HEIGHT: Picture Height

LANGUAGE: The Language Of The Sample, Only For Laion2b-Multi, Computed Using Cld3.

SIMILARITY: Cosine Between Text And Image Vit-B/32 Embeddings, Clip For An, Clip For Multi And Nolan.

WATERMARK: the probability of being a watermarked image, computed using our watermark detector.

UNSAFE: The probability of being an unsafe image, computed using our clip-based detection.

Pretrained on LAION-5B:

- Stable Diffusion has been trained on large datasets like **LAION-5B**, which consists of billions of image-text pairs sourced from the internet. This vast training data allows the model to understand and generate various images based on natural language prompts.
- One of the key features of Stable Diffusion is its ability to generate highly creative and diverse images from text descriptions. The model can create anything from photorealistic landscapes to abstract art, depending on the prompt provided.
- Libraries like Gradio can help Stable Diffusion generate images in real time based on text input interactively. This can be highly beneficial in creative industries like game development, marketing, and visual storytelling.

9.2 MODEL

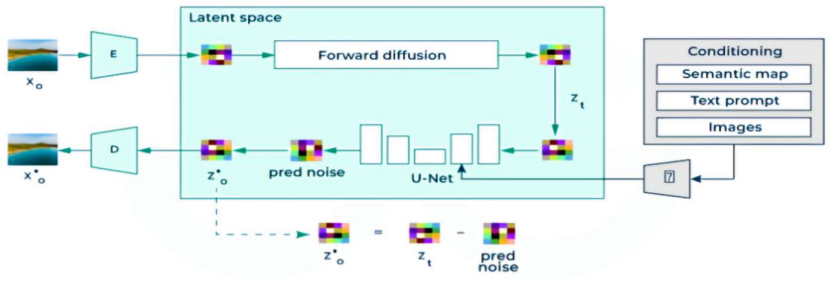


fig-2

Stable Diffusion is founded on a diffusion model known as Latent Diffusion, which is recognized for its advanced abilities in image synthesis (*fig-2*), specifically in tasks such as image painting, style transfer, and text-to-image generation. Unlike other diffusion models that focus solely on pixel manipulation, latent diffusion integrates cross-attention layers into its architecture. These layers enable the model to assimilate information from various sources, including text and other inputs.

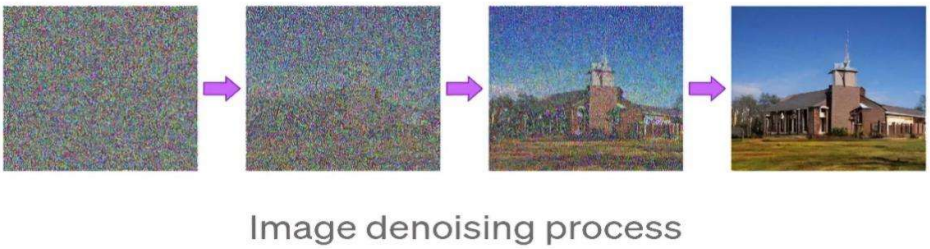


fig-3

Stable Diffusion is a text-to-image model trained on 512x512 images from a subset of the LAION-5B dataset. This model uses a frozen CLIP ViT-L/14 text encoder to condition the model on text prompts. With its 860M UNet and 123M text encoder, the model is relatively lightweight and can run on consumer GPUs. Latent diffusion is the research on top of which Stable Diffusion was built. It was proposed in High-Resolution Image Synthesis with Latent Diffusion Models

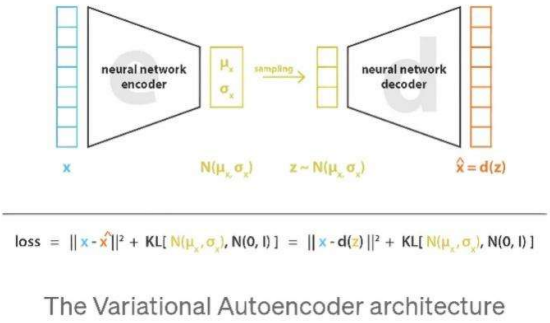
There are three main components in latent diffusion:

Autoencoder

U-Net

Text Encoder

AUTOENCODER:

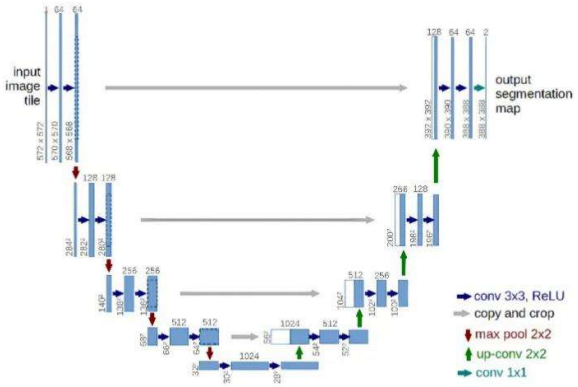


The Variational Autoencoder architecture

fig-4

An autoencoder (*fig-4*) is designed to learn a compressed version of the input image. A Variational Autoencoder consists of two main parts i.e. an encoder and a decoder. The encoder's task is to compress the image into a latent form, and then the decoder uses this latent representation to recreate the original image.

U-NET:



The U-Net architecture

fig-5

U-Net is a convolutional neural network (CNN) (fig-5) used to clean up an image's latent representation. It's made up of a series of encoder-decoder blocks that increase the image quality step by step. The encoder part of the network reduces the image to a lower resolution, and then the decoder works to restore this compressed image to its original, higher resolution and eliminate any noise in the process.

TEXT ENCODER

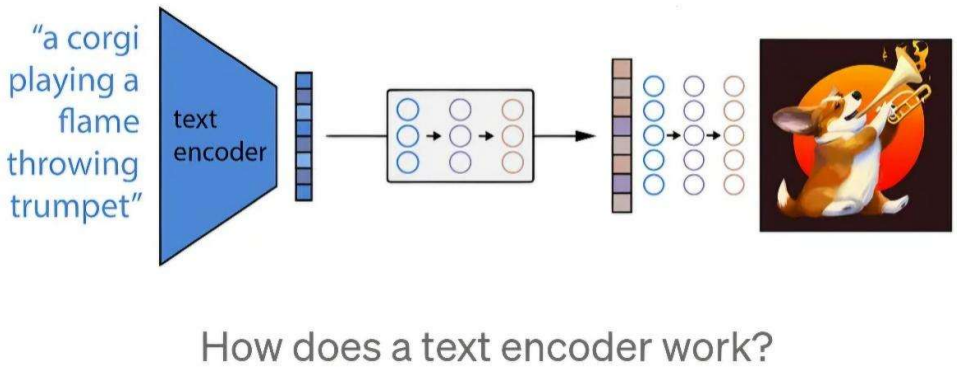


fig-6

The job of the text encoder is to convert text prompts into a latent form. Typically, this is achieved using a transformer-based model, such as the Text Encoder from CLIP, which takes a series of input tokens and transforms them into a sequence of latent text embeddings

10. USER INTERFACE

Gradio is an open-source Python library that simplifies building user interfaces (UIs) for machine learning (ML) models, APIs, or any Python functions. It allows developers to create interactive interfaces quickly, which can be used to test, showcase, or deploy models. In the provided code, Gradio serves as the UI layer for generating images using the Stable Diffusion model.

Advantages of Gradio

- **Rapid Prototyping**: Ideal for quickly building interfaces to test and debug ML models.
- **Collaboration**: Shareable links allow users or stakeholders to interact with the model remotely.
- **Flexibility**: Supports various input/output types (text, image, audio, or video).
- **Open Source**: Freely available and well-documented for easy integration.

Whether for individual use, research, or commercial deployment, Gradio offers a streamlined and accessible solution for connecting users with machine learning technologies.

11. COMPARISONS

We compare with Textual Inversion, a concurrent method by Gal et al., using their provided hyperparameters. It was evaluated with both Imagen and Stable Diffusion, while Textual Inversion was tested with Stable Diffusion. Quantitative results (Table 1) show outperforms Textual Inversion in both subject fidelity (DINO, CLIP-I) and prompt fidelity (CLIP-T). achieves the highest scores, benefiting from its superior expressive power and output quality.

In a user study, 72 participants evaluated subject fidelity and prompt fidelity through 1800 comparative questions. Users overwhelmingly preferred accurately reproducing subject identity and aligning with textual prompts. Qualitative comparisons further highlight the ability to preserve subject details and adhere to prompts better than Textual Inversion. Full details and user study samples are available in the supplementary material.

12. LIMITATIONS

The dataset used to train Stable Diffusion, primarily **LAION-5B**, is vast and diverse, but it has several limitations that can affect both the performance and ethical implications of models derived from it. Here's an overview of its key limitations:

1. Data Bias

Source Bias:

- The dataset is scraped from publicly available internet content, so it inherits biases present in online data.
- Certain demographics, cultures, or topics might be overrepresented or underrepresented.

Cultural Bias:

Images and captions often reflect a Western-centric perspective, which can result in limited applicability for diverse global contexts.

2. Content Quality

Noise in Captions:

- Captions might be noisy, irrelevant, or incomplete (e.g., poorly labeled or mismatched image-text pairs).

Low-Quality Images:

- Some images may be blurry, low resolution, or poorly composed, which can degrade model performance.

3. Ethical Concerns

NSFW (Not Safe for Work) Content:

- Includes explicit, violent, or otherwise sensitive material that could be generated inadvertently.

Copyright Issues:

- Many images in the dataset are pulled from copyrighted sources, raising questions about the legality of training and using models based on this data.

13. TESTING

Testing the code for the Stable Diffusion application involves ensuring that the model, interface, and integration work correctly to generate the desired outputs(fig-7&8).

Prompt Validation:

Test the application with various textual prompts, including simple, complex, and abstract descriptions, to ensure the generated images align with the input text.

Example: A prompt like "baby llama, grazing in an open field" should produce an image matching this description.

Input Handling:

Test the Gradio interface to ensure it accepts textual inputs correctly and handles invalid or empty inputs gracefully.

Output Display:

Verify that the generated images are displayed correctly in the Gradio interface and saved locally if required.

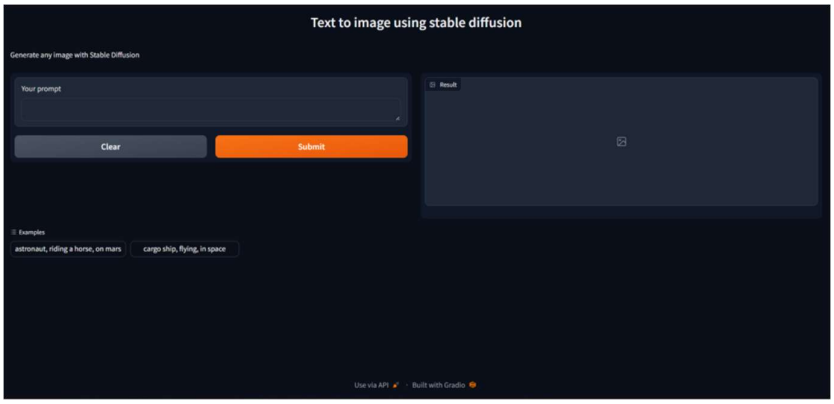


fig-7

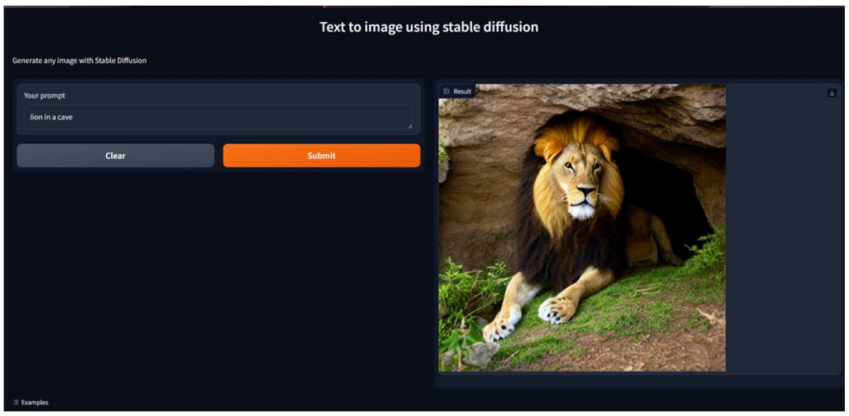


fig-8

14. CONCLUSION

There is, therefore, a critical need that has been covered here: using Stable Diffusion and deep fine-tuning techniques such as DreamBooth and LoRA to produce high-quality customized images of user requirements and unique subject identifiers. The project expands the scope of applications with the seamless integration of personalized features in novel contexts; it may range from creative industries and marketing to educational and digital design.

While computational efficiency and access make it available beyond high-resource environments, it would also make it practical for individual users and smaller organisations. Ethical safeguards including watermarking and input validation supplement the commitment of the project toward responsible AI deployment, including prevention of possible misuse and ensuring fairness.

Through its holistic evaluation, the system presents its advantages in producing realistic, contextually accurate, and diverse outputs compared to generic models. The technical innovations, ethical considerations, and user-centric design make this project a robust solution, bridging the gap between generic text-to-image systems and personalized content creation.

Pushing the boundaries of what text-to-image generation is able to do, this project lays down the groundwork for further innovation in the personalized AI arena, taking users to a new dimension of creativity and functionality.

15. FUTURE SCOPE

The area of application of Stable Diffusion in text-to-image generation is vast and has great scopes for improvement in diverse fields. The first areas of expansion are as follows:

a. More Personalization:
    i. More efficient fine-tuning techniques can be developed to adapt the model to multiple subjects at once.
    ii. Dynamic personalization that lets a model update in real-time with minimal retraining.
b. Cross-Modal Generative AI:
    i. Integration with other generative AI models, like text-to-audio or text-to-video models, to create an immersive multimedia experience.
    ii. Multi-modal input support, allowing users to generate images based on text and reference photos.
c. Scalability and Accessibility:
    i. Optimization of models for deployment on mobile devices or edge computing platforms, increasing accessibility for users with limited computational resources.
    ii. Development of lightweight versions of the model for faster inference and broader usability.
d. Creative Industries:
    i. Games, animation, and virtual reality applications to design real-time, dynamic scenarios and characters that illustrate the requirements of their users.
    ii. Fashion, interior design, and architecture applications that assist in designing custom visual prototypes.
e. Ethical and Security Enhancements:
    i. Implementation of advanced content filtering and validation to prevent any abuse.
    ii. A blockchain-based traceability of the origin of all the generated content so authenticity and accountability can be maintained with it.
f. Automated Feedback and Improvement:
    i. Use of reinforcement learning-driven user feedback loops, which continuously improve the quality as well as relevance of the images.
    ii. Develop self-learning systems that automatically adapt to various needs of different users as time progresses
g. Wider Approaches:
    i. Use in personalized education, such as creating tailored visual aids for different learning styles.
    ii. Integration into healthcare applications, such as generating medical illustrations customized for specific patient cases.
h. Collaborative AI Systems:
    i. Development of collaborative generative AI platforms where multiple users can contribute to and refine generated content in real time.

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