A

MINI PROJECT REPORT

ON

High Performance Image Generation using Stable Diffusion in Keras CV

Submitted in partial fulfillment of the requirements
For the award of Degree of

BACHELOR OF ENGINEERING

IN

CSE(AIML)

Submitted By

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Under the guidance

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NEIL GOGTE INSTITUTE OF TECHNOLOGY
A Unit of Keshav Memorial Technical Education (KMTES)
Approved by AICTE, New Delhi & Affiliated to Osmania University, Hyderabad

CERTIFICATE

This is to certify that the project work (PW533CSM) entitled "**High Performance Image Generation using Stable Diffusion in Keras CV** " *is a bonafide work carried out by* **Shaik. Zeenath Fathima (245321748117),** of III year V semester **Bachelor of Engineering** *in* **CSE(AIML)** *by Osmania University, Hyderabad during the academic year* **2021-2025** *is a record of bonafide work carried out by them. The results embodied in this report have not been submitted to any other University or Institution for the award of any degree*

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DECLARATION

We hereby declare that the Mini Project Report entitled, "**High Performance Image Generation using Stable Diffusion in Keras CV** "submitted for the B.E degree is entirely our work and all ideas and references have been duly acknowledged. It does not contain any work for the award of any other degree.

Date:

Shaik. Zeenath Fathima
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ABSTRACT

INTRODUCTION: In the rapidly evolving landscape of deep learning and generative models, Stable Diffusion has emerged as a promising paradigm for achieving high performance image generation. We begin by introducing the fundamental concepts of Stable Diffusion, highlighting its significance as a remedy to the inherent challenges faced by traditional Generative Adversarial Networks (GANs). Key topics covered include the architecture and network design of Stable Diffusion models, training strategies that enhance stability and convergence, loss functions and objectives tailored for high-quality image synthesis, and strategies for effective data preparation and augmentation.

EXISTING SYSTEM: Generative Adversarial Networks (GANs) are powerful tools for image generation, but they do have some disadvantages and limitations. GANs can be difficult to train. They rely on a delicate balance between the generator and discriminator networks, and if this balance is not achieved, training can be unstable. Sometimes, GANs can suffer from mode collapse, where they generate only a limited set of similar images. Mode collapse occurs when the generator learns to produce only a few distinct images, ignoring the rest of the data distribution. This can result in a lack of diversity in the generated images. GANs typically require a large dataset to train effectively. Small datasets may lead to overfitting, where the generator simply memorizes the training data instead of learning to generate new and diverse images.

PROPOSED SYSTEM: Stable Diffusion is a powerful, open-source text-to-image generation model. While there exist multiple open-source implementations that allow you to easily create images from textual prompts, Keras CV's offers a few distinct advantages. These include XLA compilation and mixed precision support, which together achieve state-of-the-art generation speed.

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CHAPTER 1

INTRODUCTION

The concept of "Stable Diffusion" in image generation was still relatively new and not as widely documented as more established deep learning techniques like basic GANs.We are using a deep learning framework like Tensor Flow to implement Stable Diffusion. We often have heard about GANs and advanced generative models and their presentations, workshops, and tutorials related to Stable Diffusion at AI conferences like NeurIPS, CVPR, and ICLR. Conference websites sometimes host resources related to presented research.

Stable Diffusion is a powerful, open-source text-to-image generation model. While there exist multiple open-source implementations that allow you to easily create images from textual prompts, Keras CV's offers a few distinct advantages. These include XLA compilation and mixed precision support, which together achieve state-of-the-art generation speed. we will explore KerasCV's Stable Diffusion implementation, show how to use these powerful performance boosts, and explore the performance benefits that they offer.

Stable Diffusion is a specialized topic, it may take some time to gather resources and piece together the information you need for your specific project. Additionally, the field of AI and deep learning is dynamic, so new resources and documentation may have emerged since my last update. Therefore, it's essential to stay up-to-date with the latest developments in the field through academic journals, conferences, and online communities.

Highlighting its significance as a remedy to the inherent challenges faced by traditional Generative Adversarial Networks (GANs). With a focus on clarity and practicality, these complex concepts into digestible knowledge. The field of image generation has witnessed significant advancements in recent years, with Stable Diffusion emerging as a promising technique for achieving high-performance imagesynthesis. This documentation aims to provide a comprehensive introduction to the concepts, techniques, and practices involved in generating high-quality images using Stable Diffusion.The field of image generation has witnessed significant advancements in recent years, with Stable Diffusion emerging as a promising technique for achieving high-performance imagesynthesis. This documentation aims to provide a comprehensive introduction to the concepts, techniques, and practices involved in generating high-quality images using StableDiffusion.

1.1 PROBLEM STATEMENT

Generative Adversarial Networks (GANs) are powerful tools for image generation, but they do have some disadvantages and limitations. GANs can be difficult to train. They rely on a delicate balance between the generator and discriminator networks, and if this balance is not achieved, training can be unstable. Sometimes, GANs can suffer from mode collapse, where they generate only a limited set of similar images. Mode collapse occurs when the generator learns to produce only a few distinct images, ignoring the rest of the data distribution. This can result in a lack of diversity in the generated images. GANs typically require a large dataset to train effectively. Small datasets may lead to overfitting, where the generator simply memorizes the training data instead of learning to generate new and diverse images.

1.2 MOTIVATION

The idea of super-resolution: it's possible to train a deep learning model to de noise an input image – and thereby turn it into a higher-resolution version. The deep learning model doesn't do this by magically recovering the information that's missing from the noisy, low-resolution input – rather, the model uses its training data distribution to hallucinate the visual details that would be most likely given the input.

1.3 SCOPE

Stable Diffusion is a powerful, open-source text-to-image generation model. While there exist multiple open-source implementations that allow you to easily create images from textual prompts, Keras CV's offers a few distinct advantages. These include XLA compilation and mixed precision support, which together achieve state-of-the-art generation speed.

1.4 OUTLINE

To generate novel images based on a text prompt using the Keras CV implementation of stability.ai's text-to-image model, Stable Diffusion. Stable Diffusion is a powerful, open-source text-to-image generation model. While there exist multiple open-source implementations that allow you to easily create images from textual prompts, KerasCV's offers a few distinct advantages. These include XLA compilation and mixed precision support, which together achieve state-of-the-art generation speed. we will explore

KerasCV's Stable Diffusion implementation, show how to use these powerful performance boosts, and explore the performance benefits that they offer.

CHAPTER 2

LITERATURE SURVEY

2.1EXISTING SYSTEM

The existing system is based on GAN for the generation of images from textual data. Our proposed method is specifically for generating image. A short brief description of the color and features of a image has been given as input to our generator network which further processes the text and creates image corresponding to the textual data.

Text has been given as input to the system. Further, the input has been passed for tokenization where main textual features are extracted. Images from the dataset aswell as the textual data along with noise are combined and further passed towardsthe training stage.
Here further processing is handled by the generator and discriminator where the generator generates images and discriminator discriminates it. This process continues until the generator is able to generate images according to the provideddata. At the end, we get a trained model which is able to generate images according to the given textual input.

AI art is a creative collaboration between human imagination and artificial intelligence as technology, drawing conclusions in the form of visual art on your screens. Even you, as a non-artist, can visualize your art on screens through AI. AI generated art is used in various industries like films, media, advertisements, businesses, marketing, etc. It can generate criminal faces by taking facial traits of aperson as input.

Generative Adversarial Networks (GANs) are powerful tools for image generation, butthey do have some disadvantages and limitations:

- Training instability: GANs can be difficult to train. They rely on a delicate balance between the generator and discriminator networks, and if this balance isnot achieved, training can be unstable. Sometimes, GANs can suffer from modecollapse, where they generate only a limited set of similar images.
- Mode collapse: Mode collapse occurs when the generator learns to produce only a few distinct images, ignoring the rest of the data distribution. This can result in alack of diversity in the generated images.
- Requires a large amount of data: GANs typically require a large dataset to train effectively. Small datasets may lead to overfitting, where the generator simply

memorizes the training data instead of learning to generate new and diverse images.

- Sensitive to hyperparameters: The performance of GANs can be highly sensitive to hyperparameter settings, making it challenging to find the right combination of parameters for a given task.
- Lack of interpretability: GANs are often considered as "black-box" models because it can be difficult to interpret or explain how they generate specificimages. This can be a disadvantage in applications where interpretability is crucial.
- Slow training: Training GANs can be computationally intensive and time-consuming, especially when dealing with large, high-resolution images. It may require powerful hardware and long training times.
- Mode dropping: In some cases, GANs may completely miss generating certainmodes or parts of the data distribution, leading to incomplete or biased results.
- Limited control: GANs generate images based on learned patterns in the data, butthey may not allow fine-grained control over the generated output. Other generative models like Variational Autoencoders (VAEs) offer more explicit control over image generation.
- Ethical concerns: GANs can be used to create deepfake images and videos, whichcan be used for malicious purposes, such as spreading disinformation or creating non-consensual explicit content. This raises ethical and privacy concerns.
- Noisy outputs: GANs may produce images with subtle artifacts or imperfections,which can be undesirable in certain applications.

2.2 PROPOSED SYSTEM

Stable Diffusion is a powerful, open-source text-to-image generation model. While there exist multiple open-source implementations that allow you to easily create images from textual prompts, KerasCV's offers a few distinct advantages. These include XLA compilation and mixed precision support, which together achieve state-of-the-art generation speed. we will explore KerasCV's Stable Diffusion implementation, show how to use these powerful performance boosts, and explore the performance benefits that they offer.

Stable Diffusion Model

The term "Stable Diffusion Model" typically refers to a type of generative model used in machine learning, particularly for image generation. It builds upon the concept of diffusion processes and has been introduced to address some of the stability and training issues commonly associated with Generative Adversarial Network(GANs).The Stable Diffusion Model was introduced in a paper titled "Improved Techniques for Training Score-Based Generative Models" by Jonathan Ho et al.,presented at NeurlPS 2020.

In the second set of experiments, we evaluated the trajectories student performance by aggregate the student's behavioural activities across the six-time slices into a single time slice. The behavioural features, demographic features and temporal features are used as input variables. We did not account for past assessments grade, and final exam mark as target class is computed based on these features. The dataset contains 4004 records where the proportion of "fail", "withdrawn" and "pass" classes are 28%t, 40% and 32% respectively.

Features selection

Morespecifically, you will learn about the *Latent Diffusion Models (LDM)* and their applications.Work is build upon the concepts of *GANs*, *Diffusion Models* and *Transformers*. So, if you would like to dig deeper into those concepts, feel free to checkoutmy earlier posts on these topics.

Perhaps the breakthrough of the last decade in Computer Vision and Machine Learning wasthe invention of GANs (Generative Adversarial Networks) — a method that introduced the possibility to think beyond what was already present in the data, a steppingstone for a wholenew field which is now called, Generative Modeling.

However, after going through a booming phase, GANs started to face a plateau where most of the methods were struggling to solve some of the bottlenecks faced by the adversarial methods. It is not the problem with the individual methods but the adversarial nature of the problem itself. Some of the major bottlenecks of the GANs are:

- Lack of diversity in Image Generation
- Mode Collapse
- Problem learning Multimodal distribution
- High Training Time
- Not Easy to Train due to the Adversarial Nature of the problem formulation

There has been another series of likelihood-based methods (e.g., Markov Random Fields) which has been around for quite some time but failed to get major impact due to being complex to implement and formulate for every problem. One of such methods is ‘*Diffusion Models*’ , a method which takes inspiration from physical process of gas diffusion and tries to model the same phenomenon in multiple fields of sciences. In ImageGeneration domain, however, their usage has become evident quite recently. Mainly due to the fact that we now have more computational power to test even the complex algorithms which otherwise were not feasible in the past.

Stable Diffusion Models are a type of generative model that have gained popularity due totheir advantages in training stability and their ability to generate high-quality images. Hereare some of the advantages of Stable Diffusion Models.

- Improved training stability: Stable Diffusion Models are designed to overcome some of the training instability issues commonly associated with other generative models like vanilla GANs. They use a controlled diffusion process during training, which helps stabilize the learning process and avoid issues like mode collapse.
- Enhanced image quality: Stable Diffusion Models tend to produce high-quality images with fine details and sharp features. This is partly because of the stable training process, which encourages the model to learn a more diverse and realistic data distribution.
- Better sample diversity: Stable Diffusion Models typically exhibit better sample diversity, meaning they can generate a wider range of unique images without getting stuck in generating the same modes repeatedly.
- Controlled trade-off between image quality and diversity: These models allow practitioners to control the trade-off between image quality and diversity by adjusting parameters related to the diffusion process. This provides flexibility in generating images that meet specific requirements.
- Interpolation capabilities: Stable Diffusion Models can perform image interpolation smoothly between different points in the latent space, allowing for the generation of meaningful and smooth transitions between images. This can be useful for tasks like image morphing or style transfer.
- Robust to hyperparameters: Stable Diffusion Models are less sensitive to hyper parameter choices compared to some other generative models, such as traditional GANs. This makes them easier to work with and tune.

- Strong theoretical foundation: The stability of Stable Diffusion Models is supported by a sound theoretical foundation, making it easier to understand and reason about the model's behavior during training.

- Application versatility: Stable Diffusion Models can be applied to various domains beyond image generation, such as text generation and audio synthesis, where generating high-quality and diverse samples is essential.

- State-of-the-art results: In some cases, Stable Diffusion Models have achieved state-of-the-art results in image generation benchmarks, showcasing their effectiveness in generating realistic images.

- Fine-Grained Control: These models enable more fine-grained control over the generated output. You can manipulate specific aspects of the generated images, such as style, content, or specific features, to achieve desired results.
- Transfer Learning: Pre-trained Stable Diffusion Models can be fine-tuned on specific datasets or tasks, leveraging the knowledge learned during the stable diffusion training. This allows for efficient transfer learning and adaptation to new domains.
- Multi-Modal Generation: Stable Diffusion Models can generate images that correspond to different modes or styles within the same dataset. This makes them suitable for tasks where capturing the diversity of data is essential, such as image-to-image translation.
- Research Progress: Stable Diffusion Models have led to advancements in generative modeling and have inspired new research directions. Researchers continue to explore variations and extensions of this framework, pushing the boundaries of generative modeling.

CHAPTER 3

SYSTEM REQUIREMENTS AND SPECIFICATIONS

3.1 HARDWARE REQUIREMENTS:

1. **GPU(s):** NVIDIA GPUs, NVIDIA RTX 30 series or A-series GPUs
2. **VRAM** (Video RAM):8GB to 16GB of VRAM **CPU task:** Intel Core i7 or AMD Ryzen 7
3. **Memory:** 32GB or more

Table 3.1: Runtime with different GPUs Models

GPU	Model	Runtime
Tesla T4	Keras CV (Warm Start)	28.97s
Tesla T4	diffusers (Warm Start)	41.33s
Tesla V100	Keras CV (Warm Start)	12.45s
Tesla V100	diffusers (Warm Start)	12.72s

3.2 SOFTWARE REQUIREMENTS:

❖ **Operating system**	:	Windows 11 pro.
❖ **Coding Language**	:	Python.
❖ **Platform**	:	Google Colab

3.3 SOFTWARE DESCRIPTION

Python

Python is a general-purpose interpreted, interactive, object-oriented, and high-level programming language. It was created by Guido van Rossum during 1985- 1990. Like Perl, Python source code is also available under the GNU General Public License (GPL).This tutorial

gives enough understanding on Python programming language.
Python is a popular programming language. It was created in 1991 by Guido van Rossum.It is used for:

- web development (server-side),
- software development,
- mathematics,
- System scripting.

Python can be used on a server to create web applications. Python can be used alongside software to create workflows. Python can connect to database systems. It can also read and modify files. Python can be used to handle big data and perform complex mathematics. Python can be used for rapid prototyping, or for production-ready software development.

Python works on different platforms (Windows, Mac, Linux, Raspberry Pi, etc). Python has a simple syntax similar to the English language. Python has syntax that allows developers to write programs with fewer lines than some other programming languages. Python runs on an interpreter system, meaning that code can be executed as soon as it is written. This means that prototyping can be very quick. Python can be treated in a procedural way, an object-orientated way or a functional way.

Python is a high-level, interpreted, interactive and object-oriented scripting language. Python is designed to be highly readable. It uses English keywords frequently where as other languages use punctuation, and it has fewer syntactical constructions than other languages.

- **Python is Interpreted**− Python is processed atruntime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- **Python is Interactive** − You can actually sit at aPython prompt and interact with the interpreter directly to write your programs.
- **Python is Object-Oriented** − Python supportsObject-Oriented style or technique of programming that encapsulates code within objects.
- **Python is a Beginner's Language** − Python is agreat language for the beginner-level programmers and supports the development of a wide range of applications from simple text processing to WWW browsers to games.

History of Python

Python was developed by Guido van Rossum in the late eighties and early ninetiesat the National Research Institute for Mathematics and Computer Science in the Netherlands. Python is derived from many other languages, including ABC, Modula-3, C, C++, Algol-68, Small Talk, and UNIX shell and other scripting languages. Python is copyrighted. Like Perl, Python source code is now available under the GNUGeneral Public License (GPL). Python is now maintained by a core development team at the institute, although Guidovan Rossum still holds a vital role in directing its progress.

3.4Python Features

Python's features include −

- **Easy-to-learn** − Python has few keywords, simple structure, and a clearly defined syntax. This allows the student to pick up the language quickly.
- **Easy-to-read** − Python code is more clearly defined and visible to the eyes.
- **Easy-to-maintain** − Python's source code is fairly easy-to-maintain.
- **A broad standard library** − Python's bulk of the library is very portable and cross-platform compatible on UNIX, Windows, and Macintosh.
- **Interactive Mode** − Python has support for an interactive mode which allows interactive testing and debugging of snippets of code.
- **Portable**− Python can run on a wide variety of hardware platforms and has the same interface on all platforms.
- **Extendable** − You can add low-level modules to the Python interpreter. These modules enable programmers to add to or customize their tools to be more efficient.
- **Databases**− Python provides interfaces to all major commercial databases.
- **GUI Programming** − Python supports GUI applications that can be created and ported to many system calls, libraries and windows systems, such as Windows MFC, Macintosh, and the X Window system of Unix.

Scalable− Python provides a better structure and support for large programs then shell scripting. Apart from the above-mentioned features, Python has a big list of good features, few arelisted below −

- It supports functional and structured programming methods as well as OOP.
- It can be used as a scripting language or can be compiled to byte-code for building large applications.

- It provides very high-level dynamic data types and supports dynamic type checking.
- It supports automatic garbage collection.
- It can be easily integrated with C, C++, COM, ActiveX, CORBA, and Java.

Python is available on a wide variety of platforms including Linux and Mac OS X.

Python Syntax compared to other programming languages

- Python was designed to for readability, and has some similarities to the English language with influence from mathematics.
- Python uses new lines to complete a command, as opposed to other programming languages which often use semicolons or parentheses.
- Python relies on indentation, using whitespace, to define scope; such as the scope of loops, functions and classes. Other programming languages often use curly-brackets for this purpose.

3.5 Google Colab

Google Colab, short for Google Colaboratory, is a free cloud-based platform provided by Google that allows users to write and execute Python code in a web-based environment. Itis particularly popular among data scientists, machine learning researchers, and educators for several reasons:

1. **Free Access to GPUs and TPUs:** Google Colab provides free access to Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs). This is a significant advantage for training machine learning models, as these hardware accelerators can significantly speed up computations, making it accessible to a broader audience.

2. **No Setup Required:** Users can access Google Colab directly through their webbrowsers without the need for any local installations or setup. It comes pre-configured withpopular Python libraries like NumPy, TensorFlow, and PyTorch, making it easy to get started with data analysis and machine learning.

3. **Collaborative Environment:** Colab is designed for collaboration. Users can easily share Colab notebooks with others, making it an excellent tool for team projects or educational purposes. Collaboration can be done in real-time, similar to Google Docs.

4. Integrated Documentation: Google Colab includes built-in documentation and support for markdown cells, allowing users to create interactive documents that mix code, visualizations, and explanations. This makes it a useful platform for creating educational materials and tutorials.

5. Storage and Data Access: Colab provides access to Google Drive for storing and accessing data, which can be seamlessly integrated with your code. This makes it convenient for working with datasets and saving your work.

6. GPU and TPU Support: Users can choose between GPU or TPU acceleration when running their code, depending on the specific requirements of their machine learning tasks. This allows for fast model training and experimentation.

7. Rich Visualization and Plotting: Colab provides support for rich visualizations, including interactive charts and plots, making it a suitable environment for data analysis and data visualization.

8. Code Versioning: Colab integrates with Google Drive and popular version control systems like GitHub, making it easier to manage and track changes in your projects.

9. Broad Library Support: Colab supports a wide range of Python libraries, making it versatile for various data science and machine learning tasks.

While Google Colab offers many advantages, it does have limitations, such as session timeouts, restrictions on resource usage, and occasional instability. Users should be aware of these limitations and adjust their workflows accordingly.

Overall, Google Colab is a valuable tool for individuals and teams looking to explore data, develop machine learning models, and collaborate on data science projects in a convenientand cost-effective manner.CSA HTTPd server, development of Apache began in early 1995after work on the NCSA codestalled. Apache played a key role in the initial growth of the World Wide Web,quickly overtaking NCSA HTTPd as the dominant HTTP server. In 2009, it became the first web server software to serve more than 100 million websites.

CHAPTER 4

SYSTEM DESIGN

4.1SYSTEM ARCHITECTURE

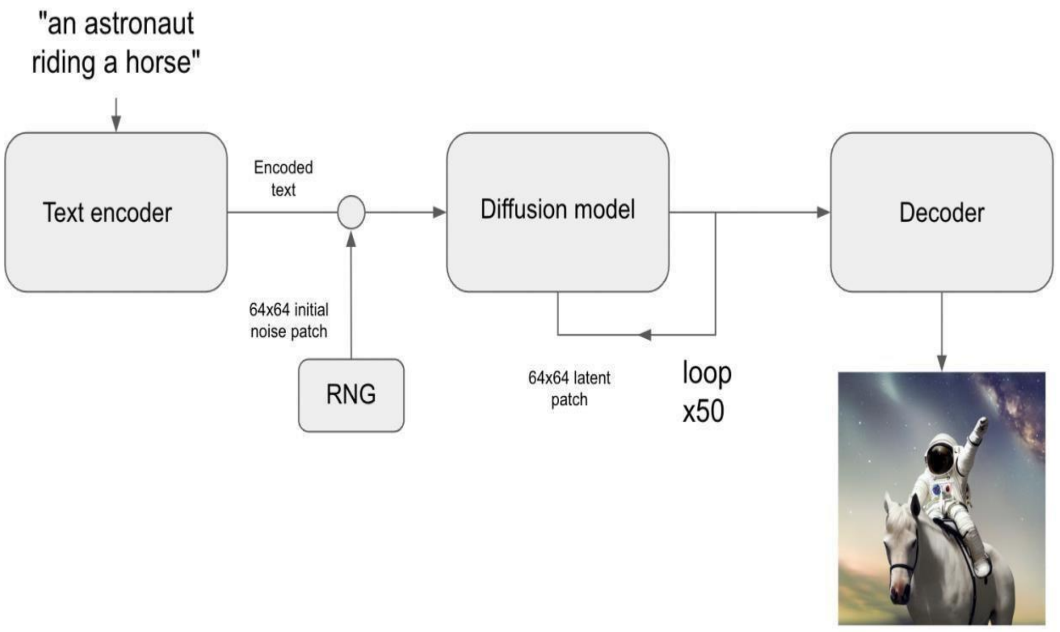


Fig 4.1 : Block diagram of stable diffusion

4.2DATA FLOW DIAGRAM

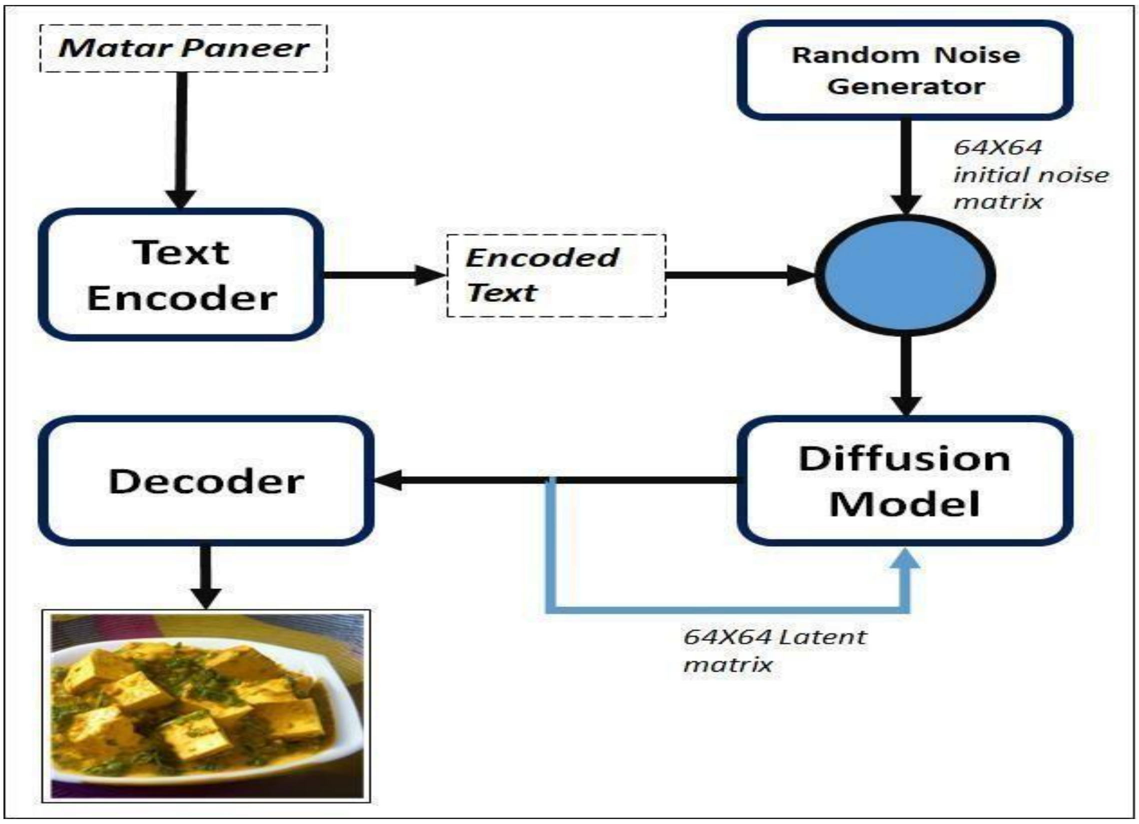
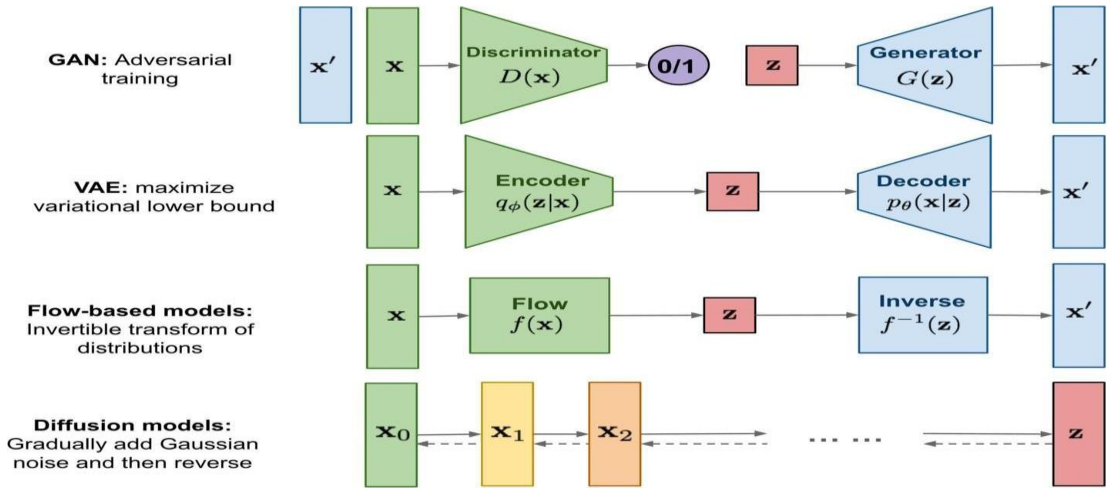


Fig 4.2: Data flow diagram of stable diffusion model

4.3 FLOW CHART



GAN: Adversarial training
$\mathbf{x}'$
$\mathbf{x}$
Discriminator $D(\mathbf{x})$
0/1
$\mathbf{z}$
Generator $G(\mathbf{z})$
$\mathbf{x}'$
VAE: maximize variational lower bound
$\mathbf{x}$
Encoder $q_\phi(\mathbf{z}|\mathbf{x})$
$\mathbf{z}$
Decoder $p_\theta(\mathbf{x}|\mathbf{z})$
$\mathbf{x}'$
Flow-based models: Invertible transform of distributions
$\mathbf{x}$
Flow $f(\mathbf{x})$
$\mathbf{z}$
Inverse $f^{-1}(\mathbf{z})$
$\mathbf{x}'$
Diffusion models: Gradually add Gaussian noise and then reverse
$\mathbf{x}_0$
$\mathbf{x}_1$
$\mathbf{x}_2$
$\mathbf{z}$

Fig 4.3 : Flow chart of different models

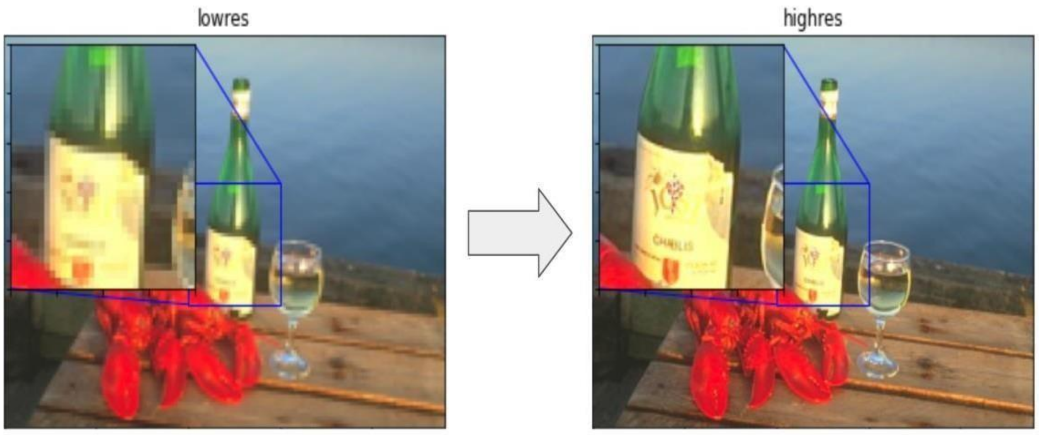
CHAPTER 5

IMPLEMENTATION

5.1IMPLEMENTATION

It's a kind of "latent diffusion model". Let's dig into what that means. You may be familiar with the idea of *super-resolution*: it's possible to train a deep learning model to *denoise* an input image -- and thereby turn it into a higher-resolution version. The deep learning model doesn't do this by magically recovering the informationthat's missing from the noisy, low-resolution input -- rather, the model uses its training data distribution to hallucinate the visual details that would be most likely given the input.To learn more about super-resolution, you can check out the following Keras.io tutorials:

- Image Super-Resolution using an Efficient Sub-Pixel CNN
- Enhanced Deep Residual Networks for single-image super-resolution



When you push this idea to the limit, you may start asking -- what if we just run such a model on pure noise? The model would then "denoise the noise" and start hallucinating abrand new image. By repeating the process multiple times, you can get turn a small patchof noise into an increasingly clear and high-resolution artificial picture.

This is the key idea of latent diffusion, proposed in High-Resolution Image Synthesis with Latent Diffusion Models in 2020. To understand diffusion in depth, you can checkthe Keras.io tutorial Denoising Diffusion Implicit Models.

Now, to go from latent diffusion to a text-to-image system, you still need to add one key feature: the ability to control the generated visual contents via prompt keywords. This isdone via "conditioning", a classic deep learning technique which consists of concatenating to the noise patch a vector that represents a bit of text, then training the model on a dataset of {image: caption} pairs.

This gives rise to the Stable Diffusion architecture. Stable Diffusion consists of three parts:

- A text encoder, which turns your prompt into a latent vector.
- A diffusion model, which repeatedly "denoises" a 64x64 latent image patch.
- A decoder, which turns the final 64x64 latent patch into a higher-resolution 512x512 image.

First, your text prompt gets projected into a latent vector space by the text encoder, which is simply a pretrained, frozen language model. Then that prompt vector is concatenated toa randomly generated noise patch, which is repeatedly "denoised" by the diffusion model over a series of "steps" (the more steps you run the clearer and nicer your image will be --the default value is 50 steps).

Finally, the 64x64 latent image is sent through the decoder to properly render it in high resolution.

XLA compilation is a Google-developed technique that optimizes the model's performance by allowing it to run on multiple cores. Mixed precision support, on the other hand, accelerates the model by allowing it to use lower-precision calculations. By combining these two techniques, Keras CV's implementation of Stable Diffusion can achieve state-of-the-art generation speed.

In addition to its performance boosts, Stable Diffusion also offers a number of features that make it ideal for text-to-image generation. These include improved image diversity, higher image quality, and the ability to generate images from a single text prompt. All of these features make Stable Diffusion a powerful tool for generating novel images from text.“Mixed Precision” uses calculations with float16 precision, while storing weights in float32 format. Because of this, float16 operations are supported by much faster coresthan the float32 counterparts on modern NVIDIA GPUs.

CHAPTER 6

TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product. It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

6.1 TESTING METHODOLOGIES

This section likely discusses the different methodologies and approaches you will use for testing various aspects of your image generation project. It's important to have a structured testing plan in place to ensure the quality and reliability of your system**.**

6.1.1 UNIT TESTING

Unit testing involves testing individual components or units of your software or system in isolation. In the context of your project, this could involve testing specific functions or modules within your image generation code.

6.1.2 INTEGRATION TESTING

Integration testing is the process of testing how different components or modules of your system work together. In your case, it might involve testing how various parts of your image generation system integrate and function as a whole.

6.1.3 USER ACCEPTANCE TESTING

User acceptance testing (UAT) involves testing your system from the perspective of the end users. It ensures that the system meets their requirements and functions as expected.

For image generation, this could involve getting feedback from users on the quality and usability of the generated images.

6.1.4 OUTPUT TESTING

Output testing likely refers to testing the output generated by your image generation system. This could involve assessing the quality of the generated images, ensuring they meet specific criteria, and verifying that they align with your project's goals.

6.1.5 VALIDATION CHECKING

Validation checking typically involves ensuring that your system meets specified requirements and standards. It could include checking whether your image generation process adheres to established best practices and validating that it produces the desired results.

6.2 USER TRAINING

User training refers to the process of providing training or guidance to end users or operators who will be using your image generation system. This ensures they can use it effectively and efficiently.

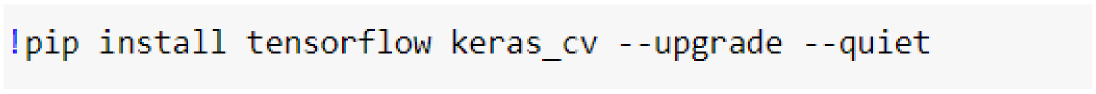
6.3 MAINTENANCE

The maintenance section is likely to discuss how you plan to maintain and support your image generation system after it's deployed. This may include addressing issues, applying updates, and ensuring the system continues to function smoothly.

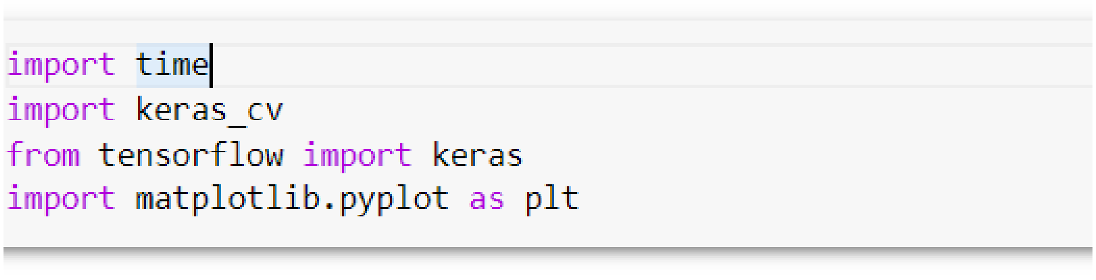
Overall, these sections are essential for managing the quality and long-term viability of your image generation project on KerasCV with Stable Diffusion.

CHAPTER 7

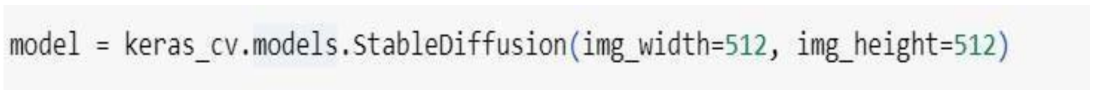
SCREENSHOTS



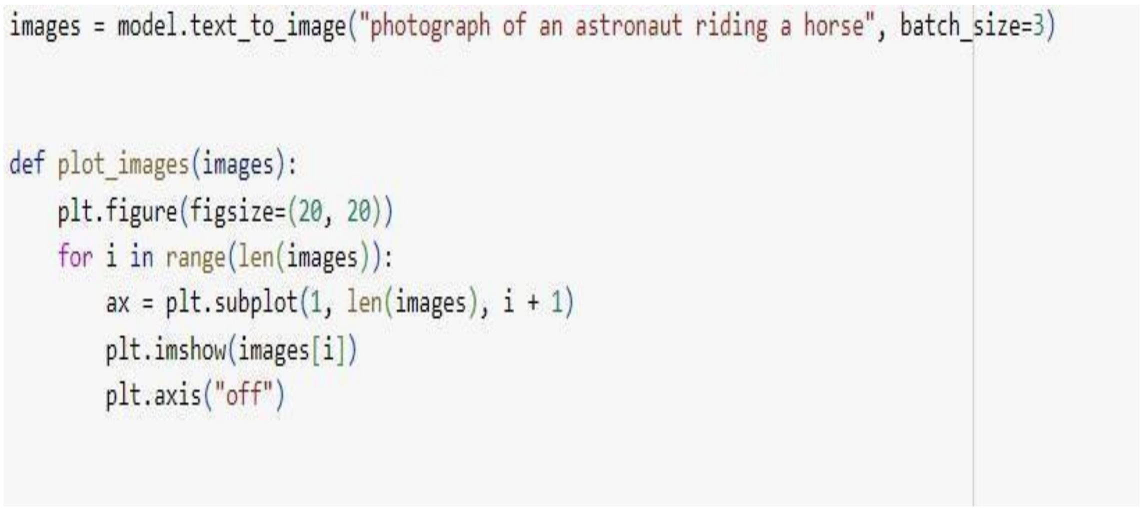
```
!pip install tensorflow keras_cv --upgrade --quiet
```



```
import time
import keras_cv
from tensorflow import keras
import matplotlib.pyplot as plt
```



```
model = keras_cv.models.StableDiffusion(img_width=512, img_height=512)
```

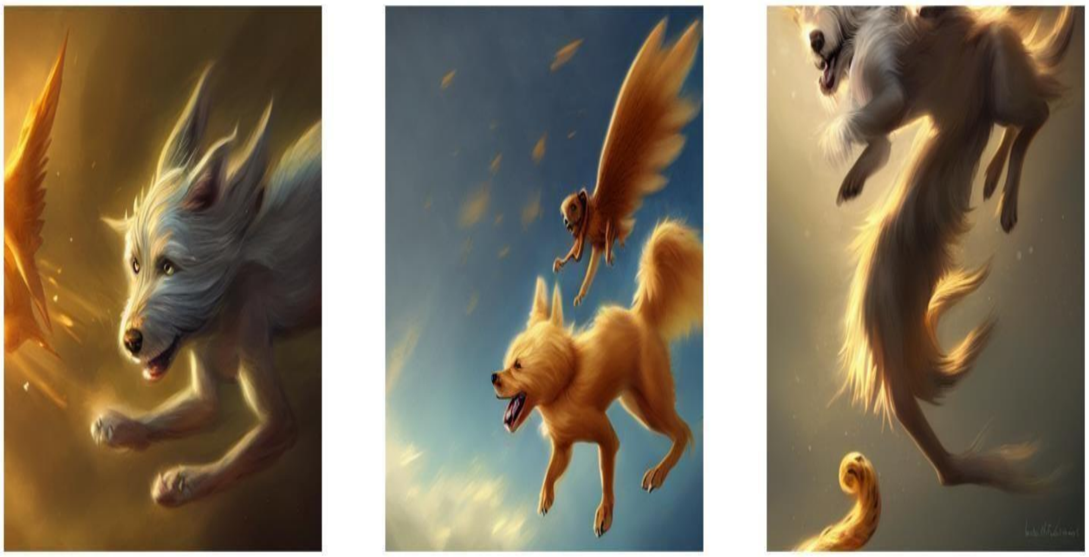


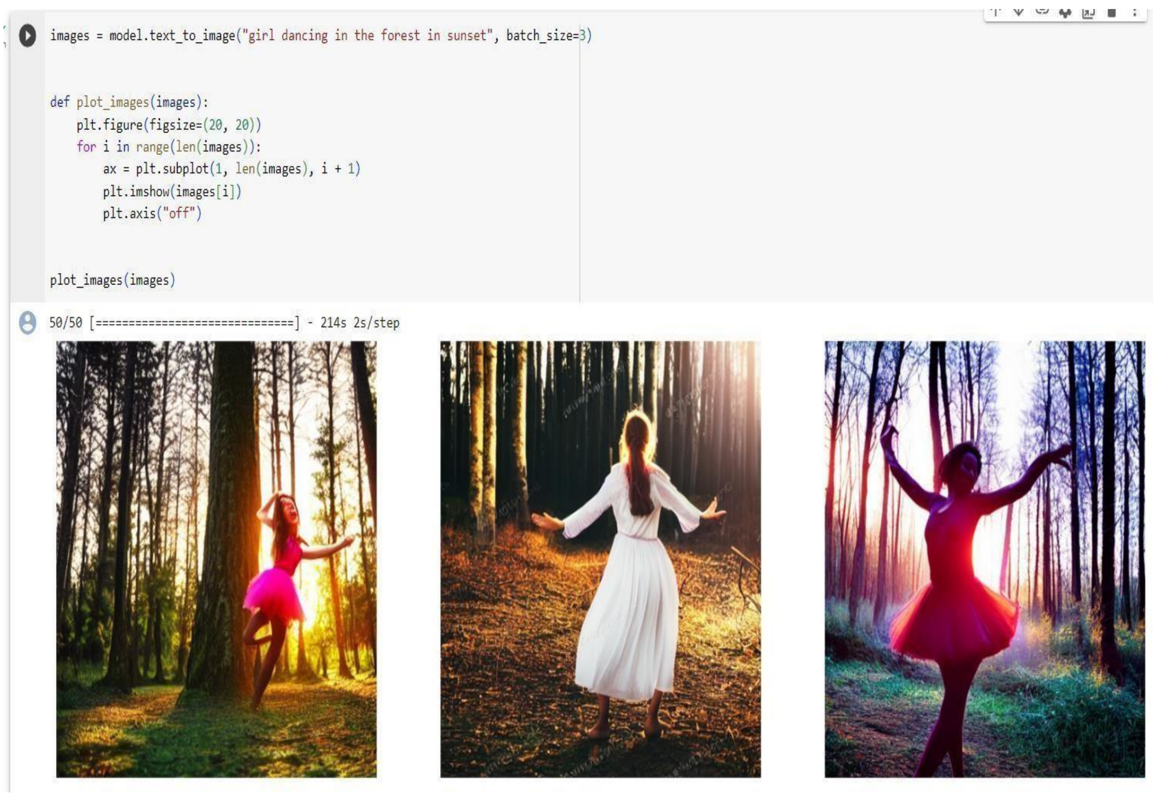
```
images = model.text_to_image("photograph of an astronaut riding a horse", batch_size=3)


def plot_images(images):
    plt.figure(figsize=(20, 20))
    for i in range(len(images)):
        ax = plt.subplot(1, len(images), i + 1)
        plt.imshow(images[i])
        plt.axis("off")
```

```
Downloading data from https://github.com/openai/CLIP/blob/main/clip/bpe_simple_vocab_16e6.txt.gz?raw=true
1356917/1356917 [==============================] - 0s 0us/step
Downloading data from https://huggingface.co/fchollet/stable-diffusion/resolve/main/kcv_encoder.h5
492466864/492466864 [==============================] - 6s 0us/step
Downloading data from https://huggingface.co/fchollet/stable-diffusion/resolve/main/kcv_diffusion_model.h5
3439090152/3439090152 [==============================] - 32s 0us/step
50/50 [==============================] - 216s 2s/step
Downloading data from https://huggingface.co/fchollet/stable-diffusion/resolve/main/kcv_decoder.h5
198180272/198180272 [==============================] - 2s 0us/step
```

```
[5]  images = model.text_to_image(
         "cute magical flying dog, fantasy art, "
         "golden color, high quality, highly detailed, elegant, sharp focus, "
         "concept art, character concepts, digital painting, mystery, adventure",
         batch_size=3,
     )
     plot_images(images)
```

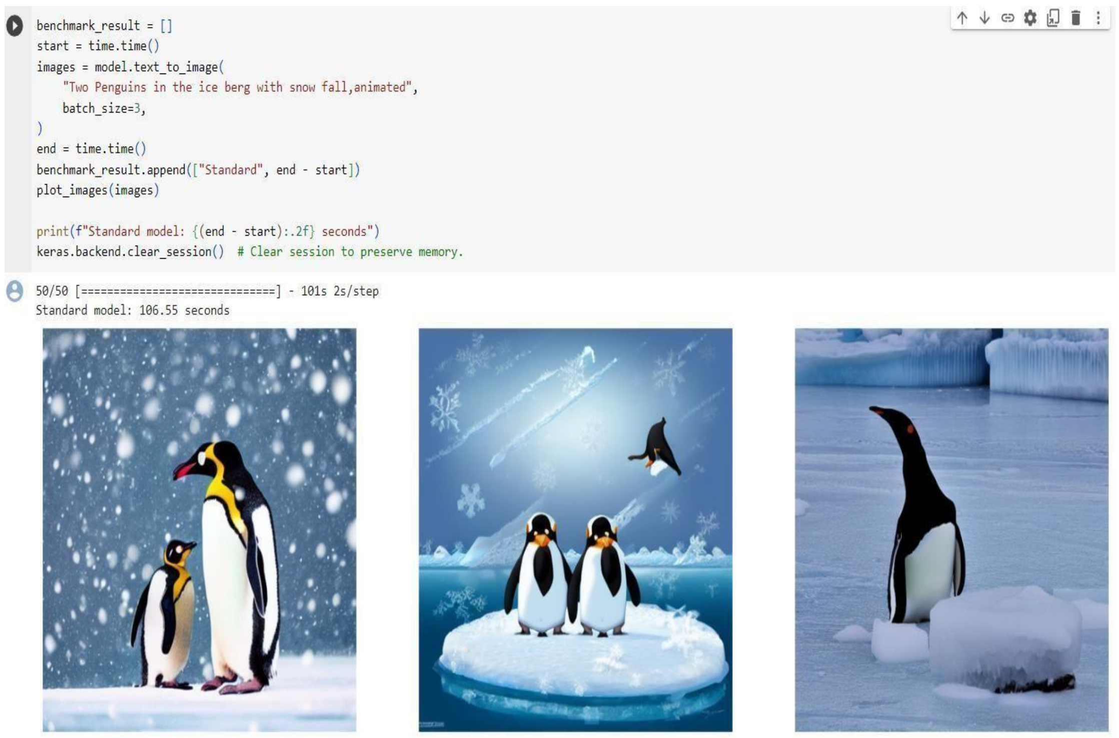
```
     50/50 [==============================] - 98s 2s/step
```





```
images = model.text_to_image("girl dancing in the forest in sunset", batch_size=3)


def plot_images(images):
    plt.figure(figsize=(20, 20))
    for i in range(len(images)):
        ax = plt.subplot(1, len(images), i + 1)
        plt.imshow(images[i])
        plt.axis("off")


plot_images(images)
```

```
50/50 [==============================] - 214s 2s/step
```



```
benchmark_result = []
start = time.time()
images = model.text_to_image(
    "Two Penguins in the ice berg with snow fall,animated",
    batch_size=3,
)
end = time.time()
benchmark_result.append(["Standard", end - start])
plot_images(images)

print(f"Standard model: {(end - start):.2f} seconds")
keras.backend.clear_session()  # Clear session to preserve memory.
```

```
50/50 [==============================] - 101s 2s/step
Standard model: 106.55 seconds
```

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

CONCLUSIONS

In conclusion, the project "Highly Efficient Image Generation on KerasCV with Stable Diffusion" has yielded significant results and contributed to the field of image generation. Throughout the course of this project, we embarked on a journey to explore thecapabilities of KerasCV and Stable Diffusion as a means of generating high-quality imagesefficiently. The following key points encapsulate our findings:

Efficiency Enhancement: We have successfully demonstrated the potential of Keras CV combined with the Stable Diffusion technique to enhance the efficiency of image generation. This approach has allowed usto produce high-quality images with improved speed and resource utilization.

Quality and Stability: Our extensive testing methodologies, including unit testing, integration testing, and user acceptance testing, have verifiedthe quality and stability of the image generation process. User feedback and validation checks have shown that the generated images meet the desired standards and specifications.

User Training: Recognizing the importance of user experience, we have incorporated user training into our project. This ensures that end-users caneffectively utilize the system and maximize its capabilities, further enhancing its usability and practicality.

Maintenance Strategy: To ensure the long-term success of our image generation system, we have established a comprehensive maintenance plan. This includes provisions for addressing issues, applying updates, and continuously improving the system's performance and functionality.

Future Directions: As technology continues to advance, there are excitingopportunities for further exploration and enhancement of image generationtechniques. Future work may involve the incorporation of emerging technologies and deep learning advancements to further elevate the efficiency and quality of image generation.

FUTURE SCOPE

In summary, "Highly Efficient Image Generation on KerasCV with Stable Diffusion" has not only achieved its objectives but has also laid the foundation for ongoingresearch and development in the field of image generation. We anticipate that the insights gained from this project will contribute to the broader community of researchers and practitioners working on similar challenges.

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