



# INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

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## Using Qualifiers In Prompts For Stable Diffusion

*An Experimental Study*

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**Abstract:** Stable Diffusion uses a text-to-image machine learning model to generate images matching the prompt specification. This paper presents the experimental study of using different qualifiers with four different types of text prompts as a method of creating variations in the generated images while preserving the semantics. It was found that all qualifiers helped in creating some variation in the images. However, depending on the type of variation created in the images, this paper presents an insight into enhancement or insertion of relevant or irrelevant features in the generated images based on one- or two-word qualifiers used.

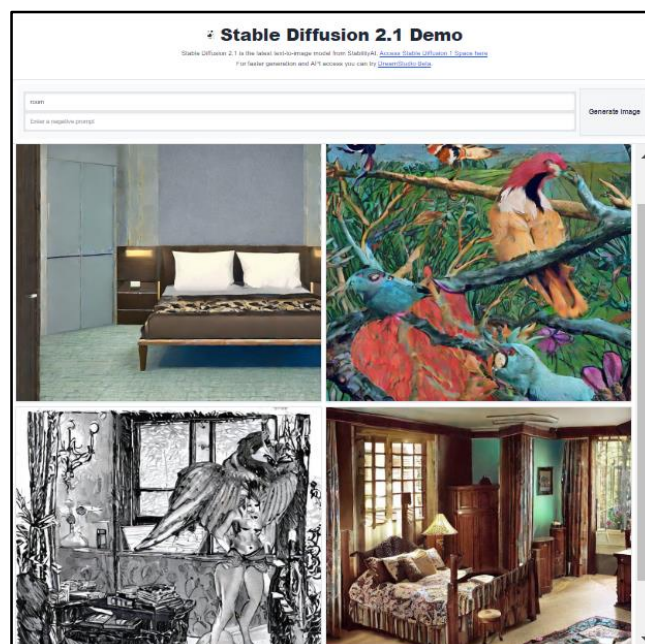
**Index Terms -** Stable Diffusion, text-to-image, Generative AI, neural networks

### I. INTRODUCTION

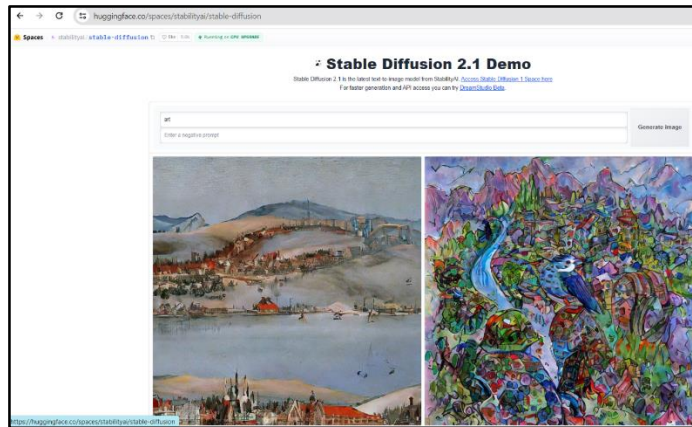
The Generative AI is creating wonders by successfully generating the intelligent text, audio and images. Stable Diffusion is a text to image model created in 2022 that can produce photograph level quality images based on the text specifications. The text given at the prompt gives the semantics to the model. Although, the type of image generated can be controlled by different factors, however the text specification at the prompt is important for the type of image that is generated.

### II. TEXT SPECIFICATION FOR STABLE DIFFUSION

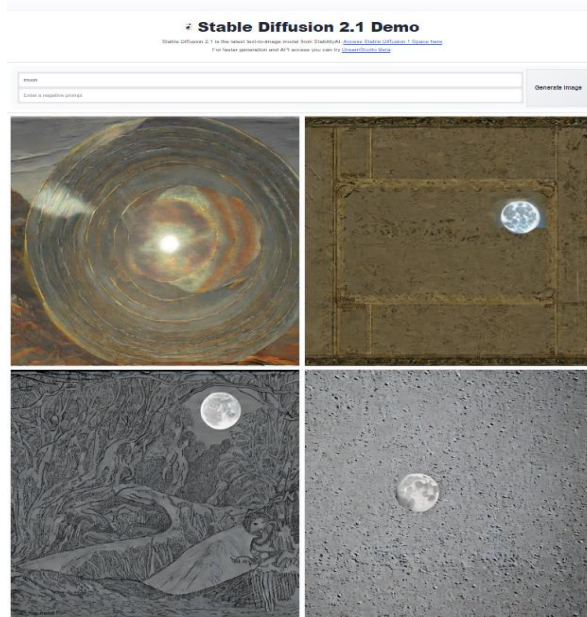
Stable Diffusion 2.1 is an important online text-to-image model from Stability AI [3], that can be used to check out the type of images generated by providing the text and other image control specifications.



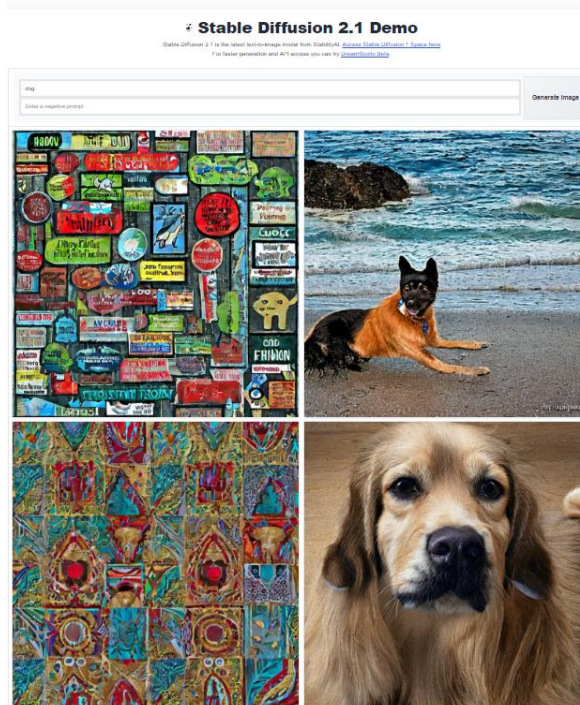
**Figure 1: Images generated using the text “room” in the prompt**



**Figure 2: Images generated using the text “art” in the prompt**



**Figure 3: Images generated using the text “moon” in the prompt**



**Figure 4: Images generated using the text “dog” in the prompt**

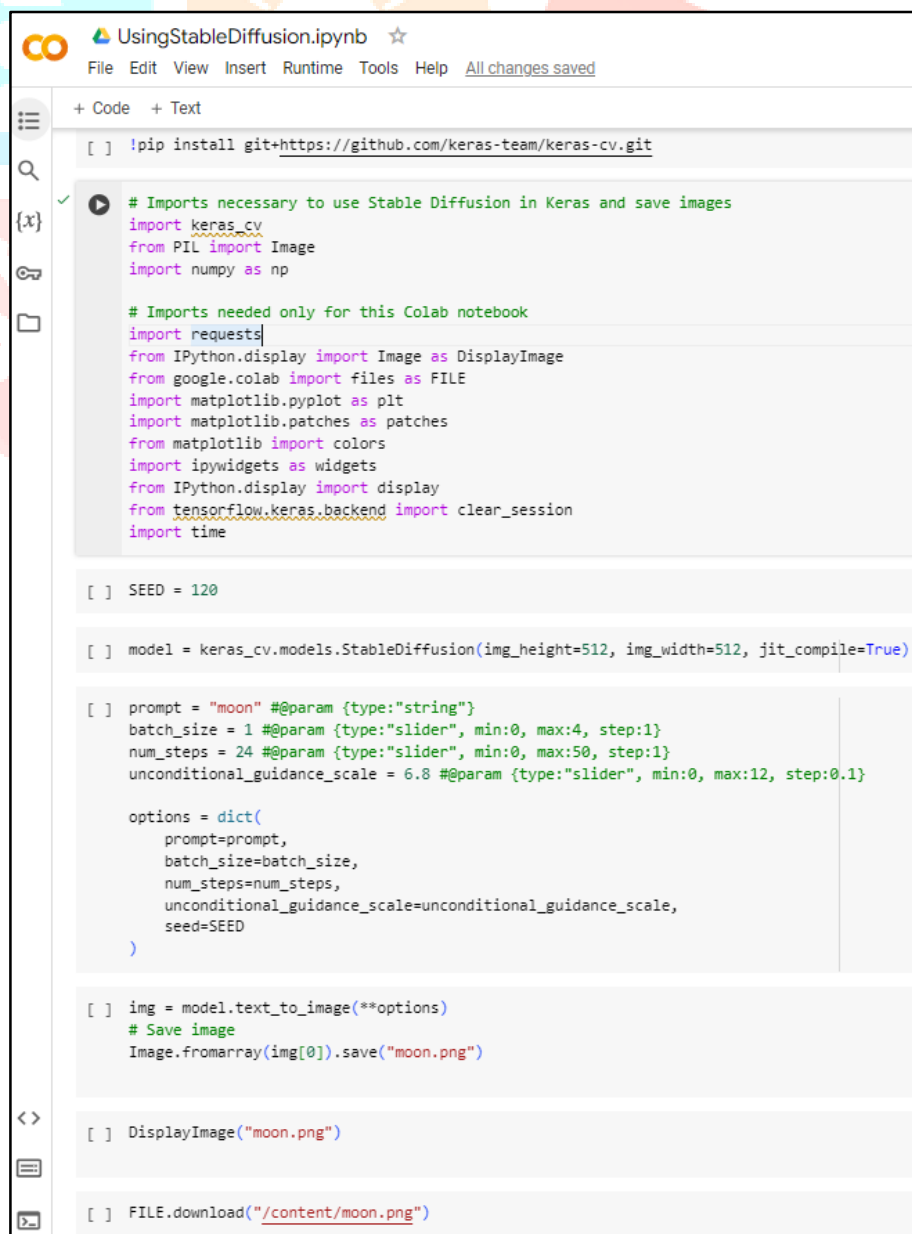
It was found that on keeping the other factors same and just changing the text specification, different types of results are produced. The types of results produced can be labelled as realistic, mixed and artistic.

Text Used	Type of Image Generated	Remarks
room	Mixed images	It was found that simple use of “room” at the prompt produced 2 out of 4 images where room was seen in the image while the other two images that were generated appeared as artworks not related to the specified text.
art	Artistic images	The model produced beautiful artworks.
moon	Artistic images	The model produced images that can be called artworks and not the realistic moon images.
dog	Mixed images	It was found that simple use of “dog” at the prompt produced 2 out of 4 images where dog was seen in the image while the other two images that were generated appeared as artworks not related to the specified text.

**Table 1: The Different types of Text Prompt Specifications with Type of Images Generated**

### III. CODE USED

The same type of text specifications for image generation can be experimented with if the following Python code is used in Google Colab. To use this TPU setting is also needed which is given below.



```

UsingStableDiffusion.ipynb
File Edit View Insert Runtime Tools Help All changes saved

+ Code + Text

[ ] !pip install git+https://github.com/keras-team/keras-cv.git

# Imports necessary to use Stable Diffusion in Keras and save images
import keras_cv
from PIL import Image
import numpy as np

# Imports needed only for this Colab notebook
import requests
from IPython.display import Image as DisplayImage
from google.colab import files as FILE
import matplotlib.pyplot as plt
import matplotlib.patches as patches
from matplotlib import colors
import ipywidgets as widgets
from IPython.display import display
from tensorflow.keras.backend import clear_session
import time

[ ] SEED = 120

[ ] model = keras_cv.models.StableDiffusion(img_height=512, img_width=512, jit_compile=True)

[ ] prompt = "moon" #@param {type:"string"}
batch_size = 1 #@param {type:"slider", min:0, max:4, step:1}
num_steps = 24 #@param {type:"slider", min:0, max:50, step:1}
unconditional_guidance_scale = 6.8 #@param {type:"slider", min:0, max:12, step:0.1}

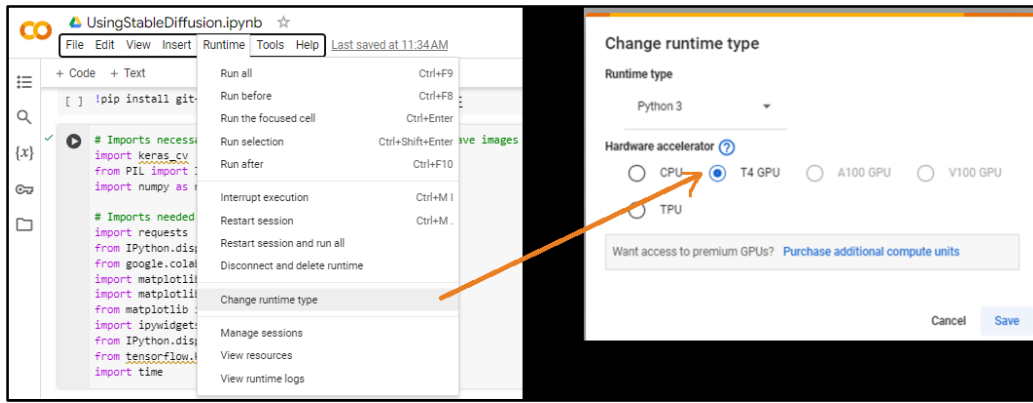
options = dict(
    prompt=prompt,
    batch_size=batch_size,
    num_steps=num_steps,
    unconditional_guidance_scale=unconditional_guidance_scale,
    seed=SEED
)

[ ] img = model.text_to_image(**options)
# Save image
Image.fromarray(img[0]).save("moon.png")

[ ] DisplayImage("moon.png")

[ ] FILE.download("/content/moon.png")

```



Images Generated by using the code given above. The prompt used was “dog”.



**Figure 5: Images generated using the text “dog” in the prompt by using the code given above**

#### IV. TEXT SPECIFICATION WITH DIFFERENT QUALIFIERS FOR STABLE DIFFUSION

The same text terms were used with different qualifiers. It was found that using qualifiers with the text makes the model introduce better semantics into the generated image, increases the realistic types and reduces the generation of non-related images or artworks.

#### V. RESULT VARIATIONS ON USING QUALIFIERS WITH PROMPTS

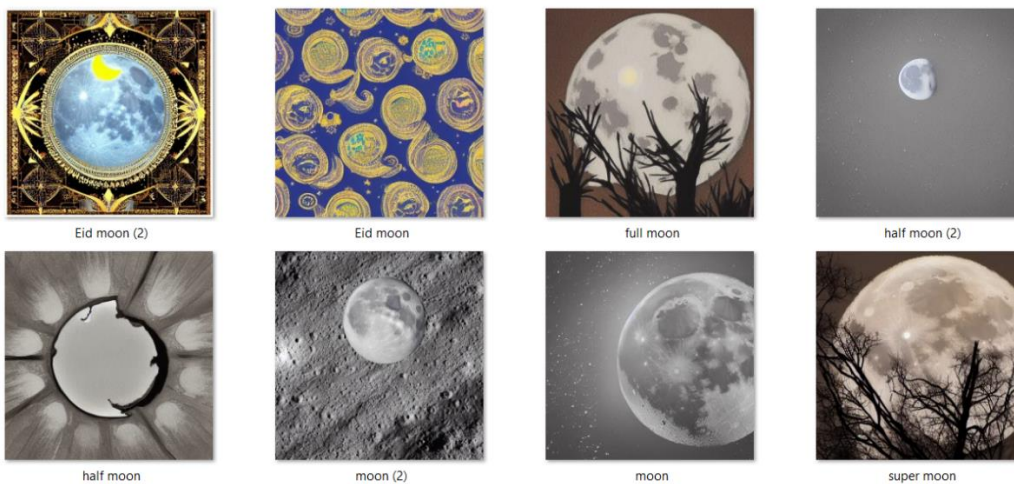
The results obtained are listed here for the different prompts:



**Figure 6: Prompt - room (With and without Qualifiers)**



**Figure 7: Prompt - art (With and without Qualifiers)**



**Figure 8: Prompt - moon (With and without Qualifiers)**



**Figure 9: Prompt - dog (With Qualifiers)**

**VI. ABOUT USING TWO-WORD QUALIFIERS WITH PROMPTS**

The use of two words qualifiers with text was seen creating mixed results. For example, the term “Bull headed dog” created the dogs with horns or as the bull. The term “cat friendly dog” produced the dog images with cat type hair.



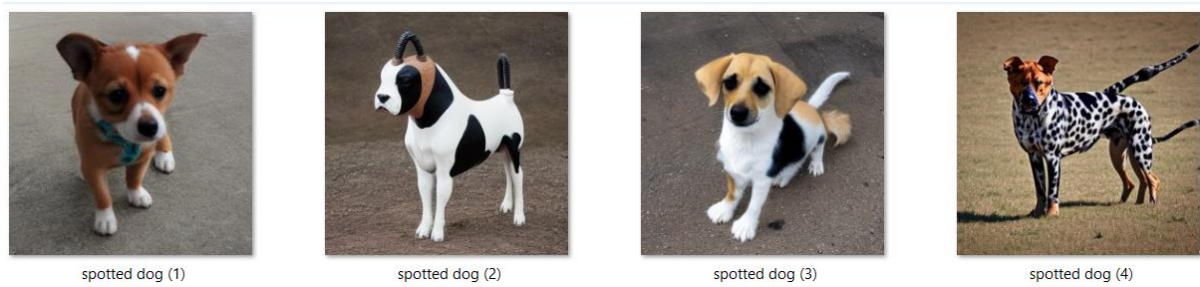
**Figure 10: Prompt - dog (With Two Word Qualifier - Bull-headed)**



**Figure 11: Prompt - dog (With Two Word Qualifier – Cat Friendly)**

## VII. SOME QUALIFIERS THAT INTRODUCED INCORRECT FEATURES IN IMAGES

The examples show here are specific to the term “dog”. Some of the qualifiers such as “naughty dog” and “spotted dog” added irrelevant features in the generated images. For example, in spotted dog (2), springs were put into the image. Also, in spotted dog (4) and naughty dog (3), the images contain two tails in the dog images.



**Figure 12: Prompt - dog (With One Word Qualifier – Spotted)**



**Figure 13: Prompt - dog (With One Word Qualifier – Naughty)**

## IV. RELATED STUDIES

Authors in [1], [2], [3], [4], [5] and [6] present different ways to provide the control in the image generation using the Stable Diffusion Model. Even in the Python code given above, the type of image generation can be controlled by providing different values for seed, num\_steps, or unconditional\_guidance\_scale. In the current study, it was seen that although the changes in these options led to creation of variations in images, however, the use of one-word qualifiers increased the meaningful features and semantic clarity for the generated images, in comparison to two-word qualifiers.

## IV. CONCLUSION

In this paper, the authors present their experimental results on testing the use of one- or two-words Qualifiers with Stable Diffusion prompts for the different types of text specifications. It was found that the meaningful one-word qualifiers enhance the meaningful features in the generated images while two-word qualifiers added some irrelevant or mixed features in the generated images.

## REFERENCES

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