National College of Ireland

Configuration Manual

MSc Research Project
Artificial Intelligence

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National College of Ireland
MSc Project Submission Sheet
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Text to Image Generation Using Gan

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X22170812

1 Introduction

This manual is created with stepwise implementation of how project implement worked and how model is created. In addition to it information and process of used libraries and tools required to carry out for project implementation is mentioned. Furthermore, information regarding specifications of location machine is mentioned in the manual. Each model information is mentioned in this configure manual.

2 HARDWARE CONFIGURATION

A. Operating system: Windows >= 7

B. Processor: Intel i5

C. System Compatibility: 64-bit

D. Hard Disk: 1TB

E. RAM: 8/16 GB

3 Research Questions

1. How can a novel deep architecture effectively integrate recurrent neural networks (RNNs) and generative adversarial networks (GANs) to synthesize realistic images from detailed textual descriptions?

2. To what extent can advancements in RNNs and GANs be harnessed to bridge the gap between text and image modelling, enabling the translation of textual concepts into visually plausible pixel-based representations?
3. What is the capability of the developed model in generating credible and realistic images of birds and flowers solely from intricate textual descriptions, and how does it compare to existing methods?
4. How can the quality, realism, and fidelity of the generated images be quantitatively and qualitatively assessed to provide comprehensive insights into the model's performance in text-to-image synthesis?
5. In what ways can the insights gained from this research contribute to advancements in Al capabilities for text-to-image generation, potentially pushing the boundaries of current technologies and enhancing the translation of textual semantics into visual realism?

4 Setup for Configuration

SOFTWARE CONFIGURATIONS

a) Python==3.7.9 :-

Python is a high-level, versatile programming language known for its readability and simplicity. It's favored for its ease of use and readability, making it an excellent choice for beginners and experienced developers alike. Python supports multiple programming paradigms (procedural, object-oriented, and functional), and its extensive standard library and third-party packages make it suitable for various applications, including web development, data analysis, machine learning, artificial intelligence, scientific computing, automation, and more. Its syntax emphasizes code readability and simplicity, enabling developers to write clear and concise code.

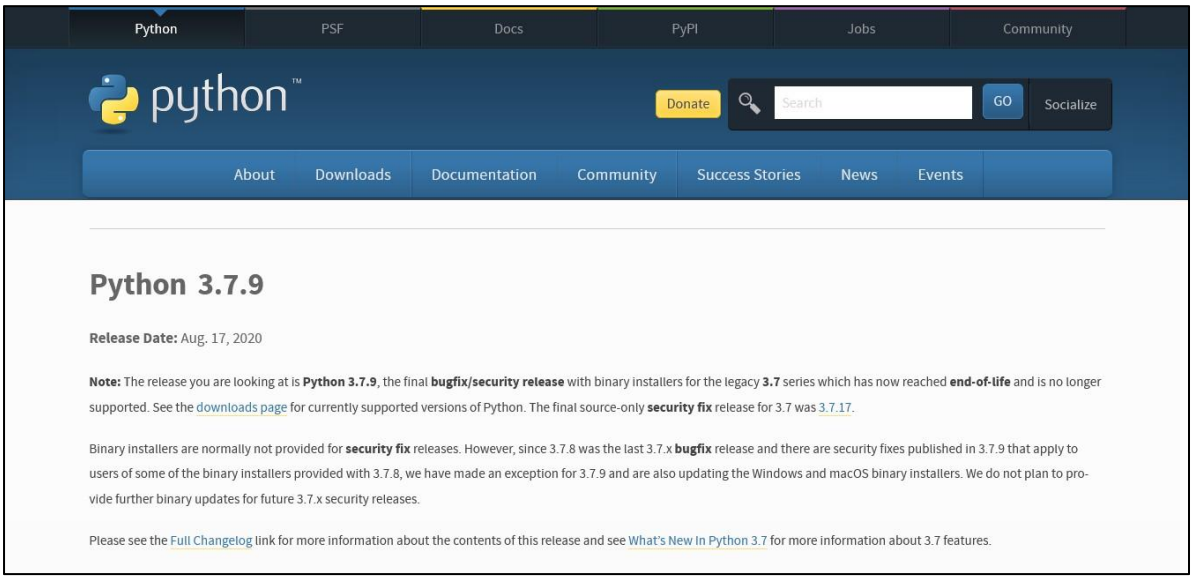


Fig 1 : Python.

b) Visual Studio Code:-

Visual Studio Code (VS Code) is a popular, free source code editor developed by Microsoft. It's known for its lightweight nature, extensive customization options, and support for a wide range of programming languages and frameworks.

Key features of VS Code include:

1. Cross-platform: Available on Windows, macOS, and Linux, ensuring a consistent experience across different operating systems.
2. Extensions: Offers a rich ecosystem of extensions contributed by the community, enabling support for various languages, debugging tools, themes, and more.
3. Integrated Development Environment (IDE) features: Provides features like IntelliSense (code completion), debugging, Git integration, syntax highlighting, and code refactoring, enhancing developer productivity.
4. Customization: Highly customizable through themes, keyboard shortcuts, and extensions, allowing developers to tailor their coding environment to suit their preferences and needs.
5. Built-in Terminal: Includes a built-in terminal within the editor, enabling developers to run commands, scripts, and various tools without leaving the coding environment.
6. Performance: Known for its speed and responsiveness, even when handling large projects or multiple files simultaneously, that cater to different programming needs.

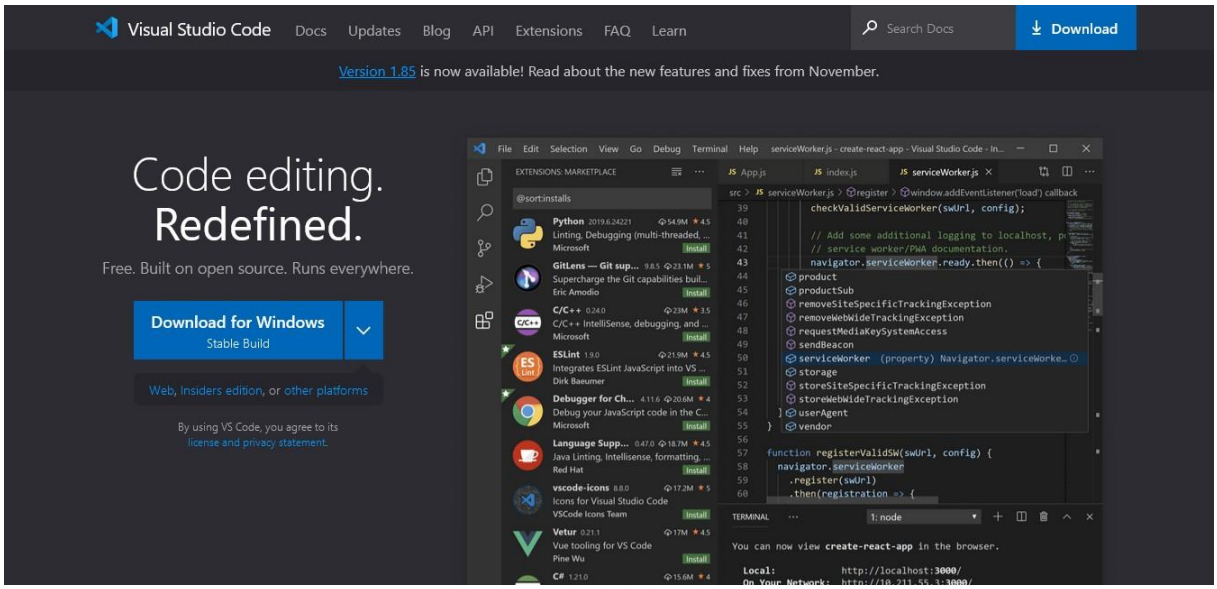


Fig 2 : Visual Studio.

c) Google Collab:-

Google Collab, short for Collaboratory, is a free cloud-based Jupiter notebook environment provided by Google. It allows users to write and execute Python code in a browser, eliminating the need to set up and configure development environments locally.

Key features of Google Collab include:

Free GPU/TPU support: Collab provides access to free GPU (Graphics Processing Unit) and TPU (Tensor Processing Unit) resources, enabling faster execution of machine learning and deep learning tasks.

Jupiter Notebook Integration: It's built on top of Jupiter notebooks, allowing users to create and share documents that contain live code, equations, visualizations, and narrative text.

Easy Collaboration: Users can share their Collab notebooks just like Google Docs, allowing for real-time collaboration among multiple users.

Pre-installed Libraries: Comes with pre-installed libraries commonly used in data science and machine learning, such as NumPy, Pandas, Matplotlib, TensorFlow, and more.

Cloud-Based: All computations are performed on Google's cloud servers, leveraging their computing power and storage.

Storage and Version Control: Integrates with Google Drive for easy storage and version control of notebooks.

Educational and Research Use: Widely used in academia and research for teaching, sharing code, experimenting with new ideas, and running data analysis or machine learning experiments. Google Collab serves as an accessible and convenient platform, particularly for those interested in experimenting with machine learning models, performing data analysis, or collaborating on coding projects without the need for high-end hardware or complex setup procedures.

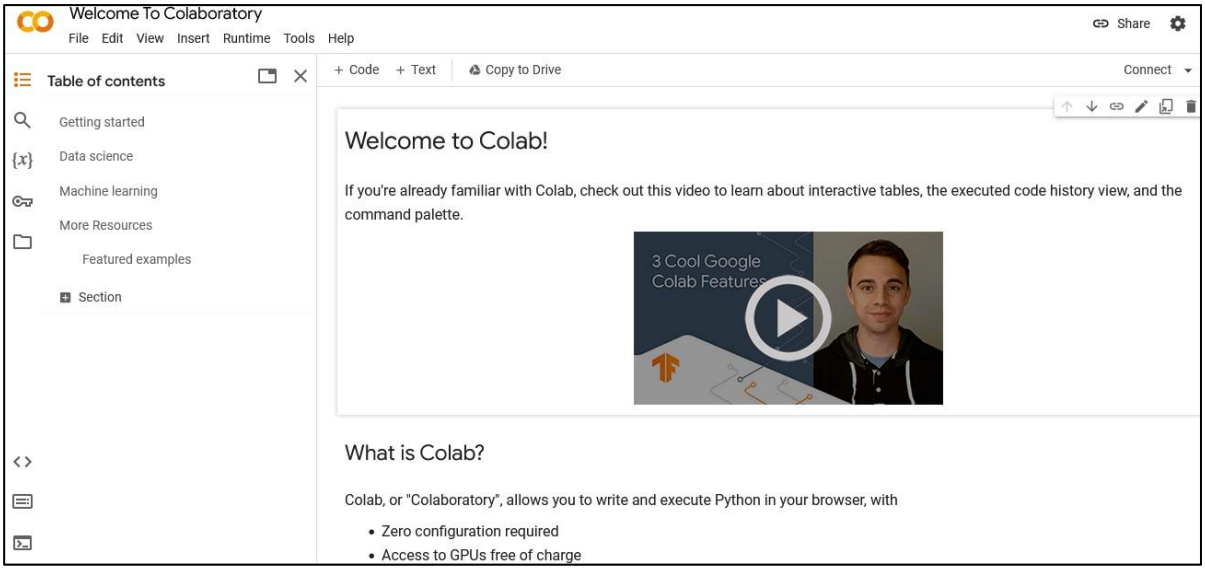


Fig 3 : Google Collab.

5 Libraries Configuration

I. Pandas: A powerful data manipulation and analysis library that provides easy-to-use data structures and tools for data cleaning, transformation, and analysis.

II. NumPy: Fundamental package for numerical computing in Python. It provides support for arrays, matrices, mathematical functions, and operations.

III. Matplotlib: A popular plotting library for creating static, interactive, and animated visualizations in Python. It offers a wide variety of plots and customization options.

IV. Seaborn: Built on top of Matplotlib, Seaborn provides a high-level interface for drawing attractive and informative statistical graphics.

V. Scikit-learn: A versatile machine learning library that provides simple and efficient tools for data mining and analysis. It includes a wide range of algorithms for classification, regression, clustering, etc.

VI. Tintern: Tintern is a standard GUI (Graphical User Interface) toolkit for Python. It's included with most Python installations, making it accessible and widely used for creating desktop applications with graphical interfaces.

VII. Imbalanced-learn: A library used for dealing with imbalanced datasets in machine learning. It provides techniques for oversampling, under sampling, and creating balanced datasets.

VIII. TensorFlow: An open-source machine learning framework developed by Google. It's widely used for building and training machine learning models, especially deep learning models.

IX. Kera's: An open-source neural network library. It's high-level and user-friendly, allowing for easy prototyping and experimentation with deep neural networks. (Note: It's often integrated with TensorFlow as of its integration into TensorFlow as tf.keras.)

X. URL lib: A Python library for opening URLs. It's used for fetching URLs, making requests, and handling responses.

XI. OpenCV (OpenCV-python): An open-source computer vision and machine learning software library. It provides tools and functions for image and video analysis, object detection, and more.

XII. Pillow: A Python Imaging Library (PIL) fork. It adds image processing capabilities to Python and supports opening, manipulating, and saving many different images file formats.

It is divided into five stages: business comprehension, data comprehension, data preparation, modelling, and evaluation. CRISP-DM acts as a guiding structure throughout the project lifecycle in the context of this study on text-to-image creation utilizing GANs.
It begins with understanding the technology's main objectives and prospective applications bridging word descriptions to visual representations—which aligns with the Business Understanding phase.
Following this, the Data Understanding step explores and comprehends the flower's dataset, verifying its eligibility for training the GAN model. The Data Preparation phase includes the preparation operations required to convert picture and text data into a model-compatible format. The modelling phase is concerned with the design and growth of the GAN architecture, whereas the evaluation phase examines the model's effectiveness in producing

realistic pictures from text descriptions. CRISP-DM was utilized in this report, which contains various stages, which are as follows:

6 Implementation

Importing All Library: -

```
[ ] # Imports
    import tensorflow as tf
    from tensorflow.keras.layers import Input, Reshape, Dropout, Dense, Concatenate
    from tensorflow.keras.layers import Flatten, BatchNormalization
    from tensorflow.keras.layers import Activation, ZeroPadding2D
    from tensorflow.keras.layers import LeakyReLU
    from tensorflow.keras.layers import UpSampling2D, Conv2D, Conv2DTranspose
    from tensorflow.keras.models import Sequential, Model, load_model
    from tensorflow.keras.optimizers import Adam
    from tensorflow.keras.utils import plot_model
    from tensorflow.keras import initializers
    from sklearn.metrics import mean_squared_error

    import numpy as np
    from PIL import Image
    from tqdm import tqdm
    import os
    import time
    import matplotlib.pyplot as plt
    import pickle
```

Fig 4 : Importing all Library.

Loading image data: -

```
+ Code + Text                                                                    Connect
    training_binary_path = os.path.join("/content/drive/MyDrive/text_to_image_generation/102flowers/npy64",
            f'training_data_{GENERATE_SQUARE}_{GENERATE_SQUARE}_')

    start = time.time()
    print("Loading training images...")

    training_data = []
    flowers_path = sorted(os.listdir(DATA_PATH))

    for filename in range(len(flowers_path)):
        path = os.path.join(DATA_PATH,flowers_path[filename])
        # print(path)
        try:
          image = Image.open(path).resize((GENERATE_SQUARE,
                GENERATE_SQUARE),Image.ANTIALIAS)
          channel = np.asarray(image).shape[2]
          if channel == 3:
            training_data.append(np.asarray(image))
        except KeyboardInterrupt:
            print("Keyboard Interrup by me...")
            break
        except:
          pass
        if len(training_data) == 100:
          training_data = np.reshape(training_data,(-1,GENERATE_SQUARE,
                    GENERATE_SQUARE,IMAGE_CHANNELS))
          training_data = training_data.astype(np.float32)
          #Normalizing the input
          training_data = training_data / 127.5 - 1.

          print("Saving training image " + str(100000 + filename) + ".npy")
          np.save(training_binary_path + str(100000 + filename) + ".npy",training_data)
          elapsed = time.time()-start
          print (f'Image preprocess time: {hms_string(elapsed)}')
          training_data = []
    print("Complete")
    Saving training image 101199.npy
    Image preprocess time: 0:03:35.32
    Saving training image 101299.npy
```

Fig 5 : Loding Image Data.

This diversity and intricacy are visualized using iso map, revealing the dataset's complexity through shape and color features, emphasizing the challenges and opportunities for image recognition and generation tasks. The dataset's unique characteristics, encompassing variations within and between categories, render it an ideal resource for training and evaluating models aimed at tasks like image classification, generation, and semantic

understanding of floral imagery.

Loading text data: -

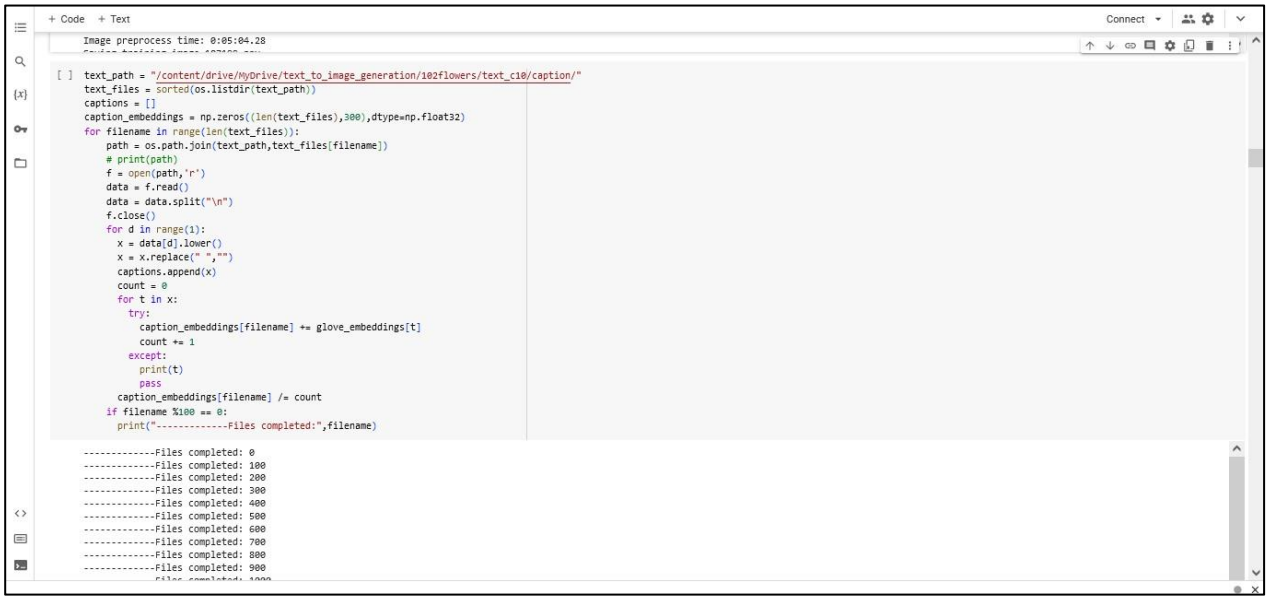


Fig 6 : Loading Text Data.

Preprocessing: -

Fig 7 : Processing the Data.

The dataset utilized in this project comprises 102 distinct categories of flower images, meticulously curated to represent commonly occurring flowers in the United Kingdom. Each category contains a variable number of images, ranging from 40 to 258 images per class. This diversity in image quantity across categories enriches the dataset, offering a comprehensive representation of various flower species. Each image is meticulously.

Annotated with descriptive sentences, providing context and information about the depicted flowers. Notably, the dataset exhibits extensive variability in terms of scale, pose, and lighting conditions, capturing the inherent complexities and nuances present in real-world

flower photography. Additionally, certain categories exhibit significant intra-category variations, contributing to the dataset's richness, while other categories showcase remarkable similarities.

\

Saving Caption Data into a csv file: -

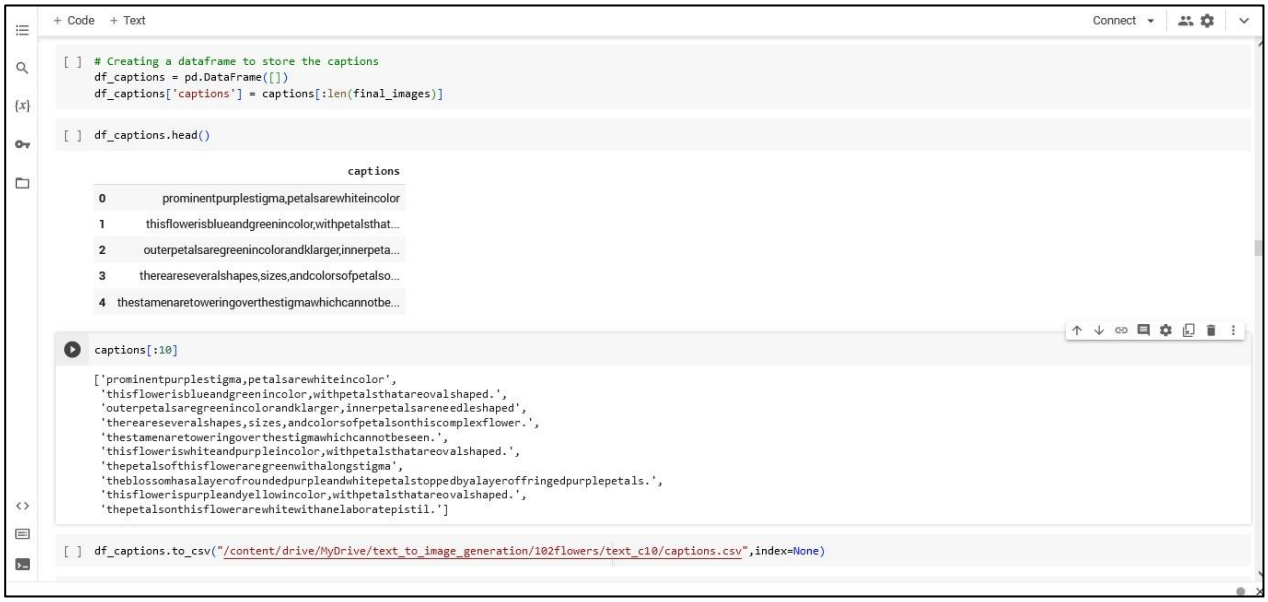


Fig 8 : Saving Caption Data.

The design specification chapter encapsulates the architectural blueprint and technical intricacies of the text-to-image generation system utilizing Generative Adversarial Networks (GANs). At its core, the system revolves around a novel deep architecture merging the power of recurrent neural networks and convolutional GANs. The primary goal is to bridge the gap between textual descriptions and visually plausible image outputs. The architectural design is segmented into key components: the Generator Layer, tasked with transforming text descriptions into high-resolution images, and the Discriminator Layer, responsible for discerning between real images from the dataset and those generated by the Generator. The Generator Layer, a pivotal element, harnesses recurrent networks or transposed convolutions to interpret text embeddings and create corresponding image representations.

7 Model Building

Generator Layer

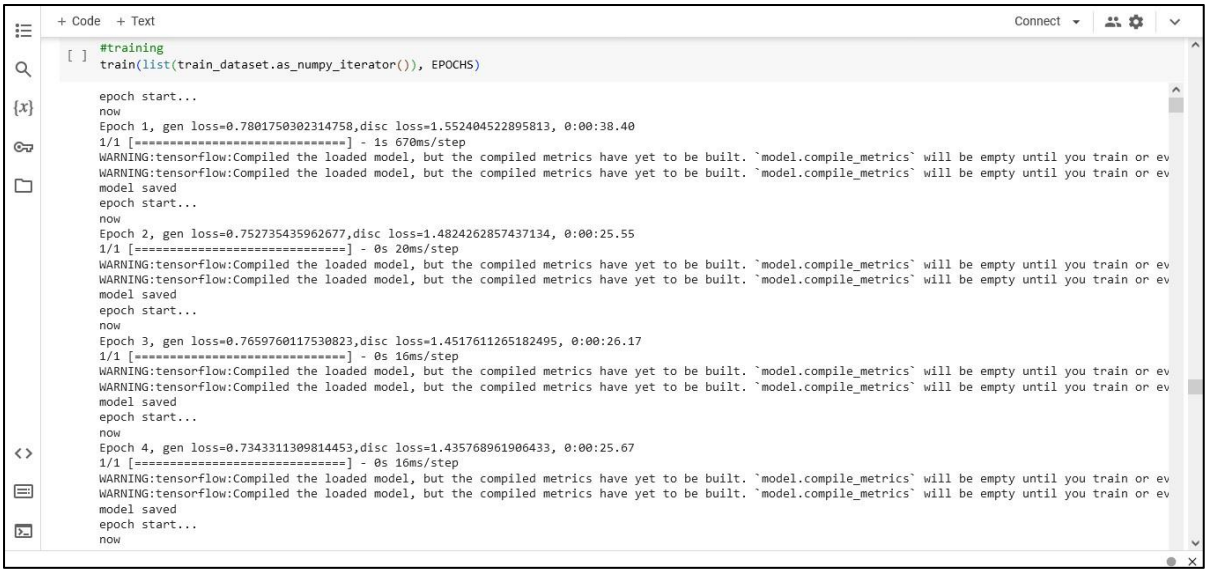
Fig 9 : Generator Layer.

Fig 10 :Discriminator Layer

```
[ ]  def build_discriminator_func(image_shape, embedding_size):
       input_shape = Input(shape=image_shape)
       input_embed = Input(shape=embedding_size)

       conv2d1 = Conv2D(32,kernel_size=4,strides=2,input_shape=image_shape,padding="same",kernel_initializer=initializers.RandomNormal(stddev=0.02))(input_shape)
       leaky1 = LeakyReLU(alpha=0.2)(conv2d1)

       drop2 = Dropout(0.25)(leaky1)
       conv2d2 = Conv2D(64, kernel_size=4, strides=2, padding="same",kernel_initializer=initializers.RandomNormal(stddev=0.02))(drop2)
       # zero2 = ZeroPadding2D(padding=((0,1),(0,1)))(conv2d2)
       batchNorm2 = BatchNormalization(momentum=0.8)(conv2d2)
       leaky2 = LeakyReLU(alpha=0.2)(batchNorm2)

       drop3 = Dropout(0.25)(leaky2)
       conv2d3 = Conv2D(128, kernel_size=4, strides=2, padding="same",kernel_initializer=initializers.RandomNormal(stddev=0.02))(drop3)
       batchNorm3 = BatchNormalization(momentum=0.8)(conv2d3)
       leaky3 = LeakyReLU(alpha=0.2)(batchNorm3)

       drop4 = Dropout(0.25)(leaky3)
       conv2d4 = Conv2D(256, kernel_size=4, strides=2, padding="same",kernel_initializer=initializers.RandomNormal(stddev=0.02))(drop4)
       batchNorm4 = BatchNormalization(momentum=0.8)(conv2d4)
       leaky4 = LeakyReLU(alpha=0.2)(batchNorm4)

       dense_embed = Dense(128,kernel_initializer=initializers.RandomNormal(stddev=0.02))(input_embed)
       leaky_embed = LeakyReLU(alpha=0.2)(dense_embed)
       reshape_embed = Reshape((4,4,8))(leaky_embed)
       merge_embed = Concatenate()([leaky4, reshape_embed])

       drop5 = Dropout(0.25)(merge_embed)
       conv2d5 = Conv2D(512, kernel_size=4,kernel_initializer=initializers.RandomNormal(stddev=0.02))(drop5)
       batchNorm5 = BatchNormalization(momentum=0.8)(conv2d5)
       leaky5 = LeakyReLU(alpha=0.2)(batchNorm5)

       drop6 = Dropout(0.25)(leaky5)
```

Fig 10 :Discriminator Layer.

Model Training Output: -



```
[ ]  #training
     train(list(train_dataset.as_numpy_iterator()), EPOCHS)

     epoch start...
     now
     Epoch 1, gen loss=0.7801750302314758,disc loss=1.552404522895813, 0:00:38.40
     1/1 [==============================] - 1s 670ms/step
     WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or ev
     WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or ev
     model saved
     epoch start...
     now
     Epoch 2, gen loss=0.752735435962677,disc loss=1.4824262857437134, 0:00:25.55
     1/1 [==============================] - 0s 20ms/step
     WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or ev
     WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or ev
     model saved
     epoch start...
     now
     Epoch 3, gen loss=0.7659760117530823,disc loss=1.4517611265182495, 0:00:26.17
     1/1 [==============================] - 0s 16ms/step
     WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or ev
     WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or ev
     model saved
     epoch start...
     now
     Epoch 4, gen loss=0.7343311309814453,disc loss=1.435768961906433, 0:00:25.67
     1/1 [==============================] - 0s 16ms/step
     WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or ev
     WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or ev
     model saved
     epoch start...
     now
```

Fig 11 : Model Training Output.

Within this design, careful consideration is given to the preprocessing pipeline, ensuring seamless integration of image and text data.

Preprocessing involves converting images into standardized NumPy arrays, adjusting pixel sizes as per predetermined specifications, and transforming textual descriptions into embeddings stored in a structured CSV format.

The system architecture also encompasses functions crucial for model training, such as the 'train_step' function, responsible for creating images based on text descriptions, calculating losses, and adjusting gradients, and the overarching 'train' function, orchestrating the training process by fetching batch data and aggregating losses.

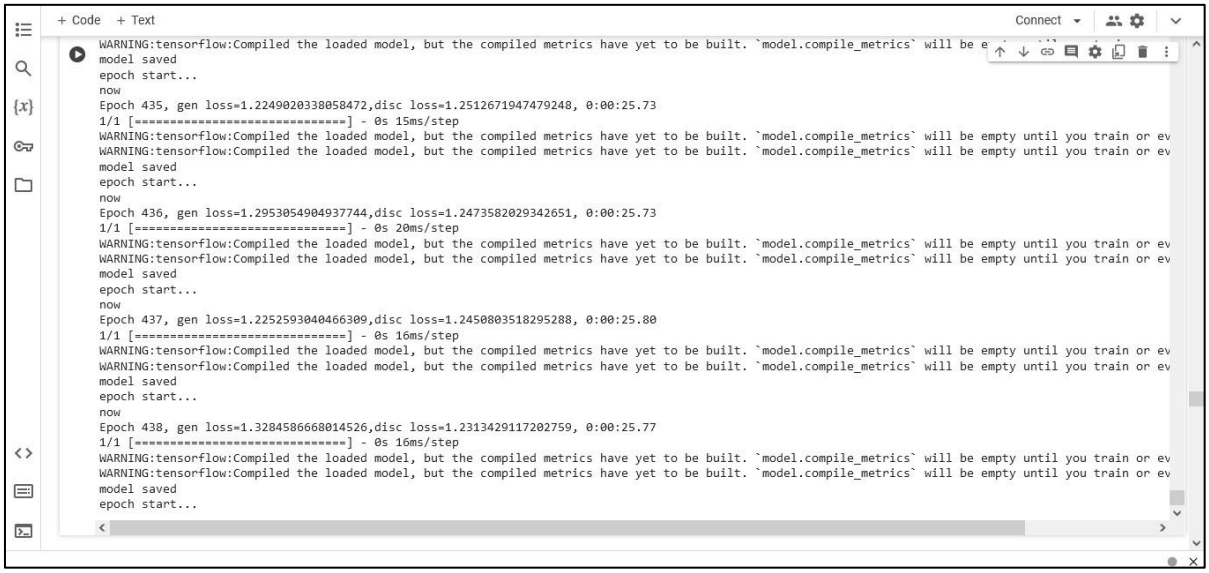


Fig 12 : Model Training.

7 Evaluation

Fig 13 : Evaluation,

The Image Generator Model's outputs represent a great achievement after a lengthy training period of roughly 450 epochs and a total training duration of 24 hours. The design of the model included both the Discriminator and Generator networks, which are critical components of the GAN framework for text-to-image creation.

Specific functions were used to calculate losses for both the Discriminator and Generator networks during the training phase. Consequently, visible progress was made by the 438th epoch, with the Generator loss measured at 1.3284586668014526 and the Discriminator loss measured at 1.2313429117202759. The achieved losses imply that the Generator and

Discriminator networks are approaching equilibrium. A decreasing Generator loss implies that the model's capacity to create more realistic pictures from textual descriptions is improving. Meanwhile, the Discriminator loss, while greater than the Generator loss as predicted in adversarial training, represents the network's capacity to distinguish between actual and created pictures.

Output Testing: -

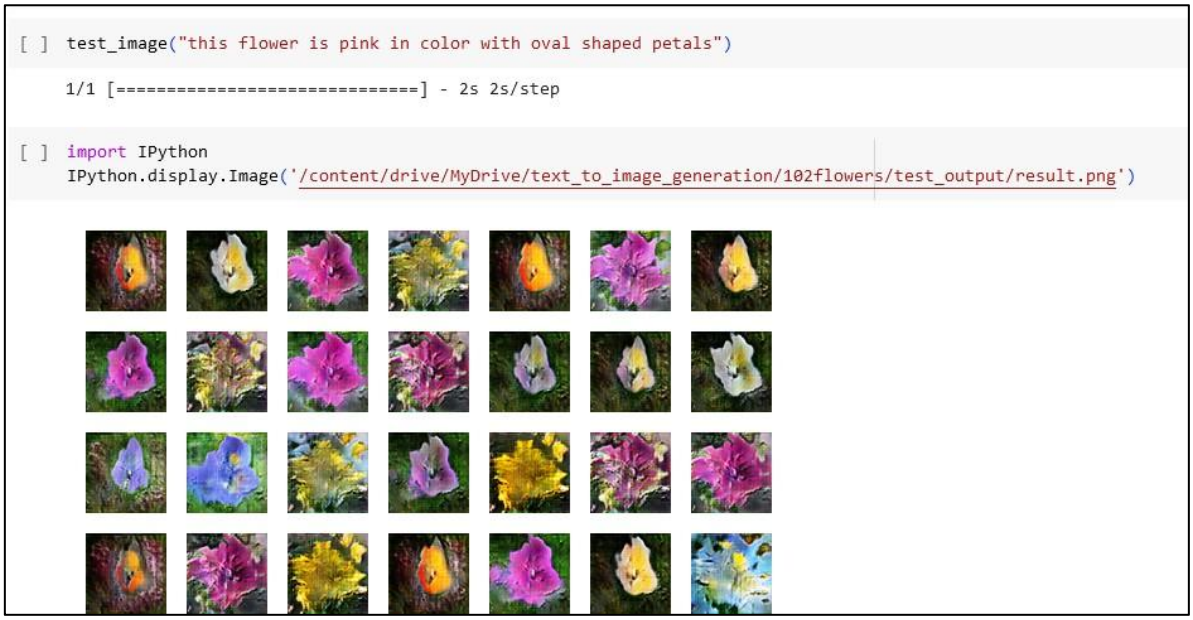


Fig 14 : Output Testing.

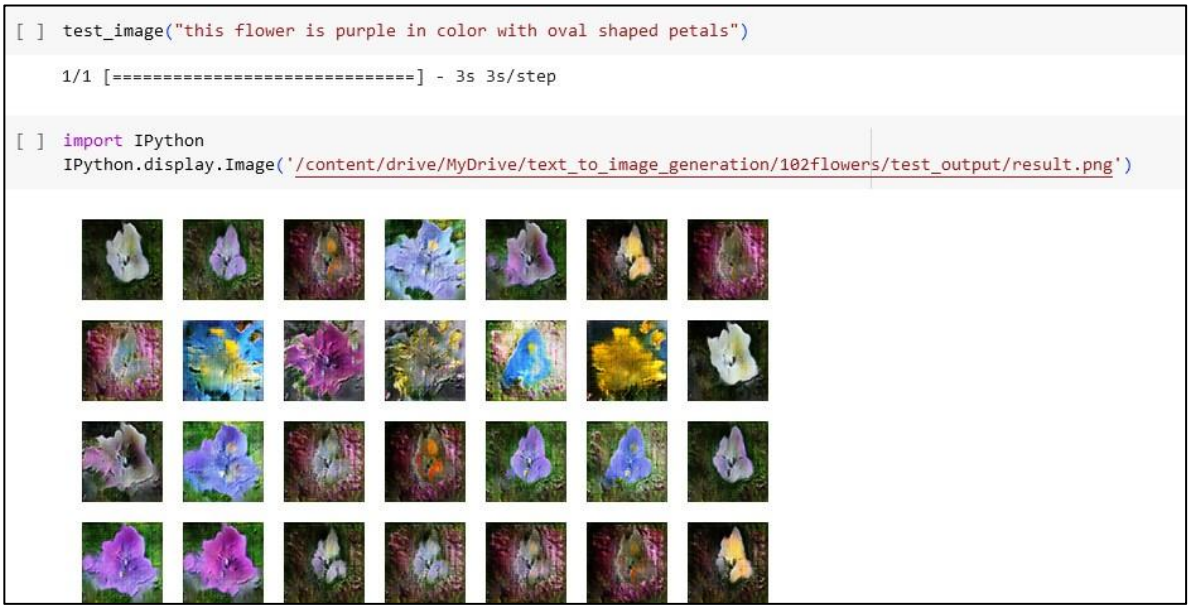


Fig 15 : Output Testing.

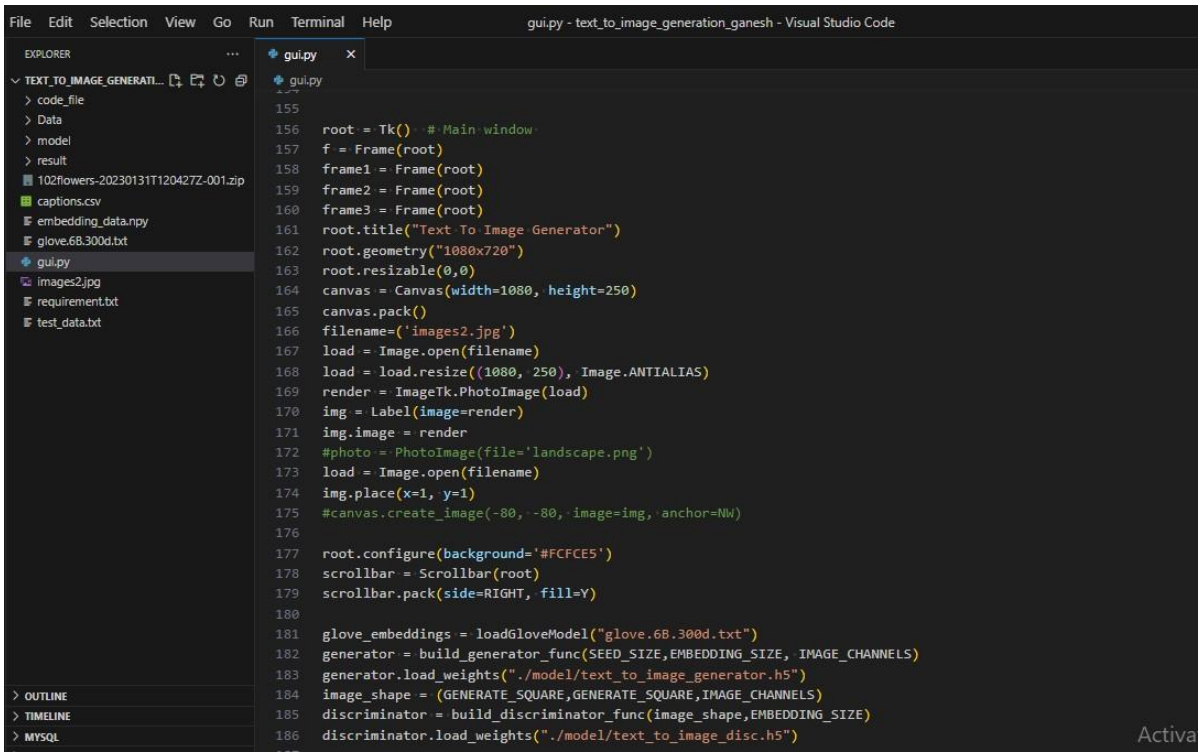
The showcased test_image portrays a flower characterized by a purple hue, exhibiting oval-shaped petals. The textual description accompanying this image emphasizes these distinct

visual attributes. Subsequently, upon examining the test_output result, it reveals a multitude of smaller images.

These images are likely the generated outputs produced by the model in response to the provided textual description. The presence of numerous smaller images suggests the model's attempts to interpret and generate various visual representations corresponding to the textual description of a purple-colored flower with oval-shaped petals.

This observation underscores the model's efforts in generating diverse outputs to encapsulate the potential variations and nuances inherent in the given textual input, aiming to produce a range of plausible floral images that align with the described characteristics. Further evaluation and analysis of these outputs would provide deeper insights into the model's ability to interpret textual descriptions.

Gui Output Tkinter:-



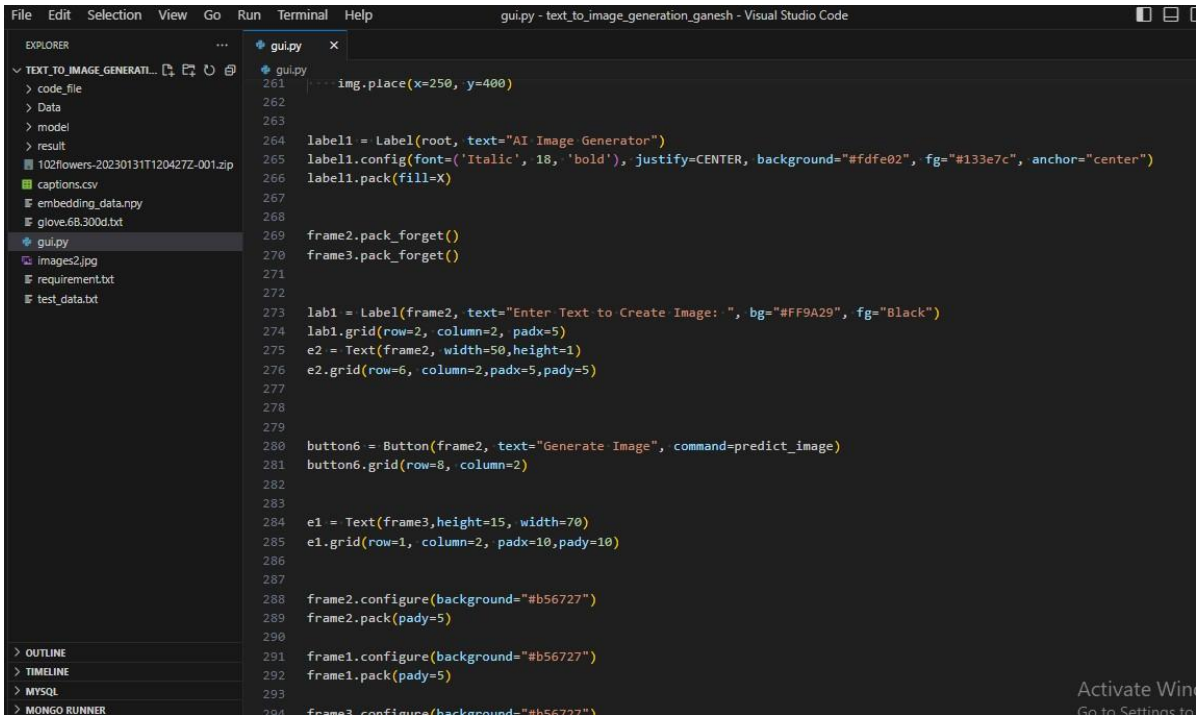


Fig 16 : Gui Output Tkinter.

Al-powered text-to-image generator interface. The displayed image represents the user interface or platform designed for generating images from textual descriptions using artificial intelligence. The interface features a message prompting the user: "Enter text to create Image then click on generate image. This message serves as an instruction or guidance for the user, outlining the required steps to utilize the image generation functionality offered by the Al system. Users are encouraged to input textual descriptions of the desired image content into the provided text entry field.

Once the desired text is entered, the user initiates the image generation process by clicking on the "generate image" button or similar interface element. This action prompts the AI image generator to interpret the input text and produce corresponding visual outputs, generating images that encapsulate the semantic content described in the entered text. This action prompts the Al image generator to interpret the input text and produce corresponding visual outputs, generating images that encapsulate the semantic content described in the entered text. The interface design aims to facilitate user interaction, enabling individuals to effortlessly create images based on their textual descriptions through a straightforward and intuitive process within the Al-powered image generation platform.

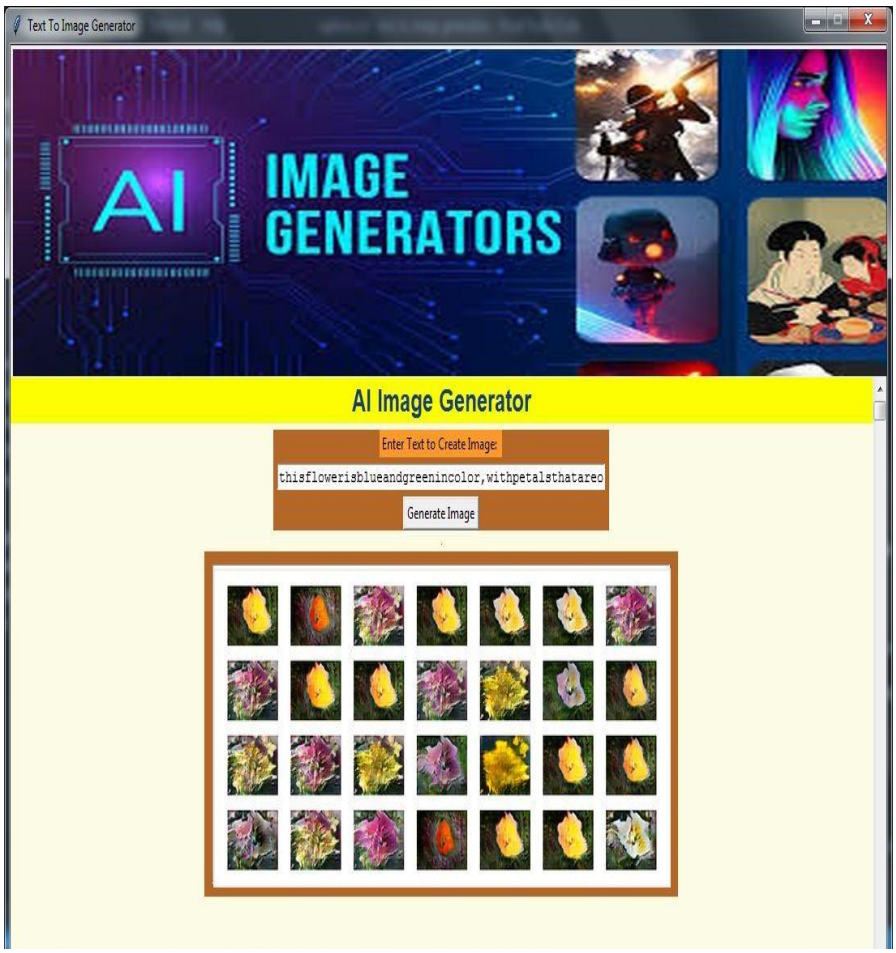


Fig 17 : AI image detector.

8 Conclusion and Future Work

Significant milestones and discoveries have occurred throughout the development of a text-to-image generating model employing GANs. Convergence in the Generator and Discriminator networks, as indicated by lowering Generator loss and maintaining Discriminator loss, demonstrates potential progress in synthesising realistic pictures from textual descriptions. The lengthy training process, which lasted around 450 epochs over 24 hours, reflects the model's intricacy and the diligent efforts made to optimise its capabilities. This checkpoint is a critical stage in the development of the model, establishing the framework for detailed assessment and potential practical implementations.

Despite development, several limits remain. The present assessment, which focuses on losses and convergence, does not fully reflect the quality and perceptual integrity of produced pictures. To support quantitative measurements, subjective assessments and sophisticated qualitative evaluations are required. Furthermore, the computational intensity and time required for training need optimization measures to improve efficiency and scalability.

Traditional Al systems have excelled in specific fields such as natural language understanding and picture identification. However, synergy across these fields remains a difficult frontier. The hunt for coherent and contextually meaningful pictures from textual descriptions has piqued the interest of many researchers. This approach combines subtle textual comprehension with elaborate visual interpretation a union that necessitates novel neural network designs and advanced learning processes.

The fundamental goal of this research is to go ahead in the field of artificial intelligence by concentrating on the creation of a revolutionary method for producing realistic visuals exclusively from precise textual descriptions. To achieve this goal, the research will take advantage of recent advances in recurrent neural networks (RNNs) for learning discriminative text features, as well as the capabilities of deep convolutional generative adversarial networks (GANs) for producing highly realistic images within specific categories. The project aims to bridge the gap between text and picture modelling by incorporating these advances, culminating in the development of a robust deep architecture and GAN formulation. The aim is to demonstrate the model's ability to translate complex textual notions like birds and flowers into visually appealing and credible image outputs, therefore greatly advancing the area of text-to-image creation in artificial intelligence.

This report delves into the pursuit of generating realistic images from textual descriptions, a compelling yet challenging task within current Al systems. While existing technologies fall short of this goal, recent advancements in recurrent neural networks have demonstrated proficiency in learning discriminative text features. Additionally, deep convolutional generative adversarial networks (GANs) have shown promise in generating highly realistic images across specific categories like faces, album covers, and interiors. In this study, I introduce a novel deep architecture and GAN formulation aimed at bridging these text and image modelling advancements. Here approach is centred on translating textual concepts into vivid visual representations, effectively converting characters into pixelated images. Through rigorous experimentation, we showcase the capability of our model to produce credible images of birds and flowers from intricate textual descriptions. This work represents a significant step toward achieving the synthesis of detailed images solely from text, offering insights into the convergence of text and image modelling within the realm of artificial intelligence.

The confluence of artificial intelligence (Al) in natural language processing (NLP) and computer vision in recent years has resulted in significant advances in the field of text-to-image creation. This emerging discipline aims to bridge the gap between verbal descriptions and visual representations, culminating in the creation of realistic visuals only from

comprehensive word inputs. The capacity to transform textual semantics into visually appealing visuals has enormous potential in a variety of disciplines, including design, content development, and augmented reality applications (Ramesh et al., 2021). The automatic production of realistic pictures from written descriptions has a wide range of possible applications, including image editing, video games, and accessibility.
Traditional Al systems have excelled in specific fields such as natural language understanding and picture identification. However, synergy across these fields remains a difficult frontier. The hunt for coherent and contextually meaningful pictures from textual descriptions has piqued the interest of many researchers. This approach combines subtle textual comprehension with elaborate visual interpretation—a union that necessitates novel neural network designs and advanced learning processes.

Future enhancements and research avenues encompass multifaceted dimensions. Comprehensive evaluation involving human ratters' subjective assessments will gauge the perceptual fidelity and realism of generated images, providing nuanced insights. Fine-tuning parameters, such as optimizing optimizer configurations and fine-tuning learning rates, can further elevate the model's performance. Exploration of advanced GAN variants or attention mechanisms might enrich the model's ability to capture intricate details and improve image quality. Furthermore, considerations for scalability and efficiency, possibly through parallel computing or hardware acceleration, will expedite model training and deployment.

In conclusion, while this phase signifies substantial progress in text-to-image generation, a comprehensive evaluation, fine-tuning, and exploration of advanced techniques remain crucial for refining the model's capabilities and ensuring its practical applicability across diverse domains. This checkpoint sets the trajectory for continued research, aiming to push the boundaries of text-to-image generation technology and unlock its potential in various real-world applications.