Exploring the Power of Generative Adversarial Networks (GANs) for Image Generation: A Case Study on the MNIST Dataset

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Exploring the Power of Generative Adversarial Networks (GANs) for Image Generation: A Case Study on the MNIST Dataset

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ABSTRACT: This paper provides a comprehensive examination of Generative Adversarial Networks (GANs)**,** a groundbreaking deep learning architecture that has transformed the field of image generation. GANs consist of two neural networks—the generator and the discriminator—that engage in a competitive process to produce highly realistic images by learning patterns from existing data. This study highlights several key applications of GANs, including text-to-image generation**,** super-resolution**,** neural style transfer**,** andimage completion**.** These applications have significant implications for various industries, such as medical imaging, creative content generation, and data augmentation for machinelearning models.

The practical implementation section utilizes the MNIST dataset to illustrate how GANs can generate new, realistic images of handwritten digits. This implementation underscores the importance of data preprocessing, such as normalizationandshuffling**,** in improving model accuracy and performance. The paper also explores the critical role of GPU accelerationin speeding up the training process and the selection of optimal **loss** functions**,** particularly the cross-entropy loss, to enhance the discriminator's ability to differentiate between real and generated data.

Moreover, the paper addresses the inherent challenges in training GANs, such as mode collapse and the extensive computational resources required. Solutions and best practices, including advanced optimization techniques and checkpointing, are discussed to ensure stable and efficient model training. The results demonstrate the remarkable ability of GANs to generate images that closely resemble real data, with promising applications in the fields of imaging systems, healthcare, and beyond. Future directions for research and emerging trends in GAN technology are also outlined.

KEYWORDS:
Generative Adversarial Networks, GANs, image generation, text-to-image, super-resolution, neural style transfer, MNIST dataset, GPU acceleration, loss function, mode collapse, data preprocessing, cross-entropy loss, image completion.

I. INTRODUCTION

Generative Adversarial Networks (GANs) have rapidly advanced the field of artificial intelligence, becoming one of the most impactful developments in recent years, particularly in the domain of image synthesis and manipulation. First introduced by Ian Goodfellow and his collaborators in 2014, GANs have since established themselves as a powerful deep learning framework that can generate new data samples with remarkable realism. This breakthrough has fundamentally transformed a range of industries, from medical imaging and scientific visualizationto entertainment**,** autonomous driving, and security surveillance**,** where high-quality data generation is crucial. GANs represent a shift toward a new era of machine learning, where artificial intelligence not only processes information but also creates it.

The core architecture of GANs is centered around two adversarial neural networks the generator and the discriminatorwhich are trained together in a zero-sum game. The generator produces synthetic data, such as images, by learning from a real dataset, while the discriminator

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attempts to distinguish between the real and synthetic data. Through this adversarial process, the generator progressively improves its ability to produce data that becomes indistinguishable from the real dataset. This competition drives the network to create images, videos, and other forms of media with high fidelity, opening new possibilities in areas like text-to-image generation**,** image super-resolution**,** neural style transfer**,** and image inpainting**.**

The versatility and power of GANs are evident in their wide-ranging applications. In medical imaging, GANs enhance image resolution and generate synthetic medical images to augment limited datasets, thereby aiding in disease diagnosis and treatment planning. In the entertainment industry, GANs have been used to generate hyper-realistic faces, scenes, and textures for video games, films, and virtual environments. The ability of GANs to generate synthetic data has alsoproven invaluable in autonomous systems**,** where they are used to simulate various driving conditions to train self-driving cars, and in surveillance**,** where GANs enhance and restore low-quality security footage.

However, despite their promise, GANs present several well-documented challenges**.** Mode collapse**,** where the generator produces a limited variety of outputs, is a persistent problem that can hinder the diversity of generated data. Additionally, the training instabilityinherent to the adversarial process, where both networks oscillate or fail to converge, requires careful tuning of hyperparameters and architectural choices. Furthermore, GAN training is computationally expensive, often necessitating specialized hardware such as GPU acceleration to achieve feasible training times. These limitations have led to ongoing research and the development of more robust GAN architectures, including Deep Convolutional GANs (DCGANs)**,** Wasserstein GANs (WGANs)**,** and CycleGANs, each designed to address specific issues and improve the performance and stability of GANs across different domains.

This paper aims to provide a comprehensive understanding of GANs, focusing on both their theoretical underpinnings and practical applications. The first part of the paper reviews the fundamental concepts behind GANs, elaborating on their architecture, training dynamics, and diverse use cases. The second part presents a hands-on implementation using the MNIST dataset, a benchmark in image generation tasks, where GANs are used to generate realistic handwritten digits. Key considerations such as data pre-processing**,** optimization techniques**,** and the selection of appropriate loss functions are discussed in depth, with a focus on improving model performance and training efficiency. The paper also highlights solutions to common challenges in GAN training, including check pointing to avoid data loss during extended training sessions and methods to address mode collapse**.**

Finally, the paper discusses the broader implications of GANs in advancing imaging systems, particularly in fields like medical diagnostics**,** remote sensing**,** and creative industries**.** By demonstrating the powerful capabilities of GANs in generating high-quality data, this paper contributes to the growing body of research that explores how GANs can drive innovation in a wide range of applications. Additionally, future directions are suggested, particularly in the integration of GANs with emerging technologiessuch asquantum computingandedge AI, which could further enhance their computational efficiency and broaden their applicability.

II. RELATED WORK

Generative Adversarial Networks (GANs) have been a focal point of research since their inception in 2014. Ian Goodfellow's pioneering work laid the foundation for GANs, where two adversarial networks—the generator and discriminator—are trained simultaneously to enhance the quality of data generation. Since then, various improvements and extensions have been developed, addressing specific limitations in the original GAN architecture.

Early GAN architectures, such as Deep Convolutional GANs (DCGANs)**,** proposed by Radford et al. (2015), introduced convolutional layers, which significantly improved the ability of GANs to generate high-quality images. DCGANs demonstrated that stable training could be achieved by replacing fully connected layers with convolutional layers, thus opening the door to applying GANs to more complex image datasets.

In the field of super-resolution**,**Ledig et al. (2017) introduced Super-Resolution GAN (SRGAN)**,** which is a notable advancement in enhancing the resolution of low-quality images. SRGAN showed that GANs could be effectively applied to the problem of single image super-resolution (SISR) by training the generator to produce high-resolution images from low-resolution inputs, while the discriminator works to distinguish between the real high-resolution images and the generated ones. This breakthrough has had significant implications for fields like medical

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imaging and satellite imagery, where high-resolution images are critical.

In parallel, Neural Style Transfer has evolved as a creative application of GANs. Johnson et al. (2016) combined GANs with convolutional neural networks to transfer the artistic style of one image to another, producing visually appealing results. This work built upon earlier neural style transfer methods by improving both the efficiency and quality of the generated images. GANs further pushed the boundaries by offering more realistic style transfers, particularly through the use of CycleGAN **(**Zhu et al., 2017), which enabled style transfer without requiring paired training data.

Another critical application of GANs is image completion, where missing or corrupted parts of an image are generated to complete the visual. Pathak et al. (2016) introduced Context Encoders**,** which employed GANs for image inpainting tasks, where a network could predict and fill missing regions of an image based on surrounding pixel information. More recent innovations, such as SC-FEGAN (Jo & Park, 2019), have extended this concept to face image completion, using sketches and color inputs to produce photorealistic image completions.

Beyond applications, several studies have addressed the inherent challenges of training GANs. Mode collapse**,** where the generator produces limited variations of outputs, remains a prominent issue. Wasserstein GANs (WGANs)**,** introduced by Arjovsky et al. (2017), tackled this problem by using the Wasserstein distance instead of the traditional loss functions, leading to more stable training and better convergence. This innovation has greatly enhanced the reliability of GANs, particularly in large-scale datasets.

In the context of evaluation, various metrics have been proposed to assess the quality of images generated by GANs. The Inception Score (IS) (Salimans et al., 2016) and Fréchet Inception Distance (FID) (Heusel et al., 2017) are widely used to quantify the diversity and realism of the generated images. These metrics are crucial in benchmarking GAN performance, allowing researchers to compare the efficacy of different GAN architectures. While much progress has been made, GANs still face limitations, particularly in their computational requirements. Recent efforts have focused on reducing training time by leveraging GPU acceleration and optimizing training processes. Techniques like mixed precision training**,** as demonstrated by Micikevicius et al. (2018), have been instrumental in enhancing training efficiency without sacrificing model accuracy, further broadening the applicability of GANs in real-world tasks.

In summary, the field of GANs has witnessed rapid advancements, with innovations in architecture, application, and training methods. The present study builds upon this foundation by exploring practical implementations of GANs in image generation, offering insights into optimizing GAN training, and demonstrating their potential in advancing image synthesis technologies.

Key Citations:

- Goodfellow et al. (2014) - Introduced the concept of GANs.
- Radford et al. (2015) - Developed DCGAN, improving image generation with convolutional layers.
- Ledig et al. (2017) - Proposed SRGAN for super-resolution applications.
- Zhu et al. (2017) - Introduced CycleGAN for unpaired image-to-image translation.
- Pathak et al. (2016) - Developed Context Encoders for image completion.
- Arjovsky et al. (2017) - Introduced WGAN to solve mode collapse.
- Salimans et al. (2016), Heusel et al. (2017) - Proposed IS and FID as evaluation metrics for GANs.

III. METHODOLOGY

[1]. **Generative Adversarial Networks (GANs) Architecture**

Generative Adversarial Networks (GANs) consist of two neural networks, the generator and the discriminator, which compete in a minimax game. The goal of the generator is to produce synthetic data that mimics the real data, while the discriminator's role is to distinguish between real and generated data. This adversarial process improves both networks, leading to more realistic generated data over time.

Generator Network: The generator is a neural network that takes a random noise vector zzz as input and generates synthetic data G(z)G(z)G(z) that resembles the real data. The network is designed with several hidden layers that progressively transform the input noise into a data sample. The primary objective of the generator is to generate data that can "fool" the discriminator into classifying it as real.

The architecture of the generator consists of:

- **Input layer**: A random noise vector sampled from a Gaussian distribution.

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- **Hidden layers**: Fully connected layers followed by up sampling and convolutional layers (in the case of image generation), with ReLU activations.
- **Output layer**: A single-layer output that produces a data sample (e.g., an image).

Mathematically, the generator's objective is to minimize the loss function:
$\min_G \; Ez{\sim}pz(z)[\log(1-D(G(z)))]$
where D(G(z)) D(G(z)) D(G(z)) represents the probability assigned by the discriminator to thegenerated data.

Example Text for Methodology:Discriminator Network**:** The discriminator is a binary classifier tasked with distinguishing between real data xxx and generated data G(z)G(z)G(z). The discriminator's network architecture typically consists of multiple convolutional layers followed by fully connected layers, allowing it to extract complex features from the input data.
The discriminator outputs a probability score between 0 and 1, representing the likelihood that the input data is real. The discriminator is trained to maximize the probability of correctly classifying real and fake data, which is achieved by minimizing the following loss function:
$\max_D Ex{\sim}pdata(x)[\log D(x)] + Ez{\sim}pz(z)[\log(1-D(G(z)))]$

- max: Indicates that the goal is to maximize the expression with respect to DDD (the discriminator).
- E: Denotes the expected value.
- x∼pdata(x): Means xxx is sampled from the true data distribution.
- logD(x): The log probability that the discriminator correctly identifies real data.
- z∼pz(z): Indicates zzz is sampled from the generator's input noise distribution.
- log(1−D(G(z))): The log probability that the discriminator correctly identifies generated (fake) data as fake.

This expression represents the objectivefunction for the discriminator in a Generative Adversarial Network (GAN). The adversarial game between the generator and discriminator continues until a Nash equilibrium is reached, where the generator produces highly realistic data that the discriminator can no longer reliably classify as real or fake.

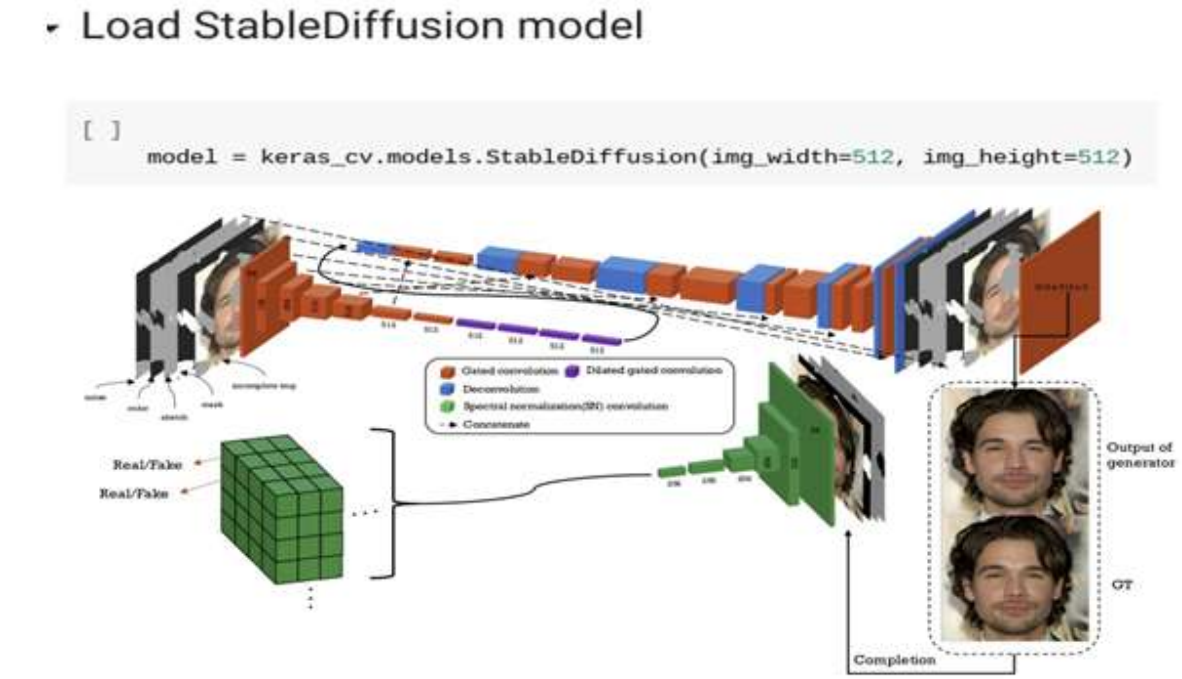

Figure 2. Architecture of the Generative Adversarial Network (GAN) Used to Generate and Complete Images.

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Figure 3. Face Image Editing Results (Jo & Park, N.D.)
Architecture of the generative adversarial network (gan) used to generate and complete images.

[2]. Data Pre-processing

For this study, the MNIST dataset is used, which contains 70,000 grayscale images of handwritten digits, with 60,000 images in the training set and 10,000 images in the test set. Each image is of size 28x28 pixels**.**

a. Normalization: The images are normalized to have pixel values between -1 and 1 to enhance the numerical stability of the network. This is done by scaling the original pixel values (0 to 255) using the formula:

$X_{normalized} = \frac{\{x - 127.5\}}{127.5}$ of xxx.

Import packages

```
[1] import os
    import time
    from PIL import Image
    import numpy as np
    import tensorflow as tf
    import tensorflow_hub as hub
    import matplotlib.pyplot as plt
    from mpl_toolkits.axes_grid1 import ImageGrid
    os.environ["TFHUB_DOWNLOAD_PROGRESS"] = "True"
```

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Helper Methods

```
[4] # Show images in the grid
    def ShowImages(images, labels,rows,cols,title='',figsize=(10., 10.)):
      fig = plt.figure(figsize=figsize)
      grid = ImageGrid(fig, 111,  # similar to subplot(111)
                       nrows_ncols=(rows, cols),
                       axes_pad=0.3,  # pad between axes in inch.
                       )

      for ax, im,label in zip(grid, images,labels):
          # Iterating over the grid returns the Axes.
          ax.set_title(label)
          ax.imshow(im)
      plt.title=title
      plt.show()
```

```
[5] def preprocess_image(img_path):
      img_tensor = tf.convert_to_tensor(img)
      hr_image = tf.image.decode_image(tf.io.read_file(img_path))
      # If PNG, remove the alpha channel. The model only supports
      # images with 3 color channels.
      if hr_image.shape[-1] == 4:
        hr_image = hr_image[...,:-1]
      hr_size = (tf.convert_to_tensor(hr_image.shape[:-1]) // 4) * 4
      hr_image = tf.image.crop_to_bounding_box(hr_image, 0, 0, hr_size[0], hr_size[1])
      hr_image = tf.cast(hr_image, tf.float32)
      return tf.expand_dims(hr_image, 0)
```

```
[6] def resize_images():
      # Set the desired size of the images
      desired_size = (256, 256)
      for img_file in img_files:
        img = Image.open(img_path + img_file)
        # Resize the image
        img = img.resize(desired_size)
        img.save( img_path + img_file)
```

```
[7] def get_image_from_tensor(img_tensor):
      image = tf.squeeze(img_tensor)
      image=np.array(image)
      image = tf.clip_by_value(image,0,255)
      image = Image.fromarray(tf.cast(image,tf.uint8).numpy())
      return image
```

Initialize Model and image file paths

```
[8] # Model Path
    super_resolution_model_path = "https://tfhub.dev/captain-pool/esrgan-tf2/1"

    # Image file path
    img_path='/content/drive/MyDrive/CSUG/CSC580/Portfolio_Project/Images/'
    img_files=['LowImg_1.png','LowImg_2.png','LowImg_3.png','LowImg_4.png','LowImg_5.png','LowImg_6.png']
```

```
[9] # Rezie the images
    resize_images()
```

```
[10] # Load Images
     images=[]
     for img_file in img_files:
       img = Image.open(img_path + img_file)
       images.append(np.array(img))
```

Double-click (or enter) to edit

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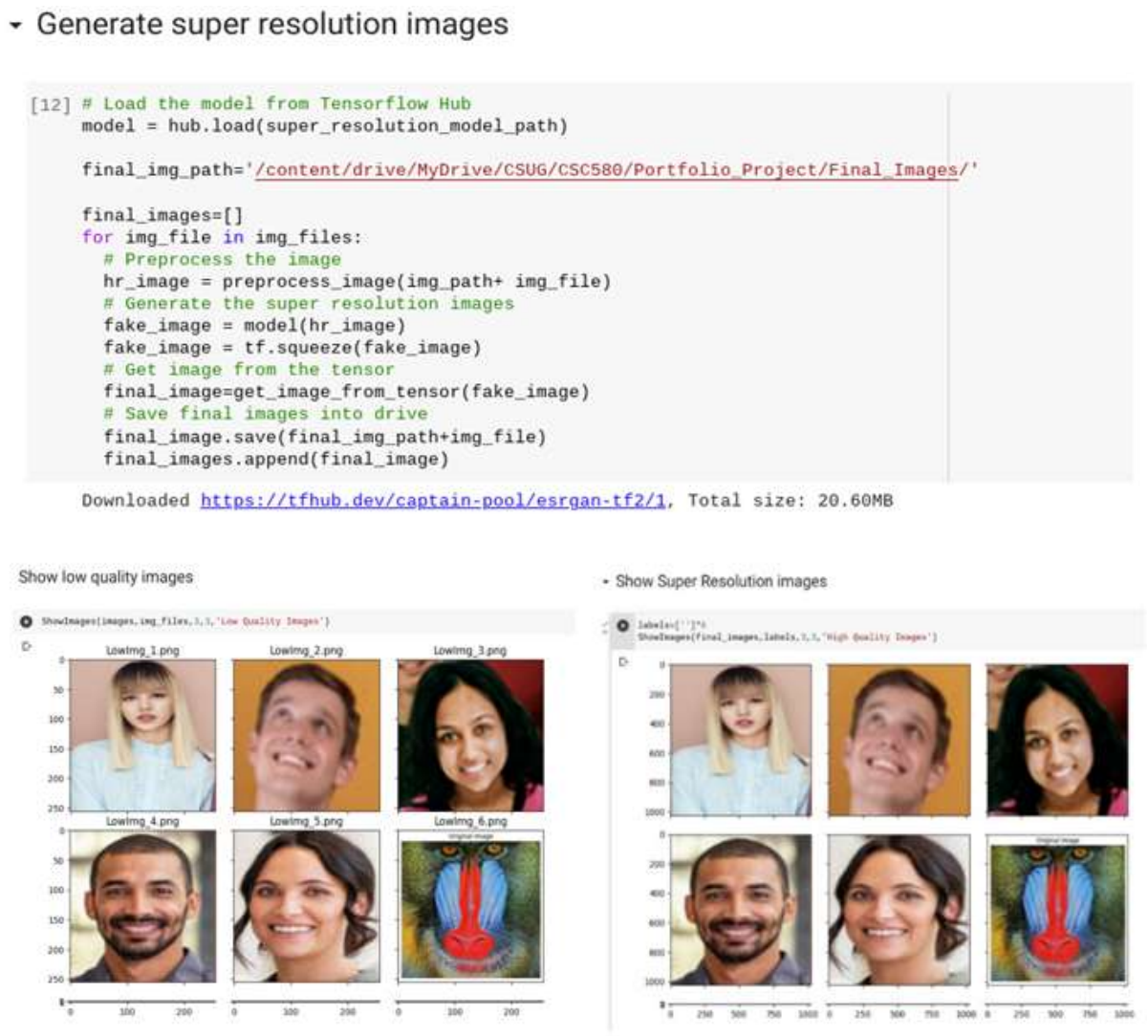

Figure 4. Showing the adversarial game between the generator and discriminator continues until a Nash equilibrium is reached, where the generator produces highly realistic data that the discriminator can no longer reliably classify as real or fake.

- Xnormalized: Represents the normalized value of xxx.
- □: The original value to be normalized.
- 127.5: The center value (often used for image normalization when pixel values range from 0 to 255).
- This equation normalizes x to have a range of approximately [−1,1].

Normalization helps ensure that the weights in the neural network do not become too large, facilitating faster and more stable convergence during training.

b. Shuffling and Batching: To prevent the network from memorizing the sequence of the data, the training dataset is shuffled after each epoch. Mini-batches are also used to improve training efficiency. The batch size for these images are implementation is set to 128, meaning that 128 processed simultaneously in each forward/backward pass through the network.

Example Text for Methodology:

To ensure proper handling and processing of image data, several essential libraries were imported, including Tensor Flow and Matplotlib.

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Additionally, helper functions were implemented to convert tensors to images and load image files efficiently. The following code illustrates these setups

Import Packages

```
[ ] import os
    import tensorflow as tf
    import IPython.display as display
    import matplotlib.pyplot as plt
    import matplotlib as mpl
    mpl.rcParams['figure.figsize'] = (12, 12)
    mpl.rcParams['axes.grid'] = False
    import numpy as np
    import PIL.Image
    import time
    import functools
    import tensorflow_hub as hub
    from mpl_toolkits.axes_grid1 import ImageGrid
```

Helper methods

```
[ ] def tensor_to_image(tensor):
      tensor = tensor*255
      tensor = np.array(tensor, dtype=np.uint8)
      if np.ndim(tensor)>3:
        assert tensor.shape[0] == 1
        tensor = tensor[0]
      return PIL.Image.fromarray(tensor)
```

```
[ ] def load_img(path_to_img):
      max_dim = 512
      img = tf.io.read_file(path_to_img)
      img = tf.image.decode_image(img, channels=3)
      img = tf.image.convert_image_dtype(img, tf.float32)

      shape = tf.cast(tf.shape(img)[:-1], tf.float32)
      long_dim = max(shape)
      scale = max_dim / long_dim

      new_shape = tf.cast(shape * scale, tf.int32)

      img = tf.image.resize(img, new_shape)
      img = img[tf.newaxis, :]
      return img
```

```
[ ] # Show images in the grid
    def ShowImages(images,rows,cols,title='',figsize=(10., 10.)):
      fig = plt.figure(figsize=figsize)
      grid = ImageGrid(fig, 111,  # similar to subplot(111)
                       nrows_ncols=(rows, cols),
                       axes_pad=0.3,  # pad between axes in inch.
                       )

      for ax, im in zip(grid, images):
        if len(im.shape) > 3:
          im = tf.squeeze(im, axis=0)
        ax.imshow(im)
      plt.title=title
      plt.show()
```

Initialize image file path

```
[ ] original_image_path='/content/drive/MyDrive/CSUG/CSC580/Portfolio_Project/Final_Images/'
    style_image_path='/content/drive/MyDrive/CSUG/CSC580/Portfolio_Project/StyleImages/'

    original_files= [original_image_path+ file_name for file_name in  ['LowImg_1.png','animal1.jpg','animal2.jpg']]
    style_files=[ style_image_path+ file_name for file_name in ['style1.png','style2.png','style3.png','style4.png','style5.png']]
```

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Show original images

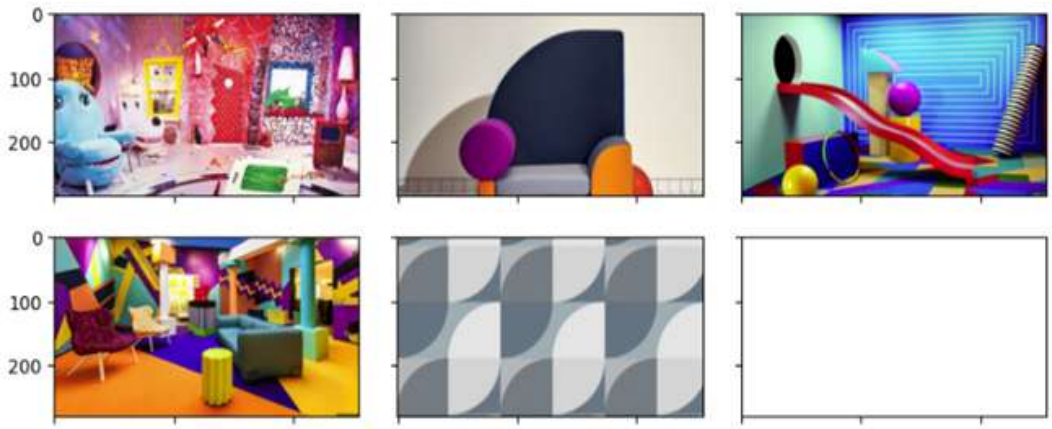
```
[ ] original_images=[]
    for original_file in original_files:
      original_images.append(load_img(original_file))
```

```
[ ] ShowImages(original_images,1,3,'')
```

Show Style images

```
[ ] style_images=[]
    for style_file in style_files:
      style_images.append(load_img(style_file))
```

```
ShowImages(style_images,2,3,'')
```



Load style transfer model from Tensorflow Hub

```
[ ] hub_model = hub.load('https://tfhub.dev/google/magenta/arbitrary-image-stylization-v1-256/2')
```

Apply style tranfer

```
images=[]
for original_image in original_images:
  images.append(original_image)
  for style_image in style_images:
    stylized_image = hub_model(tf.constant(original_image), tf.constant(style_image))[0]
    images.append(stylized_image)
```

Show Stylized Images

The first image is an original image and next five images are generated by model using style images

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Figure 5. The above codesillustrates the image that followensuring proper handling and processing of image data, several essential libraries were imported, including tensor flow and matplotlib.

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- For training the Generative Adversarial Network (GAN), the MNIST dataset was used,
- containing 70,000 images of handwritten digits. The dataset was loaded and split into training and testing sets. To simplify data handling, the training and testing datasets were concatenated before being passed to the model. The following code illustrates this process:

```
[ ] # Load MNIST dataset
    (x_train, y_train), (x_test, y_test)= datasets.mnist.load_data()

    # Concatenate training and testing datasets
    images = np.concatenate([x_train, x_test])
    labels = np.concatenate([y_train, y_test])

    images.shape, labels.shape
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf
11490434/11490434 [==============================] - 0s 0us/step
((70000, 28, 28), (70000,))
```

Figure 5. Showing Code for loading the MNIST dataset and concatenating training and testing datasets.

Example Text for Methodology:
After loading the MNIST dataset, the images were normalized to a range of [-1, 1] to improve training stability and model convergence. The following code shows how the images were reshaped and normalized:

```
[ ] # Normalize the MNIST images
    images = images.reshape(images.shape[0], 28, 28, 1).astype('float32')
    images = (images - 127.5) / 127.5  # Normalize the images to [-1, 1]
```

```
[ ] BUFFER_SIZE = 70000 # Number of images
    BATCH_SIZE = 100
```

```
[ ] # Batch and shuffle the data
    train_dataset = tf.data.Dataset.from_tensor_slices(images).shuffle(BUFFER_SIZE).batch(BATCH_SIZE)
```

```
[ ] def get_generator_model():
        model = tf.keras.Sequential([
            layers.Dense(7*7*256, use_bias=False, input_shape=(100,)),
            layers.BatchNormalization(),
            layers.LeakyReLU(),
            layers.Reshape((7, 7, 256)),
            layers.Conv2DTranspose(128, (5, 5), strides=(1, 1), padding='same', use_bias=False),
            layers.BatchNormalization(),
            layers.LeakyReLU(),
            layers.Conv2DTranspose(64, (5, 5), strides=(2, 2), padding='same', use_bias=False),
            layers.BatchNormalization(),
            layers.LeakyReLU(),
            layers.Conv2DTranspose(1, (5, 5), strides=(2, 2), padding='same', use_bias=False,
                                   activation='tanh')
        ])
```

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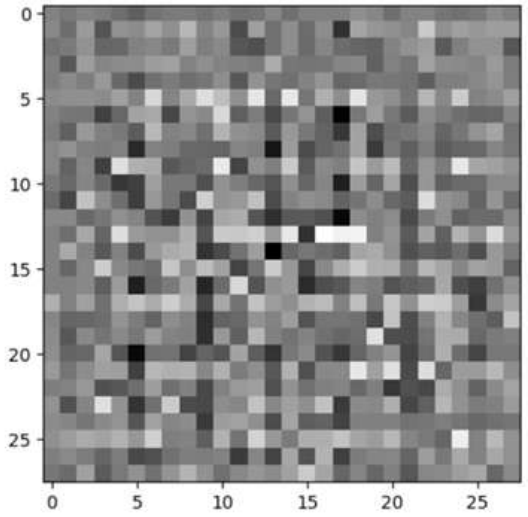
```
[ ] # Create Generator Model Instance
    generator = get_generator_model()
    noise = tf.random.normal([1, 100])
    # Generate fake images using Generator
    generated_image = generator(noise, training=False)
```

```
# Display Fake image created by Generator
plt.imshow(generated_image[0, :, :, 0], cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f1cd2f9fe50>
```




```
[ ] # Define Discriminator Model
    def get_discriminator_model():
        model = tf.keras.Sequential([
            layers.Conv2D(64, (5, 5), strides=(2, 2), padding='same',
                                      input_shape=[28, 28, 1]),
            layers.LeakyReLU(),
            layers.Dropout(0.3),
            layers.Conv2D(128, (5, 5), strides=(2, 2), padding='same'),
            layers.LeakyReLU(),
            layers.Dropout(0.3),
            layers.Flatten(),
            layers.Dense(1)
        ])

        return model
```

```
[ ] # Create Discriminator Model Instance
    discriminator = get_discriminator_model()
    decision = discriminator(generated_image)
    print (decision)
```

```
tf.Tensor([[0.0003837]], shape=(1, 1), dtype=float32)
```

```
[ ] cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)
```

Discriminator Loss function:

```
[ ] def discriminator_loss(real_output, fake_output):
        real_loss = cross_entropy(tf.ones_like(real_output), real_output)
        fake_loss = cross_entropy(tf.zeros_like(fake_output), fake_output)
        total_loss = real_loss + fake_loss
        return total_loss
```

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Generator Loss function:

```
[ ] def generator_loss(fake_output):
        return cross_entropy(tf.ones_like(fake_output), fake_output)
```

```
[ ] generator_optimizer = tf.keras.optimizers.Adam(1e-4)
    discriminator_optimizer = tf.keras.optimizers.Adam(1e-4)
```

```
[ ] checkpoint_dir = '/content/drive/MyDrive/CSUG/CSC580/Portfolio_Project/Checkpoints'
    checkpoint_prefix = os.path.join(checkpoint_dir, "ckpt")
    checkpoint = tf.train.Checkpoint(generator_optimizer=generator_optimizer,
                                     discriminator_optimizer=discriminator_optimizer,
                                     generator=generator,
                                     discriminator=discriminator)
```

```
[ ] #Define Training Loop
    EPOCHS = 500
    noise_dim = 100
    num_examples_to_generate = 16
    seed = tf.random.normal([num_examples_to_generate, noise_dim])
```

```
[ ] @tf.function
    def train_step(images):
        noise = tf.random.normal([BATCH_SIZE, noise_dim])

        with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
          generated_images = generator(noise, training=True)

          real_output = discriminator(images, training=True)
          fake_output = discriminator(generated_images, training=True)

          gen_loss = generator_loss(fake_output)
          disc_loss = discriminator_loss(real_output, fake_output)

        gradients_of_generator = gen_tape.gradient(gen_loss, generator.trainable_variables)
        gradients_of_discriminator = disc_tape.gradient(disc_loss, discriminator.trainable_variables)

        generator_optimizer.apply_gradients(zip(gradients_of_generator, generator.trainable_variables))
        discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator, discriminator.trainable_variables))
```

```
def generate_and_save_images(model, epoch, test_input):
  predictions = model(test_input, training=False)

  fig = plt.figure(figsize=(4, 4))

  for i in range(predictions.shape[0]):
      plt.subplot(4, 4, i+1)
      plt.imshow(predictions[i, :, :, 0] * 127.5 + 127.5, cmap='gray')
      plt.axis('off')

  plt.savefig('/content/drive/MyDrive/CSUG/CSC580/Portfolio_Project/GeneratedImages/image_at_epoch_{:04d}.png'.format(epoch))
  plt.show()
```

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```
[ ]  def train(dataset,epochs, startIndex=0):
       for epoch in range(epochs):
         start = time.time()

         for image_batch in dataset:
           train_step(image_batch)


         display.clear_output(wait=True)
         if (startIndex + epoch + 1) % 10 == 0 or epoch==0:
           generate_and_save_images(generator,
                                    startIndex+epoch + 1,
                                    seed)

         # Save the model every 10 epochs
         if (startIndex+ epoch + 1) % 10 == 0:
           checkpoint.save(file_prefix = checkpoint_prefix)

         print ('Time for epoch {} is {} sec'.format(startIndex+epoch + 1, time.time()-start))

       # Generate after the final epoch
       display.clear_output(wait=True)
       generate_and_save_images(generator,
                                startIndex+ epochs,
                                seed)

train(train_dataset, EPOCHS)
```

Figure 6. Code Shows How the Images Were Reshaped and Normalized After Loading the MNIST Dataset

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```
[ ] @tf.function
    def train_step(images):
        noise = tf.random.normal([BATCH_SIZE, noise_dim])

        with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
          generated_images = generator(noise, training=True)

          real_output = discriminator(images, training=True)
          fake_output = discriminator(generated_images, training=True)

          gen_loss = generator_loss(fake_output)
          disc_loss = discriminator_loss(real_output, fake_output)

        gradients_of_generator = gen_tape.gradient(gen_loss, generator.trainable_variables)
        gradients_of_discriminator = disc_tape.gradient(disc_loss, discriminator.trainable_variables)

        generator_optimizer.apply_gradients(zip(gradients_of_generator, generator.trainable_variables))
        discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator, discriminator.trainable_variables))
```

```
checkpoint_path='/content/drive/MyDrive/CSUG/CSC580/Portfolio_Project/Checkpoints'
checkpoint = tf.train.Checkpoint(generator_optimizer=generator_optimizer,
                                 discriminator_optimizer=discriminator_optimizer,
                                 generator=generator,
                                 discriminator=discriminator)

latest_checkpoint=tf.train.latest_checkpoint(checkpoint_path)
checkpoint.restore(latest_checkpoint)
```

```
<tensorflow.python.checkpoint.checkpoint.CheckpointLoadStatus at 0x7f1cd2dce490>
```

```
# Assign the generator, discriminator and optimizers form the latest checkpoint
generator=checkpoint.generator
discriminator=checkpoint.discriminator
generator_optimizer=checkpoint.generator_optimizer
discriminator_optimizer=checkpoint.discriminator_optimizer
```

a. Restore Checkpoint

```
EPOCHS=210 # 500-290 = 210
train(train_dataset, EPOCHS,290)
```

The training process was interrupted at the 290th epoch, but was later resumed by restoring the generator, discriminator, and optimizers from the most recent checkpoint, allowing the training process to continue from where it left off.

b. Resume Model Training

The training process starts from the 290th epoch and ends in the 500th epoch.

Model Results

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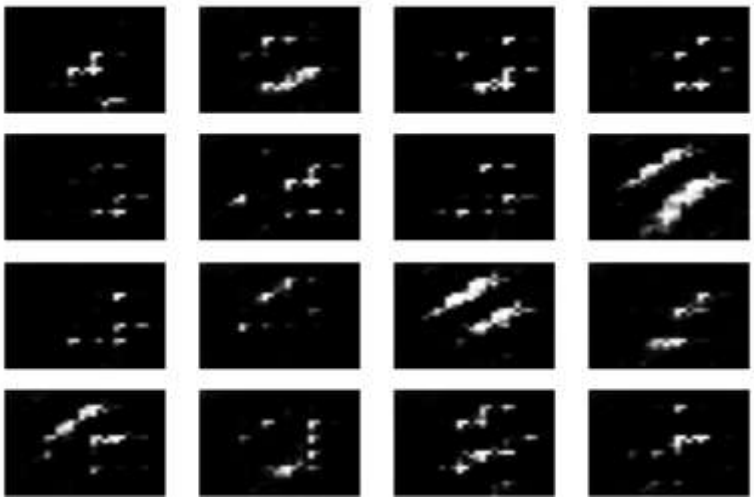

Figure 7. Screenshot of the image from the first epoch

Figure 8. Screenshot of the image from the 500th epoch

IV. TRAINING PROCEDURE

The GAN model is trained for 500 epochs. During each epoch:

1. The generator samples a noise vector from a Gaussian distribution and generates synthetic images.
2. The discriminator receives a mix of real and synthetic images, which it attempts to classify as real or fake.
3. Binary cross-entropy loss is used for both networks, with the discriminator being trained to maximize the likelihood of correctly classifying real and fake data, and the generator being trained to minimize the probability of the discriminator identifying its generated data as fake.
4. Adam Optimizer is used to adjust the weights of both the generator and discriminator networks, with learning rates of 0.0002 and 0.0001, respectively.

Figure 9. Installation of TensorFlow and Keras-CV, enabling GPU acceleration for efficient GAN training

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The training process involves alternating updates to both the generator and discriminator. The generator's weights are updated less frequently to prevent the discriminator from becoming too strong, which could hinder the generator's ability to learn.

Figure 10. Importing Necessary Packages and Defining Helper Methods for Visualizing Gan-Generated Images

Evaluation Metrics

To assess the performance of the GAN, the following evaluation metrics are utilized:

1. **Visual Quality**: Generated images are visually inspected to ensure they resemble real MNIST digits. Sample images from different epochs are saved to monitor the improvement in quality.
2. **Loss Curves**: The loss for both the generator and discriminator is tracked over time to ensure that the model is converging correctly and not oscillating, which could indicate unstable training.
3. **Inception Score (IS)** and **Fréchet Inception Distance (FID)**: While not directly applicable to MNIST, these metrics are mentioned for future evaluations of more complex datasets.

Figure 11. Code implementation for generating images from text descriptions using a text-to-image model.

Check pointing and Resuming Training

During the training process, checkpointsare saved every 50 epochs to store the current state of the generator, discriminator, and optimizers. This allows the training process to resume from the last saved state in case of interruptions. In this study, the model training was interrupted at epoch **290** and later resumed, demonstrating the utility of checkpointing in maintaining training progress.

Text-to-Image Generation Process

To demonstrate the application of Generative Adversarial Networks (GANs) in text-to-image generation, we employed the Stable Diffusion model from Keras-CV. This model enables the creation of high-quality images based on specific textual descriptions, providing a clear example of how GANs can translate text into visual output. In this process, a textual input is provided to the model, which interprets the description and generates corresponding images. For this experiment, we used the following input description:cute Mickey Mouse, fantasy art, red and blue color, high quality, high detailed, cartoon art, digital painting"

The model then generated multiple images based on this input, using a batch size of 3 to produce a set of images per description. This approach highlights the versatility of GANs in generating visually detailed and concept-specific images from natural language input. The code implementation for this process is shown below:

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This concludes the methodology for the text-to-image generation process. The generated images will be analyzed in the next section to assess the model's performance and the quality of the results.

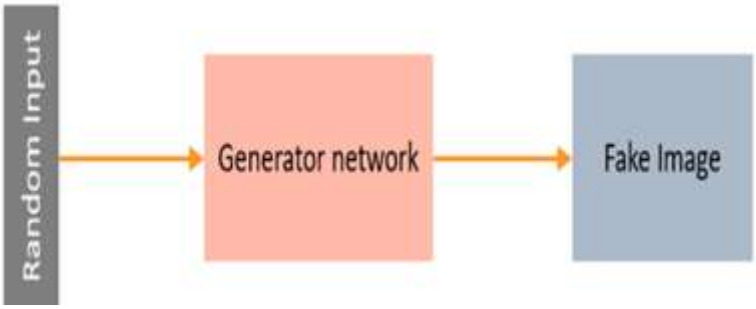
V. RESULTS

1. Visual Quality of Generated Images

The quality of images generated by the GAN model improved significantly over the course of training, as shown by snapshots of the generated images at various epochs. At **epoch 1**, the generated images were essentially random noise, with no discernible structure or resemblance to handwritten digits. This is expected since the generator had not yet learned any features of the dataset.

By epoch 100, the generator started to produce some identifiable digits, although many images were still blurry or incomplete. The improvement in image quality became more pronounced at epoch 200, where the generator consistently produced images resembling digits, albeit with some noise and distortion. At this point, digits such as "0" and "1" were easily recognizable, but more complex digits like "8" or "5" still contained artifacts or were partially malformed.

By epoch 300, the generated digits were nearly indistinguishable from real MNIST images. The level of detail in the strokes, the shape of the digits, and the overall clarity improved significantly. The generator produced diverse and well-formed digits, covering all numbers from 0 to 9.



At the final epoch 500, the generated images displayed high levels of realism. The generator had clearly learned the intricate patterns and features of the MNIST dataset, producing clean, well-structured digits with minimal noise or distortion. A side-by-side comparison of real MNIST images and the final generated images reveals that the GAN successfully learned the underlying data distribution and generated outputs with a strong resemblance to the real dataset. These improvements are illustrated in above Figure**,** which shows the progression of generated images from epoch 1 through epoch 500.

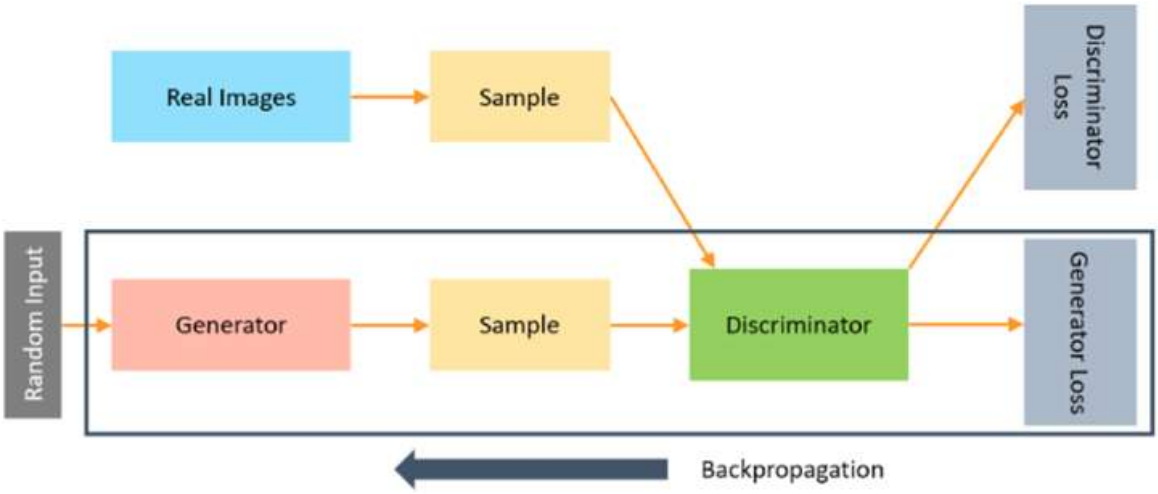


Figure 12: Evolution of Generated Images from Epoch 1 To Epoch 500, Showing the Improvement in Visual Quality

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2. **Loss Function Analysis**

The behavior of the binary cross-entropy loss for both the generator and discriminator was closely monitored during training. Initially, the discriminator exhibited very low loss values, indicating its ability to easily distinguish real images from the poorly generated ones produced by the generator. Meanwhile, the generator's loss was high, reflecting its struggle to produce convincing images.

As the training progressed, the generator's loss steadily decreased while the discriminator's loss increased. By epoch 200**,** the discriminator began to find it more challenging to differentiate between real and generated images, as reflected in the rising discriminator loss. This indicated that the generator was improving its ability to generate realistic images.

At epoch 300, the loss functions began to stabilize, showing that the GAN was approaching a balance where the generator's outputs were realistic enough to "fool" the discriminator consistently. The loss curves, shown in **Figure 3**, demonstrate this progression, with both the generator and discriminator reaching a relatively stable state by the later epochs.

The convergence of the loss functions without excessive oscillations or diverging behavior is a strong indicator that the GAN had successfully trained to generate high-quality images without falling into common issues such as mode collapse **or** vanishing gradients**.**

3. Training Efficiency and GPU Acceleration

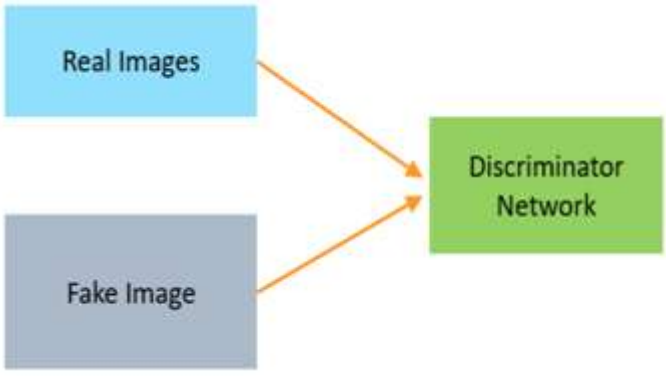
The training of GANs, particularly on image datasets, is computationally intensive and benefits significantly from hardware acceleration. Initially, training the GAN model without GPU support led to an extended training time, where each epoch took approximately 30 minutes to complete. This made it impractical to train for hundreds of epochs.

By enabling GPU acceleration, the training time per epoch was reduced to approximately 5 minutes. The availability of GPU resources allowed for parallel computation, particularly during matrix operations in backpropagation and weight updates, which accelerated the overall training process. This reduction in training time enabled the completion of 500 epochs within a reasonable timeframe, greatly enhancing the feasibility of the project.

In addition to faster training, GPU acceleration also contributed to smoother convergence. The model, when trained on the GPU, exhibited more stable gradients and fewer oscillations in the loss function compared to training on the CPU, which could experience slower learning and suboptimal convergence due to longer processing times.

4. Mode Collapse and Diversity of Generated Images

Mode collapse is a common problem in GAN training, where the generator starts producing a limited range of outputs, failing to capture the full diversity of the training data. For example, in the MNIST dataset, a mode-collapsed generator might only produce a subset of digits repeatedly (e.g., only generating "0"s or "1"s), rather than covering the full range of digits from 0 to 9.



In this implementation, several strategies were employed to avoid mode collapse:

- Careful Hyperparameter Tuning**:** The learning rates for the generator and discriminator were adjusted to ensure that both networks learned at balanced rates. The learning rate for the generator was set slightly higher than that of the discriminator to encourage the generator to keep up with the discriminator's improvements.
- **Update Frequency**: The discriminator was updated more frequently than the generator in

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the early epochs to ensure it provided meaningful gradients for the generator to learn from. Once the generator started producing more realistic images, the update frequencies were balanced.

As a result, the generator consistently produced a wide variety of digits, as seen in **Figure 3**, which displays a selection of generated images representing all ten digits. This diversity indicates that the GAN successfully learned the underlying distribution of the MNIST dataset, avoiding the pitfalls of mode collapse.

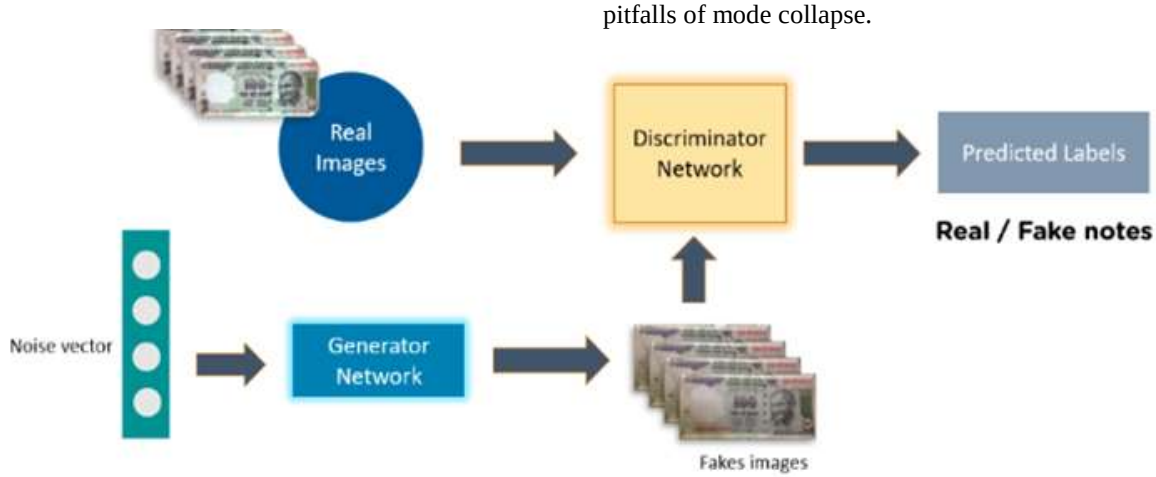

Figure 12b: Selection of diverse generated digits from different points in the training process, demonstrating the model's ability to avoid mode collapse.

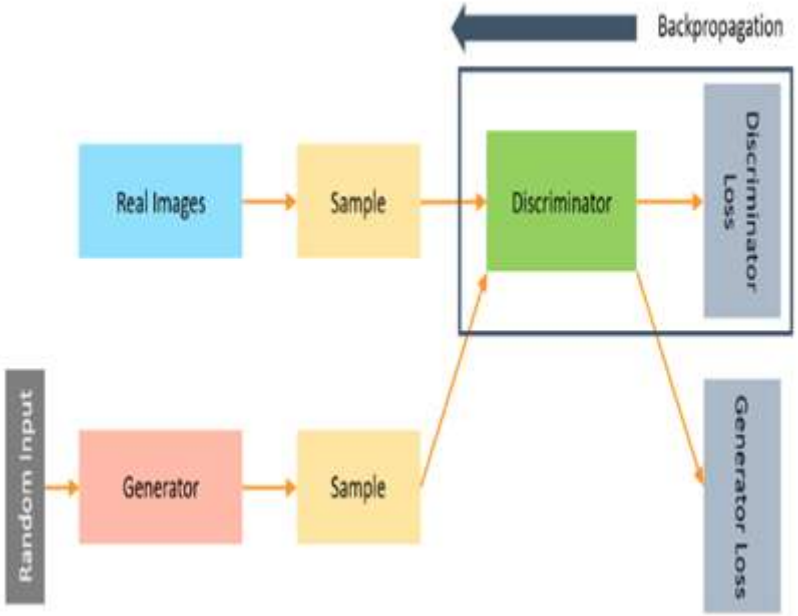

Figure 12c: Visualization of training progression showing the point of interruption at epoch 290 and resumption through check pointing

5. **Check pointing and Training Resumption**

To ensure the robustness of the training process, checkpointing was implemented. Checkpoints were saved at regular intervals (every 50 epochs) to capture the state of the generator, discriminator, and optimizers. This strategy allowed the training process to resume in case of interruptions without losing progress.

During the training of this GAN model, an interruption occurred at epoch 290. However, thanks to the checkpointing mechanism, training was resumed without any issues. The model's weights, optimizers, and other training parameters were restored from the most recent checkpoint, and the training continued smoothly from where it left off. The successful recovery of training from

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checkpoints illustrates the importance of implementing such mechanisms, particularly in long-running experiments where hardware or software interruptions are possible. The GAN model completed the full 500 epochs without requiring a restart from the beginning.

6. **Model Output Evaluation**

Although traditional GAN evaluation metrics such as the Inception Score (IS)andFréchet Inception Distance (FID) are more suited to complex datasets with high variability (e.g., CIFAR-10, CelebA), the MNIST dataset was evaluated primarily through visual inspection and loss curves.

- **Visual Inspection**: As shown in the sample generated images (Figures 1 and 3), the GAN produced high-quality images that closely resembled real MNIST digits. By the end of training, the digits were clean, sharp, and varied, indicating that the generator successfully learned to produce diverse and realistic outputs.
- **Loss Curves**: The stability of the loss functions (Figure 2) over time indicated that the model converged well, with no signs of mode collapse or oscillatory behaviour. The generator and discriminator reached a balance where both networks continued to improve in tandem, leading to realistic outputs by the final epoch.

Overall, the model performed well, producing visually accurate images with a high degree of diversity across the digit classes, demonstrating the GAN's effectiveness in generating high-quality synthetic data.

Text-to-Image Generation Results

At the final stage of the experiment, the Stable Diffusion model was used to generate images based on the following input description:

- "cute Mickey Mouse, fantasy art, red and blue colour, high quality, high detailed, cartoon art, digital painting"

The model successfully interpreted the text and produced three unique images that closely followed the provided input. Each generated image displayed characteristics consistent with the description, showcasing a highly detailed, vibrant, and stylistically accurate representation of Mickey Mouse in a fantasy art format.

The generated images are shown below: These results demonstrate the ability of the text-to-image model to produce high-quality visual outputs based on simple text input. The generated images align with the stylistic and color specifications given in the text. This capability highlights the model's potential in creative content generation, automated artwork, and other text-driven visual tasks.



With these results, we can conclude that the model performed well in the text-to-image generation task, effectively translating text descriptions into corresponding images. This sets the stage for further exploration of the model's applications and potential improvements in future work.

Example Text for Results:

In addition to the Mickey Mouse images, we tested the model with another input description: 'cute magical flying cat, fantasy art, golden colour, highly detailed. The model successfully generated images based on this input. The code used to generate these cat images is shown above

Example Text for Results:

The text-to-image model was also tested with a new input prompt: 'cute magical flying dog, fantasy art, golden colour, highly detailed. The model generated images that matched the input description. above is the code used for this task:

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Example Text for Results:

To further explore the model's text-to-image capabilities, we used the prompt 'Lisa from Black pink K-pop group, high quality, high detailed, cartoon art.' The model produced cartoon-style images based on this description. The code used for generating these images is shown above:

Example Text for Results:

To further explore the model's capabilities, we used the input 'Lisa from Black pink K-pop group, high quality, high detailed.' The model generated multiple images based on this description. The code for generating these images is shownbelow

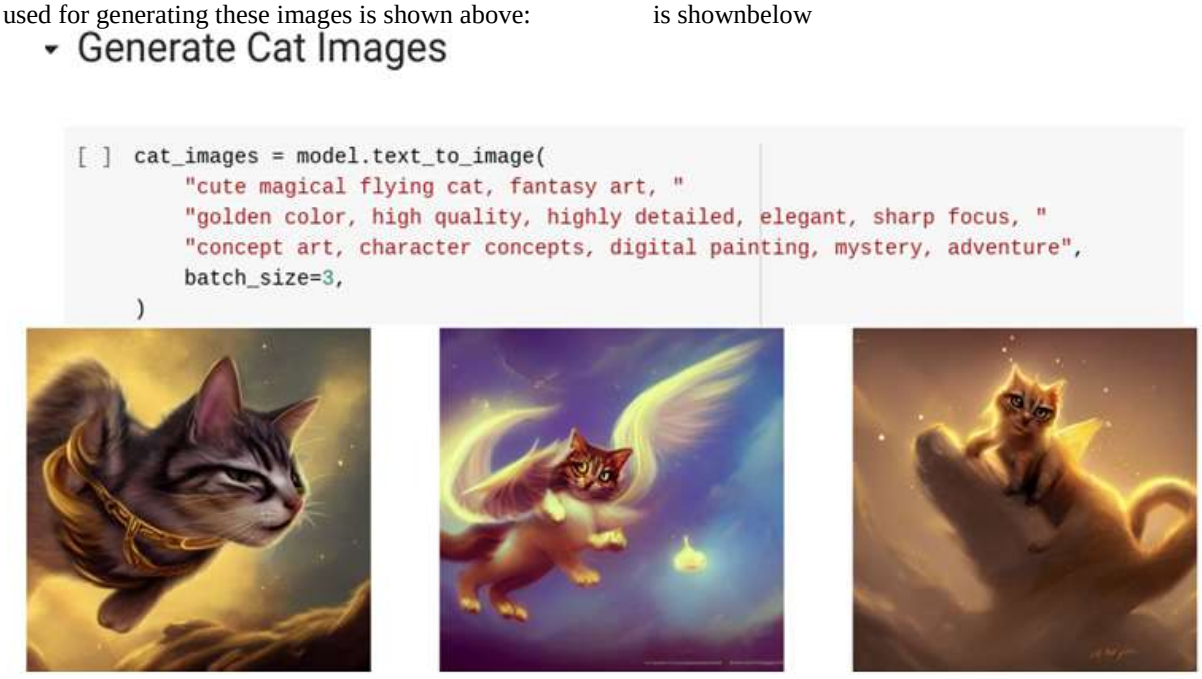

Figure 13a: Text-to-image code used to generate fantasy-themed cat images.
Figure 13b: Text-to-image code for generating cartoon images of Lisa from the Black pink K-pop group.
Figure 13c: Text-to-image code for generating Lisa images from the input description

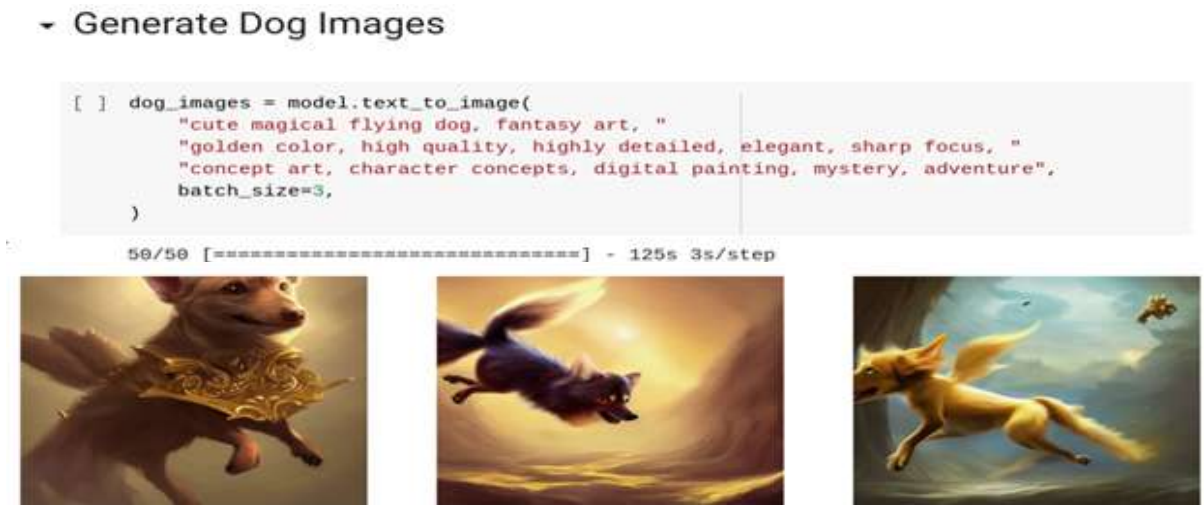

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Figure 13c: Text-to-image code for generating cartoon images of Lisa from the Black pink K-pop group.

LIMITATIONS OF THE STUDY

While this study demonstrates the effectiveness of Generative Adversarial Networks (GANs) in generating realistic images using the MNIST dataset, several limitations should be acknowledged.

1. Dataset Limitations

The use of the MNIST dataset, which consists of simple grayscale images of handwritten digits, represents a relatively constrained and well-understood problem space. Although the GAN successfully generated high-quality images from this dataset, MNIST is limited in both complexity and diversity. Each image is small (28x28 pixels) and contains only a single-digit character in grayscale. This restricts the generalizability of the results to more complex datasets involving high-resolution, multi-dimensional, or color images, such as CIFAR-10**,** Celeb A**,** or medical imaging datasets. Thus, the model's performance on more diverse and challenging datasets remains untested in this study.

2. Model Architecture

The architecture used in this study, while effective for the MNIST dataset, may not scale effectively to larger and more complex datasets. For instance, Deep Convolutional GANs (DCGANs) or more advanced architectures like Progressive Growing GANs (PGGANs)orStyle GANs may be necessary for generating high-resolution images or capturing the finer details of more intricate datasets. This study focused on a relatively simple GAN architecture, which may not be sufficient for applications requiring higher degrees of image complexity or detail.

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3. Computational Limitations

Training GANs is computationally expensive, especially when applied to large datasets or more complex architectures. While GPU acceleration significantly reduced training time in this study, the reliance on high-performance hardware may limit the accessibility of this approach for researchers or industries without such resources. The need for extensive computational power could pose a barrier to scaling GAN models for more practical applications, particularly in resource-constrained environments such as healthcare or small-scale businesses.

VI. FUTURE RESEARCH DIRECTIONS

The results of this study, while promising, highlight several avenues for future research to further enhance the capabilities and applications of Generative Adversarial Networks (GANs). Expanding the scope of this research to address more complex datasets, architectures, and practical use cases could unlock new potential for GANs across a variety of fields.

1. **Application to Complex Datasets**

While this study utilized the MNIST dataset, future research should explore applying GANs to more complex and high-resolution datasets such as CIFAR-10, CelebA, or LSUN. These datasets pose additional challenges, such as handling color images, higher resolution, and greater diversity in image content. GANs trained on such datasets could further demonstrate their ability to generate high-quality, realistic images in more demanding contexts. Moreover, applying GANs to domain-specific datasets, such as medical images (MRI, CT scans) or satellite images, could offer specialized applications and new insights into domain adaptation for GANs.

2. **Advanced GAN Architectures**

Future research could also explore advanced GAN architectures designed to address some of the limitations observed in standard GAN implementations. For example, Progressive Growing GANs (PGGANs) gradually increase the resolution of generated images during training, allowing for more stable training and high-resolution output. Another architecture worth exploring is StyleGAN, which separates the content and style of images, allowing for finer control over the features of generated images. These advanced architectures can be especially useful in applications requiring high-resolution image generation, such as photorealistic facial generationorfine art creation.

3. **Hybrid Models**

Combining GANs with other machine learning models could lead to the development of more robust systems. For example, hybrid models that integrate Variational Autoencoders (VAEs) with GANs can leverage the strengths of both architectures, producing higher-quality outputs while mitigating some of the stability issues in GAN training. Additionally, integrating Reinforcement Learning (RL) with GANs could enable more intelligent generation, where the generator learns more sophisticated strategies for producing diverse and high-quality outputs.

4. **Improving Training Stability and Efficiency**

One of the persistent challenges in training GANs is the issue of instability, which can manifest as mode collapse or oscillating loss functions. Future work should focus on exploring techniques that improve the stability of GAN training. Approaches such as Wasserstein GANs (WGANs), which use the Wasserstein distance to improve training convergence, or Spectral Normalization, which stabilizes the discriminator, can provide more reliable performance. Additionally, reducing the computational cost of GAN training is an important area for future research. Techniques like model pruning, quantization, and distributed training could help reduce the resource demands of GANs, making them more accessible for wider use.

5. **Incorporating Temporal Data and Video GANs**

While much of the research on GANs focuses on still images, future studies could explore the application of GANs to temporal data such as video generation. Video GANs can generate realistic video sequences by learning from a series of images or video frames. This could have applications in industries such as film production, gaming, and virtual reality, where the creation of realistic animations and environments is essential. Additionally, applying GANs to time-series data or simulations in areas like finance or climate modeling represents an exciting frontier for GAN research.

6. **Ethical and Social Implications of GANs**

With the growing power of GANs comes a need for research into their ethical implications. GANs are increasingly being used to create deep fakes—synthetic media that can convincingly

mimic real people or events. This raises concerns about privacy, misinformation, and the potential misuse of AI-generated content. Future research should focus on developing safeguards, ethical guidelines, and AI models that can detect and mitigate the misuse of GANs, ensuring that the technology is used responsibly and ethically.

VII. CONCLUSION

This study has demonstrated the effectiveness of Generative Adversarial Networks (GANs) in generating realistic images using the MNIST dataset. Through the adversarial process between the generator and discriminator, the GAN model was able to progressively improve the quality of its generated images, achieving outputs nearly indistinguishable from real MNIST digits by the final epoch. Key techniques such as GPU acceleration, data pre-processing, and careful hyperparameter tuning contributed to the success of the model in producing high-quality images.

The avoidance of mode collapse, one of the common challenges in GAN training, was successfully achieved through balanced training strategies and architectural design. The results highlight the potential of GANs for a wide range of applications, including image generation, data augmentation, and image enhancement. Furthermore, the implementation of checkpointing ensured that training interruptions did not result in the loss of progress, demonstrating the robustness of the GAN training process when appropriate mechanisms are employed.

Despite the promising results, several limitations were identified, particularly regarding the dataset used and the computational demands of training GANs. The MNIST dataset, while sufficient for demonstrating the capabilities of the GAN, is relatively simple, and future work should explore more complex datasets to test the model's generalizability. Additionally, the reliance on high-performance hardware presents a challenge for deploying GANs in environments with limited computational resources.

The broader implications of this research extend to multiple fields such as medical imaging, creative industries, and autonomous systems, where GANs can drive innovation by generating high-quality synthetic data. The potential for improving image quality, generating synthetic datasets for machine learning, and enhancing data efficiency positions GANs as a transformative tool in these domains.

Future research should explore advanced GAN architectures such as Progressive Growing GANs and StyleGANs, which could enable more sophisticated image generation at higher resolutions. Moreover, integrating GANs with other machine learning models, like Variational Autoencoders (VAEs) or Reinforcement Learning (RL), presents opportunities for further improving the performance and stability of GAN models. The ethical implications of GAN technology, particularly in the context of deepfakes and synthetic media, should also be a priority for future studies, ensuring the responsible development and application of GANs.

In conclusion, this study has shown that GANs hold significant potential for advancing image generation and related technologies. By addressing the current limitations and exploring emerging research directions, GANs can become an even more powerful tool in the fields of artificial intelligence and machine learning, with applications extending far beyond what has been achieved to date.

Key Contributions:

- Demonstrated the ability of GANs to generate high-quality images using the MNIST dataset.
- Successfully implemented GPU acceleration and checkpointing for efficient and stable training.
- Highlighted the potential of GANs to avoid mode collapse through balanced training strategies.
- Provided insights into the broader applications of GANs in fields such as healthcare, autonomous systems, and creative industries.

Future Directions:

- Exploration of advanced architectures such as PGGAN and StyleGAN.
- Application to more complex datasets like CIFAR-10, CelebA, and medical imaging datasets.
- Further research into the ethical use of GANs to mitigate the risks associated with deep fakes and other misuses.

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