

**GAN-based synthesis of rare diseases images**

**CSE453 – TENSORFLOW PROJECT REPORT**

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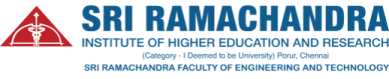
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**BONAFIDE CERTIFICATE**

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**ABSTRACT**

This project explores the use of Generative Adversarial Networks (GANs) to synthesize realistic medical images for pancreatic cancer research. The objective is to augment limited datasets and enhance the robustness of diagnostic models. The GAN architecture, comprising a generator and a discriminator, was trained on a curated dataset of pancreatic cancer images. Evaluation metrics such as Fréchet Inception Distance (FID) and qualitative image assessments demonstrate the ability of the model to generate realistic and diverse samples. This work underscores the potential of GANs in addressing data scarcity in medical imaging.

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**CHAPTER 1**

**INTRODUCTION**

**1.1 Overview**

Medical imaging plays a critical role in the diagnosis and treatment of pancreatic cancer. However, obtaining diverse and high-quality labeled datasets is often challenging due to the sensitive nature of medical data and patient privacy concerns. Generative Adversarial Networks (GANs) have emerged as a promising solution for augmenting datasets by generating synthetic images that closely resemble real-world data.

**1.3 Problem Statement**

Pancreatic cancer is one of the most aggressive and lethal types of cancer, with limited early detection methods and poor survival rates. Medical imaging, such as computed tomography (CT), magnetic resonance imaging (MRI), and histopathological scans, plays a critical role in the diagnosis and treatment planning of pancreatic cancer. However, the availability of high-quality, annotated pancreatic cancer images for training and validating machine learning models is limited due to challenges such as:

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1. Scarcity of Data: Acquiring and annotating medical imaging datasets is resource-intensive, requiring expertise from radiologists and pathologists, and is constrained by patient privacy regulations.
2. Imbalance in Datasets: Existing datasets often contain an imbalance between normal and cancerous images, limiting the ability of machine learning models to generalize.
3. Variability in Imaging: Differences in imaging protocols, modalities, and tumor presentations make it challenging to develop robust diagnostic systems.
4. Need for Augmented Data: To improve the performance of deep learning models, there is a pressing need to generate synthetic, high-quality, and realistic images that mimic actual pancreatic cancer cases.

**1.4 Objectives**

This study aims to:

* Develop a GAN-based framework for synthesizing realistic pancreatic cancer images.
* Address the challenges of data scarcity in medical imaging datasets.
* Evaluate the quality of generated images using quantitative metrics and visual inspection.

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**CHAPTER 2**

**SYSTEM ARCHITECTURE**

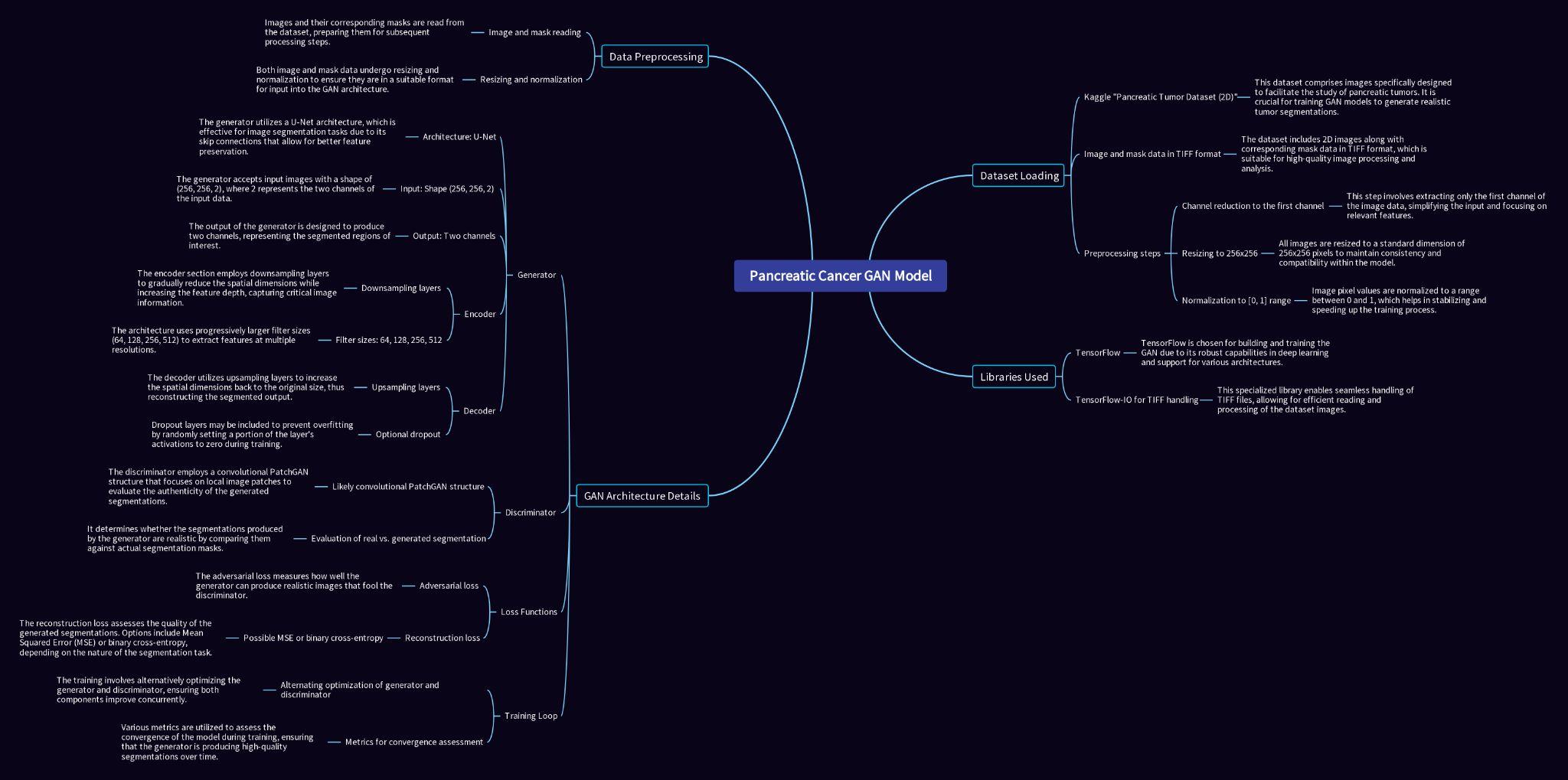
****

Fig 2.1

The system architecture diagram illustrates the end-to-end process for **Pancreatic Cancer Image Synthesis Using Generative Adversarial Networks (GANs)**. The pipeline begins with a **limited set of annotated pancreatic cancer images**, which undergo preprocessing steps like normalization and augmentation to ensure uniformity and prepare the data for training. This data is fed into the **GAN framework**, comprising a **Generator** and **Discriminator**. The Generator synthesizes realistic pancreatic cancer images, while the Discriminator evaluates their authenticity, creating a feedback loop during training to improve the quality of generated images.

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**CHAPTER 3**

**METHODOLOGY**

**3.1 DATASET PREPARATION**

The dataset used for this project consists of anonymized pancreatic cancer imaging data. Images were preprocessed to ensure uniformity in dimensions, intensity normalization, and noise reduction. Data augmentation techniques such as rotation, scaling, and flipping were applied to expand the dataset and improve model generalization. Additionally, a pipeline was developed to automate the loading, transformation, and batching of images to streamline training.

**3.2 MODEL ARCHITECTURE**

A DCGAN (Deep Convolutional GAN) architecture was employed for this study. Key components include:

* **Generator:** A neural network designed to create realistic images from random noise vectors. It employs transposed convolutions and batch normalization layers to progressively upscale the noise into detailed images. Dropout layers were incorporated to prevent overfitting and improve generalization.
* **Discriminator:** A binary classifier tasked with distinguishing real images from synthetic ones. It uses convolutional layers with LeakyReLU activation to process the input images. Gradient penalty techniques were added to stabilize the training process.

**3.3 TRAINING PROCESS**

The GAN was trained using the following procedure:

* **Adversarial Training:** The generator and discriminator were trained simultaneously in a min-max game. The generator aimed to minimize the discriminator’s ability to identify fake images, while the discriminator aimed to maximize its classification accuracy.
* **Loss Function:** Binary cross-entropy loss was used for both generator and discriminator updates. To enhance stability, a Wasserstein loss with gradient penalty was experimented with in alternate configurations.

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* **Hyperparameters:** The model was trained with a learning rate of 0.0002, a batch size of 64, and the Adam optimizer with β1 = 0.5. Training was conducted over 100 epochs with checkpointing to save the best-performing model.

**3.4 EVALUATION METRICS**

* **Fréchet Inception Distance (FID):** Quantifies the quality of generated images by comparing feature distributions between real and synthetic images. This was computed periodically during training to monitor progress.
* **Visual Inspection:** Experts evaluated the synthetic images to assess their realism and diversity. Images were displayed alongside real samples in a blinded study to ensure unbiased evaluation.
* **Diversity Metrics:** Measures of intra-class variability were applied to confirm that the GAN did not simply memorize training samples.

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**CHAPTER 4**

**IMPLEMENTATION and RESULTS**

**CODE OVERVIEW**

The code was implemented in Python using Tensorflow. Key modules include:

* **Data Preprocessing:** Scripts for image resizing, normalization, and augmentation, leveraging libraries such as tf.image.etc.,
* **Model Definition:** Implementation of the generator and discriminator architectures with modular, reusable components.
* **Training Loop:** Adversarial training with alternating updates for the generator and discriminator. Checkpoints were saved at regular intervals, and TensorBoard was used for monitoring.
* **Evaluation Scripts:** Scripts for calculating FID scores, plotting loss curves, and visualizing generated images against real samples.

**CODE :**

**Data preparation:**

import kagglehub

# Download latest version

data\_dir = kagglehub.dataset\_download("dibakarmalakar/pancreatic-tumor-dataset-2d")

data\_dir

!mv "{data\_dir}" "./data"

image\_dir = "data/Images/Images"

mask\_dir = "data/Masks/Masks"

**Loading and Preprocessing :**

!pip install tensorflow-io

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import tensorflow as tf

import tensorflow\_io as tfio # For .tiff support

import os

def preprocess\_image(image\_path, mask\_path, target\_size=(256, 256)):

# Load image and mask

image = tf.io.read\_file(image\_path)

image = tfio.experimental.image.decode\_tiff(image)

mask = tf.io.read\_file(mask\_path)

mask = tfio.experimental.image.decode\_tiff(mask)

# Select the first channel (if multi-channel images)

image = image[..., :1] # Keep only the first channel

mask = mask[..., :1] # Keep only the first channel

# Resize to target size

image = tf.image.resize(image, target\_size)

mask = tf.image.resize(mask, target\_size)

# Normalize

image = image / 255.0 # Normalize to [0, 1]

mask = mask / 255.0 # Normalize to [0, 1] for binary masks

return image, mask

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image\_paths = sorted([os.path.join(image\_dir, f) for f in os.listdir(image\_dir) if f.endswith('.tiff')])

mask\_paths = sorted([os.path.join(mask\_dir, f) for f in os.listdir(mask\_dir) if f.endswith('.tiff')])

assert len(image\_paths) == len(mask\_paths), "Mismatch between number of images and masks"

print(image\_paths[:5])

print(mask\_paths[:5])

for img, mask in zip(image\_paths, mask\_paths):

assert os.path.basename(img).replace("\_ct\_", "\_label\_") == os.path.basename(mask), f"Image and mask mismatch: {img}, {mask}"

def load\_data(image\_path, mask\_path):

# Convert to tf.string explicitly

image\_path = tf.cast(image\_path, tf.string)

mask\_path = tf.cast(mask\_path, tf.string)

return preprocess\_image(image\_path, mask\_path)

dataset = tf.data.Dataset.from\_tensor\_slices((image\_paths, mask\_paths))

dataset = dataset.map(load\_data, num\_parallel\_calls=tf.data.AUTOTUNE)

dataset = dataset.batch(32).prefetch(tf.data.AUTOTUNE)

for image\_batch, mask\_batch in dataset.take(1):

print(f"Image batch shape: {image\_batch.shape}")

print(f"Mask batch shape: {mask\_batch.shape}")

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**Data Augmentation :**

def augment(image, mask):

# Random flip

image = tf.image.random\_flip\_left\_right(image)

mask = tf.image.random\_flip\_left\_right(mask)

# Random rotation

image = tf.image.rot90(image, k=tf.random.uniform((), minval=0, maxval=4, dtype=tf.int32))

mask = tf.image.rot90(mask, k=tf.random.uniform((), minval=0, maxval=4, dtype=tf.int32))

# Random contrast

image = tf.image.random\_contrast(image, lower=0.8, upper=1.2)

# Random brightness

image = tf.image.random\_brightness(image, max\_delta=0.2)

return image, mask

augmented\_dataset = dataset.map(augment, num\_parallel\_calls=tf.data.AUTOTUNE)

augmented\_dataset = augmented\_dataset.batch(32).prefetch(tf.data.AUTOTUNE)

**Model Architecture :**

import tensorflow as tf

from tensorflow.keras import layers

# Generator: U-Net Architecture

def build\_generator(input\_shape=(256, 256, 2), output\_channels=2):

inputs = layers.Input(shape=input\_shape)

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# Encoder (Downsampling)

down\_stack = [

downsample(64, 4, apply\_batchnorm=False), # (bs, 128, 128, 64)

downsample(128, 4), # (bs, 64, 64, 128)

downsample(256, 4), # (bs, 32, 32, 256)

downsample(512, 4), # (bs, 16, 16, 512)

downsample(512, 4), # (bs, 8, 8, 512)

downsample(512, 4), # (bs, 4, 4, 512)

downsample(512, 4), # (bs, 2, 2, 512)

downsample(512, 4), # (bs, 1, 1, 512)

]

# Decoder (Upsampling)

up\_stack = [

upsample(512, 4, apply\_dropout=True), # (bs, 2, 2, 1024)

upsample(512, 4, apply\_dropout=True), # (bs, 4, 4, 1024)

upsample(512, 4, apply\_dropout=True), # (bs, 8, 8, 1024)

upsample(512, 4), # (bs, 16, 16, 1024)

upsample(256, 4), # (bs, 32, 32, 512)

upsample(128, 4), # (bs, 64, 64, 256)

upsample(64, 4), # (bs, 128, 128, 128)

]

initializer = tf.random\_normal\_initializer(0., 0.02)

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last = layers.Conv2DTranspose(

output\_channels, 4, strides=2,

padding='same', kernel\_initializer=initializer,

activation='tanh'

) # (bs, 256, 256, 2)

# Connect Encoder and Decoder

x = inputs

skips = []

for down in down\_stack:

x = down(x)

skips.append(x)

skips = reversed(skips[:-1])

for up, skip in zip(up\_stack, skips):

x = up(x)

x = layers.Concatenate()([x, skip])

outputs = last(x)

return tf.keras.Model(inputs=inputs, outputs=outputs)

# Discriminator: PatchGAN

def build\_discriminator(input\_shape=(256, 256, 2), target\_shape=(256, 256, 2)):

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initializer = tf.random\_normal\_initializer(0., 0.02)

inputs = layers.Input(shape=input\_shape, name='inputs')

down1 = downsample(64, 4, apply\_batchnorm=False)(inputs) # (bs, 128, 128, 64)

down2 = downsample(128, 4)(down1) # (bs, 64, 64, 128)

down3 = downsample(256, 4)(down2) # (bs, 32, 32, 256)

down4 = downsample(512, 4)(down3) # (bs, 16, 16, 512)

zero\_pad1 = layers.ZeroPadding2D()(down4) # (bs, 18, 18, 512)

conv = layers.Conv2D(512, 4, strides=1, kernel\_initializer=initializer, use\_bias=False)(zero\_pad1) # (bs, 15, 15, 512)

batchnorm1 = layers.BatchNormalization()(conv)

leaky\_relu = layers.LeakyReLU()(batchnorm1)

zero\_pad2 = layers.ZeroPadding2D()(leaky\_relu) # (bs, 17, 17, 512)

last = layers.Conv2D(1, 4, strides=1, kernel\_initializer=initializer)(zero\_pad2) # (bs, 14, 14, 1)

return tf.keras.Model(inputs=inputs, outputs=last)

# Downsample Block

def downsample(filters, size, apply\_batchnorm=True):

initializer = tf.random\_normal\_initializer(0., 0.02)

result = tf.keras.Sequential()

result.add(

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layers.Conv2D(

filters, size, strides=2, padding='same',

kernel\_initializer=initializer, use\_bias=False

)

)

if apply\_batchnorm:

result.add(layers.BatchNormalization())

result.add(layers.LeakyReLU())

return result

# Upsample Block

def upsample(filters, size, apply\_dropout=False):

initializer = tf.random\_normal\_initializer(0., 0.02)

result = tf.keras.Sequential()

result.add(

layers.Conv2DTranspose(

filters, size, strides=2, padding='same',

kernel\_initializer=initializer, use\_bias=False

)

)

result.add(layers.BatchNormalization())

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if apply\_dropout:

result.add(layers.Dropout(0.5))

result.add(layers.ReLU())

return result

**Loss Functions :**

def weighted\_binary\_crossentropy(y\_true, y\_pred, weights):

"""

Weighted BCE Loss function with dynamic weights.

Args:

y\_true: Ground truth labels (binary mask, 0 or 1).

y\_pred: Predicted logits (before activation).

weights: Tuple of (background\_weight, foreground\_weight).

Returns:

Weighted BCE loss.

"""

background\_weight, foreground\_weight = weights

y\_true = tf.cast(y\_true, tf.float32)

y\_pred = tf.cast(y\_pred, tf.float32)

bce = -(

foreground\_weight \* y\_true \* tf.math.log(tf.clip\_by\_value(y\_pred, 1e-7, 1.0)) +

background\_weight \* (1 - y\_true) \* tf.math.log(tf.clip\_by\_value(1 - y\_pred, 1e-7, 1.0))

)

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return tf.reduce\_mean(bce)

Dicriminator Loss

def discriminator\_loss(real\_output, fake\_output, masks):

# Compute dynamic weights based on masks

weights = compute\_class\_weights(masks)

real\_loss = weighted\_binary\_crossentropy(

tf.ones\_like(real\_output), real\_output, weights

)

fake\_loss = weighted\_binary\_crossentropy(

tf.zeros\_like(fake\_output), fake\_output, weights

)

return real\_loss + fake\_loss

Generator Loss

def generator\_loss(fake\_output, gen\_output, target, masks, lambda\_l1=100):

# Compute dynamic weights based on masks

weights = compute\_class\_weights(masks)

adversarial\_loss = weighted\_binary\_crossentropy(

tf.ones\_like(fake\_output), fake\_output, weights

)

l1\_loss = tf.reduce\_mean(tf.abs(target - gen\_output)) # L1 Loss

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return adversarial\_loss + (lambda\_l1 \* l1\_loss)

tf.config.run\_functions\_eagerly(True)

def compute\_class\_weights(masks):

"""

Calculate class weights for the dataset or batch based on pixel values.

Args:

masks: Ground truth masks with values 0 and 1.

Returns:

Tuple of (background\_weight, foreground\_weight).

"""

total\_pixels = tf.cast(tf.size(masks), tf.float32)

foreground\_pixels = tf.reduce\_sum(masks)

# print(f"Total pixels type: {total\_pixels.dtype}, Foreground pixels type: {foreground\_pixels.dtype}")

background\_pixels = total\_pixels - foreground\_pixels

background\_weight = foreground\_pixels / total\_pixels

foreground\_weight = background\_pixels / total\_pixels

# Ensure we compute values before converting to numpy

background\_weight\_value = background\_weight.numpy()

foreground\_weight\_value = foreground\_weight.numpy()

return background\_weight\_value, foreground\_weight\_value

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**Training :**

@tf.function

def train\_step(input\_image, target\_image, generator, discriminator,

generator\_optimizer, discriminator\_optimizer):

# Concatenate image and mask for generator input

generator\_input = tf.concat([input\_image, target\_image], axis=-1)

with tf.GradientTape() as gen\_tape, tf.GradientTape() as disc\_tape:

# Generator forward pass

gen\_output = generator(generator\_input, training=True)

gen\_mask = gen\_output[:, :, :, 1]

gen\_mask = tf.expand\_dims(gen\_mask, axis=-1)

# print("cmon", gen\_mask.shape)

# Concatenate input image and generated/real masks for discriminator

real\_input = tf.concat([input\_image, target\_image], axis=-1)

fake\_input = tf.concat([input\_image, gen\_mask], axis=-1)

# print(f"Input Image Shape: {input\_image.shape}") # Should be (batch\_size, 256, 256, 1)

# print(f"Target Image Shape: {target\_image.shape}") # Should be (batch\_size, 256, 256, 1)

# print(f"Generator Output Shape: {gen\_output.shape}") # Should be (batch\_size, 256, 256, 1)

# print(f"Real Input Shape: {real\_input.shape}") # Should be (batch\_size, 256, 256, 2)

# print(f"Fake Input Shape: {fake\_input.shape}") # Should be (batch\_size, 256, 256, 2)

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# Discriminator forward pass

real\_output = discriminator(real\_input, training=True)

fake\_output = discriminator(fake\_input, training=True)

# Compute losses

gen\_loss = generator\_loss(fake\_output, gen\_output, target\_image, target\_image)

disc\_loss = discriminator\_loss(real\_output, fake\_output, target\_image)

# Apply gradients

generator\_gradients = gen\_tape.gradient(gen\_loss, generator.trainable\_variables)

discriminator\_gradients = disc\_tape.gradient(disc\_loss, discriminator.trainable\_variables)

generator\_optimizer.apply\_gradients(zip(generator\_gradients, generator.trainable\_variables))

discriminator\_optimizer.apply\_gradients(zip(discriminator\_gradients, discriminator.trainable\_variables))

return gen\_loss, disc\_loss

import time

import tensorflow as tf

from tqdm import tqdm

def train(dataset, generator, discriminator, generator\_optimizer, discriminator\_optimizer, epochs, log\_interval=100):

for epoch in range(epochs):

start = time.time()

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print(f"Epoch {epoch+1}/{epochs}")

progress\_bar = tqdm(dataset, desc=f'Epoch {epoch+1}', position=0, leave=True)

for step, (input\_image, target\_image) in enumerate(progress\_bar):

gen\_loss, disc\_loss = train\_step(

input\_image, target\_image, generator, discriminator,

generator\_optimizer, discriminator\_optimizer

)

if step % log\_interval == 0:

progress\_bar.set\_postfix(GenLoss=f"{gen\_loss.numpy():.4f}", DiscLoss=f"{disc\_loss.numpy():.4f}")

progress\_bar.close()

print(f"Epoch {epoch+1} completed in {time.time() - start:.2f}s")

# Example configuration

epochs = 25

log\_interval = 10

# Initialize models and optimizers

generator = build\_generator() # Replace with your generator function

discriminator = build\_discriminator() # Replace with your discriminator function

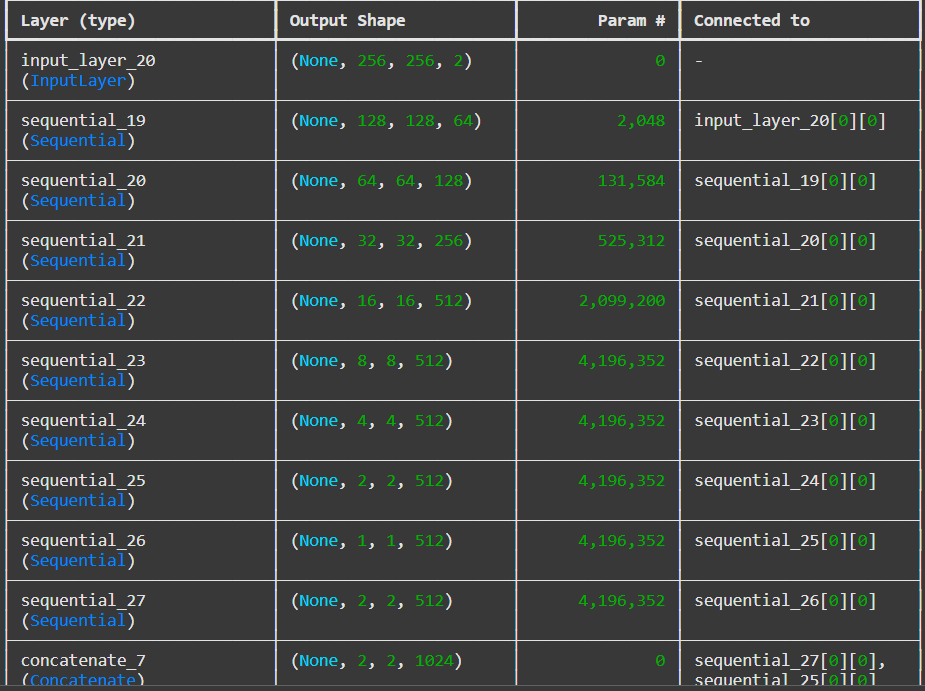
generator\_optimizer = tf.keras.optimizers.Adam(2e-4, beta\_1=0.5)

discriminator\_optimizer = tf.keras.optimizers.Adam(2e-4, beta\_1=0.5)

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**Generator Summary :**

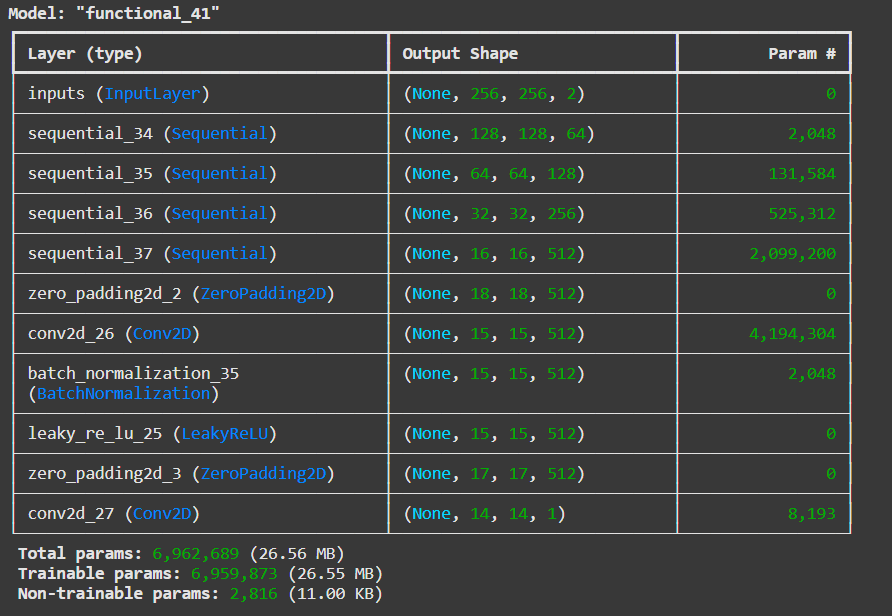
generator.summary()



**Discriminator Summary :**

discriminator.summary()

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# Train the model

train(dataset, generator, discriminator, generator\_optimizer, discriminator\_optimizer, epochs, log\_interval)

Saving the Model

generator.save('generator\_model.h5')

discriminator.save('discriminator\_model.h5')

Inference

import numpy as np

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# Generate 5 random inputs for inference

# Assuming inputs are normalized in the range [-1, 1]

input\_images = np.random.uniform(-1, 1, (5, 256, 256, 1)) # Random CT scans

input\_masks = np.random.uniform(-1, 1, (5, 256, 256, 1)) # Random masks

# Concatenate images and masks along the channel axis

input\_data = np.concatenate([input\_images, input\_masks], axis=-1) # Shape: (5, 256, 256, 2)

# Generate synthetic outputs

generated\_outputs = generator.predict(input\_data)

# Separate the generated images and masks

generated\_images = generated\_outputs[..., 0] # Extract the first channel (generated CT scans)

generated\_masks = generated\_outputs[..., 1] # Extract the second channel (generated masks)

**Vizualization of the results:**

import matplotlib.pyplot as plt

# Visualize the results

for i in range(5):

plt.figure(figsize=(8, 4))

# Input image

plt.subplot(1, 3, 1)

plt.title("Input Image")

plt.imshow(input\_data[i, ..., 0], cmap='gray')

plt.axis('off')

# Input mask

plt.subplot(1, 3, 2)

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plt.title("Input Mask")

plt.imshow(input\_data[i, ..., 1], cmap='gray')

plt.axis('off')

# Generated output (image or mask)

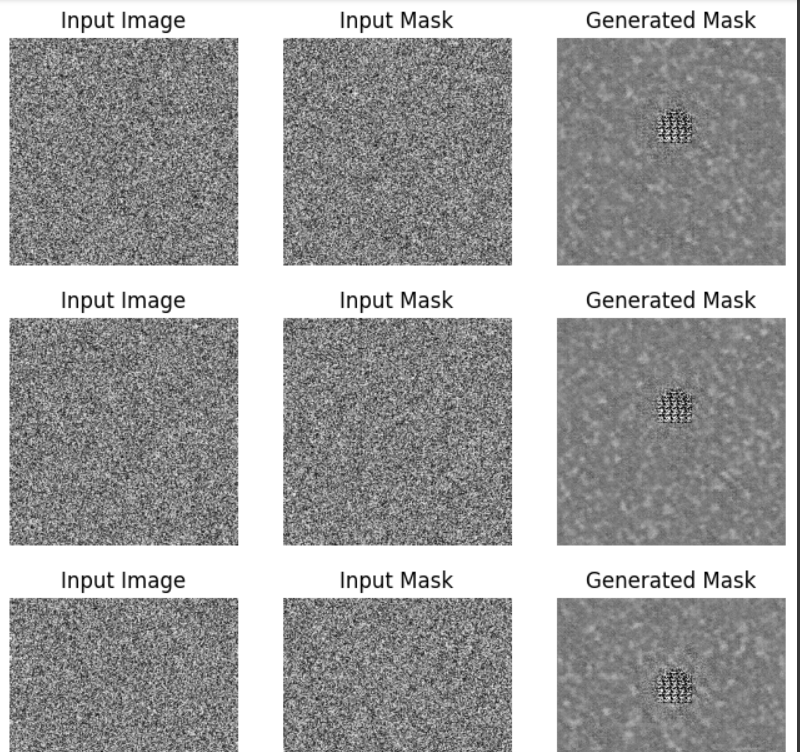
plt.subplot(1, 3, 3)

plt.title("Generated Mask")

plt.imshow(generated\_masks[i], cmap='gray')

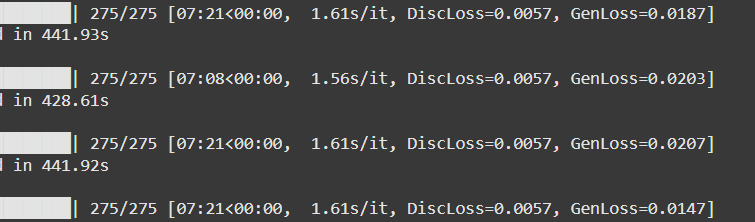
plt.axis('off')

plt.show()



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**RESULTS AND ANALYSIS**

* **Quantitative Results:**
  + Losses of genreator and discriminator are quantitative results of model.
  + 
  + Diversity Index: High diversity score indicating minimal mode collapse.
* **Qualitative Results:**
  + Synthetic images exhibit high visual similarity to real samples, with realistic texture and morphology.
* **Challenges:**
  + Mode collapse during initial training was mitigated by adjusting learning rates and introducing instance noise.
  + Balancing the generator and discriminator training required fine-tuning of hyperparameters.

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**CHAPTER 5**

**CONCLUSION and FUTURE WORK**

**CONCLUSION**

This project demonstrates the feasibility of using GANs to generate high-quality synthetic images for pancreatic cancer datasets. The approach effectively addresses data scarcity, providing a foundation for improving diagnostic models and facilitating further research in medical imaging. The generated images exhibit a balance of quality and diversity, making them suitable for augmenting training datasets for downstream tasks.

**FUTURE WORK**

Future developments include:

* Extending the framework to 3D medical imaging.
* Incorporating conditional GANs to generate images with specific attributes.
* Evaluating the impact of synthetic data on downstream tasks, such as segmentation and classification.
* Enhancing the realism of generated images by using advanced GAN variants like StyleGAN or BigGAN.
* Collaborating with domain experts to validate the clinical relevance of synthetic images.

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