```
import os
from PIL import Image
import matplotlib.pyplot as plt
from keras.layers import Input, Dense, Reshape, Flatten
from keras.layers import Activation
from glob import glob
from keras.models import Sequential, Model
from keras.optimizers import Adam
import matplotlib.pyplot as plt
import sys
import numpy as np
from google.colab import drive
drive.mount('/content/drive')
Mounted at /content/drive
dataset path = "/content/drive/MyDrive/HEART US IMAGE FETUS"
print("Dataset path:", dataset path)
Dataset path: /content/drive/MyDrive/HEART US IMAGE FETUS
from glob import glob
dataset path = "/content/drive/MyDrive/HEART US IMAGE FETUS"
print("Dataset path:", dataset_path)
# Use glob to get all image paths in the specified directory
image paths = glob(dataset path + '/*.ipg')
# Print all image paths
print("Image paths:")
for path in image paths:
    print(path)
Dataset path: /content/drive/MyDrive/HEART US IMAGE FETUS
Image paths:
/content/drive/MyDrive/HEART US IMAGE FETUS/1950612.jpg
/content/drive/MyDrive/HEART US IMAGE FETUS/531643.jpg
/content/drive/MyDrive/HEART US IMAGE FETUS/1830719.jpg
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```

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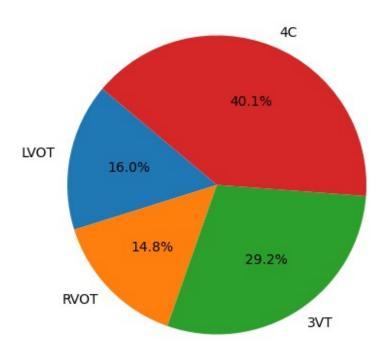
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```

```
# Count the number of images in the dataset
original size = len(image paths)
# Print the original size of the dataset
print("Original size of the dataset:", original size)
Original size of the dataset: 257
import os
import pandas as pd
import matplotlib.pyplot as plt
dataset path = '/content/drive/MyDrive/HEART US IMAGE FETUS'
# Get a list of all image files in the dataset folder
image files = [file for file in os.listdir(dataset path) if
file.endswith(('.jpg', '.png', '.jpeg'))]
# List of image labels
image_labels = ['LVOT', 'RVOT', '3VT', '4C']
# List of corresponding counts
part counts = [41,38,75,103]
# Calculate the total number of images
total images = sum(part counts)
# Calculate the percentage distribution of each label
percentage distribution = [count / total images * 100 for count in
part counts]
# Create a DataFrame with filenames, labels, and counts
label list = [f"{count}-{label}" for count, label in zip(part counts,
image labels) for in range(count)]
df = pd.DataFrame({'Image': image files[:len(label list)], 'Label':
label list})
# Display the percentage distribution
for label, percentage in zip(image labels, percentage distribution):
    print(f"{label}: {percentage:.2f}%")
# Create a pie chart
plt.figure(figsize=(5, 5))
plt.pie(percentage distribution, labels=image labels, autopct='%1.1f%
%', startangle=140)
plt.title('Percentage Distribution of Image Labels')
plt.show()
LVOT: 15.95%
RVOT: 14.79%
```

3VT: 29.18% 4C: 40.08%

Percentage Distribution of Image Labels



```
from PIL import Image
import os
dataset path = "/content/drive/MyDrive/HEART US IMAGE FETUS"
def check_image_color_mode(image_path):
    with Image.open(image path) as img:
        return img.mode
def check dataset color mode(dataset path):
    for filename in os.listdir(dataset path):
        if filename.endswith(('.png', '.jpg', '.jpeg')):
            image path = os.path.join(dataset path, filename)
            color_mode = check_image_color_mode(image_path)
            print(f"{filename}: {color_mode}")
# Call the function to check color modes in the dataset
check dataset color mode(dataset path)
1950612.jpg: RGB
531643.jpg: RGB
```

```
1830719.jpg: RGB
1947161.jpg: RGB
1761038.jpg: RGB
1741778.jpg: RGB
1184842.jpg: RGB
1184845.jpg: RGB
531639.jpg: RGB
878716.jpg: RGB
1741782.jpg: RGB
910907.jpg: RGB
1829682.jpg: RGB
1828656.jpg: RGB
1947162.jpg: RGB
1829684.jpg: RGB
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1766429.jpg: RGB
1184841.jpg: RGB
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1158799.jpg: RGB
1875058.jpg: RGB
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```

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1910761.jpg: RGB
1917328.jpg: RGB
1184901.jpg: RGB
1910734.jpg: RGB
1912590.jpg: RGB
1917253.ipg: RGB
1936139.jpg: RGB
1917267.jpg: RGB
1923234.jpg: RGB
1917265.jpg: RGB
1923230.jpg: RGB
1940641.jpg: RGB
1912624.jpg: RGB
1931521.jpg: RGB
1931529.jpg: RGB
1917327.jpg: RGB
1912626.jpg: RGB
1940653.jpg: RGB
1902286.ipg: RGB
1923231.jpg: RGB
1931532.jpg: RGB
1912605.jpg: RGB
1912630.jpg: RGB
1936136.jpg: RGB
1945545.jpg: RGB
1910763.jpg: RGB
1917261.jpg: RGB
1945600.jpg: RGB
1902301.jpg: RGB
1940640.jpg: RGB
1940663.jpg: RGB
1931525.jpg: RGB
1923233.jpg: RGB
1940642.ipg: RGB
1940701.jpg: RGB
1936135.jpg: RGB
1929103.jpg: RGB
1940728.jpg: RGB
1940647.jpg: RGB
1945552.jpg: RGB
1945551.jpg: RGB
1946146.jpg: RGB
```

```
1931495.jpg: RGB
1946158.jpg: RGB
1946147.jpg: RGB
1945713.jpg: RGB
1946161.jpg: RGB
1946157.jpg: RGB
1940636.jpg: RGB
1946159.jpg: RGB
1946000.jpg: RGB
1939941.jpg: RGB
1946347.jpg: RGB
1946374.jpg: RGB
1945549.ipg: RGB
1940643.jpg: RGB
1946149.jpg: RGB
1940645.jpg: RGB
1945983.jpg: RGB
1940644.jpg: RGB
1946156.jpg: RGB
1946150.jpg: RGB
1945986.jpg: RGB
1946155.jpg: RGB
1946211.jpg: RGB
1945982.jpg: RGB
1940633.jpg: RGB
1946653.jpg: RGB
1947159.jpg: RGB
1946148.jpg: RGB
1945712.jpg: RGB
1946373.jpg: RGB
1945987.jpg: RGB
1945989.ipg: RGB
1946349.jpg: RGB
1947150.jpg: RGB
1945546.jpg: RGB
1946022.jpg: RGB
1946645.jpg: RGB
1947151.jpg: RGB
1939986.jpg: RGB
1947155.jpg: RGB
1947163.ipg: RGB
1946353.jpg: RGB
1949793.jpg: RGB
1947156.jpg: RGB
1947164.jpg: RGB
1946354.jpg: RGB
1946002.jpg: RGB
1949583.jpg: RGB
1949407.jpg: RGB
```

```
1946365.jpg: RGB
1949439.jpg: RGB
1949584.jpg: RGB
1946344.jpg: RGB
1946021.jpg: RGB
1946222.jpg: RGB
1949647.jpg: RGB
1947152.jpg: RGB
1949394.jpg: RGB
1946643.jpg: RGB
1940649.jpg: RGB
1946367.jpg: RGB
1947153.ipg: RGB
1949775.jpg: RGB
1949589.jpg: RGB
1949597.jpg: RGB
1949945.jpg: RGB
1950148.jpg: RGB
1950552.jpg: RGB
1949794.jpg: RGB
1949942.jpg: RGB
1947158.jpg: RGB
1949648.jpg: RGB
1947160.jpg: RGB
1946345.jpg: RGB
1949972.ipg: RGB
1950188.ipg: RGB
1949406.jpg: RGB
1947000.jpg: RGB
1947165.jpg: RGB
1949471.jpg: RGB
1950150.jpg: RGB
1950151.jpg: RGB
1949400.jpg: RGB
1950152.jpg: RGB
1950185.jpg: RGB
1949588.jpg: RGB
1950187.jpg: RGB
1950556.jpg: RGB
1949452.jpg: RGB
1950549.ipg: RGB
1951010.jpg: RGB
1951151.jpg: RGB
1950554.jpg: RGB
1950564.jpg: RGB
1949879.jpg: RGB
1949469.jpg: RGB
1950560.jpg: RGB
1950184.jpg: RGB
```

```
1950551.jpg: RGB
1949943.jpg: RGB
1949592.jpg: RGB
1947157.jpg: RGB
1950610.jpg: RGB
1949435.jpg: RGB
1949963.jpg: RGB
1950831.jpg: RGB
1950550.jpg: RGB
1950586.jpg: RGB
import matplotlib.image as mpimg
import os
num_images_to_display = 12
# List all files in the dataset directory
files = os.listdir(dataset path)
# Select the first 12 images
selected_images = files[:num_images to display]
# Create a subplot with rows and columns
rows = 3 # Change this based on your preference
columns = 4 # Change this based on your preference
fig, axs = plt.subplots(rows, columns, figsize=(12, 9))
# Display each image in the subplot
for i in range(rows):
    for j in range(columns):
        img path = os.path.join(dataset path, selected images[i *
columns + j])
        img = mpimg.imread(img path)
        axs[i, j].imshow(img, cmap='gray')
        axs[i, j].axis('off')
# Adjust layout for better visualization
plt.tight layout()
plt.show()
```



```
from PIL import Image
import os
dataset path = "/content/drive/MyDrive/HEART US IMAGE FETUS"
def check image properties(image path):
    with Image.open(image_path) as img:
         return img.size, img.mode
def check dataset properties(dataset path):
    for filename in os.listdir(dataset path):
        if filename.endswith(('.png', '.jpg', '.jpeg')):
    image_path = os.path.join(dataset_path, filename)
            size, color mode = check_image_properties(image_path)
             print(f"{filename}: Size={size}, Mode={color_mode}")
# Call the function to check properties of images in the dataset
check dataset properties(dataset path)
1950612.jpg: Size=(800, 600), Mode=RGB
531643.jpg: Size=(1136, 852), Mode=RGB
1830719.jpg: Size=(1136, 852), Mode=RGB
1947161.jpg: Size=(258, 243), Mode=RGB
1761038.jpg: Size=(970, 727), Mode=RGB
```

```
1741778.jpg: Size=(970, 727), Mode=RGB
1184842.jpg: Size=(970, 727), Mode=RGB
1184845.jpg: Size=(970, 727), Mode=RGB
531639.jpg: Size=(1136, 852), Mode=RGB
878716.jpg: Size=(1136, 852), Mode=RGB
1741782.jpg: Size=(970, 727), Mode=RGB
910907.jpg: Size=(1136, 852), Mode=RGB
1829682.jpg: Size=(970, 727), Mode=RGB
1828656.jpg: Size=(1136, 852), Mode=RGB
1947162.jpg: Size=(800, 600), Mode=RGB
1829684.jpg: Size=(970, 727), Mode=RGB
1766431.jpg: Size=(1136, 852), Mode=RGB
1766429.jpg: Size=(1136, 852), Mode=RGB
1184841.jpg: Size=(970, 727), Mode=RGB
1829680.jpg: Size=(970, 727), Mode=RGB
1830127.jpg: Size=(1136, 852), Mode=RGB
1158827.jpg: Size=(800, 564), Mode=RGB
531640.jpg: Size=(1136, 852), Mode=RGB
1829253.jpg: Size=(970, 727), Mode=RGB
1184843.jpg: Size=(387, 356), Mode=RGB
531642.jpg: Size=(1136, 852), Mode=RGB
1875066.jpg: Size=(1136, 852), Mode=RGB
1950611.jpg: Size=(435, 305), Mode=RGB
1806269.jpg: Size=(1136, 852), Mode=RGB
1931522.jpg: Size=(305, 228), Mode=RGB
1882730.jpg: Size=(970, 727), Mode=RGB
1184844.jpg: Size=(970, 727), Mode=RGB
1830718.jpg: Size=(487, 378), Mode=RGB
1829679.jpg: Size=(970, 727), Mode=RGB
1795969.jpg: Size=(970, 727), Mode=RGB
1184902.jpg: Size=(970, 727), Mode=RGB
910911.jpg: Size=(1136, 852), Mode=RGB
1931523.jpg: Size=(800, 600), Mode=RGB
1875070.jpg: Size=(1136, 852), Mode=RGB
531630.jpg: Size=(1136, 852), Mode=RGB
1902291.jpg: Size=(800, 600), Mode=RGB
1891555.jpg: Size=(800, 600), Mode=RGB
1875062.jpg: Size=(1136, 852), Mode=RGB
1158799.jpg: Size=(800, 564), Mode=RGB
1875058.jpg: Size=(1136, 852), Mode=RGB
1875055.jpg: Size=(1136, 852), Mode=RGB
1882868.jpg: Size=(970, 727), Mode=RGB
1875059.jpg: Size=(1136, 852), Mode=RGB
1891560.jpg: Size=(800, 600), Mode=RGB
1875054.jpg: Size=(1136, 852), Mode=RGB
1886834.jpg: Size=(970, 727), Mode=RGB
1766430.jpg: Size=(1136, 852), Mode=RGB
1882866.jpg: Size=(970, 727), Mode=RGB
1886839.jpg: Size=(970, 727), Mode=RGB
```

```
1828928.jpg: Size=(1136, 852), Mode=RGB
1875052.jpg: Size=(1136, 852), Mode=RGB
1875051.jpg: Size=(1136, 852), Mode=RGB
1886825.jpg: Size=(970, 727), Mode=RGB
1184900.jpg: Size=(970, 727), Mode=RGB
1886840.jpg: Size=(970, 727), Mode=RGB
1875063.jpg: Size=(1136, 852), Mode=RGB
1889650.jpg: Size=(800, 600), Mode=RGB
1931524.jpg: Size=(800, 600), Mode=RGB
1875130.jpg: Size=(1136, 852), Mode=RGB
877955.jpg: Size=(800, 600), Mode=RGB
1902289.jpg: Size=(800, 600), Mode=RGB
1902305.jpg: Size=(800, 600), Mode=RGB
1889676.jpg: Size=(800, 600), Mode=RGB
1902304.jpg: Size=(800, 600), Mode=RGB
1902288.jpg: Size=(800, 600), Mode=RGB
877956.jpg: Size=(800, 600), Mode=RGB
1875128.jpg: Size=(1136, 852), Mode=RGB
878717.jpg: Size=(1136, 852), Mode=RGB
1830717.jpg: Size=(1136, 852), Mode=RGB
1886838.jpg: Size=(970, 727), Mode=RGB
1882731.jpg: Size=(970, 727), Mode=RGB
1184838.jpg: Size=(970, 727), Mode=RGB
1875127.jpg: Size=(1136, 852), Mode=RGB
1912631.jpg: Size=(800, 600), Mode=RGB
1912591.jpg: Size=(800, 600), Mode=RGB
1875060.jpg: Size=(1136, 852), Mode=RGB
1908509.jpg: Size=(800, 600), Mode=RGB
1917262.jpg: Size=(800, 600), Mode=RGB
1910702.jpg: Size=(800, 600), Mode=RGB
1875065.jpg: Size=(1136, 852), Mode=RGB
1917254.jpg: Size=(800, 600), Mode=RGB
1908510.jpg: Size=(800, 600), Mode=RGB
1887391.jpg: Size=(970, 727), Mode=RGB
1902292.jpg: Size=(800, 600), Mode=RGB
1889678.jpg: Size=(800, 600), Mode=RGB
1741780.jpg: Size=(970, 727), Mode=RGB
1889685.jpg: Size=(800, 600), Mode=RGB
1889645.jpg: Size=(800, 600), Mode=RGB
1875069.jpg: Size=(1136, 852), Mode=RGB
1910701.jpg: Size=(800, 600), Mode=RGB
1882739.jpg: Size=(970, 727), Mode=RGB
1917255.jpg: Size=(800, 600), Mode=RGB
1912627.jpg: Size=(800, 600), Mode=RGB
1882740.jpg: Size=(970, 727), Mode=RGB
1891562.jpg: Size=(800, 600), Mode=RGB
1889682.jpg: Size=(800, 600), Mode=RGB
1902293.jpg: Size=(800, 600), Mode=RGB
1902287.jpg: Size=(800, 600), Mode=RGB
```

```
1912628.jpg: Size=(800, 600), Mode=RGB
1936137.jpg: Size=(800, 600), Mode=RGB
1917257.jpg: Size=(800, 600), Mode=RGB
1917268.jpg: Size=(800, 600), Mode=RGB
1910761.jpg: Size=(800, 600), Mode=RGB
1917328.jpg: Size=(800, 600), Mode=RGB
1184901.jpg: Size=(970, 727), Mode=RGB
1910734.jpg: Size=(800, 600), Mode=RGB
1912590.jpg: Size=(800, 600), Mode=RGB
1917253.jpg: Size=(800, 600), Mode=RGB
1936139.jpg: Size=(800, 600), Mode=RGB
1917267.jpg: Size=(800, 600), Mode=RGB
1923234.jpg: Size=(800, 600), Mode=RGB
1917265.jpg: Size=(800, 600), Mode=RGB
1923230.jpg: Size=(800, 600), Mode=RGB
1940641.jpg: Size=(800, 600), Mode=RGB
1912624.jpg: Size=(800, 600), Mode=RGB
1931521.jpg: Size=(800, 600), Mode=RGB
1931529.jpg: Size=(800, 600), Mode=RGB
1917327.jpg: Size=(800, 600), Mode=RGB
1912626.jpg: Size=(800, 600), Mode=RGB
1940653.jpg: Size=(800, 600), Mode=RGB
1902286.jpg: Size=(800, 600), Mode=RGB
1923231.jpg: Size=(800, 600), Mode=RGB
1931532.jpg: Size=(800, 600), Mode=RGB
1912605.jpg: Size=(800, 600), Mode=RGB
1912630.jpg: Size=(800, 600), Mode=RGB
1936136.jpg: Size=(800, 600), Mode=RGB
1945545.jpg: Size=(800, 600), Mode=RGB
1910763.jpg: Size=(800, 600), Mode=RGB
1917261.jpg: Size=(800, 600), Mode=RGB
1945600.jpg: Size=(800, 600), Mode=RGB
1902301.jpg: Size=(800, 600), Mode=RGB
1940640.jpg: Size=(800, 600), Mode=RGB
1940663.jpg: Size=(800, 600), Mode=RGB
1931525.jpg: Size=(800, 600), Mode=RGB
1923233.jpg: Size=(800, 600), Mode=RGB
1940642.jpg: Size=(800, 600), Mode=RGB
1940701.jpg: Size=(800, 600), Mode=RGB
1936135.jpg: Size=(800, 600), Mode=RGB
1929103.jpg: Size=(800, 600), Mode=RGB
1940728.jpg: Size=(800, 600), Mode=RGB
1940647.jpg: Size=(800, 600), Mode=RGB
1945552.jpg: Size=(800, 600), Mode=RGB
1945551.jpg: Size=(800, 600), Mode=RGB
1946146.jpg: Size=(800, 600), Mode=RGB
1931495.jpg: Size=(800, 600), Mode=RGB
1946158.jpg: Size=(800, 600), Mode=RGB
1946147.jpg: Size=(800, 600), Mode=RGB
```

```
1945713.jpg: Size=(800, 600), Mode=RGB
1946161.jpg: Size=(800, 600), Mode=RGB
1946157.jpg: Size=(800, 600), Mode=RGB
1940636.jpg: Size=(800, 600), Mode=RGB
1946159.jpg: Size=(800, 600), Mode=RGB
1946000.jpg: Size=(800, 600), Mode=RGB
1939941.jpg: Size=(800, 600), Mode=RGB
1946347.jpg: Size=(800, 600), Mode=RGB
1946374.jpg: Size=(800, 600), Mode=RGB
1945549.jpg: Size=(800, 600), Mode=RGB
1940643.jpg: Size=(800, 600), Mode=RGB
1946149.jpg: Size=(800, 600), Mode=RGB
1940645.jpg: Size=(800, 600), Mode=RGB
1945983.jpg: Size=(800, 600), Mode=RGB
1940644.jpg: Size=(800, 600), Mode=RGB
1946156.jpg: Size=(800, 600), Mode=RGB
1946150.jpg: Size=(800, 600), Mode=RGB
1945986.jpg: Size=(800, 600), Mode=RGB
1946155.jpg: Size=(800, 600), Mode=RGB
1946211.jpg: Size=(800, 600), Mode=RGB
1945982.jpg: Size=(800, 600), Mode=RGB
1940633.jpg: Size=(800, 600), Mode=RGB
1946653.jpg: Size=(800, 600), Mode=RGB
1947159.jpg: Size=(800, 600), Mode=RGB
1946148.jpg: Size=(800, 600), Mode=RGB
1945712.jpg: Size=(800, 600), Mode=RGB
1946373.jpg: Size=(800, 600), Mode=RGB
1945987.jpg: Size=(800, 600), Mode=RGB
1945989.jpg: Size=(800, 600), Mode=RGB
1946349.jpg: Size=(800, 600), Mode=RGB
1947150.jpg: Size=(800, 600), Mode=RGB
1945546.jpg: Size=(800, 600), Mode=RGB
1946022.jpg: Size=(800, 600), Mode=RGB
1946645.jpg: Size=(800, 600), Mode=RGB
1947151.jpg: Size=(800, 600), Mode=RGB
1939986.jpg: Size=(800, 600), Mode=RGB
1947155.jpg: Size=(800, 600), Mode=RGB
1947163.jpg: Size=(800, 600), Mode=RGB
1946353.jpg: Size=(800, 600), Mode=RGB
1949793.jpg: Size=(800, 600), Mode=RGB
1947156.jpg: Size=(800, 600), Mode=RGB
1947164.jpg: Size=(800, 600), Mode=RGB
1946354.jpg: Size=(800, 600), Mode=RGB
1946002.jpg: Size=(800, 600), Mode=RGB
1949583.jpg: Size=(800, 600), Mode=RGB
1949407.jpg: Size=(800, 600), Mode=RGB
1946365.jpg: Size=(800, 600), Mode=RGB
1949439.jpg: Size=(800, 600), Mode=RGB
1949584.jpg: Size=(800, 600), Mode=RGB
```

```
1946344.jpg: Size=(800, 600), Mode=RGB
1946021.jpg: Size=(800, 600), Mode=RGB
1946222.jpg: Size=(800, 600), Mode=RGB
1949647.jpg: Size=(800, 600), Mode=RGB
1947152.jpg: Size=(800, 600), Mode=RGB
1949394.jpg: Size=(800, 600), Mode=RGB
1946643.jpg: Size=(800, 600), Mode=RGB
1940649.jpg: Size=(800, 600), Mode=RGB
1946367.jpg: Size=(800, 600), Mode=RGB
1947153.jpg: Size=(800, 600), Mode=RGB
1949775.jpg: Size=(800, 600), Mode=RGB
1949589.jpg: Size=(800, 600), Mode=RGB
1949597.jpg: Size=(800, 600), Mode=RGB
1949945.jpg: Size=(800, 600), Mode=RGB
1950148.jpg: Size=(800, 600), Mode=RGB
1950552.jpg: Size=(800, 600), Mode=RGB
1949794.jpg: Size=(800, 600), Mode=RGB
1949942.jpg: Size=(800, 600), Mode=RGB
1947158.jpg: Size=(800, 600), Mode=RGB
1949648.jpg: Size=(800, 600), Mode=RGB
1947160.jpg: Size=(800, 600), Mode=RGB
1946345.jpg: Size=(800, 600), Mode=RGB
1949972.jpg: Size=(800, 600), Mode=RGB
1950188.jpg: Size=(800, 600), Mode=RGB
1949406.jpg: Size=(800, 600), Mode=RGB
1947000.jpg: Size=(800, 600), Mode=RGB
1947165.jpg: Size=(800, 600), Mode=RGB
1949471.jpg: Size=(800, 600), Mode=RGB
1950150.jpg: Size=(800, 600), Mode=RGB
1950151.jpg: Size=(800, 600), Mode=RGB
1949400.jpg: Size=(800, 600), Mode=RGB
1950152.jpg: Size=(800, 600), Mode=RGB
1950185.jpg: Size=(800, 600), Mode=RGB
1949588.jpg: Size=(800, 600), Mode=RGB
1950187.jpg: Size=(800, 600), Mode=RGB
1950556.jpg: Size=(800, 600), Mode=RGB
1949452.jpg: Size=(800, 600), Mode=RGB
1950549.jpg: Size=(800, 600), Mode=RGB
1951010.jpg: Size=(800, 600), Mode=RGB
1951151.jpg: Size=(800, 600), Mode=RGB
1950554.jpg: Size=(800, 600), Mode=RGB
1950564.jpg: Size=(800, 600), Mode=RGB
1949879.jpg: Size=(800, 600), Mode=RGB
1949469.jpg: Size=(800, 600), Mode=RGB
1950560.jpg: Size=(800, 600), Mode=RGB
1950184.jpg: Size=(800, 600), Mode=RGB
1950551.jpg: Size=(800, 600), Mode=RGB
1949943.jpg: Size=(800, 600), Mode=RGB
1949592.jpg: Size=(800, 600), Mode=RGB
```

```
1947157.jpg: Size=(800, 600), Mode=RGB
1950610.jpg: Size=(800, 600), Mode=RGB
1949435.jpg: Size=(800, 600), Mode=RGB
1949963.jpg: Size=(800, 600), Mode=RGB
1950831.jpg: Size=(800, 600), Mode=RGB
1950550.jpg: Size=(800, 600), Mode=RGB
1950586.jpg: Size=(800, 600), Mode=RGB
```

PREPROCESSING

A) RESIZING

```
from PIL import Image
import os
# Path to the original dataset
original dataset path = "/content/drive/MyDrive/HEART US IMAGE FETUS"
# Path to the new location to store resized images
resized dataset path =
"/content/drive/MyDrive/Resized HEART US IMAGE FETUS"
# Create the new directory if it doesn't exist
if not os.path.exists(resized dataset path):
    os.makedirs(resized dataset path)
# Function to resize and save images
def resize and save(image path, output path, target size=(256, 256)):
    with Image.open(image path) as img:
        resized img = img.resize(target size, Image.ANTIALIAS)
        resized img.save(output path)
# Loop through each image in the original dataset
for filename in os.listdir(original dataset path):
    if filename.endswith(('.png', '.jpg', '.jpeg')):
        # Create the full path for the original and resized images
        original image path = os.path.join(original dataset path,
filename)
        resized image path = os.path.join(resized dataset path,
filename)
        # Resize and save the image
        resize and save(original image path, resized image path)
# Display some resized images for reference
num images to display = 4
selected resized images = os.listdir(resized dataset path)
[:num images to display]
```

```
# Create a subplot with rows and columns
rows = 1
columns = num images to display
fig, axs = plt.subplots(rows, columns, figsize=(12, 3))
# Display each resized image in the subplot
for i in range(columns):
    img path = os.path.join(resized dataset path,
selected resized images[i])
    img = mpimg.imread(img path)
    axs[i].imshow(img, cmap='gray')
    axs[i].axis('off')
# Adjust layout for better visualization
plt.tight layout()
plt.show()
<ipython-input-12-746f01e1b3a1>:17: DeprecationWarning: ANTIALIAS is
deprecated and will be removed in Pillow 10 (2023-07-01). Use LANCZOS
or Resampling.LANCZOS instead.
  resized img = img.resize(target size, Image.ANTIALIAS)
```









NORMALIZATION

```
import numpy as np

# Path to the resized dataset
resized_dataset_path =
  "/content/drive/MyDrive/Resized_HEART_US_IMAGE_FETUS"

# Path to the location to store normalized images
normalized_dataset_path =
  "/content/drive/MyDrive/Normalized_HEART_US_IMAGE_FETUS"

# Create the new directory if it doesn't exist
if not os.path.exists(normalized_dataset_path):
    os.makedirs(normalized_dataset_path)

# Function to normalize and save images
```

```
def normalize and save(image path, output path):
    with Image.open(image path) as img:
        # Convert image to NumPy array
        img array = np.array(img)
        # Normalize pixel values to the range [0, 1]
        normalized img = img array / 255.0
        # Save the normalized image
        normalized img = Image.fromarray((normalized img *
255).astype(np.uint8))
        normalized img.save(output path)
# Loop through each image in the resized dataset
for filename in os.listdir(resized dataset path):
    if filename.endswith(('.png', '.jpg', '.jpeg')):
    # Create the full path for the resized and normalized images
        resized image path = os.path.join(resized dataset path,
filename)
        normalized image path = os.path.join(normalized dataset path,
filename)
        # Normalize and save the image
        normalize and save(resized image path, normalized image path)
# Display some normalized images for reference
num images to display = 4
selected_normalized_images = os.listdir(normalized_dataset_path)
[:num images to display]
# Create a subplot with rows and columns
rows = 1
columns = num images to display
fig, axs = plt.subplots(rows, columns, figsize=(12, 3))
# Display each normalized image in the subplot
for i in range(columns):
    img path = os.path.join(normalized dataset path,
selected normalized images[i])
    img = mpimg.imread(img path)
    axs[i].imshow(img, cmap='gray')
    axs[i].axis('off')
# Adjust layout for better visualization
plt.tight_layout()
plt.show()
```









SHARPENING

```
from PIL import Image, ImageFilter
# Path to the normalized dataset
normalized dataset path =
"/content/drive/MyDrive/Normalized HEART US IMAGE FETUS"
# Path to the location to store sharpened images
sharpened dataset path =
"/content/drive/MyDrive/Sharpened HEART US IMAGE FETUS"
# Create the new directory if it doesn't exist
if not os.path.exists(sharpened dataset path):
    os.makedirs(sharpened dataset path)
# Function to sharpen and save images
def sharpen and save(image path, output path):
    with Image.open(image path) as img:
        # Apply a sharpening filter
        sharpened img = img.filter(ImageFilter.SHARPEN)
        # Save the sharpened image
        sharpened img.save(output path)
# Loop through each image in the normalized dataset
for filename in os.listdir(normalized dataset path):
    if filename.endswith(('.png', '.jpg', '.jpeg')):
        # Create the full path for the normalized and sharpened images
        normalized image path = os.path.join(normalized dataset path,
filename)
        sharpened image path = os.path.join(sharpened dataset path,
filename)
        # Sharpen and save the image
        sharpen and save(normalized image path, sharpened image path)
# Display some sharpened images for reference
num images to display = 4
selected sharpened images = os.listdir(sharpened dataset path)
[:num_images_to_display]
```

```
# Create a subplot with rows and columns
rows = 1
columns = num_images_to_display
fig, axs = plt.subplots(rows, columns, figsize=(12, 3))
# Display each sharpened image in the subplot
for i in range(columns):
    img_path = os.path.join(sharpened_dataset_path,
selected_sharpened_images[i])
    img = mpimg.imread(img_path)
    axs[i].imshow(img, cmap='gray')
    axs[i].axis('off')

# Adjust layout for better visualization
plt.tight_layout()
plt.show()
```









CONTRAST ADJUSTMENT

```
from PIL import Image, ImageFilter, ImageEnhance

# Path to the sharpened dataset
sharpened_dataset_path =
  "/content/drive/MyDrive/Sharpened_HEART_US_IMAGE_FETUS"

# Path to the location to store contrast-stretched images
contrast_stretched_dataset_path =
  "/content/drive/MyDrive/Contrast_Stretched_HEART_US_IMAGE_FETUS"

# Create the new directory if it doesn't exist
if not os.path.exists(contrast_stretched_dataset_path):
    os.makedirs(contrast_stretched_dataset_path)

# Function to apply contrast stretching and save images
def contrast_stretch_and_save(image_path, output_path,
enhancement_factor=1.5):
    with Image.open(image_path) as img:
```

```
# Apply contrast stretching using ImageEnhance
        contrast = ImageEnhance.Contrast(img)
        stretched_img = contrast.enhance(enhancement_factor)
        # Save the contrast-stretched image
        stretched img.save(output path)
# Loop through each image in the sharpened dataset
for filename in os.listdir(sharpened dataset path):
    if filename.endswith(('.png', '.jpg', '.jpeg')):
        # Create the full path for the sharpened and contrast-
stretched images
        sharpened image path = os.path.join(sharpened dataset path,
filename)
        contrast stretched image path =
os.path.join(contrast stretched dataset path, filename)
        # Contrast stretch and save the image
        contrast stretch and save(sharpened image path,
contrast stretched image path)
# Display some contrast-stretched images for reference
num images to display = 4
selected contrast stretched images =
os.listdir(contrast stretched dataset path)[:num images to display]
# Create a subplot with rows and columns
rows = 1
columns = num images to display
fig, axs = plt.subplots(rows, columns, figsize=(12, 3))
# Display each contrast-stretched image in the subplot
for i in range(columns):
    img path = os.path.join(contrast stretched dataset path,
selected contrast stretched images[i])
    img = mpimg.imread(img path)
    axs[i].imshow(img, cmap='gray')
    axs[i].axis('off')
# Adjust layout for better visualization
plt.tight layout()
plt.show()
```









CLUSTER ANALYSIS

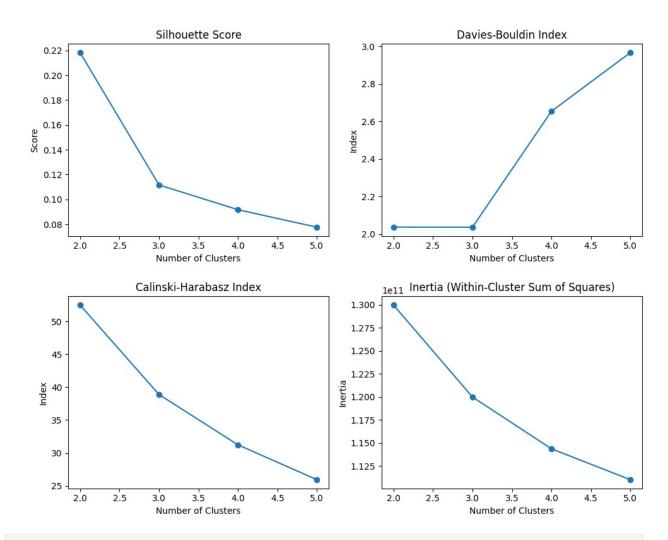
K-Means Clustering Before PCA

```
import os
import cv2
import numpy as np
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette score, davies bouldin score,
calinski harabasz score
import matplotlib.pyplot as plt
# Define the path to your image dataset
dataset path ="/content/drive/MyDrive/HEART US IMAGE FETUS"
# Function to load and preprocess images
def load and preprocess images(dataset path, image shape):
    image_list = []
    for filename in os.listdir(dataset path):
        if filename.endswith('.jpg'):
            img = cv2.imread(os.path.join(dataset path, filename))
            img = cv2.cvtColor(img, cv2.COLOR BGR2RGB) # Convert to
RGB format
            img = cv2.resize(img, image shape) # Resize the image
            image list.append(img)
    return image list
# Load and preprocess the images
image shape = (256, 256)
images = load and preprocess images(dataset path, image shape)
# Convert the list of images to a numpy array
image data = np.array(images).reshape(len(images), -1)
# Range of clusters to trv
cluster range = range(2, 6)
```

```
# Lists to store metrics for plotting
silhouette scores = []
davies bouldin indices = []
calinski harabasz indices = []
inertia values = []
# Perform K-Means Clustering for different cluster numbers
for n clusters in cluster range:
    # Perform K-Means Clustering
    kmeans = KMeans(n clusters=n clusters, random state=0)
    cluster labels = kmeans.fit predict(image data)
    # Calculate validation measures
    silhouette avg = silhouette score(image data, cluster labels)
    davies bouldin index = davies bouldin score(image data,
cluster labels)
    calinski harabasz index = calinski harabasz score(image data,
cluster labels)
    inertia = kmeans.inertia
    # Append metrics to lists
    silhouette scores.append(silhouette avg)
    davies bouldin indices.append(davies bouldin index)
    calinski harabasz indices.append(calinski harabasz index)
    inertia values.append(inertia)
    # Print the results for each iteration
    print(f"\nClusters: {n clusters}")
    print(f"Silhouette Score: {silhouette avg}")
    print(f"Davies-Bouldin Index: {davies bouldin index}")
    print(f"Calinski-Harabasz Index: {calinski harabasz index}")
    print(f"Inertia (Within-Cluster Sum of Squares): {inertia}")
    # Plotting the results
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))
# Silhouette Score
axes[0, 0].plot(cluster range, silhouette scores, marker='o')
axes[0, 0].set_title('Silhouette Score')
axes[0, 0].set xlabel('Number of Clusters')
axes[0, 0].set ylabel('Score')
# Davies-Bouldin Index
axes[0, 1].plot(cluster_range, davies bouldin indices, marker='o')
axes[0, 1].set_title('Davies-Bouldin Index')
axes[0, 1].set xlabel('Number of Clusters')
axes[0, 1].set_ylabel('Index')
# Calinski-Harabasz Index
```

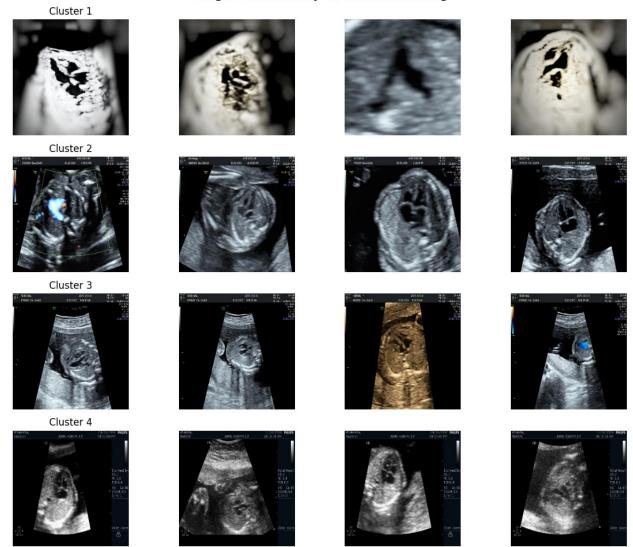
```
axes[1, 0].plot(cluster range, calinski harabasz indices, marker='o')
axes[1, 0].set title('Calinski-Harabasz Index')
axes[1, 0].set xlabel('Number of Clusters')
axes[1, 0].set ylabel('Index')
# Inertia
axes[1, 1].plot(cluster_range, inertia_values, marker='o')
axes[1, 1].set title('Inertia (Within-Cluster Sum of Squares)')
axes[1, 1].set_xlabel('Number of Clusters')
axes[1, 1].set ylabel('Inertia')
plt.tight layout()
plt.show()
# Function to plot images with K-Means cluster labels
def plot_kmeans_clusters(images, cluster_labels, n_clusters):
    plt.figure(figsize=(12, 10))
    for i in range(n clusters):
        cluster images = np.array(images)[cluster labels == i]
        for j, img in enumerate(cluster images[:4]): # Plot the first
4 images in each cluster
            plt.subplot(n clusters, 4, i * 4 + j + 1)
            plt.imshow(img)
            plt.axis('off')
            if j == 0:
                plt.title(f"Cluster {i+1}")
    plt.suptitle("Images clustered by K-Means Clustering",
fontsize=16)
    plt.tight layout()
    plt.show()
# Perform K-Means Clustering with the optimal number of clusters
(choose the one with the best metrics)
optimal n clusters = 4 # Change this based on the optimal number of
clusters from metrics evaluation
# Perform K-Means Clustering
kmeans = KMeans(n clusters=optimal n clusters, random state=0)
kmeans labels = kmeans.fit predict(image data)
# Plot images with K-Means cluster labels
plot kmeans clusters(images, kmeans labels, optimal n clusters)
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
_kmeans.py:870: FutureWarning: The default value of `n init` will
change from 10 to 'auto' in 1.4. Set the value of `n init` explicitly
to suppress the warning
 warnings.warn(
```

Clusters: 2 Silhouette Score: 0.21831584385645292 Davies-Bouldin Index: 2.0366010319213683 Calinski-Harabasz Index: 52.47932861076172 Inertia (Within-Cluster Sum of Squares): 129982164882.10896 /usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: The default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning warnings.warn(Clusters: 3 Silhouette Score: 0.1116258412019826 Davies-Bouldin Index: 2.036148998803733 Calinski-Harabasz Index: 38.88229007875694 Inertia (Within-Cluster Sum of Squares): 119995016069.84192 /usr/local/lib/python3.10/dist-packages/sklearn/cluster/ _kmeans.py:870: FutureWarning: The default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n init` explicitly to suppress the warning warnings.warn(Clusters: 4 Silhouette Score: 0.09169623173001427 Davies-Bouldin Index: 2.6543221381193884 Calinski-Harabasz Index: 31.23418685763801 Inertia (Within-Cluster Sum of Squares): 114372860125.29172 /usr/local/lib/python3.10/dist-packages/sklearn/cluster/ _kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning warnings.warn(Clusters: 5 Silhouette Score: 0.0775871354154438 Davies-Bouldin Index: 2.9673434854456824 Calinski-Harabasz Index: 25.942897772548857 Inertia (Within-Cluster Sum of Squares): 111016820321.53664



/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
_kmeans.py:870: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly
to suppress the warning
 warnings.warn(

Images clustered by K-Means Clustering



Hierarchical Clustering Before PCA

```
import os
import cv2
import numpy as np
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score, davies_bouldin_score,
calinski_harabasz_score
from scipy.cluster.hierarchy import linkage
import matplotlib.pyplot as plt

# Define the path to your image dataset
dataset_path = "/content/drive/MyDrive/HEART US IMAGE FETUS"
```

```
# Function to load and preprocess images
def load and preprocess images(dataset path, image shape):
    image list = []
    for filename in os.listdir(dataset path):
        if filename.endswith('.jpg'):
            img = cv2.imread(os.path.join(dataset path, filename))
            img = cv2.cvtColor(img, cv2.COLOR BGR2RGB) # Convert to
RGB format
            img = cv2.resize(img, image shape) # Resize the image
            image list.append(img)
    return image list
# Load and preprocess the images
image shape = (256, 256)
images = load_and_preprocess_images(dataset path, image shape)
# Convert the list of images to a numpy array
image data = np.array(images).reshape(len(images), -1)
# Number of clusters to print
n clusters to print = 4
# Perform Hierarchical Clustering for different cluster numbers
for n clusters in cluster range:
    # Perform Hierarchical Clustering
    linkage matrix = linkage(image data, method='ward')
    cluster labels = AgglomerativeClustering(n clusters=n clusters,
linkage='ward').fit predict(image data)
    # Calculate validation measures
    silhouette avg = silhouette score(image data, cluster labels)
    davies bouldin index = davies bouldin score(image data,
cluster labels)
    calinski harabasz index = calinski harabasz score(image data,
cluster labels)
    # Print the results for each iteration
    print(f"\nClusters: {n clusters}")
    print(f"Silhouette Score: {silhouette avg}")
    print(f"Davies-Bouldin Index: {davies bouldin index}")
    print(f"Calinski-Harabasz Index: {calinski harabasz index}")
    import matplotlib.pyplot as plt
# Plotting the results
fig, axes = plt.subplots(nrows=3, ncols=1, figsize=(10, 8))
# Silhouette Score
axes[0].plot(cluster range, silhouette scores, marker='o')
```

```
axes[0].set title('Silhouette Score')
axes[0].set xlabel('Number of Clusters')
axes[0].set ylabel('Score')
# Davies-Bouldin Index
axes[1].plot(cluster range, davies bouldin indices, marker='o')
axes[1].set title('Davies-Bouldin Index')
axes[1].set xlabel('Number of Clusters')
axes[1].set ylabel('Index')
# Calinski-Harabasz Index
axes[2].plot(cluster range, calinski harabasz indices, marker='o')
axes[2].set title('Calinski-Harabasz Index')
axes[2].set xlabel('Number of Clusters')
axes[2].set ylabel('Index')
plt.tight_layout()
plt.show()
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram
# Visualize the dendrogram
plt.figure(figsize=(10, 8))
dendrogram(linkage matrix, truncate mode='level', p=3)
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Sample Index')
plt.ylabel('Distance')
plt.show()
# Plot images with cluster labels for 5 clusters
def plot clusters(images, cluster labels, n clusters):
    plt.figure(figsize=(12, 8))
    for i in range(n clusters):
        cluster images = np.array(images)[cluster labels == i]
        for j, img in enumerate(cluster images[:4]): # Plot the first
4 images in each cluster
            plt.subplot(n clusters, 4, i * 4 + j + 1)
            plt.imshow(img)
            plt.axis('off')
            if j == 0:
                plt.title(f"Cluster {i+1}")
    plt.suptitle("Images clustered by Hierarchical Clustering",
fontsize=16)
    plt.tight layout()
    plt.show()
```

Plot images with cluster labels for 5 clusters plot_clusters(images, cluster_labels, n_clusters_to_print)

Clusters: 2

Silhouette Score: 0.2118013531330989 Davies-Bouldin Index: 2.086092478685209 Calinski-Harabasz Index: 50.44523228771401

Clusters: 3

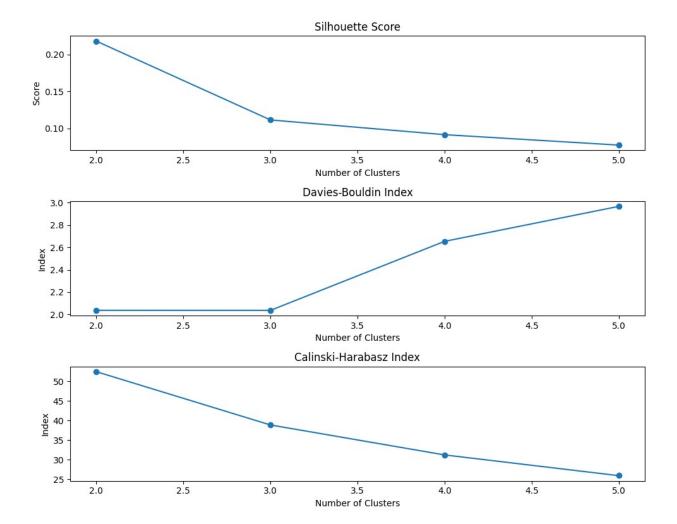
Silhouette Score: 0.10989746772157044 Davies-Bouldin Index: 2.0620912233509574 Calinski-Harabasz Index: 37.65589167609462

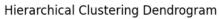
Clusters: 4

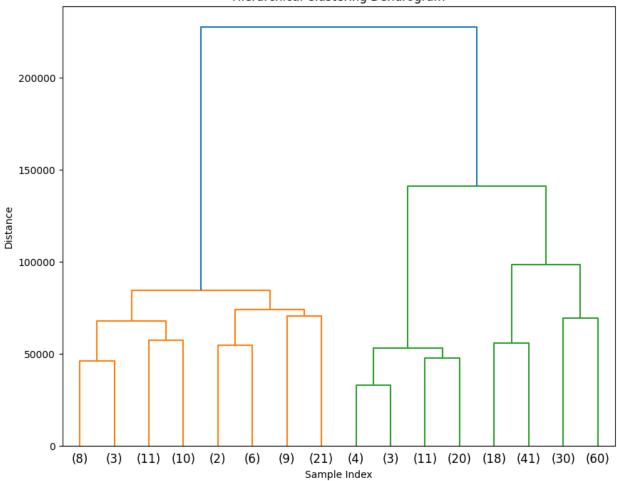
Silhouette Score: 0.08222164933862167 Davies-Bouldin Index: 2.8479662492596383 Calinski-Harabasz Index: 29.557593549365208

Clusters: 5

Silhouette Score: 0.08437409196898955 Davies-Bouldin Index: 3.145034498265756 Calinski-Harabasz Index: 24.77350995415099







Images clustered by Hierarchical Clustering



Principal Component Analysis (PCA)

```
from sklearn.decomposition import PCA
from sklearn.metrics import mean_squared_error

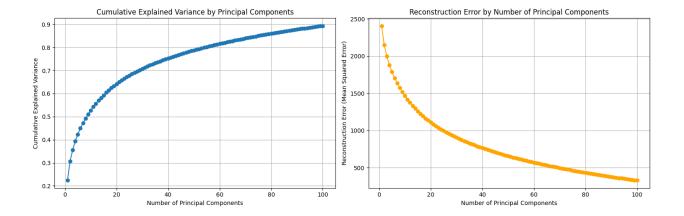
# Load the preprocessed images
image_shape = (256, 256)
images = load_and_preprocess_images(dataset_path, image_shape)

# Convert the list of images to a numpy array
image_data = np.array(images).reshape(len(images), -1)

# Define the range of principal components to try
max_num_components = min(image_data.shape[0], image_data.shape[1],
100)
num_components_range = range(1, max_num_components + 1)

# Initialize lists to store results
cumulative_explained_variance = []
```

```
reconstruction errors = []
# Iterate over different numbers of principal components
for num components in num components range:
    # Initialize PCA
    pca = PCA(n components=num components)
    # Fit PCA on the image data
    pca.fit(image_data)
    # Transform the image data using the fitted PCA
    image data pca = pca.transform(image data)
    # Reconstruct the original data from the reduced representation
    reconstructed_data = pca.inverse_transform(image_data_pca)
    # Calculate cumulative explained variance
cumulative explained variance.append(np.sum(pca.explained variance rat
io_))
    # Calculate reconstruction error (mean squared error)
    reconstruction_error = mean_squared_error(image_data,
reconstructed data)
    reconstruction errors.append(reconstruction error)
# Plot the explained variance ratio and reconstruction error
plt.figure(figsize=(15, 5))
# Explained Variance Ratio
plt.subplot(1, 2, 1)
plt.plot(num components range, cumulative explained variance,
marker='o')
plt.title('Cumulative Explained Variance by Principal Components')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.grid(True)
# Reconstruction Error
plt.subplot(1, 2, 2)
plt.plot(num components range, reconstruction errors, marker='o',
color='orange')
plt.title('Reconstruction Error by Number of Principal Components')
plt.xlabel('Number of Principal Components')
plt.ylabel('Reconstruction Error (Mean Squared Error)')
plt.grid(True)
plt.tight layout()
plt.show()
```



K-Means Clustering After PCA

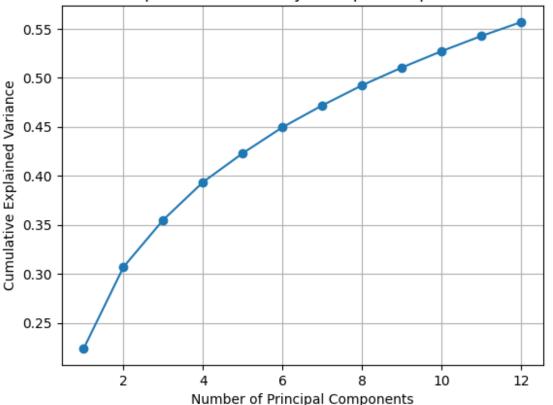
```
# Principal Component Analysis (PCA)
from sklearn.decomposition import PCA
from sklearn.metrics import mean squared error
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette score, davies bouldin score,
calinski harabasz score
# Load the preprocessed and normalized images
image shape = (256, 256)
images = load and preprocess images(dataset path, image shape)
# Convert the list of images to a numpy array
image data = np.array(images).reshape(len(images), -1)
# Reduce the number of components
num components = \min(image data.shape[0], image data.shape[1], 12)
# Initialize PCA with the chosen number of components
pca = PCA(n components=num components)
# Fit PCA on the normalized image data
image data pca = pca.fit transform(image data)
# Reconstruct the original data from the reduced representation
reconstructed data = pca.inverse transform(image data pca)
# Display the explained variance ratio
explained_variance_ratio = pca.explained variance ratio
cumulative explained variance = np.cumsum(explained variance ratio)
# Plot the explained variance ratio
plt.plot(range(1, num components + 1), cumulative explained variance,
marker='o')
plt.title('Cumulative Explained Variance by Principal Components
```

```
(After PCA)')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.arid(True)
plt.show()
# Print the explained variance ratio for each component
for i, ratio in enumerate(explained variance ratio, 1):
    print(f"Explained Variance Ratio for Component {i}: {ratio:.4f}")
# Print the cumulative explained variance for each component
for i, cumulative ratio in enumerate(cumulative explained variance,
1):
    print(f"Cumulative Explained Variance for Components 1 to {i}:
{cumulative ratio:.4f}")
# Print the reconstruction error (mean squared error) after PCA
reconstruction error after pca = mean squared error(image data,
reconstructed data)
print(f"\nReconstruction Error (Mean Squared Error) After PCA:
{reconstruction error after pca:.4f}")
# K-Means Clustering After PCA
# Use the reduced representation obtained from PCA for K-Means
clustering
# Range of clusters to try
cluster range after pca = range(2, 6)
# Lists to store metrics for plotting
silhouette scores after pca = []
davies bouldin indices after pca = []
calinski harabasz indices after pca = []
inertia values after pca = []
# Perform K-Means Clustering for different cluster numbers after PCA
for n clusters after pca in cluster range after pca:
    # Perform K-Means Clustering
    kmeans after pca = KMeans(n clusters=n clusters after pca,
random state=0)
    cluster labels after pca =
kmeans after pca.fit predict(image data pca)
    # Calculate validation measures
    silhouette avg after pca = silhouette score(image data pca,
cluster labels after pca)
    davies bouldin index after pca =
davies bouldin score(image data pca, cluster labels after pca)
    calinski harabasz index after pca =
```

```
calinski harabasz score(image data pca, cluster labels after pca)
    inertia after pca = kmeans after pca.inertia
    # Append metrics to lists
    silhouette scores after pca.append(silhouette avg after pca)
davies bouldin indices after pca.append(davies bouldin index after pca
calinski harabasz indices after pca.append(calinski harabasz index aft
er pca)
    inertia values after pca.append(inertia after pca)
    # Print the results for each iteration after PCA
    print(f"\nClusters (after PCA): {n_clusters_after_pca}")
    print(f"Silhouette Score: {silhouette avg after pca}")
    print(f"Davies-Bouldin Index: {davies bouldin index after pca}")
    print(f"Calinski-Harabasz Index:
{calinski harabasz index after pca}")
    print(f"Inertia (Within-Cluster Sum of Squares):
{inertia after pca}")
# Plotting the results after PCA
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))
# Silhouette Score
axes[0, 0].plot(cluster range after pca, silhouette scores after pca,
marker='o')
axes[0, 0].set title('Silhouette Score (After PCA)')
axes[0, 0].set xlabel('Number of Clusters')
axes[0, 0].set ylabel('Score')
# Davies-Bouldin Index
axes[0, 1].plot(cluster range after pca,
davies bouldin indices after pca, marker='o')
axes[0, 1].set title('Davies-Bouldin Index (After PCA)')
axes[0, 1].set xlabel('Number of Clusters')
axes[0, 1].set ylabel('Index')
# Calinski-Harabasz Index
axes[1, 0].plot(cluster_range after pca,
calinski harabasz indices after pca, marker='o')
axes[1, 0].set_title('Calinski-Harabasz Index (After PCA)')
axes[1, 0].set xlabel('Number of Clusters')
axes[1, 0].set ylabel('Index')
# Inertia
axes[1, 1].plot(cluster range after pca, inertia values after pca,
marker='o')
axes[1, 1].set title('Inertia (Within-Cluster Sum of Squares) (After
```

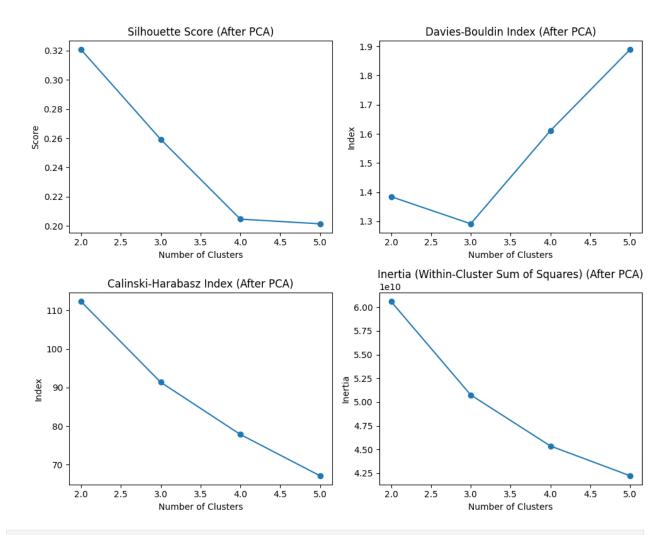
```
PCA)')
axes[1, 1].set xlabel('Number of Clusters')
axes[1, 1].set ylabel('Inertia')
plt.tight layout()
plt.show()
# Function to plot images with K-Means cluster labels after PCA
def plot kmeans clusters after pca(images, cluster labels after pca,
n clusters after pca):
    plt.figure(figsize=(12, 10))
    for i in range(n clusters after pca):
        cluster images = np.array(images)[cluster labels after pca ==
i]
        for j, img in enumerate(cluster images[:4]): # Plot the first
4 images in each cluster
            plt.subplot(n clusters after pca, 4, i * 4 + j + 1)
            plt.imshow(img)
            plt.axis('off')
            if j == 0:
                plt.title(f"Cluster {i+1}")
    plt.suptitle("Images clustered by K-Means Clustering After PCA",
fontsize=16)
    plt.tight layout()
    plt.show()
# Perform K-Means Clustering with the optimal number of clusters after
PCA
optimal n clusters after pca = 4 # Change this based on the optimal
number of clusters from metrics evaluation
# Perform K-Means Clustering after PCA
kmeans after pca = KMeans(n clusters=optimal n clusters after pca,
random state=0)
kmeans labels after pca = kmeans after pca.fit predict(image data pca)
# Plot images with K-Means cluster labels after PCA
plot kmeans clusters after pca(images, kmeans labels after pca,
optimal n clusters after pca)
```

Cumulative Explained Variance by Principal Components (After PCA)



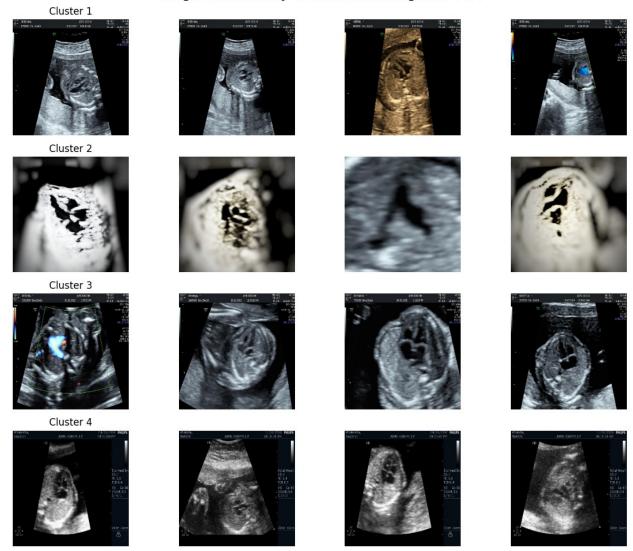
```
Explained Variance Ratio for Component 1: 0.2239
Explained Variance Ratio for Component 2: 0.0831
Explained Variance Ratio for Component 3: 0.0481
Explained Variance Ratio for Component 4: 0.0385
Explained Variance Ratio for Component 5: 0.0295
Explained Variance Ratio for Component 6: 0.0265
Explained Variance Ratio for Component 7: 0.0223
Explained Variance Ratio for Component 8: 0.0205
Explained Variance Ratio for Component 9: 0.0181
Explained Variance Ratio for Component 10: 0.0167
Explained Variance Ratio for Component 11: 0.0155
Explained Variance Ratio for Component 12: 0.0142
Cumulative Explained Variance for Components 1 to 1: 0.2239
Cumulative Explained Variance for Components 1 to 2: 0.3070
Cumulative Explained Variance for Components 1 to 3: 0.3551
Cumulative Explained Variance for Components 1 to 4: 0.3936
Cumulative Explained Variance for Components 1 to 5: 0.4231
Cumulative Explained Variance for Components 1 to 6: 0.4496
Cumulative Explained Variance for Components 1 to 7: 0.4719
Cumulative Explained Variance for Components 1 to 8: 0.4923
Cumulative Explained Variance for Components 1 to 9: 0.5105
Cumulative Explained Variance for Components 1 to 10: 0.5272
Cumulative Explained Variance for Components 1 to 11: 0.5427
```

```
Cumulative Explained Variance for Components 1 to 12: 0.5568
Reconstruction Error (Mean Squared Error) After PCA: 1374.6607
Clusters (after PCA): 2
Silhouette Score: 0.32078068706981205
Davies-Bouldin Index: 1.3847942966732052
Calinski-Harabasz Index: 112.27024746848204
Inertia (Within-Cluster Sum of Squares): 60594972681.136826
Clusters (after PCA): 3
Silhouette Score: 0.25930023543800274
Davies-Bouldin Index: 1.2917181180199082
Calinski-Harabasz Index: 91.37644133156405
Inertia (Within-Cluster Sum of Squares): 50755147907.43767
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
_kmeans.py:870: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n init` explicitly
to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870
: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n init` explicitly to suppress the
warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870
: FutureWarning: The default value of `n init` will change from 10 to
'auto' in 1.4. Set the value of `n init` explicitly to suppress the
warning
 warnings.warn(
Clusters (after PCA): 4
Silhouette Score: 0.20461041660912876
Davies-Bouldin Index: 1.6108482715663852
Calinski-Harabasz Index: 77.86092021372241
Inertia (Within-Cluster Sum of Squares): 45378064105.871185
Clusters (after PCA): 5
Silhouette Score: 0.20142929809609408
Davies-Bouldin Index: 1.8890287298819533
Calinski-Harabasz Index: 67.16392883688395
Inertia (Within-Cluster Sum of Squares): 42240792914.61592
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
kmeans.py:870: FutureWarning: The default value of `n init` will
change from 10 to 'auto' in 1.4. Set the value of `n init` explicitly
to suppress the warning
 warnings.warn(
```



/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ _kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning warnings.warn(

Images clustered by K-Means Clustering After PCA



Hierarchical Clustering After PCA

```
from sklearn.cluster import AgglomerativeClustering

# **Hierarchical Clustering After PCA**

# Range of clusters to try
cluster_range_after_pca_hierarchical = range(2, 6)

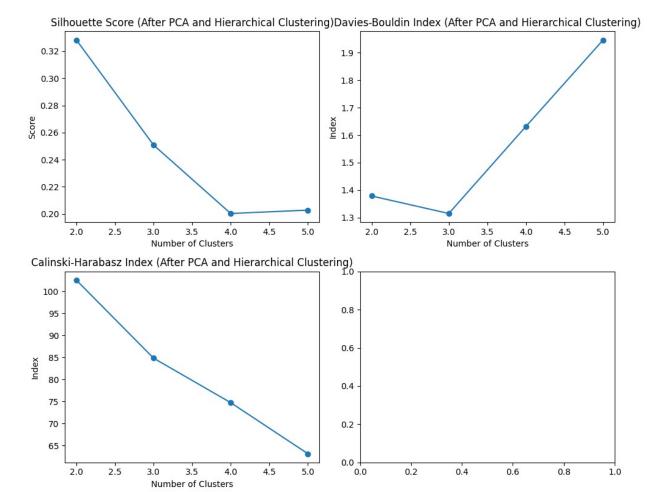
# Lists to store metrics for plotting
silhouette_scores_after_pca_hierarchical = []
davies_bouldin_indices_after_pca_hierarchical = []
calinski_harabasz_indices_after_pca_hierarchical = []

# Perform Hierarchical Clustering for different cluster numbers after
```

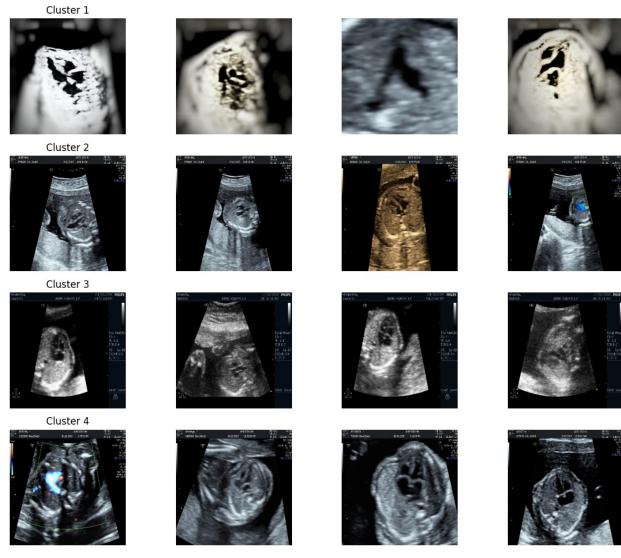
```
PCA
for n clusters_after_pca_hierarchical in
cluster_range_after_pca_hierarchical:
    # Perform Hierarchical Clustering
    hierarchical after pca =
AgglomerativeClustering(n clusters=n clusters after pca hierarchical)
    cluster labels after pca hierarchical =
hierarchical after pca.fit predict(image data pca)
    # Calculate validation measures
    silhouette avg after pca hierarchical =
silhouette score(image data pca,
cluster labels after pca hierarchical)
    davies bouldin index after pca hierarchical =
davies bouldin score(image data pca,
cluster_labels_after_pca_hierarchical)
    calinski harabasz index after pca hierarchical =
calinski harabasz score(image data pca,
cluster labels after pca hierarchical)
    # Append metrics to lists
silhouette scores after pca hierarchical.append(silhouette avg after p
ca hierarchical)
davies bouldin indices after pca hierarchical.append(davies bouldin in
dex after pca hierarchical)
calinski harabasz indices after pca hierarchical.append(calinski harab
asz index after pca hierarchical)
    # Print the results for each iteration after PCA and Hierarchical
Clustering
    print(f"\nClusters (after PCA and Hierarchical Clustering):
{n clusters after pca hierarchical}")
    print(f"Silhouette Score:
{silhouette avg after pca hierarchical}")
    print(f"Davies-Bouldin Index:
{davies bouldin index after pca hierarchical}")
    print(f"Calinski-Harabasz Index:
{calinski harabasz index after pca hierarchical}")
# Plotting the results after PCA and Hierarchical Clustering
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))
# Silhouette Score
axes[0, 0].plot(cluster_range_after_pca_hierarchical,
silhouette_scores_after_pca_hierarchical, marker='o')
axes[0, 0].set title('Silhouette Score (After PCA and Hierarchical
Clustering)')
```

```
axes[0, 0].set xlabel('Number of Clusters')
axes[0, 0].set ylabel('Score')
# Davies-Bouldin Index
axes[0, 1].plot(cluster range after_pca_hierarchical,
davies_bouldin_indices_after_pca_hierarchical, marker='o')
axes[0, 1].set title('Davies-Bouldin Index (After PCA and Hierarchical
Clustering)')
axes[0, 1].set xlabel('Number of Clusters')
axes[0, 1].set ylabel('Index')
# Calinski-Harabasz Index
axes[1, 0].plot(cluster_range_after_pca_hierarchical,
calinski_harabasz_indices_after_pca_hierarchical, marker='o')
axes[1, 0].set title('Calinski-Harabasz Index (After PCA and
Hierarchical Clustering)')
axes[1, 0].set xlabel('Number of Clusters')
axes[1, 0].set ylabel('Index')
plt.tight layout()
plt.show()
# Function to plot images with Hierarchical cluster labels after PCA
def plot hierarchical clusters after pca(images,
cluster labels after pca hierarchical,
n clusters after pca hierarchical):
    plt.figure(figsize=(12, 10))
    for i in range(n clusters after pca hierarchical):
        cluster images hierarchical = np.array(images)
[cluster labels after pca hierarchical == i]
        for j, img hierarchical in
enumerate(cluster images hierarchical[:4]): # Plot the first 4 images
in each cluster
            plt.subplot(n clusters after pca hierarchical, 4, i * 4 +
i + 1
            plt.imshow(img hierarchical)
            plt.axis('off')
            if j == 0:
                plt.title(f"Cluster {i+1}")
    plt.suptitle("Images clustered by Hierarchical Clustering After
PCA", fontsize=16)
    plt.tight layout()
    plt.show()
# Perform Hierarchical Clustering with the optimal number of clusters
after PCA
optimal n clusters after pca hierarchical = 4 # Change this based on
the optimal number of clusters from metrics evaluation
# Perform Hierarchical Clustering after PCA
```

```
hierarchical after pca =
AgglomerativeClustering(n clusters=optimal n clusters after pca hierar
chical)
hierarchical labels after pca =
hierarchical after pca.fit predict(image data pca)
# Plot images with Hierarchical cluster labels after PCA
plot hierarchical clusters after pca(images,
hierarchical_labels_after_pca,
optimal_n_clusters_after_pca_hierarchical)
Clusters (after PCA and Hierarchical Clustering): 2
Silhouette Score: 0.3283172198992113
Davies-Bouldin Index: 1.378474766144968
Calinski-Harabasz Index: 102.51767646892412
Clusters (after PCA and Hierarchical Clustering): 3
Silhouette Score: 0.25081513987976933
Davies-Bouldin Index: 1.31471585865028
Calinski-Harabasz Index: 84.84436603168552
Clusters (after PCA and Hierarchical Clustering): 4
Silhouette Score: 0.20032026804782224
Davies-Bouldin Index: 1.6320601027968022
Calinski-Harabasz Index: 74.75762137889707
Clusters (after PCA and Hierarchical Clustering): 5
Silhouette Score: 0.2027966344066904
Davies-Bouldin Index: 1.9467104388303718
Calinski-Harabasz Index: 63.186862359089794
```



Images clustered by Hierarchical Clustering After PCA



```
import os
import cv2
import numpy as np
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, davies_bouldin_score,
calinski_harabasz_score
import matplotlib.pyplot as plt

# Define paths
original_dataset_path = "/content/drive/MyDrive/HEART US IMAGE FETUS"
mask_dataset_path =
"/content/drive/MyDrive/FETUS_ULTRASOUND_IMAGES_HEART_CHAMBERS/Segment
ationClass"

# Function to load and preprocess segmented mask images
```

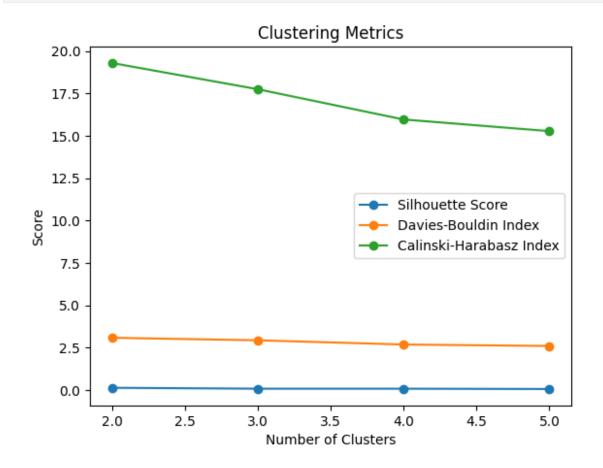
```
def load and preprocess masks(dataset path, image shape):
    mask list = []
    for filename in os.listdir(dataset path):
        if filename.endswith('.png'):
            img = cv2.imread(os.path.join(dataset path, filename),
cv2.IMREAD GRAYSCALE) # Load as grayscale
            img = cv2.resize(img, image shape) # Resize the mask
image
            mask list.append(img)
    return mask list
# Load and preprocess the segmented mask images
mask shape = (256, 256)
masks = load and preprocess masks(mask dataset path, mask shape)
# Convert the list of masks to a numpy array
mask_data = np.array(masks).reshape(len(masks), -1)
# Define clustering function using the mask data
def perform clustering(data, cluster range):
    # Define lists to store metrics
    silhouette scores = []
    davies bouldin indices = []
    calinski harabasz indices = []
    # Perform clustering for different cluster numbers
    for n clusters in cluster range:
        # Perform K-Means Clustering
        kmeans = KMeans(n clusters=n clusters, random state=0)
        cluster labels = kmeans.fit predict(data)
        # Calculate validation measures
        silhouette avg = silhouette score(data, cluster labels)
        davies bouldin index = davies bouldin score(data,
cluster labels)
        calinski harabasz index = calinski harabasz score(data,
cluster_labels)
        # Append metrics to lists
        silhouette scores.append(silhouette avg)
        davies bouldin indices.append(davies bouldin index)
        calinski harabasz indices.append(calinski harabasz index)
        # Print the results for each iteration
        print(f"\nClusters: {n clusters}")
        print(f"Silhouette Score: {silhouette avg}")
        print(f"Davies-Bouldin Index: {davies bouldin index}")
        print(f"Calinski-Harabasz Index: {calinski harabasz index}")
    # Plot the results
```

```
plt.plot(cluster range, silhouette scores, marker='o',
label='Silhouette Score')
    plt.plot(cluster_range, davies_bouldin_indices, marker='o',
label='Davies-Bouldin Index')
    plt.plot(cluster range, calinski harabasz indices, marker='o',
label='Calinski-Harabasz Index')
    plt.xlabel('Number of Clusters')
    plt.ylabel('Score')
    plt.title('Clustering Metrics')
    plt.legend()
    plt.show()
# Perform clustering on the mask data
cluster range = range(2, 6) # Adjust as needed
perform clustering(mask data, cluster range)
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
kmeans.py:870: FutureWarning: The default value of `n init` will
change from 10 to 'auto' in 1.4. Set the value of `n init` explicitly
to suppress the warning
 warnings.warn(
Clusters: 2
Silhouette Score: 0.135270996628909
Davies-Bouldin Index: 3.088019793559278
Calinski-Harabasz Index: 19.305082526154386
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
kmeans.py:870: FutureWarning: The default value of `n init` will
change from 10 to 'auto' in 1.4. Set the value of `n init` explicitly
to suppress the warning
 warnings.warn(
Clusters: 3
Silhouette Score: 0.0832238563473491
Davies-Bouldin Index: 2.9391619168362855
Calinski-Harabasz Index: 17.756692206257163
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
kmeans.py:870: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n init` explicitly
to suppress the warning
 warnings.warn(
Clusters: 4
Silhouette Score: 0.08254175747304328
Davies-Bouldin Index: 2.6893354911207403
Calinski-Harabasz Index: 15.970156819785982
```

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ _kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning warnings.warn(

Clusters: 5

Silhouette Score: 0.064298214299714 Davies-Bouldin Index: 2.60396321416787 Calinski-Harabasz Index: 15.282118715639866



PIX2PIX GAN SEGMENTATION

```
import numpy as np # linear algebra
import tensorflow as tf # for tensorflow based registration
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import skimage
import os
from cv2 import imread, createCLAHE # read and equalize images
import cv2
from glob import glob
%matplotlib inline
```

```
import matplotlib.pyplot as plt
import pathlib
import time
import datetime
from IPython import display
from skimage.util import montage as montage2d
mask dataset path =
"/content/drive/MyDrive/FETUS ULTRASOUND IMAGES HEART CHAMBERS"
# Print all mask paths
print("Mask paths:")
for filename in os.listdir(mask dataset path):
    print(os.path.join(mask_dataset_path, filename))
Mask paths:
/content/drive/MyDrive/FETUS ULTRASOUND IMAGES HEART CHAMBERS/labelmap
/content/drive/MyDrive/FETUS ULTRASOUND IMAGES HEART CHAMBERS/Segmenta
tionObject
/content/drive/MyDrive/FETUS ULTRASOUND IMAGES HEART CHAMBERS/Segmenta
tionClass
/content/drive/MyDrive/FETUS ULTRASOUND IMAGES HEART CHAMBERS/ImageSet
import os
# Define the path to the dataset
mask dataset path =
"/content/drive/MyDrive/FETUS ULTRASOUND IMAGES HEART CHAMBERS"
# Print all mask file paths
print("Mask file paths:")
for filename in os.listdir(mask_dataset_path):
    file path = os.path.join(mask dataset path, filename)
    if os.path.isfile(file path):
        print(file_path)
Mask file paths:
/content/drive/MyDrive/FETUS ULTRASOUND IMAGES HEART CHAMBERS/labelmap
.txt
import os
import cv2
from glob import glob
# Define the paths
original dataset path =
"/content/drive/MyDrive/Sharpened HEART US IMAGE FETUS"
mask dataset path =
```

```
"/content/drive/MyDrive/FETUS ULTRASOUND IMAGES HEART CHAMBERS/Segment
ationClass"
# Function to load and resize images
def load and resize images(image paths, mask paths, image shape):
    images = []
    masks = []
    for image path, mask path in zip(image paths, mask paths):
        # Load and resize the image
        img = cv2.imread(image path)
        img = cv2.cvtColor(img, cv2.COLOR BGR2RGB) # Convert to RGB
format
        img = cv2.resize(img, image shape)
        images.append(img)
        # Load and resize the mask
        mask = cv2.imread(mask path, cv2.IMREAD GRAYSCALE) # Read
mask as grayscale
        mask = cv2.resize(mask, image shape)
        masks.append(mask)
    return images, masks
# Get all image paths
image paths = glob(os.path.join(original_dataset_path, '*.jpg'))
# Get corresponding mask paths
mask paths = []
for image path in image paths:
    image filename = os.path.basename(image path)
    mask path = os.path.join(mask dataset path,
image filename.replace('.jpg', '.png'))
    mask paths.append(mask path)
# Define the desired image shape
#image shape = (256, 256) # Set your desired image shape
# Load and resize images with masks
images, masks = load and resize images(image paths, mask paths,
image shape)
# Check the number of loaded images
print("Number of images loaded:", len(images))
print("Number of masks loaded:", len(masks))
Number of images loaded: 257
Number of masks loaded: 257
import os
from glob import glob
import numpy as np
```

```
from skimage.io import imread as imread_raw
from skimage.transform import resize
from tqdm import tqdm
import warnings
warnings.filterwarnings('ignore', category=UserWarning,
module='skimage') # Suppress skimage warnings
OUT DIM = (256, 256)
def imread(in path, apply clahe=False):
    img data = imread raw(in path)
    n img = (255 * resize(img data, OUT DIM, mode='constant')).clip(0,
255).astype(np.float64)
   if apply clahe:
        clahe tool = createCLAHE(clipLimit=2.0, tileGridSize=(16, 16))
        n img = clahe tool.apply(n img)
    return np.expand dims(n img, -1)
# Loading the ultrasound images and resizing them
ultrasound data = []
for u path, m path in tgdm(ultrasound images):
   u img = imread(u path)
   m img = imread(m path)
   ultrasound data.append((u img, m img))
100% | 257/257 [00:24<00:00, 10.49it/s]
img\ vol,\ seg\ vol = [], []
for img path, m path in tgdm(ultrasound images):
    img vol.append(np.squeeze(imread(img path)))
    seg vol.append(np.squeeze(imread(m path, apply clahe=False)))
img\ vol = np.stack(img\ vol, 0)
seg\ vol = np.stack(seg\ vol, 0)
print('Images:', img vol.shape, 'Masks:', seg vol.shape)
100% | 257/257 [00:24<00:00, 10.43it/s]
Images: (257, 256, 256, 3) Masks: (257, 256, 256, 3)
import os
from glob import glob
from tgdm import tgdm
import numpy as np
from PIL import Image
```

```
# Define dataset paths
original dataset path =
"/content/drive/MyDrive/Sharpened HEART US IMAGE FETUS"
mask dataset path =
"/content/drive/MyDrive/FETUS_ULTRASOUND_IMAGES_HEART_CHAMBERS/Segment
ationClass"
# Define the target size for resizing
target size = (256,256) # Specify the desired width and height
# Get paths of ultrasound images (JPG format)
ultrasound image paths = glob(os.path.join(original dataset path,
'*.ipg'))
print('ULTRASOUND IMAGES:', len(ultrasound image paths))
# Get paths of corresponding mask images (PNG format)
mask image paths = [os.path.join(mask dataset path,
os.path.splitext(os.path.basename(img_path))[0] + '.png') for img_path
in ultrasound image paths]
# Initialize lists to store resized image volumes and segmentation
volumes
imq vol = []
seg vol = []
# Iterate through image paths and corresponding mask paths
for img path, mask path in tqdm(zip(ultrasound image paths,
mask_image_paths), total=len(ultrasound_image_paths)):
    # Load image and resize
    img = Image.open(img path).resize(target size, Image.ANTIALIAS)
    # Load mask and resize
    mask = Image.open(mask path).resize(target size, Image.ANTIALIAS)
    # Convert to numpy arrays
    img = np.array(img)
    mask = np.array(mask)
    # Append resized image and mask to lists
    img vol.append(img)
    seg vol.append(mask)
# Convert lists to numpy arrays
img vol = np.stack(img vol, axis=0)
seg vol = np.stack(seg vol, axis=0)
print('Images:', img vol.shape, 'Segmentations:', seg vol.shape)
ULTRASOUND IMAGES: 257
```

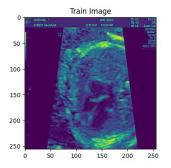
```
| 0/257 [00:00<?, ?it/s]<ipython-input-25-
0a20db12e2e8>:28: DeprecationWarning: ANTIALIAS is deprecated and will
be removed in Pillow 10 (2023-07-01). Use LANCZOS or
Resampling.LANCZOS instead.
  img = Image.open(img path).resize(target size, Image.ANTIALIAS)
<ipython-input-25-0a20db12e2e8>:31: DeprecationWarning: ANTIALIAS is
deprecated and will be removed in Pillow 10 (2023-07-01). Use LANCZOS
or Resampling.LANCZOS instead.
  mask = Image.open(mask path).resize(target size, Image.ANTIALIAS)
      | 257/257 [00:07<00:00, 32.38it/s]
Images: (257, 256, 256, 3) Segmentations: (257, 256, 256, 3)
import numpy as np
import matplotlib.pyplot as plt
# Select the first image and its corresponding mask
t_{img}, m_{img} = img_{vol}[0], seg_{vol}[0]
# Plotting the image and its mask
fig, (ax img, ax mask) = plt.subplots(\frac{1}{2}, figsize=(\frac{12}{6}))
# Display the ultrasound image
ax img.imshow(t img, cmap='gray') # Assuming ultrasound images are
aravscale
ax img.set title('Ultrasound Image')
# Display the mask
ax_mask.imshow(m_img, cmap='gray')
ax mask.set title('Mask Image')
plt.show()
```

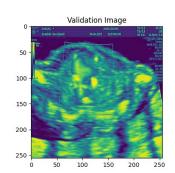


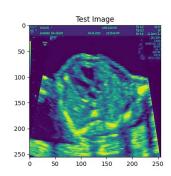
```
from sklearn.model selection import train test split
# Assuming img vol and seg vol are your image and segmentation volumes
# Adjust the test size parameter for your desired split
train vol, test vol, train seg, test seg = train test split((img vol -
127.0) / 127.0,
                                                             (seg vol >
127).astype(np.float32),
test size=0.2, # 20% for test set
random state=2018)
# Split the remaining data (80% of the original) into train and
validation sets
train vol, val vol, train seg, val seg = train test split(train vol,
train seg,
test size=0.25, # 25% of the 80% for validation set
random state=2018)
print('Train:', train vol.shape, 'Validation:', val vol.shape,
'Test:', test vol.shape)
print('Train Set Mean:', train vol.mean(), 'Train Set Max:',
train vol.max())
print('Validation Set Max:', val vol.max())
print('Test Set Mean:', test vol.mean(), 'Test Set Max:',
test vol.max())
# Plotting code for visualizing samples from each set
```

```
fig, axes = plt.subplots(1, 3, figsize=(20, 4))
axes[0].imshow(train_vol[0, :, :, 0])
axes[0].set_title('Train Image')
axes[1].imshow(val_vol[0, :, :, 0])
axes[1].set_title('Validation Image')
axes[2].imshow(test_vol[0, :, :, 0])
axes[2].set_title('Test Image')
plt.show()

Train: (153, 256, 256, 3) Validation: (52, 256, 256, 3) Test: (52, 256, 256, 3)
Train Set Mean: -0.5410883464416989 Train Set Max: 1.0078740157480315
Validation Set Max: 1.0078740157480315
Test Set Mean: -0.5288979114245187 Test Set Max: 1.0078740157480315
```





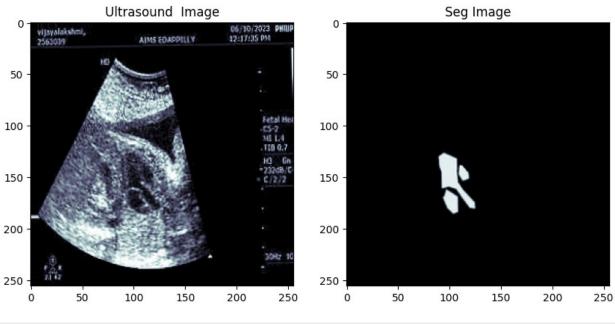


```
from keras.preprocessing.image import ImageDataGenerator
# Define the data augmentation parameters
dg args = dict(
    featurewise center=False,
    samplewise center=False,
    rotation range=5,
    width shift range=0.05,
    height shift range=0.05,
    shear range=0.01,
    zoom_range=[0.8, 1.2], # Random zoom
    horizontal flip=True,
    vertical flip=False,
    fill mode='nearest'
    data format='channels last'
)
# Additional data augmentation techniques such as elastic deformations
and contrast adjustments
additional augmentation = dict(
    elastic deformation=True,
    contrast adjustment=True
)
```

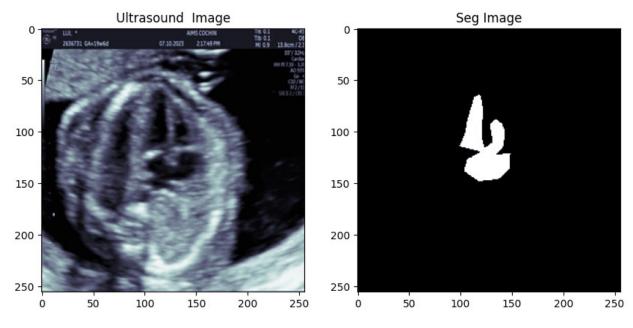
```
# Initialize the ImageDataGenerator object
image gen = ImageDataGenerator(**dg args)
# Define a generator function to yield augmented data with additional
transformations
def gen augmented pairs(in vol, in seg, batch size=1, train=True):
    while True:
        if train:
            seed = np.random.choice(range(9999))
            g vol = image gen.flow(in vol, batch size=batch size,
seed=seed)
            g_seg = image_gen.flow(in_seg, batch_size=batch_size,
seed=seed)
            for i vol, i seg in zip(g_vol, g_seg):
                # Apply additional transformations
                if additional augmentation['elastic deformation']:
                    # Apply elastic deformations
                    i_vol, i_seg = apply_elastic_deformations(i_vol,
i seg)
                if additional augmentation['contrast adjustment']:
                    # Apply contrast adjustments
                    i vol, i seg = apply contrast adjustment(i vol,
i seg)
                yield i vol, i seg
        else:
            seed = 0
            g vol = image gen.flow(in vol, batch size=batch size,
seed=seed)
            g seg = image gen.flow(in seg, batch size=batch size,
seed=seed)
            for i_vol, i_seg in zip(g_vol, g_seg):
                yield i_vol, i_seg
# Generate augmented data with additional transformations for training
train generator = gen augmented pairs(train vol, train seg,
batch size=1, train=True)
# Generate augmented data with additional transformations for
validation
val generator = gen augmented pairs(val vol, val seg, batch size=\frac{1}{1},
train=True)
# Generate augmented data for testing without additional
transformations
test generator = gen augmented pairs(test vol, test seg, batch size=1,
train=False)
# Define the generators for training, validation, and testing
train generator = gen augmented pairs(train vol, train seg,
```

```
batch size=1, train=True)
val generator = gen augmented pairs(val vol, val seg, batch size=1,
train=True)
test generator = gen augmented pairs(test vol, test seg, batch size=1,
train=False)
# Generate a batch of augmented data for training
train X, train Y = next(train generator)
# Generate a batch of augmented data for testing
test X, test Y = next(test generator)
# Print the shapes of the generated data
print("Training Data Shape:", train_X.shape, train_Y.shape)
print("Testing Data Shape:", test_X.shape, test_Y.shape)
Training Data Shape: (1, 256, 256, 3) (1, 256, 256, 3)
Testing Data Shape: (1, 256, 256, 3) (1, 256, 256, 3)
import matplotlib.pyplot as plt
import numpy as np
# Define a function to visualize a montage of 2D images
def montage2d(images):
    # Calculate the number of rows and columns for the montage
    num images = images.shape[0]
    num_cols = int(np.ceil(np.sqrt(num images)))
    num rows = int(np.ceil(num images / num cols))
    # Create an empty array for the montage
    montage = np.zeros((num rows * images.shape[1], num cols *
images.shape[2]))
    # Fill in the montage with images
    for i in range(num images):
        row = i // num cols
        col = i % num cols
        montage[row * images.shape[1] : (row + 1) * images.shape[1],
col * images.shape[2] : (col + 1) * images.shape[2]] = images[i, :, :]
    return montage
# Generate a batch of augmented data for training
train X, train Y = \frac{\text{next}}{\text{train generator}}
# Generate a batch of augmented data for testing
test X, test Y = next(test generator)
fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (10, 5))
ax1.imshow(montage2d(train_X[:, :, :, 0]), cmap = 'bone')
ax1.set title('Ultrasound Image')
```

```
ax2.imshow(montage2d(train_Y[:, :, :, 0]), cmap = 'bone')
ax2.set_title('Seg Image')
Text(0.5, 1.0, 'Seg Image')
```



```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (10, 5))
ax1.imshow(montage2d(test_X[:, :, :, 0]), cmap = 'bone')
ax1.set_title('Ultrasound Image')
ax2.imshow(montage2d(test_Y[:, :, :, 0]), cmap = 'bone')
ax2.set_title('Seg Image')
Text(0.5, 1.0, 'Seg Image')
```



```
import numpy as np
import tensorflow as tf
# Define the input shape
IMG\ WIDTH = 256
IMG\ HEIGHT = 256
OUTPUT CHANNELS = 3
BUFFER SIZE = 133
# The batch size of 1 produced better results for the U-Net in the
original pix2pix experiment
BATCH SIZE = 1
import tensorflow as tf
# Convert the input image to single-channel (grayscale)
t img single_channel = tf.image.rgb_to_grayscale(t_img)
# Repeat the single-channel image along the channel dimension to make
it three channels
t img rgb = tf.tile(t img single channel, [1, 1, 3])
# Ensure the shape matches the expected input shape of the generator
print(t_img_rgb.shape)
(256, 256, 3)
import tensorflow as tf
def downsample(filters, size, apply batchnorm=True,
apply dropout=False, dropout rate=0.2):
```

```
initializer = tf.random normal initializer(0., 0.02)
    result = tf.keras.Sequential()
    result.add(
        tf.keras.layers.Conv2D(filters, size, strides=2,
padding='same',
                               kernel initializer=initializer,
use bias=False))
    if apply batchnorm:
        result.add(tf.keras.layers.BatchNormalization())
    result.add(tf.keras.layers.LeakyReLU())
    if apply dropout:
        result.add(tf.keras.layers.Dropout(dropout rate))
    return result
down model = downsample(3, 4)
# Convert the input tensor to float32
t img = tf.cast(t img, tf.float32)
down result = down model(tf.expand dims(t img, 0))
print(down result.shape)
(1, 128, 128, 3)
def upsample(filters, size, apply_dropout=False, dropout_rate=0.2):
    initializer = tf.random normal initializer(0., 0.02)
    result = tf.keras.Sequential()
    result.add(
        tf.keras.layers.Conv2DTranspose(filters, size, strides=2,
                                         padding='same',
kernel initializer=initializer,
                                         use bias=False))
    result.add(tf.keras.layers.BatchNormalization())
    if apply dropout:
        result.add(tf.keras.layers.Dropout(dropout rate))
    result.add(tf.keras.layers.ReLU())
    return result
up model = upsample(3, 4)
up result = up model(down result)
print (up result.shape)
(1, 256, 256, 3)
def Generator(dropout rate=0.2):
    inputs = tf.keras.layers.Input(shape=[256, 256, 3])
    down stack = [
        downsample(64, 4, apply batchnorm=False, apply dropout=True,
dropout_rate=dropout_rate), # (batch_size, 128, 128, 64)
        downsample(1\overline{28}, 4, apply_dropout=True,
dropout rate=dropout rate), # (batch size, 64, 64, 128)
```

```
downsample(256, 4, apply_dropout=True,
dropout rate=dropout rate), # (batch size, 32, 32, 256)
        downsample(512, 4, apply_dropout=True,
dropout_rate=dropout_rate), # (batch_size, 16, 16, 512)
        downsample(512, 4, apply_dropout=True,
dropout_rate=dropout_rate), # (batch_size, 8, 8, 512)
        downsample(512, 4, apply_dropout=True,
dropout_rate=dropout_rate), # (batch_size, 4, 4, 512)
        downsample(512, 4, apply dropout=True,
dropout rate=dropout rate), # (batch size, 2, 2, 512)
        downsample(512, 4, apply_dropout=True,
dropout_rate=dropout_rate), # (batch_size, 1, 1, 512)
    up stack = [
        upsample(512, 4, apply_dropout=True,
dropout rate=dropout rate), # (batch size, 2, 2, 1024)
        upsample(512, 4, apply_dropout=True,
dropout_rate=dropout_rate), # (batch_size, 4, 4, 1024)
        upsample(512, 4, apply dropout=True,
dropout_rate=dropout_rate), # (batch_size, 8, 8, 1024)
        upsample(512, 4), # (batch size, 16, 16, 1024)
        upsample(256, 4), # (batch_size, 32, 32, 512)
        upsample(128, 4), # (batch size, 64, 64, 256)
        upsample(64, 4), # (batch size, 128, 128, 128)
    initializer = tf.random normal initializer(0., 0.02)
    last = tf.keras.layers.Conv2DTranspose(3, 4,
                                           strides=2,
                                           padding='same',
kernel initializer=initializer,
                                           activation='tanh') #
(batch size, 256, 256, 3)
    x = inputs
    # Downsampling through the model
    skips = []
    for down in down stack:
        x = down(x)
        skips.append(x)
    skips = reversed(skips[:-1])
    # Upsampling and establishing the skip connections
    for up, skip in zip(up_stack, skips):
        x = up(x)
        x = tf.keras.layers.Concatenate()([x, skip])
    x = last(x)
    return tf.keras.Model(inputs=inputs, outputs=x)
# Instantiate the Generator model with dropout rate of 0.2
generator = Generator(dropout rate=0.2)
```

generator.compile(loss='binary_crossentropy', optimizer='adam')

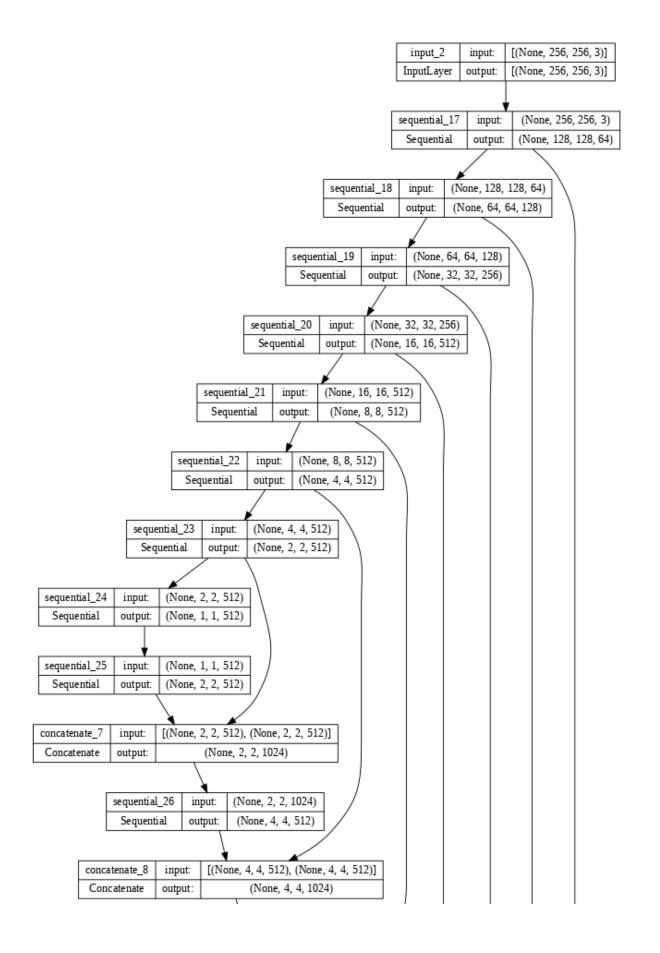
Print the summary of the Generator model
generator.summary()

Model: "model"

Layer (type) Connected to	Output Shape	Param #
=======================================		
<pre>input_1 (InputLayer)</pre>	[(None, 256, 256, 3)]	0 []
<pre>sequential_2 (Sequential) ['input_1[0][0]']</pre>	(None, 128, 128, 64)	3072
- -		
<pre>sequential_3 (Sequential) ['sequential 2[0][0]']</pre>	(None, 64, 64, 128)	131584
[56446[0][0]]		
<pre>sequential_4 (Sequential) ['sequential 3[0][0]']</pre>	(None, 32, 32, 256)	525312
[Sequentiat_3[0][0]]		
sequential_5 (Sequential)	(None, 16, 16, 512)	2099200
['sequential_4[0][0]']		
sequential_6 (Sequential)	(None, 8, 8, 512)	4196352
['sequential_5[0][0]']		
sequential_7 (Sequential)	(None, 4, 4, 512)	4196352
['sequential_6[0][0]']		
sequential 8 (Sequential)	(None, 2, 2, 512)	4196352
['sequential_7[0][0]']	(, _, _,,	
sequential 9 (Sequential)	(None, 1, 1, 512)	4196352
['sequential_8[0][0]']	(NOIIE, 1, 1, 312)	7130332
	(1)	44000=-
sequential_10 (Sequential)	(None, 2, 2, 512)	4196352

```
['sequential 9[0][0]']
concatenate (Concatenate)
                             (None, 2, 2, 1024)
                                                          0
['sequential 10[0][0]',
'sequential 8[0][0]']
sequential_11 (Sequential) (None, 4, 4, 512)
                                                          8390656
['concatenate[0][0]']
concatenate 1 (Concatenate (None, 4, 4, 1024)
                                                          0
['sequential_11[0][0]',
'sequential 7[0][0]']
sequential 12 (Sequential) (None, 8, 8, 512)
                                                          8390656
['concatenate_1[0][0]']
concatenate 2 (Concatenate
                            (None, 8, 8, 1024)
                                                          0
['sequential 12[0][0]',
'sequential 6[0][0]']
sequential 13 (Sequential) (None, 16, 16, 512)
                                                          8390656
['concatenate 2[0][0]']
concatenate 3 (Concatenate (None, 16, 16, 1024)
['sequential 13[0][0]',
'sequential 5[0][0]']
sequential 14 (Sequential) (None, 32, 32, 256)
                                                          4195328
['concatenate 3[0][0]']
concatenate 4 (Concatenate (None, 32, 32, 512)
                                                          0
['sequential 14[0][0]',
'sequential 4[0][0]']
sequential 15 (Sequential) (None, 64, 64, 128)
                                                          1049088
```

```
['concatenate_4[0][0]']
concatenate_5 (Concatenate (None, 64, 64, 256)
['sequential_15[0][0]',
'sequential_3[0][0]']
sequential 16 (Sequential) (None, 128, 128, 64)
                                                   262400
['concatenate 5[0][0]']
concatenate 6 (Concatenate (None, 128, 128, 128)
['sequential 16[0][0]',
'sequential_2[0][0]']
conv2d_transpose_8 (Conv2D (None, 256, 256, 3)
                                                   6147
['concatenate 6[0][0]']
Transpose)
______
_____
Total params: 54425859 (207.62 MB)
Trainable params: 54414979 (207.58 MB)
Non-trainable params: 10880 (42.50 KB)
generator = Generator()
tf.keras.utils.plot model(generator, show shapes=True, dpi=64)
```



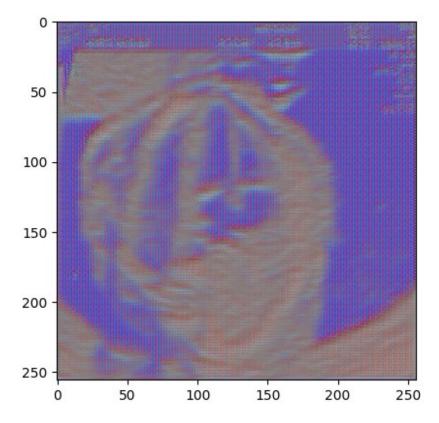
```
import tensorflow as tf

# Assuming 'inp' represents a sample input image
inp = test_X[0]

# Generate output from the generator
gen_output = generator(inp[tf.newaxis, ...], training=False)

# Rescale pixel values to [0, 1]
gen_output = (gen_output - tf.reduce_min(gen_output)) /
(tf.reduce_max(gen_output) - tf.reduce_min(gen_output))

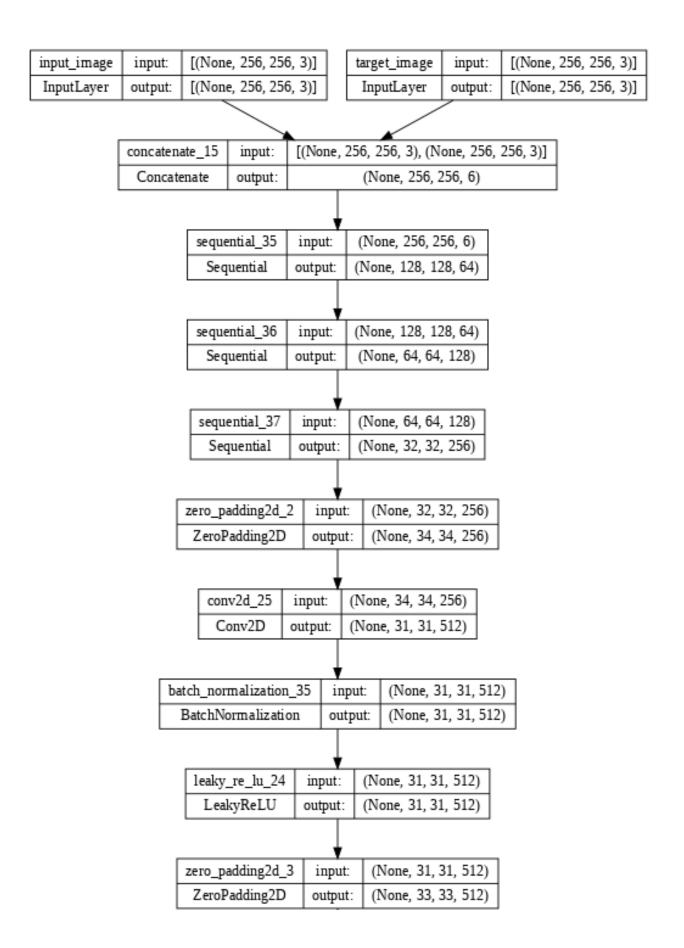
# Plot the generated output
plt.imshow(gen_output[0, ...])
plt.show()
```



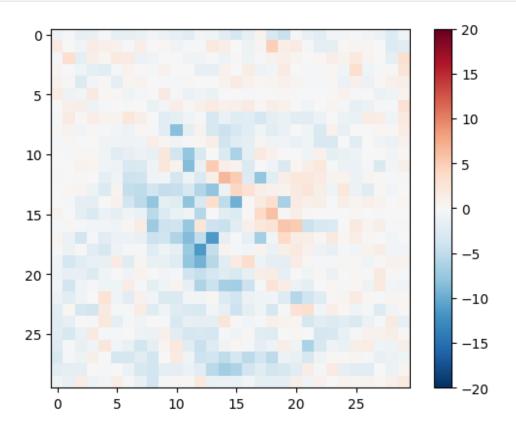
```
LAMBDA = 100
loss_object = tf.keras.losses.BinaryCrossentropy(from_logits=True)
def generator_loss(disc_generated_output, gen_output, target):
    gan_loss = loss_object(tf.ones_like(disc_generated_output),
disc_generated_output)
# Mean absolute error
```

```
l1 loss = tf.reduce mean(tf.abs(target - gen_output))
  total gen loss = gan loss + (LAMBDA * l1 loss)
  return total gen loss, gan loss, l1 loss
def Discriminator():
  initializer = tf.random normal initializer(0., 0.02)
  inp = tf.keras.layers.Input(shape=[256, 256, 3], name='input image')
  tar = tf.keras.layers.Input(shape=[256, 256, 3],
name='target image')
  x = tf.keras.layers.concatenate([inp, tar]) # (batch size, 256,
256, channels*2)
  down1 = downsample(64, 4, False)(x) # (batch_size, 128, 128, 64)
  down2 = downsample(128, 4)(down1) # (batch_size, 64, 64, 128)
 down3 = downsample(256, 4)(down2) # (batch_size, 32, 32, 256)
  zero pad1 = tf.keras.layers.ZeroPadding2D()(down3) # (batch size,
34, 34, 256)
  conv = tf.keras.layers.Conv2D(512, 4, strides=1,
                                kernel initializer=initializer,
                                use bias=False)(zero pad1) #
(batch size, 31, 31, 512)
  batchnorm1 = tf.keras.layers.BatchNormalization()(conv)
 leaky relu = tf.keras.layers.LeakyReLU()(batchnorm1)
  zero pad2 = tf.keras.layers.ZeroPadding2D()(leaky relu) #
(batch size, 33, 33, 512)
  last = tf.keras.layers.Conv2D(1, 4, strides=1,
                                kernel initializer=initializer)
(zero pad2) # (batch size, 30, 30, 1)
  return tf.keras.Model(inputs=[inp, tar], outputs=last)
# Instantiate the Generator model
discriminator = Discriminator()
# Print the summary of the Generator model
discriminator.summary()
discriminator.compile(loss='binary_crossentropy', optimizer='adam')
```

Model: "model_2"		
Layer (type) Connected to	Output Shape	Param #
input_image (InputLayer)	[(None, 256, 256, 3)]	0 []
target_image (InputLayer)	[(None, 256, 256, 3)]	0 []
<pre>concatenate_14 (Concatenat ['input_image[0][0]', e) 'target_image[0][0]']</pre>	(None, 256, 256, 6)	0
<pre>sequential_32 (Sequential) ['concatenate_14[0][0]']</pre>	(None, 128, 128, 64)	6144
<pre>sequential_33 (Sequential) ['sequential_32[0][0]']</pre>	(None, 64, 64, 128)	131584
<pre>sequential_34 (Sequential) ['sequential_33[0][0]']</pre>	(None, 32, 32, 256)	525312
<pre>zero_padding2d (ZeroPaddin ['sequential_34[0][0]'] g2D)</pre>	(None, 34, 34, 256)	0
<pre>conv2d_20 (Conv2D) ['zero_padding2d[0][0]']</pre>	(None, 31, 31, 512)	2097152
<pre>batch_normalization_32 (Ba ['conv2d_20[0][0]'] tchNormalization)</pre>	(None, 31, 31, 512)	2048
<pre>leaky_re_lu_20 (LeakyReLU) ['batch_normalization_32[0][</pre>		0



```
disc_out = discriminator([t_img[tf.newaxis, ...],
m_img[tf.newaxis, ...]], training=False)
plt.imshow(disc_out[0, ..., -1], vmin=-20, vmax=20, cmap='RdBu_r')
plt.colorbar()
<matplotlib.colorbar.Colorbar at 0x7cb37bd07bb0>
```



```
def discriminator_loss(disc_real_output, disc_generated_output):
    real_loss = loss_object(tf.ones_like(disc_real_output),
    disc_real_output)

    generated_loss = loss_object(tf.zeros_like(disc_generated_output),
    disc_generated_output)

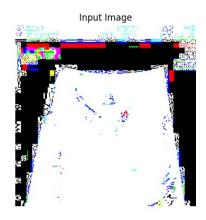
    total_disc_loss = real_loss + generated_loss
    return total_disc_loss

generator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_l=0.5)
    discriminator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_l=0.5)

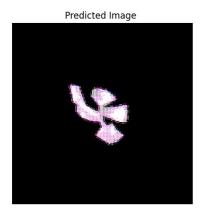
checkpoint_dir = './training_checkpoints'
    checkpoint_prefix = os.path.join(checkpoint_dir, "ckpt")
    checkpoint =
    tf.train.Checkpoint(generator_optimizer=generator_optimizer,
```

```
discriminator optimizer=discriminator optimizer,
                                 generator=generator,
                                 discriminator=discriminator)
def generate images(model, test input, tar, metric=None, show=False,
return prediction=False):
    # Generate prediction using the provided model
    prediction = model(test input, training=True)
    # Adjust brightness of the predicted image
    prediction = prediction * 0.5 + 0.5
    # Apply ground truth mask to the predicted image
    masked prediction = prediction * tar
    if show:
        # Plotting the images if show is True
        plt.figure(figsize=(15, 15))
        display list = [test input[0], tar[0], masked prediction[0]]
# Using masked prediction
        title = ['Input Image', 'Ground Truth', 'Predicted Image ']
        for i in range(3):
            plt.subplot(1, 3, i+1)
            plt.title(title[i])
            plt.imshow(display list[i])
            plt.axis('off')
        plt.show()
    if metric is not None:
        # Update the provided metric if not None
        metric.update state(tar, prediction)
    if return prediction:
        # Return prediction if specified
        return prediction
# Assuming generator is the model from code 1
generator = Generator()
# Load the weights of the generator from the checkpoint
checkpoint.restore(tf.train.latest checkpoint(checkpoint dir))
# Generate images using the modified function
generate images(generator, t img[tf.newaxis, ...],
m img[tf.newaxis, ...], show=True)
WARNING:matplotlib.image:Clipping input data to the valid range for
imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).







```
import tensorflow as tf
# Define the loss functions
def dice_loss(y_true, y_pred):
    numerator = 2 * tf.reduce_sum(y_true * y_pred)
    denominator = tf.reduce_sum(y_true + y_pred)
    return 1 - (numerator + 1) / (denominator + 1)
def focal_loss(y_true, y_pred, gamma=2.0, alpha=0.25):
    y pred = tf.clip by value(y pred, 1e-7, 1.0 - 1e-7)
    p_t = tf.where(tf.equal(y_true, 1), y_pred, 1 - y_pred)
    modulating factor = tf.pow(1.0 - p t, gamma)
    cross entropy = -alpha * tf.pow(1.0 - p t, gamma) *
tf.math.log(p t)
    return tf.reduce mean(cross entropy)
def tversky loss(y true, y pred, alpha=0.7, beta=0.3, smooth=1e-7):
    numerator = tf.reduce_sum(y_true * y_pred, axis=-1)
    denominator = numerator + alpha * tf.reduce_sum(y_true * (1 -
y_pred), axis=-1) + beta * tf.reduce_sum((1 - y_true) * y_pred, axis=-1)
    return 1 - (numerator + smooth) / (denominator + smooth)
# Define the loss function with class weights
def weighted_loss(y_true, y_pred, class_weights):
    return tf.reduce mean(class weights *
tf.keras.losses.binary crossentropy(y true, y pred))
import datetime
log dir = "logs/"
summary writer = tf.summary.create file writer(
  log dir + "fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M
```

```
%S"))
# Update the train step function to use the desired loss function
@tf.function
def train step(input image, target, step, metric):
    with tf.GradientTape() as gen tape, tf.GradientTape() as
disc tape:
        gen output = generator(input image, training=True)
        disc real output = discriminator([input image, target],
training=True)
        disc generated output = discriminator([input image,
gen output], training=True)
        gen_total_loss, gen_gan_loss, gen_l1_loss =
generator loss(disc generated output, gen output, target)
        disc loss = discriminator loss(disc real output,
disc generated output)
        # Use the desired loss function here
        gen loss = dice loss(target, gen output)
    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))
    metric.update state(target, gen output)
    with summary writer.as default():
        tf.summary.scalar('gen total loss', gen total loss,
step=step//10)
        tf.summary.scalar('gen gan loss', gen gan loss, step=step//10)
        tf.summary.scalar('gen_l1_loss', gen_l1_loss, step=step//10)
        tf.summary.scalar('disc loss', disc loss, step=step//10)
train accuracies = []
test accuracies = []
validation accuracies = []
import tensorflow as tf
def fit(train ds, val ds, steps, class weights=None): # Update the
fit function to accept class weights
    example input, example target = next(iter(val ds))
```

```
train metric = tf.keras.metrics.BinaryAccuracy()
    val metric = tf.keras.metrics.BinaryAccuracy()
    start = time.time()
    step = 0
    for input image, target in train_ds:
        if (step) % 10 == 0:
            display.clear output(wait=True)
            train accuracies.append(train metric.result().numpy())
            if step != 0:
                print(f'Time taken for 10 steps: {time.time()-
start:.2f} sec\n')
            start = time.time()
            # Validation step
            generate images(generator, example input, example target,
metric=None, show=True)
            val count = 0
            for val_img, val_target in val_ds:
                generate images(generator, val img, val target,
val metric)
                val count += 1
                if val count >= 28:
                    break
            validation accuracies.append(val metric.result().numpy())
            print(f"Step: {step}")
            print(f"Training Accuracy:
{train metric.result().numpy()}")
            print(f"Validation Accuracy:
{val metric.result().numpy()}")
            train metric.reset states()
            val_metric.reset_states()
            if validation_accuracies[-1] ==
max(validation accuracies):
                checkpoint.save(file_prefix=checkpoint_prefix)
        # Pass class weights to the train step function only if
provided
        if class weights is not None:
            train step(input image, target, step, train metric,
class weights)
        else:
            train step(input image, target, step, train metric)
        # Training step
        if (step + 1) % 10 == 0:
            print('.', end='', flush=True)
        step += 1
        if step == steps:
```

break

Assuming train_gen and test_gen are the training and testing data
generators respectively

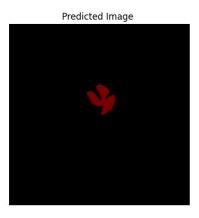
fit(train_generator, test_generator, steps=100)

Time taken for 10 steps: 82.74 sec

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



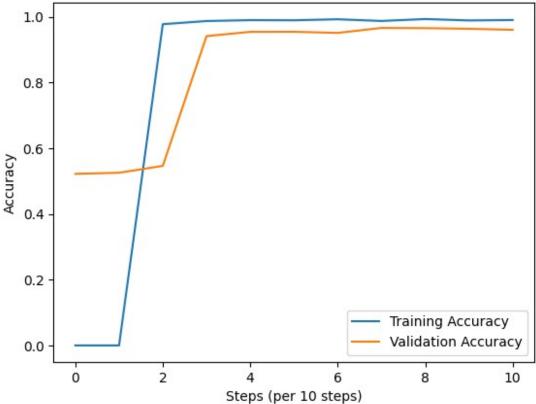




```
Step: 90
Training Accuracy: 0.9899856448173523
Validation Accuracy: 0.9601934552192688
.
import matplotlib.pyplot as plt

# Plotting training and validation accuracies
plt.plot(train_accuracies, label='Training Accuracy')
plt.plot(validation_accuracies, label='Validation Accuracy')
plt.xlabel('Steps (per 10 steps)')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracies')
plt.legend()
plt.grid(False) # Turning off grid
plt.show()
```



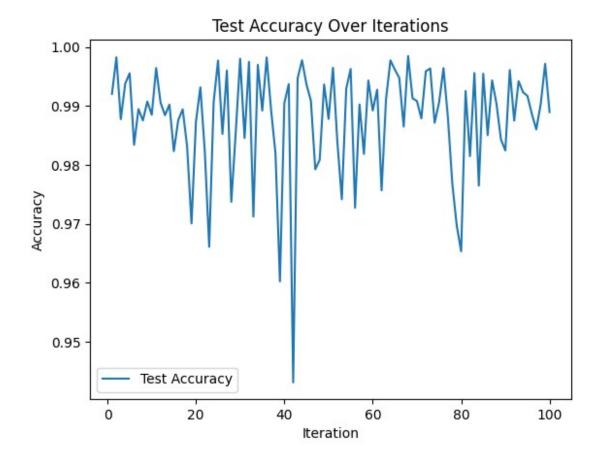


```
import matplotlib.pyplot as plt
import numpy as np
# Define a function to calculate the test accuracy for a subset of the
test dataset
def calculate_test_accuracy(test_ds, num_samples=100):
    test metric = tf.keras.metrics.BinaryAccuracy()
    count = 0
    for test input, test target in test ds:
        predictions = generator(test input, training=False)
        test metric.update state(test target, predictions)
        count += 1
        if count >= num samples:
    test_accuracy = test_metric.result().numpy()
    return test accuracy
# Load the saved checkpoint
checkpoint.restore(tf.train.latest checkpoint(checkpoint dir))
# Define the number of test samples to use for evaluation
num_test samples = 100
```

```
# Initialize the test accuracy list to store accuracies at each
iteration
test accuracies = []
# Pass a subset of the test dataset through the generator to generate
images
for i, (test_input, test_target) in enumerate(test_gen):
   # Calculate and print the test accuracy at each iteration
   test accuracy = calculate test accuracy([(test input,
test target)], num samples=1)
   print("Test Accuracy at iteration", i+1, ":", test accuracy)
   test accuracies.append(test accuracy)
   # Break the loop if the desired number of test samples is reached
   if i \ge num test samples - 1:
        break
# Plot the accuracy graph
plt.figure()
plt.plot(np.arange(1, len(test accuracies) + 1), test accuracies,
label='Test Accuracy')
plt.xlabel('Iteration')
plt.ylabel('Accuracy')
plt.title('Test Accuracy Over Iterations')
plt.legend()
plt.show()
Test Accuracy at iteration 1: 0.99204504
Test Accuracy at iteration 2 : 0.99825543
Test Accuracy at iteration 3 : 0.9877523
Test Accuracy at iteration 4: 0.99377954
Test Accuracy at iteration 5: 0.99553937
Test Accuracy at iteration 6 : 0.98339844
Test Accuracy at iteration 7 : 0.9894613
Test Accuracy at iteration 8 : 0.98753864
Test Accuracy at iteration 9 : 0.9907481
Test Accuracy at iteration 10: 0.9884898
Test Accuracy at iteration 11: 0.99642944
Test Accuracy at iteration 12: 0.9905497
Test Accuracy at iteration 13: 0.98843384
Test Accuracy at iteration 14: 0.99022925
Test Accuracy at iteration 15: 0.9823303
Test Accuracy at iteration 16: 0.9875996
Test Accuracy at iteration 17: 0.98942566
Test Accuracy at iteration 18: 0.98316956
Test Accuracy at iteration 19: 0.97006726
Test Accuracy at iteration 20 : 0.9873403
Test Accuracy at iteration 21: 0.99316406
```

```
Test Accuracy at iteration 22: 0.98236084
Test Accuracy at iteration 23: 0.9661001
Test Accuracy at iteration 24 : 0.9906209
Test Accuracy at iteration 25: 0.9976959
Test Accuracy at iteration 26: 0.9852396
Test Accuracy at iteration 27: 0.9960073
Test Accuracy at iteration 28: 0.9737295
Test Accuracy at iteration 29: 0.9854635
Test Accuracy at iteration 30: 0.9980062
Test Accuracy at iteration 31: 0.984553
Test Accuracy at iteration 32: 0.9974823
Test Accuracy at iteration 33: 0.971227
Test Accuracy at iteration 34: 0.9969737
Test Accuracy at iteration 35 : 0.98921204
Test Accuracy at iteration 36: 0.9982351
Test Accuracy at iteration 37: 0.98933923
Test Accuracy at iteration 38: 0.98191833
Test Accuracy at iteration 39: 0.9602407
Test Accuracy at iteration 40: 0.99048364
Test Accuracy at iteration 41: 0.9937083
Test Accuracy at iteration 42: 0.9430949
Test Accuracy at iteration 43: 0.9946645
Test Accuracy at iteration 44: 0.99775183
Test Accuracy at iteration 45: 0.99367774
Test Accuracy at iteration 46 : 0.9909159
Test Accuracy at iteration 47: 0.97924805
Test Accuracy at iteration 48: 0.9808604
Test Accuracy at iteration 49: 0.9936371
Test Accuracy at iteration 50: 0.98779297
Test Accuracy at iteration 51: 0.9964752
Test Accuracy at iteration 52 : 0.9838358
Test Accuracy at iteration 53: 0.97416687
Test Accuracy at iteration 54: 0.992925
Test Accuracy at iteration 55: 0.99627686
Test Accuracy at iteration 56: 0.97273254
Test Accuracy at iteration 57: 0.99024963
Test Accuracy at iteration 58: 0.98186237
Test Accuracy at iteration 59 : 0.9943085
Test Accuracy at iteration 60: 0.9892222
Test Accuracy at iteration 61: 0.9927572
Test Accuracy at iteration 62: 0.97566736
Test Accuracy at iteration 63: 0.99110925
Test Accuracy at iteration 64: 0.99773663
Test Accuracy at iteration 65 : 0.9961548
Test Accuracy at iteration 66: 0.9947561
Test Accuracy at iteration 67: 0.986496
Test Accuracy at iteration 68: 0.99846905
Test Accuracy at iteration 69: 0.99129736
Test Accuracy at iteration 70: 0.9908295
```

```
Test Accuracy at iteration 71: 0.9878794
Test Accuracy at iteration 72: 0.9958852
Test Accuracy at iteration 73: 0.9963583
Test Accuracy at iteration 74: 0.9871521
Test Accuracy at iteration 75 : 0.9905446
Test Accuracy at iteration 76: 0.9964142
Test Accuracy at iteration 77: 0.9880625
Test Accuracy at iteration 78: 0.9768473
Test Accuracy at iteration 79: 0.9697011
Test Accuracy at iteration 80: 0.96533203
Test Accuracy at iteration 81: 0.99253845
Test Accuracy at iteration 82: 0.98148096
Test Accuracy at iteration 83: 0.9955699
Test Accuracy at iteration 84: 0.97647095
Test Accuracy at iteration 85 : 0.9954732
Test Accuracy at iteration 86: 0.9850464
Test Accuracy at iteration 87: 0.994339
Test Accuracy at iteration 88 : 0.99033105
Test Accuracy at iteration 89 : 0.9843241
Test Accuracy at iteration 90: 0.98244226
Test Accuracy at iteration 91: 0.9960989
Test Accuracy at iteration 92: 0.9875081
Test Accuracy at iteration 93: 0.9941966
Test Accuracy at iteration 94: 0.992335
Test Accuracy at iteration 95 : 0.9916891
Test Accuracy at iteration 96: 0.98862714
Test Accuracy at iteration 97 : 0.9860179
Test Accuracy at iteration 98: 0.990331
Test Accuracy at iteration 99 : 0.99715173
Test Accuracy at iteration 100: 0.9889577
```



GRAD CAM VISUALIZATION

```
import os
os.environ["KERAS_BACKEND"] = "tensorflow"
import numpy as np
import tensorflow as tf
import keras
# Display
from IPython.display import Image, display
import matplotlib as mpl
import matplotlib.pyplot as plt
original_dataset_path = "/content/drive/MyDrive/HEART US IMAGE FETUS"
mask_dataset_path =
"/content/drive/MyDrive/FETUS ULTRASOUND IMAGES HEART CHAMBERS/Segment
ationClass"
import os
import random
import matplotlib.pyplot as plt
from PIL import Image
```

```
# Function to get random pairs of original image and mask paths from
the dataset
def get random img and mask paths(original dataset path,
mask dataset path, num images=15):
    all files = os.listdir(original dataset path)
    image_files = [f for f in all_files if f.endswith('.jpg')]
    random img paths = random.sample(image files, min(num images,
len(image files)))
    mask_paths = [os.path.join(mask_dataset_path, img.replace('.jpg',
'.png')) for img in random img paths]
    return [(os.path.join(original dataset path, img), mask) for img,
mask in zip(random img paths, mask paths)]
# Get random pairs of original image and mask paths
random img and mask paths =
get random img and mask paths(original dataset path,
mask dataset path, num images=15)
# Define the save and display gradcam function for images and masks
def save and display gradcam for images and masks(img and mask paths,
model, preprocess input, get img array, make gradcam heatmap,
last conv layer name):
    for img path, mask path in img and mask paths:
        # Prepare original image
        original img array = preprocess input(get img array(img path,
size=(299, 299)))
        # Prepare mask
        mask img = Image.open(mask path).convert('L') # Convert to
gravscale
        mask img = mask img.resize((original img array.shape[2],
original_img_array.shape[1]), Image.NEAREST) # Resize mask to match
image dimensions
        mask array = np.array(mask img) / 255.0 # Normalize mask
        mask array = mask array.reshape((original img array.shape[1],
original img array.shape[\frac{1}{2}], 1)) # Add extra dimension to match
channels
        # Combine original image and mask
        img with mask = original img array * mask array
        # Make model
        model = model builder(weights="imagenet")
        # Remove last laver's softmax
        model.layers[-1].activation = None
        # Generate class activation heatmap
        heatmap = make gradcam heatmap(img with mask, model,
```

```
last conv layer name)
        # Load the original image
        img = keras.preprocessing.image.load img(img path)
        img = keras.preprocessing.image.img to array(img)
        # Rescale heatmap to a range 0-255
        heatmap = np.uint8(255 * heatmap)
        # Use jet colormap to colorize heatmap
        jet = plt.cm.get cmap("jet")
        # Use RGB values of the colormap
        jet colors = jet(np.arange(256))[:, :3]
        jet_heatmap = jet_colors[heatmap]
        # Create an image with RGB colorized heatmap
        jet heatmap =
keras.preprocessing.image.array to img(jet heatmap)
        jet heatmap = jet heatmap.resize((img.shape[1], img.shape[0]))
        iet heatmap =
keras.preprocessing.image.img to array(jet heatmap)
        # Superimpose the heatmap on original image
        superimposed img = jet heatmap * 0.4 + img
        superimposed img =
keras.preprocessing.image.array to img(superimposed img)
        # Display Grad CAM
        plt.figure()
        plt.imshow(superimposed img)
        plt.axis('off')
        plt.show()
# Use the save and display gradcam for images and masks function
save_and_display_gradcam_for_images_and_masks(random_img_and_mask_path
s, model builder, preprocess input, get img array,
make gradcam heatmap, last conv layer name)
<ipython-input-100-9dacdcb4a280>:49: MatplotlibDeprecationWarning: The
get cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get cmap(obj)`` instead.
  jet = plt.cm.get cmap("jet")
```

