

ai-project-248

April 1, 2024

```
[ ]: # This Python 3 environment comes with many helpful analytics libraries
      ↳ installed
      # It is defined by the kaggle/python Docker image: https://github.com/kaggle/
      ↳ docker-python
      # For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list
↳ all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that
↳ gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved
↳ outside of the current session
```

```
[3]: !pip install patchify
```

```
Collecting patchify
  Downloading patchify-0.2.3-py3-none-any.whl.metadata (3.0 kB)
Requirement already satisfied: numpy<2,>=1 in /opt/conda/lib/python3.10/site-
packages (from patchify) (1.26.4)
Downloading patchify-0.2.3-py3-none-any.whl (6.6 kB)
Installing collected packages: patchify
Successfully installed patchify-0.2.3
```

```
[4]: import numpy as np
import pandas as pd
```

```

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

```

```

/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/classes.json
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/images/image_part_002.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/images/image_part_006.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/images/image_part_005.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/images/image_part_003.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/images/image_part_004.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/images/image_part_007.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/images/image_part_009.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/images/image_part_008.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/images/image_part_001.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/masks/image_part_001.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/masks/image_part_003.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/masks/image_part_006.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/masks/image_part_002.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/masks/image_part_008.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/masks/image_part_007.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/masks/image_part_009.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/masks/image_part_005.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 7/masks/image_part_004.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 8/images/image_part_002.jpg
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 8/images/image_part_006.jpg

```

[illegible]

[illegible]

[illegible]

```

/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 4/masks/image_part_007.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 4/masks/image_part_009.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 4/masks/image_part_005.png
/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic segmentation
dataset/Tile 4/masks/image_part_004.png

```

```

[5]: import os
import cv2
import numpy as np
from matplotlib import pyplot as plt
from patchify import patchify
from PIL import Image
import torch
from sklearn.preprocessing import MinMaxScaler, StandardScaler

```

```

[7]: def create_dir(dir_name):
    if not os.path.exists(dir_name):
        os.makedirs(dir_name, exist_ok=True)

```

```

[10]: scaler = MinMaxScaler()
root_dir = '/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic_
segmentation dataset/'
patch_size = 256

```

```

[11]: image_dataset=[]
for path,subdirs,files in os.walk(root_dir):
    dirname = path.split(os.path.sep)[-1]
    if dirname == "images":
        images = os.listdir(path)
        for i,image_name in enumerate(images):
            if image_name.endswith(".jpg"):
                image = cv2.imread(path+'/'+image_name,cv2.IMREAD_COLOR)
                # Crop
                # Height Width Channel
                SIZE_X = (image.shape[1]//patch_size)*patch_size
                SIZE_Y = (image.shape[0]//patch_size)*patch_size
                image = Image.fromarray(image)
                image = image.crop((0,0,SIZE_X,SIZE_Y))

                image = np.array(image)

                patches_img =
patchify(image,(patch_size,patch_size,3),step=patch_size)
                for i in range(patches_img.shape[0]):

```



```

        for j in range(patches_img.shape[1]):
            single_patch_img = patches_img[i,j,:,:]
            # img need flatten
            single_patch_img = scaler.
↪fit_transform(single_patch_img.reshape(-1, single_patch_img.shape[-1])).
↪reshape(single_patch_img.shape)
            single_patch_img = single_patch_img[0] #Drop the extra
↪unnecessary dimension that patchify adds.
            image_dataset.append(single_patch_img)

```

```

[12]: mask_dataset = []
for path,subdirs,files in os.walk(root_dir):
    dirname = path.split(os.path.sep)[-1]
    if dirname == "masks":
        masks = os.listdir(path)
        for i,mask_name in enumerate(masks):
            if mask_name.endswith(".png"):
                mask = cv2.imread(path+'/'+mask_name,1)
                mask = cv2.cvtColor(mask, cv2.COLOR_BGR2RGB)
                SIZE_X = (mask.shape[1]//patch_size)*patch_size
                SIZE_Y = (mask.shape[0]//patch_size)*patch_size
                mask = Image.fromarray(mask)
                mask = mask.crop((0,0,SIZE_X,SIZE_Y))
                mask = np.array(mask)

                patches_mask = patchify(mask,(patch_size,patch_size,3),step =
↪patch_size)

                for i in range(patches_mask.shape[0]):
                    for j in range(patches_mask.shape[1]):
                        single_patch_mask = patches_mask[i,j,:,:]
                        single_patch_mask = single_patch_mask[0]
                        mask_dataset.append(single_patch_mask)

```

```

[13]: image_dataset =np.asarray(image_dataset)
mask_dataset =np.asarray(mask_dataset)
image_dataset.shape

```

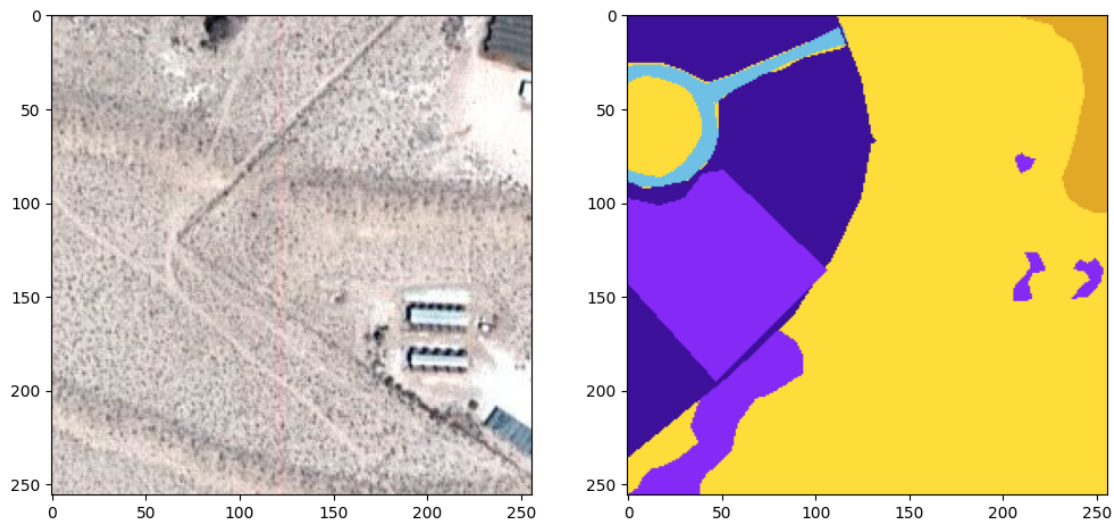
[13]: (1305, 256, 256, 3)

```

[14]: import random
import numpy as np
image_number = random.randint(0,len(image_dataset))
plt.figure(figsize=(12,6))
plt.subplot(121)
plt.imshow(np.reshape(image_dataset[image_number], (patch_size, patch_size, 3)))
plt.subplot(122)

```

```
plt.imshow(np.reshape(mask_dataset[image_number], (patch_size, patch_size, 3)))
plt.show()
```



```
[15]: Building = '#3C1098'.lstrip('#')
Building = np.array(tuple(int(Building[i:i+2], 16) for i in (0, 2, 4))) # 60, 16, 152

Land = '#8429F6'.lstrip('#')
Land = np.array(tuple(int(Land[i:i+2], 16) for i in (0, 2, 4))) #132, 41, 246

Road = '#6EC1E4'.lstrip('#')
Road = np.array(tuple(int(Road[i:i+2], 16) for i in (0, 2, 4))) #110, 193, 228

Vegetation = 'FEDD3A'.lstrip('#')
Vegetation = np.array(tuple(int(Vegetation[i:i+2], 16) for i in (0, 2, 4))) #254, 221, 58

Water = 'E2A929'.lstrip('#')
Water = np.array(tuple(int(Water[i:i+2], 16) for i in (0, 2, 4))) #226, 169, 41

Unlabeled = '#9B9B9B'.lstrip('#')
Unlabeled = np.array(tuple(int(Unlabeled[i:i+2], 16) for i in (0, 2, 4)))
```

```
[16]: def rgb_to_2D_label(label,num_class=6):
    """
    Suply our labale masks as input in RGB format.
    Replace pixels with specific RGB values ...
    """
    label_seg = np.zeros(label.shape,dtype=np.uint8)
```

```

label_seg [np.all(label == Building,axis=-1)] = 0
label_seg [np.all(label==Land,axis=-1)] = 1
label_seg [np.all(label==Road,axis=-1)] = 2
label_seg [np.all(label==Vegetation,axis=-1)] = 3
label_seg [np.all(label==Water,axis=-1)] = 4
label_seg [np.all(label==Unlabeled,axis=-1)] = 5

label_seg = label_seg[:, :, 0]

new_label = np.zeros(label_seg.shape + (num_class,))

for i in range(num_class):
    new_label[label_seg == i,i] = 1
label_seg=new_label

return label_seg

```

```

[17]: labels = []
for i in range(mask_dataset.shape[0]):
    label = rgb_to_2D_label(mask_dataset[i])
    labels.append(label)

labels = np.array(labels)

```

```

[18]: image_dataset[0].shape,labels.shape

```

```

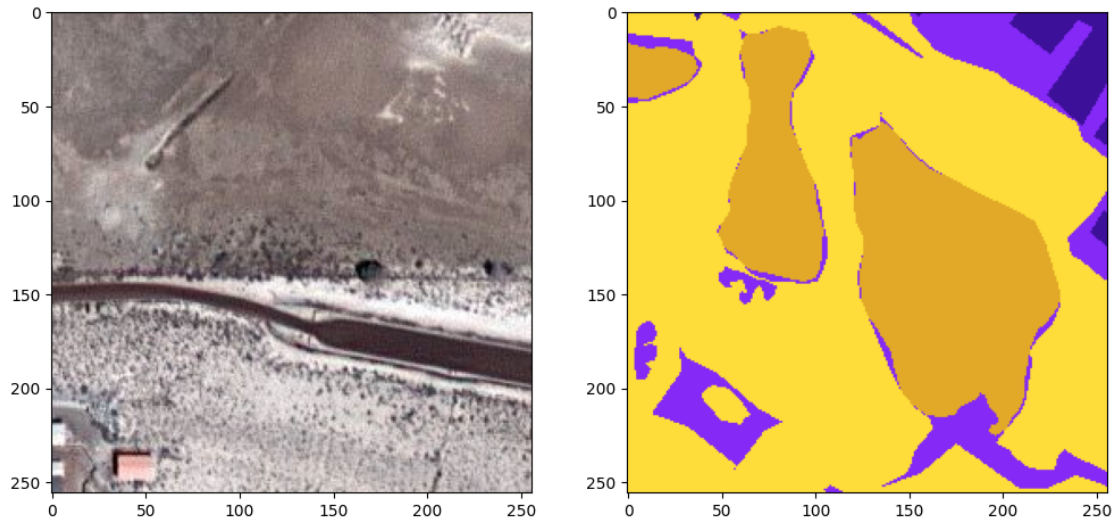
[18]: ((256, 256, 3), (1305, 256, 256, 6))

```

```

[19]: image_number = random.randint(0,len(image_dataset))
plt.figure(figsize=(12,6))
plt.subplot(121)
plt.imshow(np.reshape(image_dataset[image_number], (patch_size, patch_size, 3)))
plt.subplot(122)
plt.imshow(np.reshape(mask_dataset[image_number], (patch_size, patch_size, 3)))
plt.show()

```



```
[21]: import torch.nn as nn
from torch.utils.data import DataLoader, Dataset
class Aerial(Dataset):
    def __init__(self, images, masks):
        super(Aerial, self).__init__()
        self.images = images
        self.masks = masks
        self.n_samples = len(images)

    def __getitem__(self, index):
        image = self.images[index]
        image = image/255.0
        image = np.transpose(image, (2,0,1))
        image = image.astype(np.float32)
        image = torch.from_numpy(image)

        mask = self.masks[index]
        mask = np.transpose(mask, (2,0,1))
        mask = mask.astype(np.float32)
        mask = torch.from_numpy(mask)

        return image, mask
    def __len__(self):
        return self.n_samples
```

```
[22]: create_dir("files/")
create_dir("Results/")
H = 256
```

```

W =256
num_class = len(np.unique(labels))
size =(H,W)
batch_size =2
num_epochs = 100
lr=1e-4
checkpoints_path ="files/checkpoints.pth"

```

```

[25]: from sklearn.model_selection import train_test_split
train_x,val_x,train_y,val_y = train_test_split(image_dataset,labels,test_size=0.
↳2, random_state = 42)

train_dataset = Aerial(train_x,train_y)
val_dataset = Aerial(val_x,val_y)

```

```

[27]: train_loader = DataLoader(
    train_dataset,
    batch_size=batch_size,
    shuffle = True,
    num_workers=2,
)
val_loader = DataLoader(
    val_dataset,
    batch_size=batch_size,
    shuffle=False,
    num_workers=2
)

```

```

[54]: import torch.nn as nn
import torch
import torchvision

class DoubleConv(nn.Module):
    def __init__(self, in_ch, out_ch):
        super(DoubleConv, self).__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(in_ch, out_ch, 3, padding=1),
            nn.BatchNorm2d(out_ch),
            nn.ReLU(inplace=True),
            nn.Conv2d(out_ch, out_ch, 3, padding=1),
            nn.BatchNorm2d(out_ch),
            nn.ReLU(inplace=True)
        )

    def forward(self, x):
        return self.conv(x)

```

```

class UNet(nn.Module):
    def __init__(self, in_ch, out_ch):
        super(UNet, self).__init__()
        self.conv1 = DoubleConv(in_ch, 64)
        self.pool1 = nn.MaxPool2d(2)
        self.conv2 = DoubleConv(64, 128)
        self.pool2 = nn.MaxPool2d(2)
        self.conv3 = DoubleConv(128, 256)
        self.pool3 = nn.MaxPool2d(2)
        self.conv4 = DoubleConv(256, 512)
        self.pool4 = nn.MaxPool2d(2)
        self.conv5 = DoubleConv(512, 1024)

        self.up6 = nn.ConvTranspose2d(1024, 512, 2, stride=2)
        self.conv6 = DoubleConv(1024, 512)
        self.up7 = nn.ConvTranspose2d(512, 256, 2, stride=2)
        self.conv7 = DoubleConv(512, 256)
        self.up8 = nn.ConvTranspose2d(256, 128, 2, stride=2)
        self.conv8 = DoubleConv(256, 128)
        self.up9 = nn.ConvTranspose2d(128, 64, 2, stride=2)
        self.conv9 = DoubleConv(128, 64)

        self.conv10 = nn.Conv2d(64, out_ch, 1)
        self.sigmoid = nn.Sigmoid()
    def forward(self, x):
        c1 = self.conv1(x)
        p1 = self.pool1(c1)
        c2 = self.conv2(p1)
        p2 = self.pool2(c2)
        c3 = self.conv3(p2)
        p3 = self.pool3(c3)
        c4 = self.conv4(p3)
        p4 = self.pool4(c4)
        c5 = self.conv5(p4)
        up_6 = self.up6(c5)
        merge6 = torch.cat([up_6, c4], dim=1)
        c6 = self.conv6(merge6)
        up_7 = self.up7(c6)
        merge7 = torch.cat([up_7, c3], dim=1)
        c7 = self.conv7(merge7)
        up_8 = self.up8(c7)
        merge8 = torch.cat([up_8, c2], dim=1)
        c8 = self.conv8(merge8)
        up_9 = self.up9(c8)
        merge9 = torch.cat([up_9, c1], dim=1)

```

```

c9 = self.conv9(merge9)
c10 = self.conv10(c9)

out = self.sigmoid(c10)
return out

```

```

[56]: import torch
import torch.nn as nn

class DiceLoss(nn.Module):
    def __init__(self):
        super(DiceLoss, self).__init__()

    def forward(self, input, target):
        smooth = 1.0

        iflat = input.reshape(-1)
        tflat = target.reshape(-1)
        intersection = (iflat * tflat).sum()

        dice_loss = 1 - ((2.0 * intersection + smooth) / (iflat.sum() + tflat.
↪sum() + smooth))

        return dice_loss

    def calculate_average_dice_loss(self, inputs, targets):
        num_channels = inputs.size(1)

        dice_losses = []
        for channel in range(num_channels):
            input_channel = inputs[:, channel, ...].unsqueeze(1)
            target_channel = targets[:, channel, ...].unsqueeze(1)
            dice_loss_channel = self.forward(input_channel, target_channel)
            dice_losses.append(dice_loss_channel)

        average_dice_loss = torch.mean(torch.stack(dice_losses))

        return average_dice_loss

```

```

[57]: model = UNet(3,6)
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)
optimizer = torch.optim.Adam(model.parameters(),lr=lr)
weights = [0.1666, 0.1666, 0.1666, 0.1666, 0.1666, 0.1666]
loss_fn = DiceLoss()

```

```
[58]: from tqdm import tqdm
def train(model, loader, loss_fn, optimizer, device):
    epoch_loss=0.
    model.train()

    for x,y in tqdm(loader):
        x =x.to(device, dtype = torch.float32)
        y = y.to(device, dtype = torch.float32)
        optimizer.zero_grad()
        outputs = model(x)
        loss = loss_fn.calculate_average_dice_loss(outputs, y)
        loss.backward()
        optimizer.step()
        epoch_loss +=loss.item()

    return epoch_loss/len(loader)
```

```
[61]: def validate(model, loader, loss_fn, device):
    epoch_loss = 0.0
    model.eval()
    with torch.no_grad():
        for x,y in loader:
            x =x.to(device, dtype = torch.float32)
            y = y.to(device, dtype = torch.float32)
            outputs = model(x)
            loss = loss_fn.calculate_average_dice_loss(outputs, y)
            epoch_loss +=loss.item()

    return epoch_loss/len(loader)
```

```
[ ]: REAL_img_path = "/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic_
segmentation dataset/Tile 6/masks/image_part_001.png"
img_path = "/kaggle/input/semantic-segmentation-of-aerial-imagery/Semantic_
segmentation dataset/Tile 6/images/image_part_001.jpg"
```

```
[51]: def label_to_rgb(predicted_image):

    Building = '#3C1098'.lstrip('#')
    Building = np.array(tuple(int(Building[i:i+2], 16) for i in (0, 2, 4)))
    Land = '#8429F6'.lstrip('#')
    Land = np.array(tuple(int(Land[i:i+2], 16) for i in (0, 2, 4)))

    Road = '#6EC1E4'.lstrip('#')
    Road = np.array(tuple(int(Road[i:i+2], 16) for i in (0, 2, 4)))

    Vegetation = 'FEDD3A'.lstrip('#')
    Vegetation = np.array(tuple(int(Vegetation[i:i+2], 16) for i in (0, 2, 4)))
```



```

Water = 'E2A929'.lstrip('#')
Water = np.array(tuple(int(Water[i:i+2], 16) for i in (0, 2, 4)))

Unlabeled = '#9B9B9B'.lstrip('#')
Unlabeled = np.array(tuple(int(Unlabeled[i:i+2], 16) for i in (0, 2, 4)))

segmented_img = np.empty((predicted_image.shape[0], predicted_image.
↪shape[1], 3))

segmented_img[(predicted_image == 0)] = Building
segmented_img[(predicted_image == 1)] = Land
segmented_img[(predicted_image == 2)] = Road
segmented_img[(predicted_image == 3)] = Vegetation
segmented_img[(predicted_image == 4)] = Water
segmented_img[(predicted_image == 5)] = Unlabeled

segmented_img = segmented_img.astype(np.uint8)
return(segmented_img)

```

```

[64]: from PIL import Image
import numpy as np
import matplotlib.pyplot as plt

G_img = Image.open(img_path)
REAL_img = Image.open(REAL_img_path)

patch_size = 256
SIZE_X = (G_img.size[0] // patch_size) * patch_size
SIZE_Y = (G_img.size[1] // patch_size) * patch_size
G_img = G_img.crop((0, 0, SIZE_X, SIZE_Y))
G_img = np.array(G_img)

patch_size = 256
SIZE_X = (REAL_img.size[0] // patch_size) * patch_size
SIZE_Y = (REAL_img.size[1] // patch_size) * patch_size
REAL_img = REAL_img.crop((0, 0, SIZE_X, SIZE_Y))
REAL_img = np.array(REAL_img)
REAL_img = np.array(REAL_img)

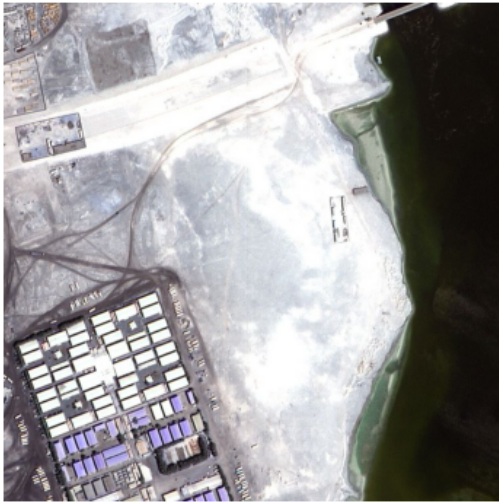
```

```
plt.figure(figsize=(15, 5))
plt.subplot(1, 3, 1)
plt.imshow(G_img)
plt.title("The Image")
plt.axis('off')

plt.subplot(1, 3, 2)
plt.imshow(REAL_img)
plt.title("Real Mask")
plt.axis('off')

plt.show()
```

The Image



Real Mask

