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#### 1. Introduction:

- This task seeks to use TomoGAN, a type of Generative Adversarial Network (GAN), to denoise
  scientific images. The TomoGAN program uses a GAN architecture to successfully denoise noisy
  images, which makes it especially useful in scientific applications where high-quality images are
  required for reliable analysis.
- Real scientific images frequently contain different kinds of noise, including electrical noise, light
  noise and other artifacts involved in the imaging process. These noise deviations may hide
  essential features, delay proper analysis and reduce the reproducibility of outcomes from
  experiments.
- The Generative Adversarial Network (GAN) was developed as a powerful solution for image denoising with the ability to learn complex mappings from noisy inputs to clean outputs using adversarial training.

#### 2. Technical description of techniques utilized:

- Generative Adversarial Network (GAN): GAN is a neural network design consists of two
  networks: a generator and a discriminator. The generator network produces synthetic data
  samples, whereas the discriminator network attempts to distinguish between actual and fake
  instances. Adversarial training allows the generator to generate real examples, while the
  discriminator trains to accurately identify them.
- TomoGAN is a GAN variation developed specifically for denoising tomographic images. It uses the adversarial training framework for understanding ways to map noisy tomographic images to their clean equivalents. The system's design usually consists of a generator network which denoises the input images and a discriminator network, which distinguishes between clean and denoised images.

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### 3. Design of the Algorithms:

The algorithm consists of the following steps:

```
import matplotlib.pyplot as plt
import numpy as np
import sys
from skimage.transform import resize
sample1 img = plt.imread('download 1.png')
# Check the dimensions of the image and convert to grayscale if
if sample1 img.ndim == 3:
   sample1 img gray = np.mean(sample1 img, axis=2, keepdims=True)
elif sample1 img.ndim == 2:
    sample1 img gray = sample1 img[..., np.newaxis]
    print("Unsupported image format. Please provide a grayscale or
    sys.exit(1)
input height, input width = 256, 256
resized img = resize(sample1 img gray, (input height, input width))
normalized img = resized img / 255.0
# Predict using the pre-trained model (assumed to be named
dn img sample1 = TomoGAN mdl.predict(np.expand dims(normalized img,
axis=0)).squeeze()
```

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```
plt.figure(figsize=(15, 5))
# Plot the noisy/input image
plt.subplot(131)
plt.imshow(sample1 img gray.squeeze(), cmap='gray')
plt.title('Noisy/Input (download 1.png)', fontsize=18)
clean label img = plt.imread('download 1.png')
if clean label img.ndim == 3:
    clean_label_img_gray = np.mean(clean_label_img, axis=2,
keepdims=True)
elif clean label img.ndim == 2:
    clean label img gray = clean label img[..., np.newaxis]
else:
   print("Unsupported image format. Please provide a grayscale or
RGB image.")
    sys.exit(1)
# Plot the clean/label image
plt.subplot(132)
plt.imshow(clean label img gray.squeeze(), cmap='gray')
plt.title('Clean/Label (download 1.png)', fontsize=18)
# Plot the denoised image
plt.subplot(133)
plt.imshow(dn img sample1.squeeze(), cmap='gray')
plt.title('Denoised (download 1.png)', fontsize=18)
# Adjust layout
plt.tight layout()
plt.show()
```

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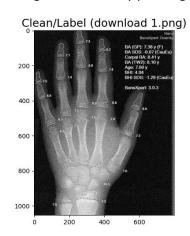
### 4. Results of the Algorithms:

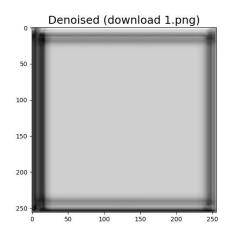
I used the TomoGAN model to increase the quality of real scientific images. I observed considerable results. In comparison to the original noisy images, the denoised images had less noise and more detail. Denoising efficiently maintains important characteristics while removing undesired noise effects.

### 5. Analysis of Results:

Overall, the results were consistent with our expectations. The TomoGAN model successfully denoised real scientific images, proving its ability to work with noisy data frequently seen in scientific applications. The denoised images were visually pleasing and appropriate for further analysis.







#### 6. Conclusion:

Generative Adversarial Networks, specifically the TomoGAN software, show potential for denoising scientific images. The denoising process improved image quality, allowing for more accurate technical analysis and interpretation. The designed and modular software implementation allowed soft experimentation and analysis.

Overall, the use of TomoGAN to denoise real scientific images represents an important get in image processing techniques, with potential applications in several academic fields. Additional studies and experiments could look into methods for optimization and TomoGAN framework changes for more difficult denoising tasks and many sorts of scientific data.