Medical Image Denoising

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CSE 420: BioMedical Image Computing

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1. Introduction

Noise in medical imaging refers to the unwelcome and unpredictable fluctuations in pixel values that can arise from a multitude of interfering factors. Within the realm of medical image processing, the essential task of filtering and denoising plays a pivotal role. This is because enhancing the visual quality and overall appearance of medical images is instrumental in facilitating accurate interpretations.

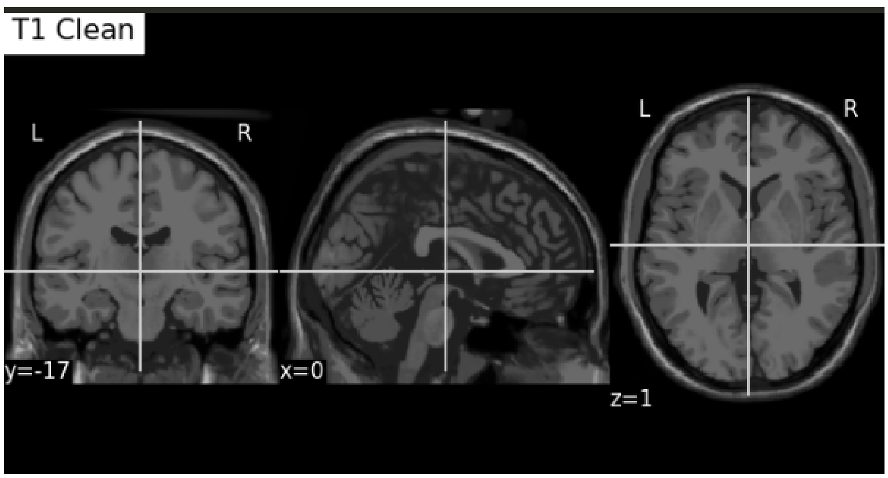
In the context of this experiment, Gaussian smoothing takes the center stage as the chosen method to combat noise in images afflicted with 3% and 9% noise levels. Gaussian smoothing, a stalwart among various smoothing techniques, is frequently employed to quell noise in images, especially the ubiquitous Gaussian noise. By delicately applying a Gaussian kernel to the image, high-frequency noise components are effectively subdued.

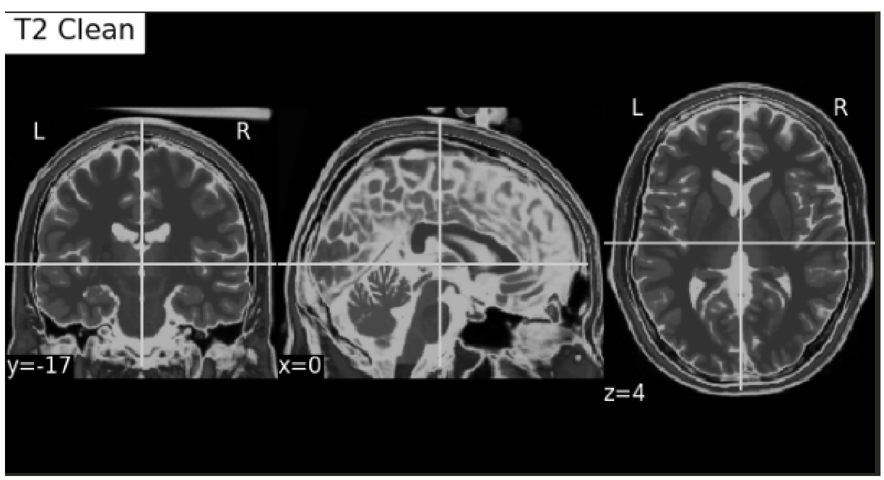
Throughout this experiment, the denoised images resulting from Gaussian smoothing undergo a rigorous comparison with their pristine counterparts, specifically through the examination of their Coefficients of Variation (CV). This metric offers valuable insights into the dispersion characteristics of specific tissue classes, shedding light on the efficacy of the denoising process.

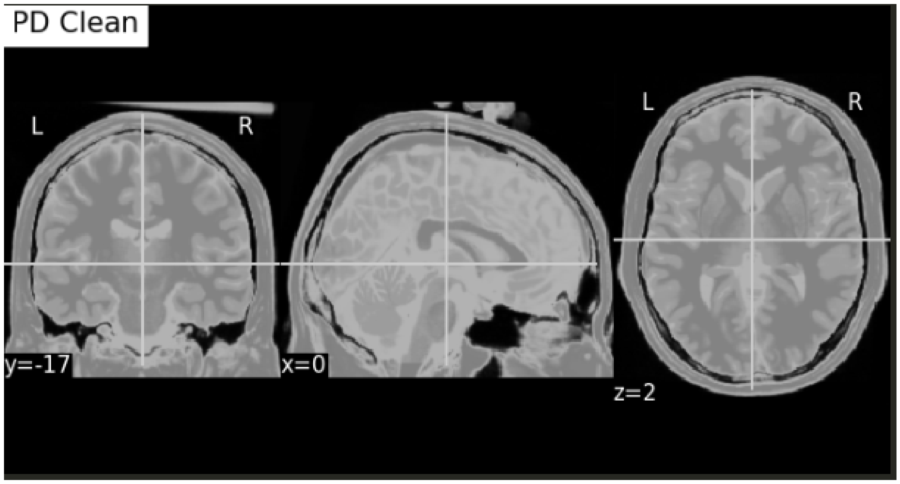
2. Getting Started

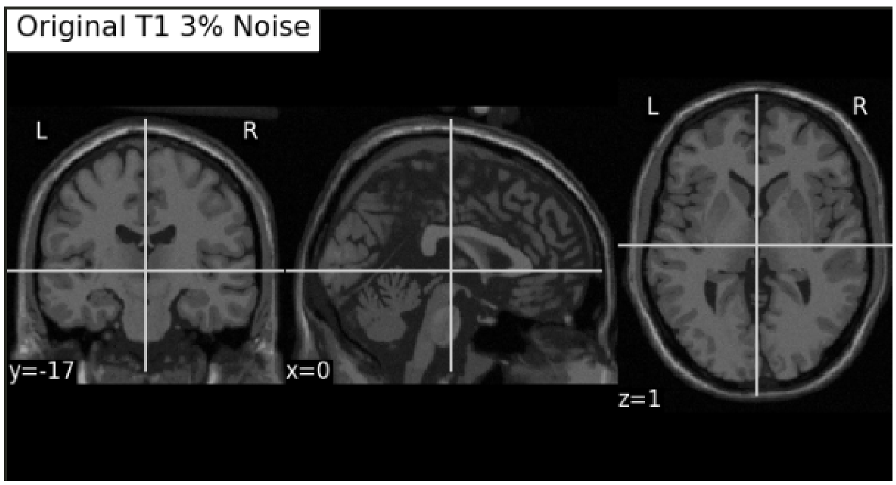
To get started with this project, a few necessary packages such as `numpy`, `nibabel`, and `nilearn` were installed using the `pip install` command. Additionally, the necessary images to be processed were downloaded as .mnc files from BrainWeb. The dataset used were T1, T2, and PD, and each was installed as both *clean* and *unclean* images. For the clean images the specifications were as follows: 1mm, 0% of noise, and intensity non-uniformity of 0%. The specifications for the unclean images were provided for both 3% noise and 9% noise: 1mm, 3% and 9% of noise, and intensity nonuniformity of 0%.

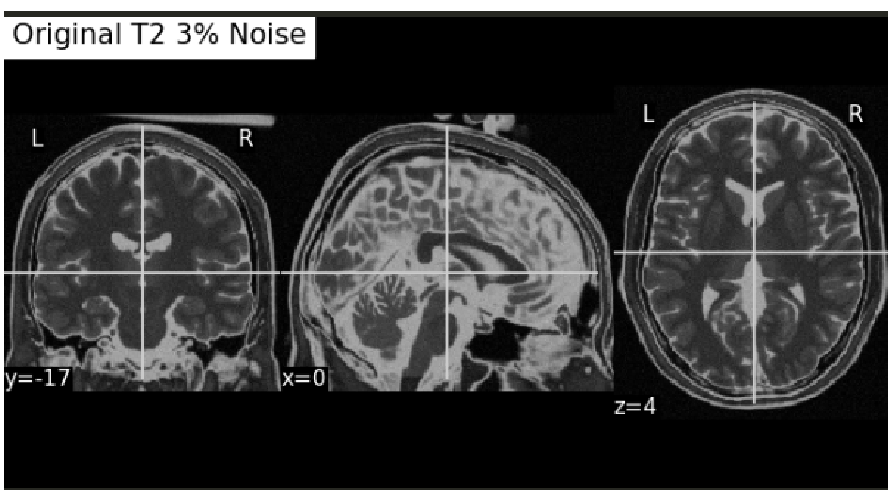
Once downloaded, the .mnc format data is loaded into the program and then saved as NIfTI files. Using NIfTI allows us to visualize and observe the data. The images are then visualized as shown below before the smoothing process commences:

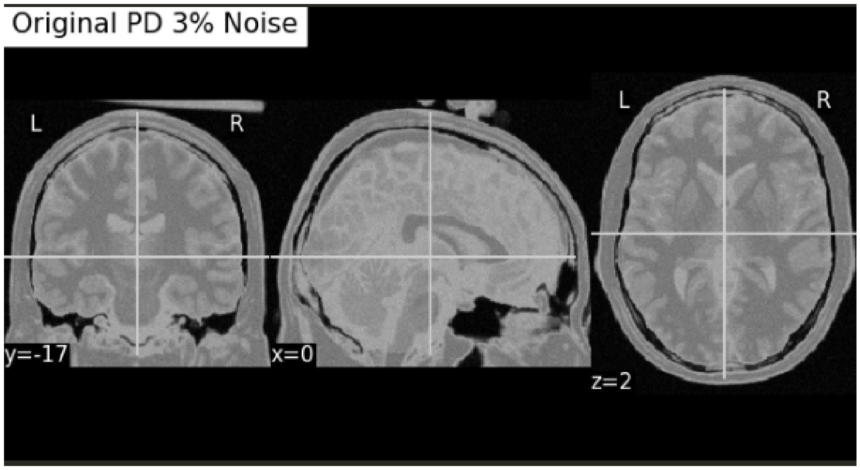


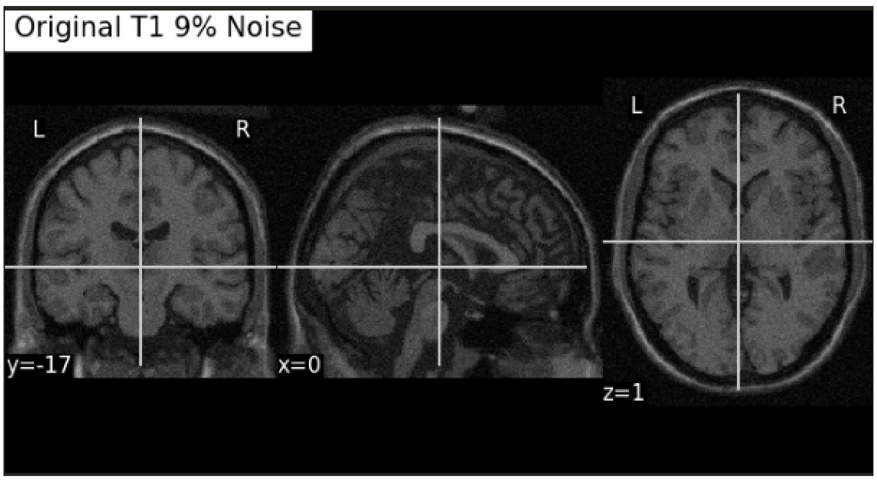


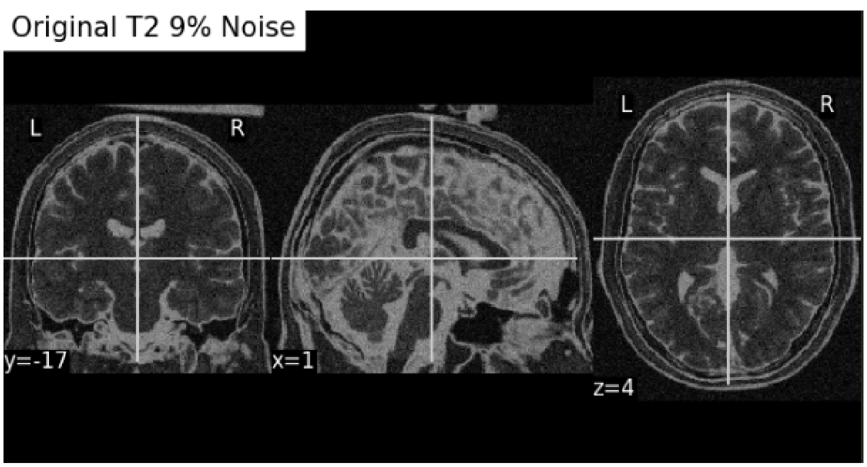

PD Clean
L
R
L
R
y=-17
x=0
z=2

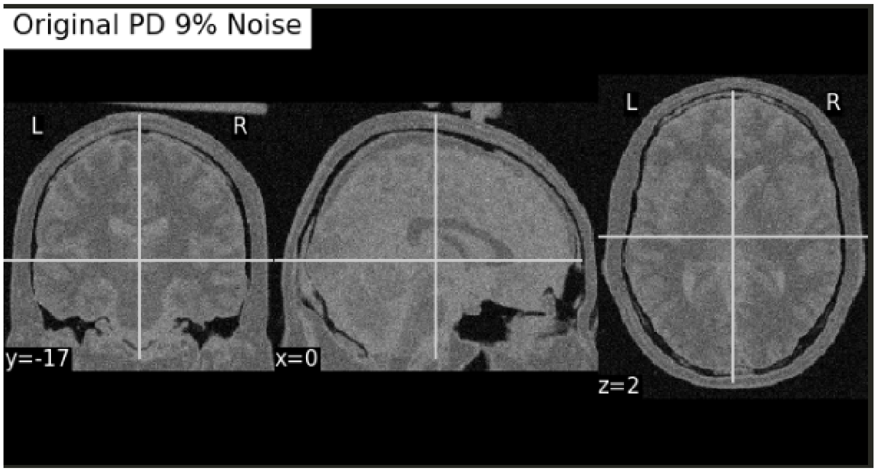

Original T1 3% Noise
L
R
L
R
y=-17
x=0
z=1


Original T2 3% Noise
L
R
L
R
y=-17
x=0
z=4


Original PD 3% Noise
L
R
y=-17
x=0
L
R
z=2


Original T1 9% Noise
L
R
y=-17
x=0
L
R
z=1


Original T2 9% Noise
L
R
y=-17
x=1
L
R
z=4



All of these pictures are output into respective files located in folders called visual_clean_images, visual_unclean_images, and visual_processed.

3. Testing

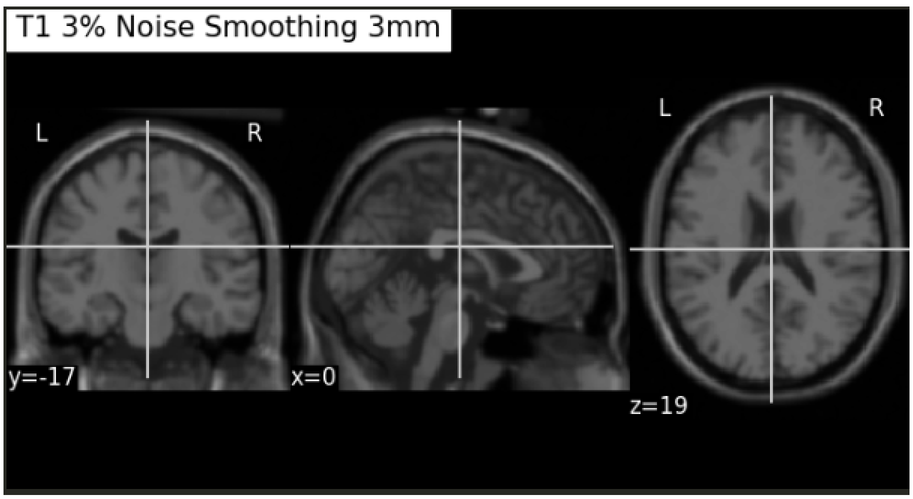
Testing was conducted by first performing Gaussian smoothing on the unclean images, and then evaluating their dispersion by calculating their Coefficient of Variation. The Gaussian smoothing was achieved using the `image.smooth_img()` function in the part of the Nilearn library. This function applies a spatial kernel (usually a Gaussian filter) to the image data. The full width at half maximum (FWHM) of the Gaussian smoothing kernel applied was 3, and this was determined experimentally by observing the effects of other values in terms of their smoothing and blurring effects. A value of 3 provided images that were both smoother and more visible.

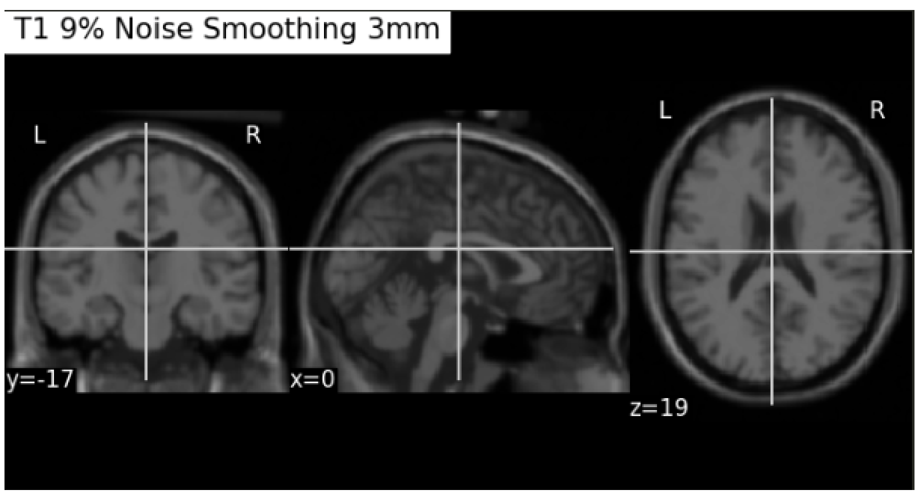
The CV values obtained tell us how much the pixel values within these ROIs vary relative to their mean values. A higher CV suggests that the pixel values within the region are more spread out, indicating greater variability. Conversely, a lower CV suggests that the pixel values are closer to the mean, indicating less variability. By comparing the CV values between the clean and denoised images, we can assess the impact of denoising on image variability. If denoising is effective, we expect to see a reduction in CV for certain structures, indicating that noise has been reduced and pixel values are more consistent.

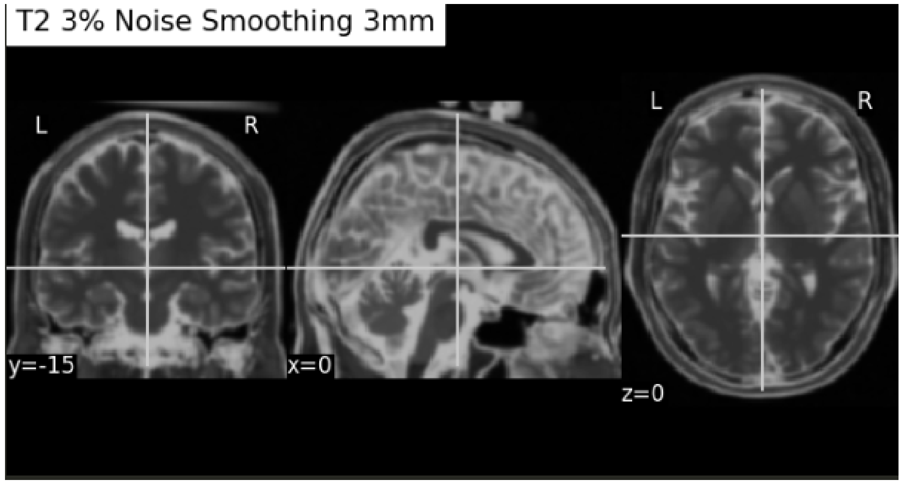
4. Results

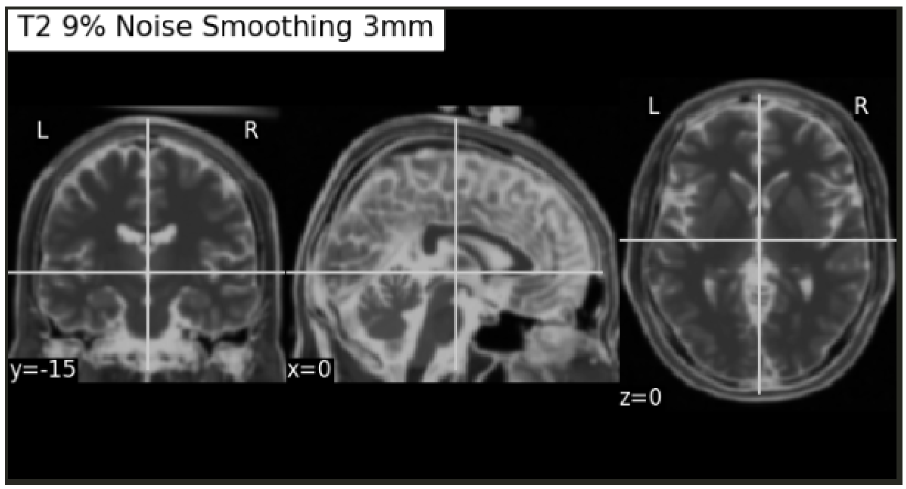
4.1 Visualization of Denoised Images

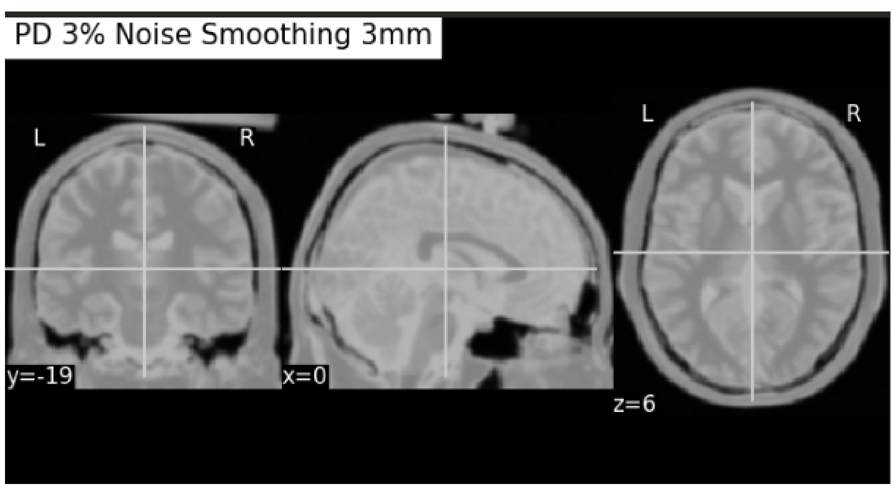
Below are the resulting images from the denoising process:

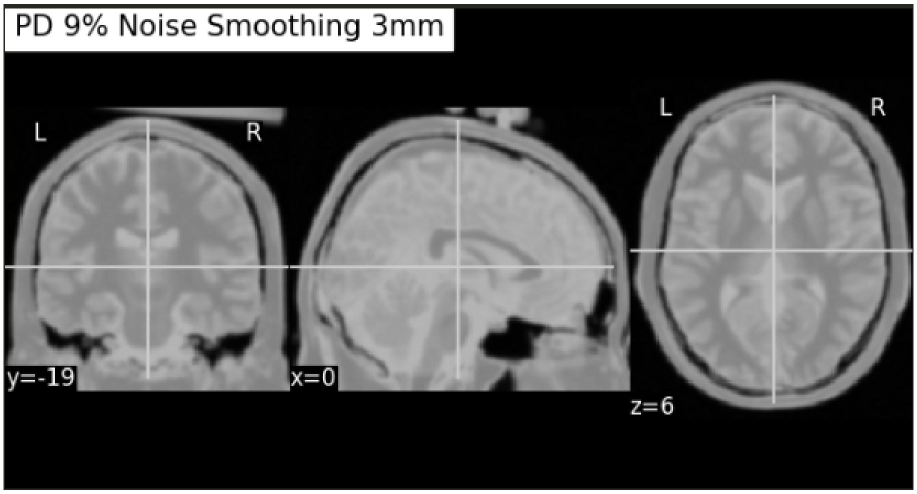





T2 3% Noise Smoothing 3mm
L
R
L
R
y=-15
x=0
z=0


T2 9% Noise Smoothing 3mm
L
R
L
R
y=-15
x=0
z=0


PD 3% Noise Smoothing 3mm
L
R
L
R
y=-19
x=0
z=6



4.2 Coefficient of Variation

	Clean Image	Original 3% Noise	Processed 3% Noise	Original 9% Noise	Processed 9% Noise
T1	Mean = 261.84 STD = 289.79 **CV = 1.07**	Mean = 272.09 STD = 271.47 **CV = 0.998**	Mean = 272.09 STD = 256.02 **CV = 0.94**	Mean = 297.89 STD = 257.07 **CV = 0.86**	Mean = 272.09 STD = 256.02 **CV = 0.94**
T2	Mean = 1258.02 STD = 1312.02 **CV =1.04**	Mean = 1319.39 STD = 1265.59 **CV = 0.96**	Mean = 1319.386 STD = 1099.10 **CV = 0.83**	Mean = 1488.34 STD = 1197.74 **CV = 0.804**	Mean = 1488.33 STD = 978.26 **CV = 0.66**
PD	Mean = 2734.24 STD = 2399.19 **CV = 0.88**	Mean = 2810.24 STD = 2323.63 **CV = 0.83**	Mean = 2810.24 STD = 2216.22 **CV = 0.79**	Mean = 3011.09 STD = 2178.75 **CV = 0.72**	Mean = 3011.09 STD = 2026.92 **CV = 0.67**

5. Conclusions

The mean represents the average pixel intensity within each image. We can observe that the mean values vary between different image types and noise levels. For example, T1 images generally have lower mean values compared to T2 images, and T2 images in general are lower than PD images. The STD (standard deviation) measures the spread or dispersion of pixel intensities within each image. A higher std indicates greater variability in pixel values. In general, images with noise (both 3% and 9%) tend to have higher standard deviations compared to their clean counterparts. This is expected since noise introduces random variations in pixel values.

The CV (Coefficient of Variation) expresses the relative variability of pixel values as a percentage of the mean. A lower CV suggests that pixel values are less variable relative to the mean, while a higher CV indicates greater relative variability. Notably, the CV values are consistently lower for the processed (denoised) images compared to their noisy counterparts. This indicates that the denoising process has reduced the relative variability of pixel values. Comparing the CV values between original clean images and their corresponding noisy counterparts (3% and 9% noise), we can observe that noise increases the relative variability. This is evident in the higher CV values for noisy images.

When comparing the noisy images (3% and 9% noise) to their processed (denoised) versions, we see a decrease in CV values for the denoised images. This suggests that the denoising process has been effective in reducing the relative variability introduced by noise. Lower CV values in processed images indicate that denoising has improved the image quality and reduced the relative variability in pixel intensities. This can be beneficial for accurate interpretation of medical images, as it enhances the visual clarity of structures of interest.