Multi-domain image denoising using optimization algorithm and sequential filters.

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List of Acronyms

PSO	Particle Swarm Optimization
RFO	Red Fox Optimization
EO	Equilibrium Optimizer
WHO	Wild Horse Optimization
WOA	Whale Optimization Algorithm
GA	Genetic Algorithm
GCRA	Greater Cane Rat Algorithm
GA-RFO	Hybrid Genetic Algorithm and Red Fox Optimization
PSNR	Peak Signal-to-noise ratio
MSE	Mean Squared Error
SSIM	Structural Similarity Index Measurement
FSIM	Feature Similarity Index Measurement
GM	Gradient Magnitude
PC	Phase Congruency
PET	Positron Emission Tomography
SPECT	Single Photon Emission Computerized Tomography
CNN	Convolutional Neural Network

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Abstract

The progress of technology have led images to become part and parcel of everyday life. From medical diagnosis to surveillance, the digital signal containing visual information is deeply integrated and requires several steps of processing before it serves any purpose. As images are subjected to various interference in the environment, they're often corrupted by naturally occurring and synthetic noises during transmission and acquisition. Noises can distort or overshadow important image data, therefore, they require elimination before further processing can be completed. For such reasons, various types of Spatial Domain Filters and Transform Domain methods have been devised. In our work, we seek to devise an image denoising method utilizing Spatial Domain Filters such as median, Gaussian, mean, Bilateral, and Wiener filters, and use recent optimization algorithms to tune the parameters to achieve optimum PSNR for image denoising. Aside from PSNR, we have used various other performance metrics in order to ensure edge and detail preservation, as well as the prevention of generating new information and oversmoothing.

Chapter 1

Introduction

Image denoising is a key step in image preprocessing across various domains. Images are incredibly important in almost every domain. The most obvious one being medical image diagnostics, which require denoising, segmentation, thresholding etc before a correct diagnosis can be reached. Surveillance image, object detection, wildlife photography etc require clear visuals. Aside from images that need to analyzed, image processing is often done to simply create better visuals.

As we've discussed before, images may be subject to various types of naturally occurring noises or corrupted by transmission. We can observe various types of noises occurring according to different domains, such as medical images are more prone to speckle images that are commonly known as texture, whereas natural images often become corrupted by salt and pepper noises. Detailed explanations about these various types of noises and the best ways to denoise them will be elaborated upon in the subsequent sections.

Images are signals that contain information in pixel values ranging from 0-255. The corruption by noises end up compromising these values. This may lead to important information getting lost in transmission, which may render the image useless or even lead to false diagnosis and information extraction in domains such as biomedical images and surveillance. The purpose of denoising images is to ensure the information contained in the image is not lost due to the presence of noise. Hence, we use various techniques to extract the useful information contained by the image and separate the noises from it.

1.1 Basic Functionalities of Image Denoising

If we're to explain the phenomenon of images being corrupted by noise and denoising said noisy image more quantitatively, we have to know what exactly it means for noise to interfere with a signal itself. If we are to extract a clean signal x from an observed image y which has been corrupted by noise n, the equation will look as follows [1]:

$$y=x+n \qquad (1)$$

As we become more dependent on technology and integrate it into our daily lives, it creates more windows for computer vision and object detection, which requires precise image processing. Image denoising is genera lly handled independently in performing high level tasks in computer vision, although studies connecting the two using deep learning have been conducted and yielded results. [2]

Aside from object detection and computer vision, image processing has been crucial in fields like medical diagnostics. Medical images are often corrupted due to instruments used, transmission issues, external interferences etc. Various types of noises may be introduced to the image that may blur sharp lines or create unwanted 'texture', which is essentially speckle noise [3]. For precise diagnosis, such noises must be eradicated while simultaneously ensuring there is no blurring.

Aside from medical images, image denoising can be useful in studying wildlife. Especially in lowlit environments underwater, it's essential to eliminate noises that may further hinder the study of marine ecosystems. The uses of image denoising are versatile and multifaceted. Satellite imagery for geographical analysis, surveillance for security,and computer graphics are some examples where image denoising can play a crucial role in improvement. Image denoising can even enhance photography, especially for shots in dimly lit environments.

There are various kinds of noise that can corrupt the image, but the ones of special interest are Gaussian, Speckle, Salt and Pepper and Poisson. Gaussian noise is a random type of noise that has a normal distribution and is often added into signals in signal processing to mimic the practical noise corruption in signals. They're characterized by mean and dispersion (also known as standard deviation) and have the following formula:

$$P(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \qquad (2)$$

Here, z is the value of noise, μ is the average value of the noise, and σ is the standard deviation, this represents the spread of the noise.

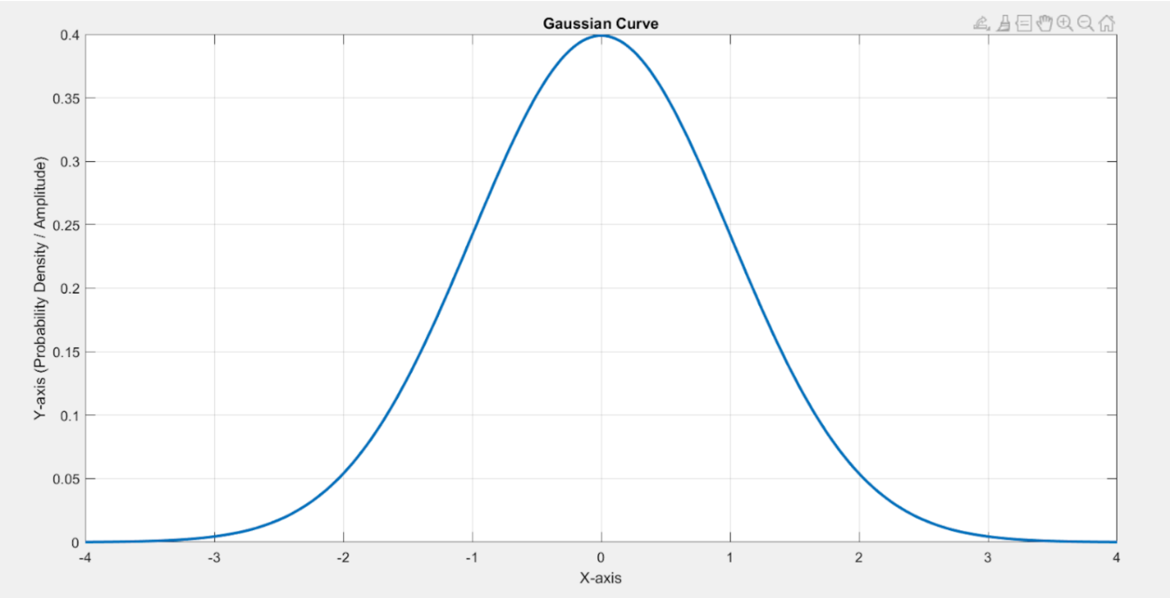

Figure 1 1 Gaussian distribution of noise

Speckle noise is very relevant as this is the most common type of noise that corrupts medical images, such as ultrasound images, and the distinguishing point here is that the equation stated above does not hold for speckle noise, as it is not additive in nature but multiplicative. It adds a textured appearance to the image, and is often removed using spatial filtering methods. We can mathematically model speckle noise as:

$$I_{noisy} = I_{original} + nI_{original} \qquad (3)$$

Where n is a random noise with a mean of 0.

Poisson noise is also referred to as shot noise, and it occurs due to the discrete nature of photons and electrons in image acquisition. The noise follows a poisson distribution, which can be mathematically expressed as:

$$P(k;\lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \qquad (4)$$

Here, k is both the mean and variance of noise. Finally, we have another additive type of noise which is known as Salt and Pepper noise. This is the most straightforward to understand. Randomly occurring black and white pixels cause these noises to exist, where random pixels end up containing 0 (black) or 255 (white) value. The black pixels are known as pepper and the white pixels are known as salt, and these occur due to bit errors or faulty memory locations. Median filters are generally capable of removing this noise.

1.2 Different Aspects of Image Denoising Methods

The research delves into overcoming the gaps in existing literature for image denoising methods. Traditionally, filtering methods are classified as spatial domain and transform domain filtering [4]. In spatial domain, Mean Filters and Order Statistics Filters are used [5] to denoise images. Sequential filters are a pipeline of filtering techniques where the output of one filter is the input of the next filtering technique, and this shows a superior mean average Precision [6].

Image denoising methods are broadly categorized into spatial domain filtering and variational denoising methods. [7] Various studies have been conducted using spatial domain filtering, which include linear and non-linear filters. Spatial Domain filtering works directly on the pixels of the images themselves, and involve application of various filters without changing the image value.

On the other hand, we also have transform domain filtering. This involves transforming image data to a different domain (i.e. fourier or wavelet domain) and filtering or thresholding the coordinates before reconstructing it.

There are some disadvantages that may come along with filtering. Some filters oversmooth the image, getting rid of data on the image edges. It may also blur the image or the edges in order to get rid of noise, and sometimes it may generate additional pixel data that was not present in the original image. There's generally a computational cost associated with filtering images.

Using optimization algorithms with spatial domain or transform domain filtering has been gaining popularity in recent times. Studies have been conducted using optimization algorithms in conjunction with linear filtering [8] or sequential filtering as well as hybridizing two or more optimization algorithms [9], which has proven to be quite effective.

As time passes, newer and improved optimization algorithms are being developed, which may have significant potential in image processing purposes. Algorithms such as Particle Swarm

Optimization (PSO), Cuckoo Optimization Algorithm, Artificial Bee Colony (ABC) optimization are well researched upon, however, newer algorithms have been developed and contain potential. Algorithms such as Red Fox Optimization (RFO), Equilibrium Optimizer (EO), Wild Horse Optimization (WHO) etc are yet to be explored in image denoising. We aim to see whether using such algorithms in conjunction with spatial domain filtering can improve performance.

We also aim to utilize some of the newer algorithms to develop a hybrid approach and observe how they perform in comparison to the single algorithmic approach. The subsequent sections will review the existing literature in image denoising, the methodology and mathematical models of our work, the implementation, results, and the analysis of our contribution.

1.3 Background and Motivation

Significant progress has been achieved in the filed of image denoising that exists within the current literature. Traditional approaches use filtering to eliminate unwanted noises such as Gaussian noise, speckle noise etc. In order to denoise images it is necessary to maintain the smoothness of flat areas, preservation of texture and edges, and an absence of new artifact generation [7].

The existing literature in spatial and transform domain filtering display impressive results. Tomasi et al uses bilateral filtering to denoise gray and color images to preserve edges without blurring and to ensure phantom colors are not generated anew [10]. Benesty et al develops a widely linear Wiener filter for noise reduction that also minimizes MSE [11]. Pitas and Venetsanopoulous have studied nonlinear filters including median filters and their effectiveness on noise reduction [12]. Yang et al have used weighted median filtering under structural constraints for image denoising purposes [13].

Wavelet based image denoising works by reducing the wavelet coefficients in wavelet domain. Balster et al proposes a wavelet shrinkage algorithm that uses a two threshold validation process based on coefficients with large magnitudes and their spatial regularity across the image to identify important features to distinguish from noise [14]. Fodor and Kamath perform an empirical study on wavelet shrinkage methods and explores different ways of choosing thresholds to modify wavelet coefficients in order to test the denoising performance [15].

In recent times, CNN based image denoising methods have gained popularity. Liu et al have developed a CNN based denoising model to remove Gaussian noise from images to improve the performance of traditional image denoising methods [16]. Kaur et al have embedded an image denoising layer to a CNN to compare against traditional tehniques [17], Zhang et al have developed a fast and flexible convolutional neural network that works with downsampled sub-images to achieve a tradeoff between speed and denoising performance that has shown significant improvement over state of the art image denoising methods[18].

Versatile literature exists in denoising medical images. Hanafy M. Ali has used fundamental filters like Median, Adaptive Median, and Adaptive Wiener filters on MRI images for noise reduction [19]. Hamad et al have used Wiener, Median, Log and Average filter to denoise medical images [20].

Narayanan et al have used single scale spatial filtering methods, multi-scale wavelet and pyramid based speckle reduction methods on ultrasound imaging [3]. Bhonsle et al have used bilateral filtering technique on MRI, ultrasound, and X-ray images [21]. Loupas et al have used an adaptive weighted median filter for speckle suppression in ultrasonic images [22]. Filtering introduces some blurring effect at the edges. Dong et al have devised a method Combining Mean-Median (CMM) Filtering to preserve the image edges [23].

Andria et al have devised a method linear filtering 2-D wavelet co-efficients were on ultrasound images [24]. Naimi et al use dual tree complex wavelet thresholding transform in conjunction with Wiener filter to denoise images. In wavelet domain, large coefficients correspond to signal and smaller ones generally correspond to noise, thresholding functions are used to separate the coefficients. Dual tree complex wavelet thresholding transform has additional properties like shift invariability and lower redundancy, allows for separate filtering along columns and rows. Using this algorithm in conjunction with Wiener filter have yielded improved results [25]. Cui et al have used deep learning methods to learn the intrinstic structure information of noisy PET images to restore a corrupted image by training the model on patient dataset [26].

In recent times, denoising image using optimization algorithm has gained popularity. Gupta et al. have used novel SGO and Adaptive PSO to denoise images [8]. Hu et al. have used a Modified Whale Optimization Algorithm to optimize the parameters of Wavelet Transform to create an improved image denoising method [27]. Zhu et al. have utilized an improved whale optimization algorithm in conjunction with BP neural network to achieve improved image denoising performance. Moteghaed et al. have used sequential filters alongside PSO, GA, and a hybrid of GAPSO to denoise biomedical CT scan images, finding that the hybrid outperforms both individually [9]. Sekhar et al. have used Novel Social Grouping Optimization (SGO) in conjunction with transform domain techniques to denoise monochrome and color image alike [28]. Malik et al have used Adaptive Cuckoo Algorithm (ACA) in wavelet transform domain to devise an image denoising method and compare it against Genetic Algorithm (GA) [29].

Aside from these, we have found significant research gap in the fact that newer algorithms are underexplored in image denoising domain. PSO, GA, ACA, WOA are commonly used algorithms however, they are dated and newer optimization algorithms have been developed since then that hold significant potential. For example, Faramarzi et al. have developed Equilibrium Optimizer, which is inspired by control volume mass balance models used to estimate both dynamic and equilibrium states [30]. Naruei et al. have developed Wild Horse Optimizer (WHO), that mimics the social behavior of wild horses that live in groups with a stallion and several mares and foals, and they engage in behavior like grazing, chasing, dominating, leading, and mating [31]. Polap et al. have developed a novel metaheuristic algorithm mimicking the searching for food, hunting, and developing population behavior of the red fox groups [32]. Agushaka et al. have developed another optimization algorithm that is based on the intelligent foraging behavior of the greater cane rats during and off mating season that involves leaving trails during nocturnal foraging [33]. Aside from these newer algorithms, we have also noticed a significant untapped potential that exist within the hybridization of newer algorithms that balance the exploration and exploitation qualities of two or more algorithms.

Chapter 2

Overview of Image Denoising Methods Using Sequential Filters and Optimization Algorithms

In order to meet the continued progress in the domain of image processing and the advent of novel optimization algorithms, we have worked with several optimization algorithms including the widely used Particle Swarm Optimization Algorithm and Genetic Algorithm, and worked our way to the newer, underexplored algorithms such as Equilibrium Optimizer, Wild Horse Optimization algorithm etc. At the same time, we have used open source images across various domains which we will expand upon in the subsequent sections.

2.1 Introduction

For the purpose of our work, we used a number of versatile domain images from open source datasets, with a focus on medical images. We have ensured to use images that represent different environments and image resolution. For medical images, we have used retinal scan images, Positron Emission Tomography (PET) and SPECT (Single Photon Emission Computerized Tomography) scan images. Among these, the first image is very high in resolution and contrast, whereas PET and SPECT are low res, low contrast images. We have also taken an underwater image as input in order to have a representative of dimly lit environments, and the image of a corn field for a low resolution surveillance image.

To move onto the processing segment of our work, we've previously stated that we're using sequential filters in conjunction with optimization algorithm. The sequences in which the filters will be applied as well as the parameters for different filters will be optimized by the metaheuristic algorithm. The sequential filters consist of median, gaussian, mean, bilateral, and wiener filters. The parameters tuned by the algorithm are: gaussian mean and variance, wiener window, wiener noise, median window, bilateral sigma, and bilateral degree of smoothness. We will specify an upper and lower range for these parameters and keep them clipped within the bounds.

Once the optimum sequence and parameters have been found for the sequential filters, it is then applied on the image. Thus, on the output end we receive a denoised image.

The simplified workflow is shown below:

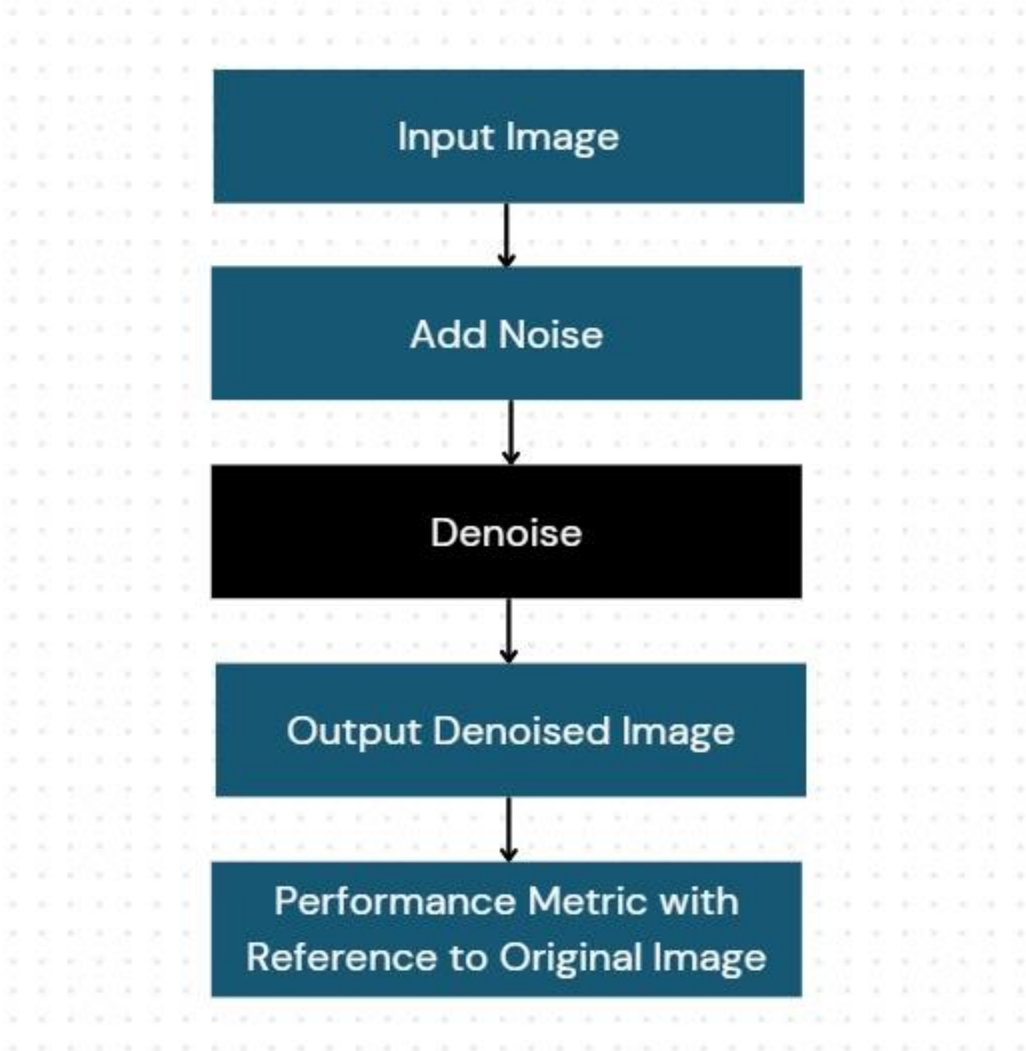

Figure 2.1 1 Simplified workflow of Multi-domain image denoising using optimization algorithm and sequential filters.

2.2 Network Architecture

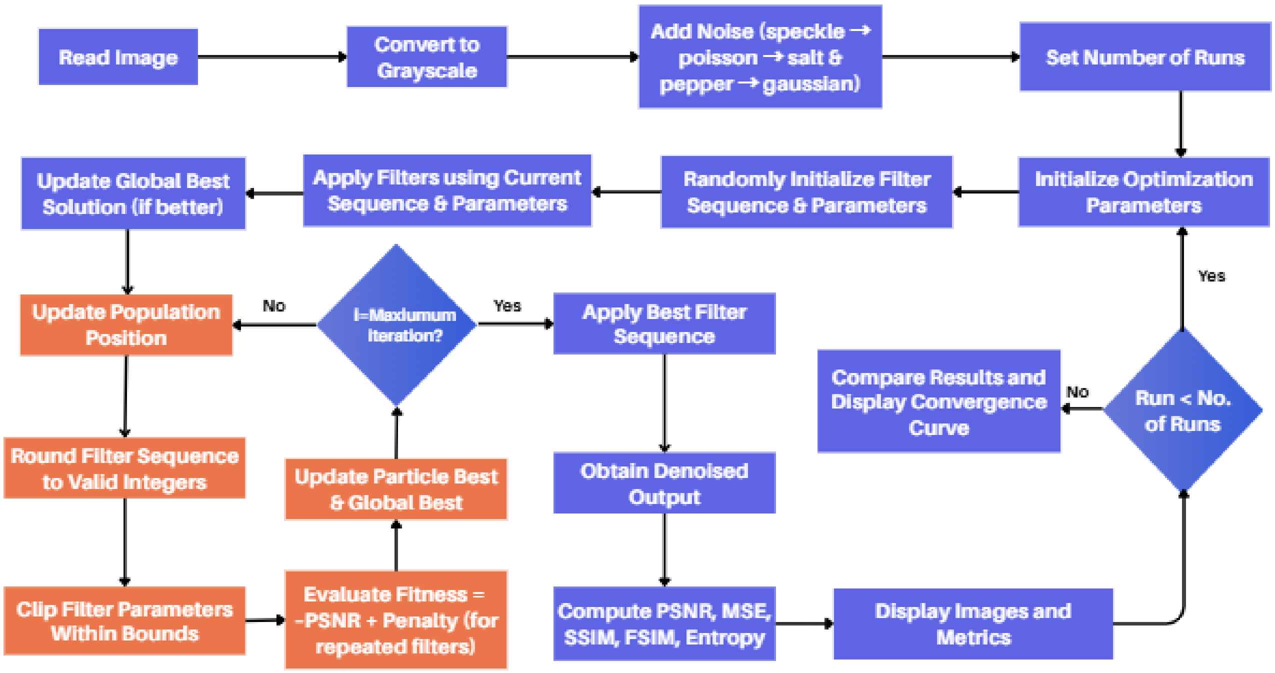

Figure 2.2 1 Detailed flow diagram

The entire system framework can be illustrated as above. Firstly, we read the image in MATLAB and convert it to grayscale as the software is incapable of processing RGB images unless separated by channels. Afterwards, we add all the different types of noises to create a noisy image with various types of naturally occurring noises. We arbitrarily set a certain number of runs so that the entire algorithm can be repeated n number of times, which will increase the reliability of our collected data.

After this step, we initialize the optimization parameters. This includes number of population or particles as well as maximum iterations. In accordance with the workflow of optimization algorithms, the particles or population will start on random initialized sequence and parameter values. As such, the population position will also be updated, and the filter sequences will be rounded to valid integers. It will be ensured that the parameters of the filters are within bound, and then the fitness will be evaluated as a minimization program. Finally, particle best and global best will be updated, and the whole process will be repeated until maximum number of iterations has been achieved.

Finally, the best sequence and parameter values will be applied on the image and the performance metrics will be updated and displayed. This process will be repeated until the number of runs as set previously is reached.

2.2.1 The Algorithmic Components

Sequential Filters:

Let us talk about the filters we've used to create our sequential filters, as the concept of sequential filters was explained in previous sections. The filters we

Gaussian Filter

The Gaussian filter's impulse response is an approximation of the Gaussian function. It eliminates noise from an image by blurring or smoothing the image by moving a Gaussian kernel across the image and performing convolution. The central pixels in the Gaussian kernel will have the highest weight or value, and this weight will move as the pixels are further away from the kernel center. It gives the image a soft blurring and smoothing effect while simultaneously preserving the edge.

Wiener Filter

The Wiener filter is a linear filter that operates by minimizing the MSE between the estimated and original image. It will assume the local mean, variance, and noise characteristics and then calculatean optimal estimate of the true pixel value. Since Wiener filter adapts to the local image statistics unlike averaging filters, it preserves important details like edges and texture. Wiener filter removes Gaussian noises with efficacy.

Bilateral Filter

The Bilateral filter is a nonlinear filter that works by combining two Gaussian functions. One of the functions considers spatial proximity or how close pixels are. The other function considers intensity similarity or how similar pixels' brightness values are. Pixels that are spatially close and have similar intensities contribute more to the output pixel's value. As a result, the Bilateral filter can remove the noise from flat regions while avoiding the blurring of edges, which are typically high-contrast areas. This is good for high contrast applications.

Median Filter

The Median filter is a nonlinear filtering technique. A median window or kernel will slide over the image and replace each pixel's value with the median of the intensity values of the window itself. Unlike linear filters, it does not compute averages but instead selects the middle value, which makes it really good for noises caused by outlier intensities i.e. salt and pepper noises. Because of this property, the Median filter effectively removes such noise while preserving sharp edges better than linear smoothing filters. It may not be too great for Gaussian noises or may lead to oversmoothing.

Mean Filter

Mean filter slides a kernel over the image and replaces the pixel values with the average value within the kernel. This works well for removing noises, but it often causes overblurring or smoothing, and an outlier can affect it heavily. However, it does work decently in getting rid of salt and pepper noise and texture.

Design of Optimization Algorithm:

2.2.1.1 Equilibrium Optimizer

In our work, we have employed seven optimization algorithms excluding hybridized algorithms Most of the algorithms are swarm based algorithms, with the exception of Genetic Algorithm, which is an evolutionary algorithms. Most of these algorithms follow a similar pattern, and it is redundant to discuss the working principles of every single one. Hence, we will simply elaborate on Equilibrium Optimizer, which has had the best performance in our results.

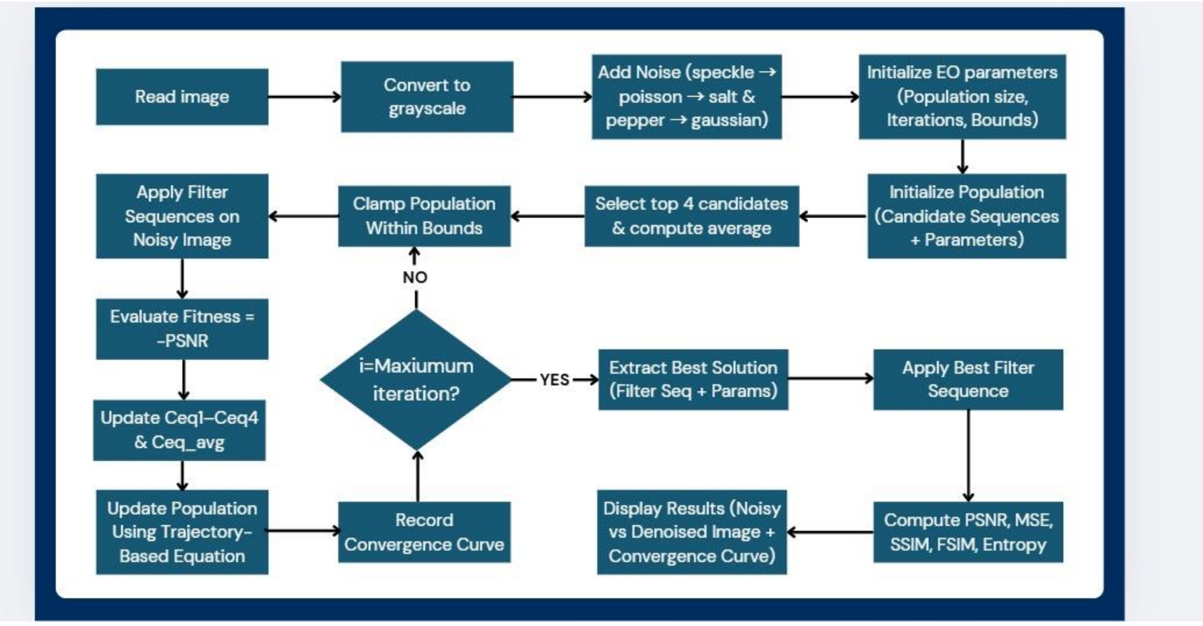

Figure 2.2 2 Working principle of Equilibrium Optimizer

Initialization

1. Problem encoding (how each particle = candidate solution is represented): we pick a fixed maximum sequence length L. We represent a candidate as a vector that contains

(a) L filter IDs (integers: 0 = no-op, 1 = Wiener, 2 = Bilateral, 3 = Median, 4 = Mean, etc.) and

(b) the associated parameters for each filter (e.g. kernel size, sigma, window size). Example:[Wiener, k=5][Median, k=3] encoded as [1,5, 3,3, 0,0].

2. EO hyperparameters: population size N (20–50 typical), max iterations T (50–200), bounds for every vector component (filter-ID range, parameter ranges), Generation Probability GP (≈0.5 recommended), and any EO-specific control constants.

EO uses an *equilibrium pool* made of the top solutions (the canonical EO uses an equilibrium pool of five particles: four best + the average). [30]

3. Random initialization: sample N candidate vectors uniformly within bounds (for filter IDs sample continuous then round; for kernel sizes sample odd integers in allowed range). Evaluate the initial population's fitness (next step) so an initial equilibrium pool can be formed.

Fitness evaluation (apply sequence and compute score)

1. **Apply decoded sequence to the noisy image exactly in order:** for each candidate, decode the vector into a sequence and parameter set. For each filter in sequence: apply that filter to the *current* image (start from the noisy image and pass the output of filter i to filter i+1).

2. **Compute objective:** compute PSNR (and other metrics if you want). Because PSNR is higher = better, and many EO implementations treat the problem as minimization, map the quality metric to a minimization objective: e.g. fitness = -PSNR.

Position update (EO's core)

1. **Form the equilibrium pool:** after evaluating every particle, pick the top k (canonical k=4) best solutions and compute their average vector — that yields a pool of five equilibrium candidates (Ceq1..Ceq4 and Ceq_avg). EO updates every particle with respect to a randomly selected equilibrium candidate from this pool. [30]

2. **Compute the generation-rate and exploitation/exploration factors:** EO defines a *generation rate* term (G) and an exponential-like factor (denoted F in the paper) that control how much a particle moves toward or away from an equilibrium candidate. GP controls whether the generation-rate contributes on a per-dimension basis. The design intentionally gives large moves early (exploration) and fine adjustments later (exploitation).

3. **Update (conceptual form):** for particle i and each of the dimensions d, we will pick an equilibrium candidate Ceq from the pool, then compute the EO terms F and G (functions of random numbers, iteration, and GP), and finally we compute the new

concentration as an equilibrium term plus exploration and generation contributions.

4. **Clamp & discrete repair:** after update, we will **clamp** all continuous components to their bounds. For filter IDs, we round to nearest integer and then apply a repair rule. For kernel sizes that must be odd integers, so we round to the nearest integer and then force it to be odd.

5. **Re-evaluate any repaired particle**: if rounding/repair changed the candidate, re-evaluate its fitness; otherwise carry its previous fitness forward. Update the equilibrium pool (recompute top 4 and avg) before the next iteration.

Termination

1. **Stopping criteria:** the algorithm stops when it hits the maximum number of iterations.

2. **Extract best solution:** once terminated, extract the best particle (filter sequence + parameters), apply it to the original noisy image one final time, and compute the full set of evaluation metrics you listed (PSNR, MSE, SSIM, FSIM, Entropy). Display or save the convergence curve for diagnostics.

2.2.1.2 Discussion on other algorithms

Particle Swarm Optimization (PSO):
PSO is a swarm-based optimization algorithm that is inspired by the social behavior of birds flocking together or fishes schooling. Each particle in the swarm tends to represent a potential solution that will move through the search space and update its position based on its own best solution (personal best) and the best solution of the swarm (global best). There is a position vector and velocity vector that aids the process. By combining particle's personal best and the swarm's global best, PSO can achieve a balance between exploration and exploitation easily, which is why it performs well across most domains.

Greater Cane Rat Algorithm (GCRA):

The Greater Cane Rat Algorithm was based on the foraging behavior of the intelligent greater cane rat species. They are mostly nocturnal, and they leave trails they can retrace during foraging. Their group dynamic inspired an algorithm that balances exploration, which is searching for new areas, and exploitation that is refining the good solutions. This effectively avoids local minima and leads the optimization algorithm to converge towards optimal solutions.

Whale Optimization Algorithm (WOA)

Whale optimization algorithm mimics the hunting behavior of the humpback whale. This is also a swarm based optimization algorithm. Whale optimization algorithm creates a bubble net spiral as they encircle the prey to trap the prey. This is mathematically modeled using a shrinking spiral equation. As such, this algorithm converges very fast, and doesn't get stuck on local minima.

Wild Horse Optimizer (WHO)

The Wild Horse Optimizer is based on the social hierarchy and behavior of the wild horse herds. The horse groups are divided into stallions, which leads the pack, and mares and foals, who follow the stallion. Hence, stallions lead "exploration", while mares and foals follow in adaptive movements which facilitate "exploitation." This dynamic causes fast convergence.

Genetic Algorithm (GA):

The Genetic Algorithm is inspired by the principles of natural selection as well as genetics, which is why it's known as an evolutionary algorithm. It begins with a population of potential solutions that are known as chromosomes. Chromosomes evolve through processes like selection, crossover (recombination), and mutation. Thus, some randomization is added to the mix in order to facilitate exploration. Over generations, fitter candidates are more likely to reproduce, which means with each generation we get highly optimized solutions across a diversified optimization landscape.

Red Fox Optimizer (RFO):

The Red Fox Optimizer is inspired by the intelligent hunting and social behaviors of red foxes. Foxes will use techniques like stalking and ambushing to hunt their prey. They also have to adapt to environmental changes, reproduce, as well as leave the pack if they are weak. This means the worse solutions are filtered out, and better solutions are likely to be accepted. Thus, the global exploration and local exploitation are evenly emphasized.

2.2.2 Hybrid Genetic Algorithm and Red Fox Optimization (GA–RFO) Model for Image Denoising

For our work, we have hybridized Genetic Algorithm with PSO and RFO to get better performance. As GAPSO has failed to give substantially better results, we will elaborate on the hybrid GA-RFO model, which combines the exploration ability of the Genetic Algorithm (GA) with the exploitation abilities of the Red Fox Optimization (RFO).

- **Representation of solution:** Each candidate (chromosome) will encode both the filter sequence (the order of Wiener, Gaussian, Median, Average, and Bilateral filters) as well as the several filter parameters (e.g., window sizes, noise levels, σ values).

- **Initialization:** The GA initializes a random population of candidate solutions within the defined upper and lower parameter bounds.
- **Fitness evaluation:** Each candidate is applied to the noisy image. The denoised result is compared with the original image using **PSNR** as the fitness metric (fitness = –PSNR). Higher PSNR means better denoising.

- **GA operators for global search:** The GA's selection, crossover, and mutation generates new populations, ensuring extensive exploration of the order of the filters, their combinations and parameter values.

- **RFO for local refinement:** After GA evolution, the best individuals are refined using the Red Fox Optimization strategy. RFO adjusts parameters around the current best solution. This step improves local accuracy and prevents premature convergence.

- **Hybrid synergy:** GA explores diverse global regions of the search space (filter combinations) and RFO fine-tunes the promising solutions for precise optimization of parameters. Together, they balance exploration and exploitation effectively.

Objective Function:

PSNR and MSE

PSNR or Peak Signal-to-noise ratio is a mathematical representation of the highest value of the signal and its ratio to the noise distorting said signal. PSNR is expressed in the logarithmic decibel scale. It's a performance metric that quantifies the signal to noise ratio of the images, the higher the PSNR, the lesser amount of noise is present in the image. The equation for PSNR are given below [34]:

$$PSNR = 10 \times \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \qquad [5]$$

The value of MAX_I^2 in image is generally 255. The MSE stands for Mean Squared Error, which is the mathematical representation of the average squared difference between the estimated value and the actual value. The formula for MSE is as follows:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - N(i,j)]^2 \qquad [6]$$

Performance Metrics

SSIM

SSIM stands for Structural Similarity Index Measurement, which quantifies the structural similarity between two images. In context of our work, the closer the denoised image will get to the original image before noise is added to it, the higher the structural similarity index measurement or SSIM will be. The formula for SSIM is as follows:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (7)$$

Where:

- μ_x and μ_y are the average luminance of the two images being corrupted.
- σ_x^2 and σ_y^2 are the variances of the pixel intensities in the two images.
- σ_{xy} is the covariance of the pixel intensities between the two images.
- C_1 and C_2 are constants added to prevent instability when denominators are close to zero [35]

FSIM

FSIM is a metric that aims to quantify human perception of image quality by measuring the quality of a distorted image against a reference image by using Gradient Magnitude (GM) and Phase Congruency(PC), where the former refers to a scalar value that represents the strength of change in scalar field (the image). Basically, the higher the value of GM, the stronger the intensity of the change. An edge, for example, would have a strong change. Phase Congruency on the other hand, is a method of detecting edges in an image that is capable of feature extraction in applications. In image denoising, a higher FSIM is a metric that can quantify how well the edges have been preserved in an image after the denoising process is complete, as filters often add blurring effects and are unable to preserve edges. The equation for FSIM is written below:

$$FSIM(x,y) = \frac{\sum_{x\epsilon\Omega} S_L(X) PC_m(x)}{\sum_{x\epsilon\Omega} PC_m(x)} \qquad (8)$$

Runtime

The runtime for each algorithm represents how computationally heavy they are. We have implemented this metric using a built-in MATLAB function. A lower runtime is desirable over a higher one, however, there’s often a trade off between how effective the algorithm is and the runtime.

Results

3.1 Visual Comparison of Denoising Performance

The results of our work will be presented in the following segments. First, we will look at the images visually, by performing a side by side comparison of the original image, the noisy image, and finally, the denoised image. After that, we will quantitatively perform analysis by looking at the numerical data extracted from the separate runs for each of the algorithms. Finally, we will look at the convergence curves to have an understanding of how fast each algorithm performs.

It is to be noted that all the data was collected from the same device. The configuration of said device is:

- **Processor (CPU):** AMD Ryzen 5 5600X 6-Core Processor 3.70 GHz
- **Graphics Card (GPU):** NVIDIA GTX 1050 Ti, 4 GB)
- **RAM:** 16 GB DDR4
- **Storage:** 466 GB HDD + 932 GB HDD + 512 GB SSD
- **Operating System:** Windows 10 Pro

3.1.1 Equilibrium Optimiser:

In this section, we will look at the side by side comparison of the original image, noisy image, and the denoised image for the Equilibrium Optimizer. The sequence is as follows: we have the original image read into MATLAB that has been converted into grayscale, the image corrupted by Gaussian, Salt and Pepper, Speckle, and Poisson images.

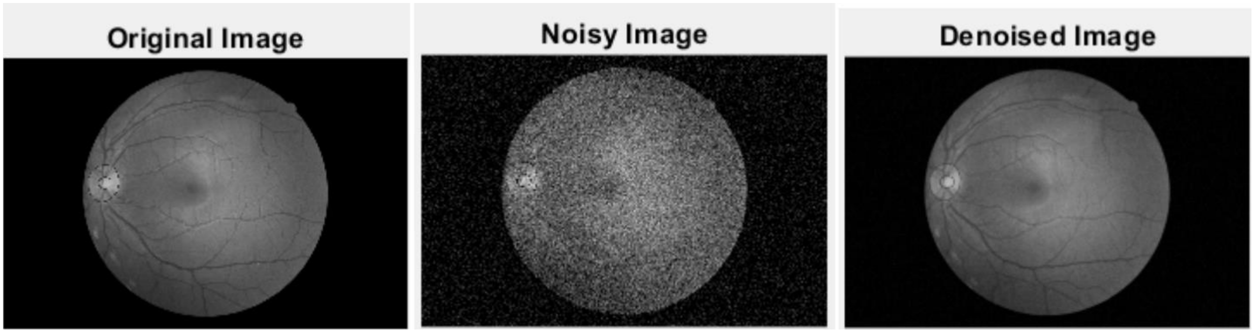

Figure 3.1.1 1: Retinal Scan

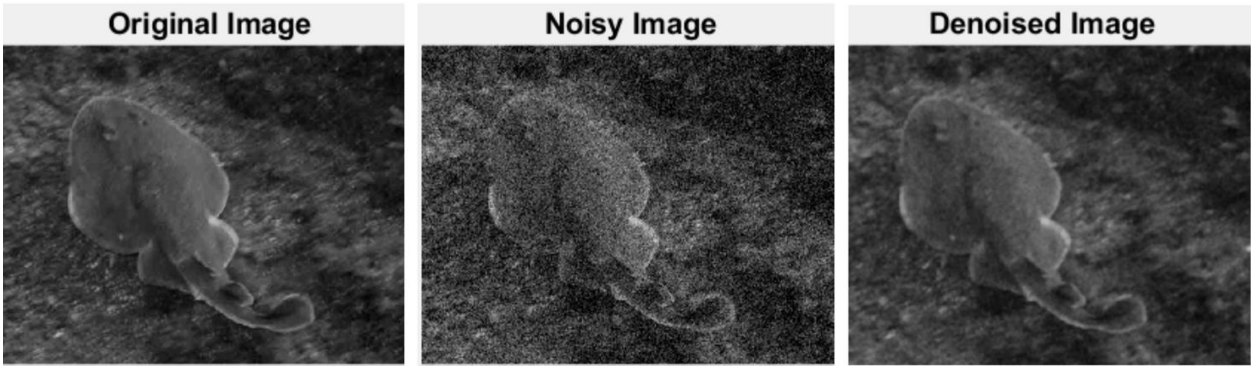

Figure 3.1.1 2 Underwater Image

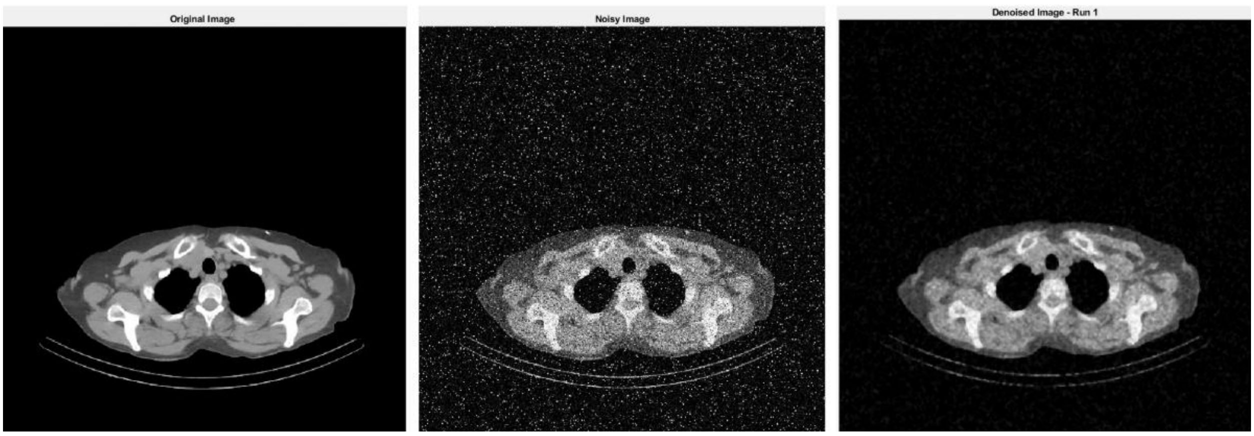

Figure 3.1.1 3: SPECT Image

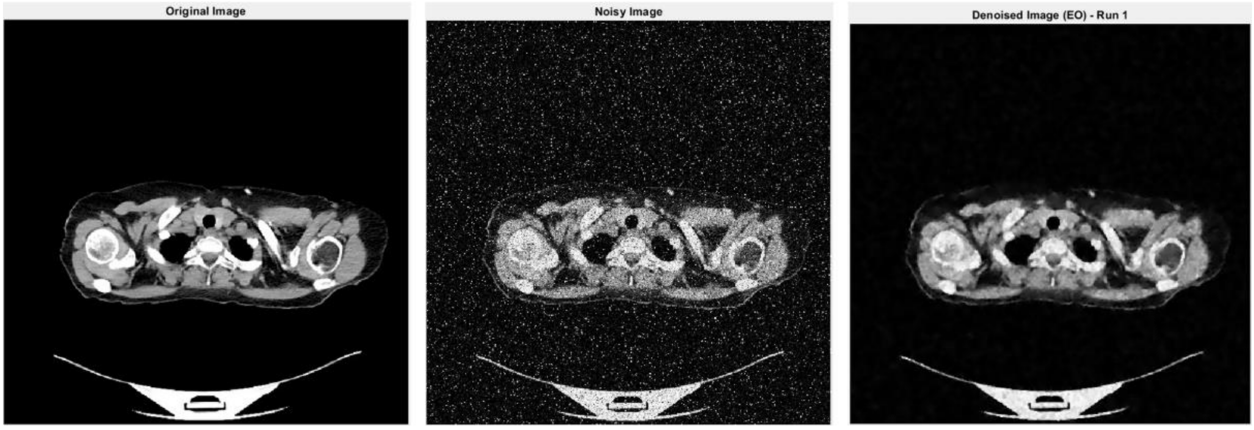

Figure 3.1.1 4: PET Image

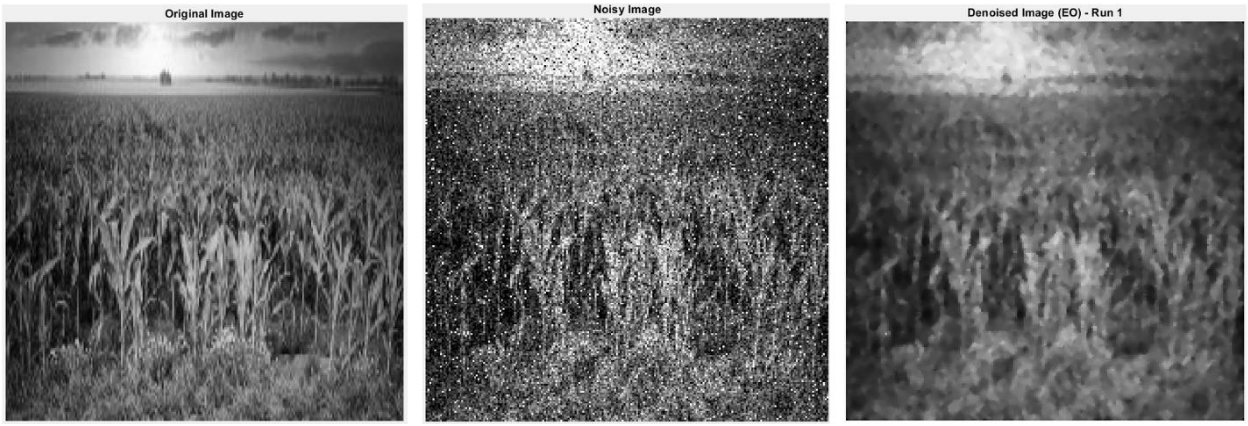

Figure 3.1.1 5: Maize Image

3.1.2 Wild Horse Optimization Algorithm:

In this section, we will look at the side by side comparison of the original image, noisy image, and the denoised image for the Wild Horse Optimization. The sequence is as follows: we have the original image read into MATLAB that has been converted into grayscale, the image corrupted by Gaussian, Salt and Pepper, Speckle, and Poisson images.

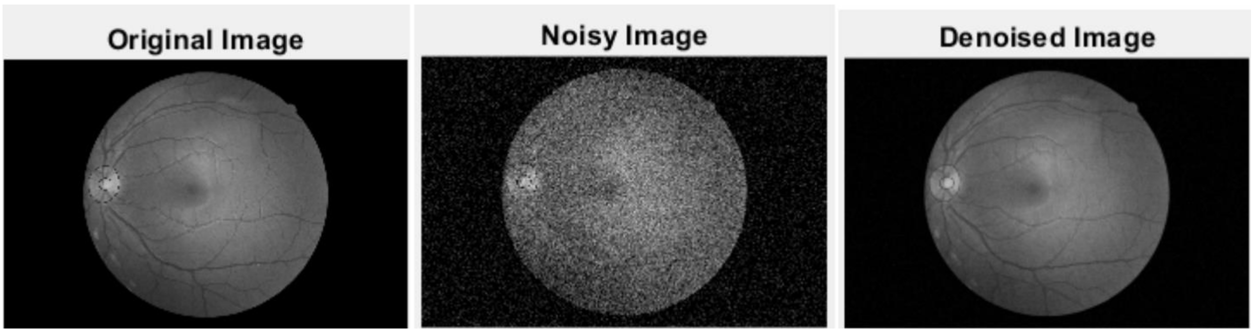

Figure 3.1.2 1: Retinal Scan

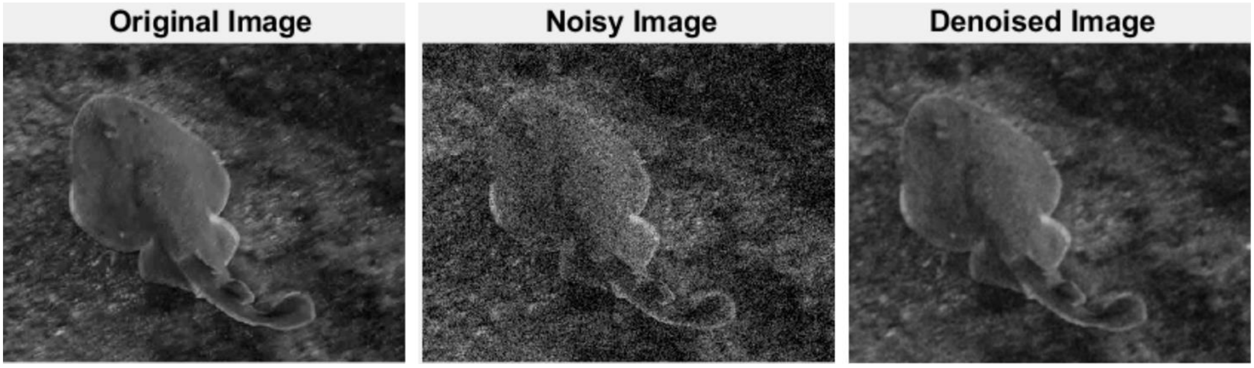

Figure 3.1.2 2: Underwater Image

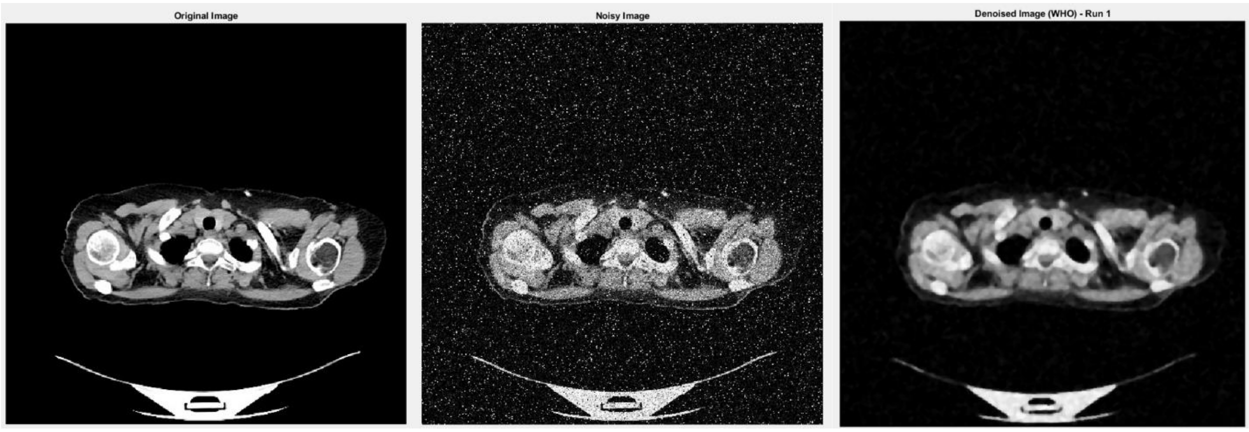

Figure 3.1.2 3: PET Image

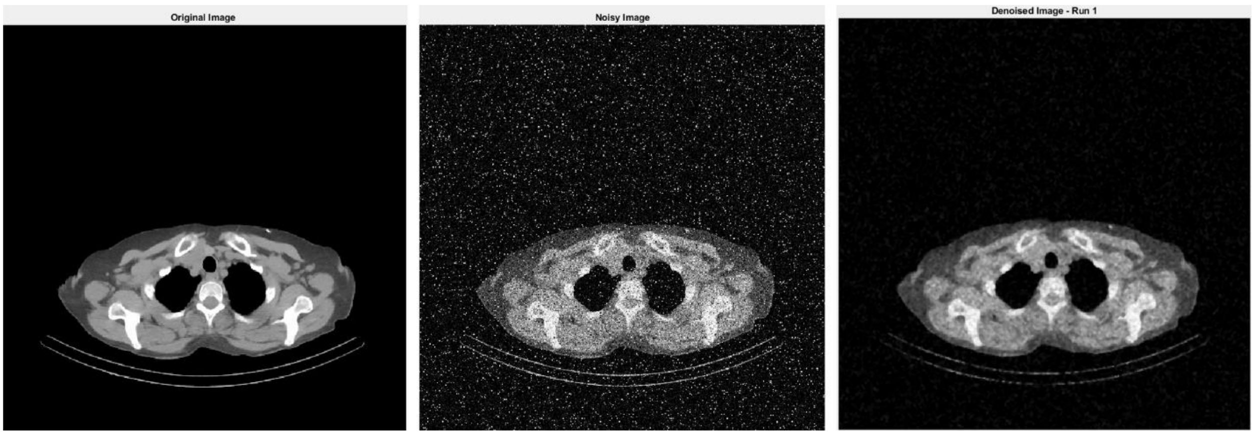

Figure 3.1.2 4: SPECT Image

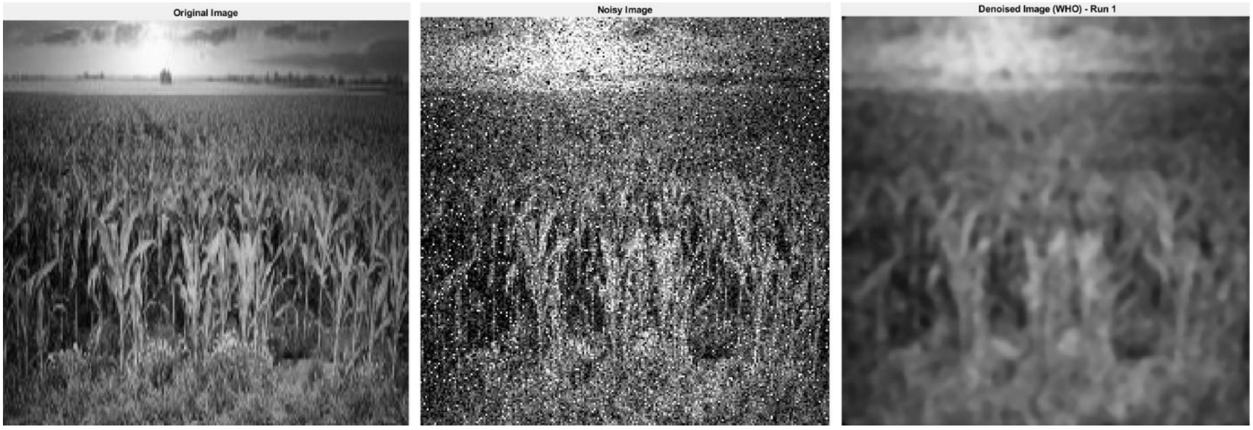

Figure 3.1.2 5: Maize Image

3.1.3 Genetic Algorithm:

In this section, we will look at the side by side comparison of the original image, noisy image, and the denoised image for the Genetic Algorithm. The sequence is as follows: we have the original image read into MATLAB that has been converted into grayscale, the image corrupted by Gaussian, Salt and Pepper, Speckle, and Poisson images.

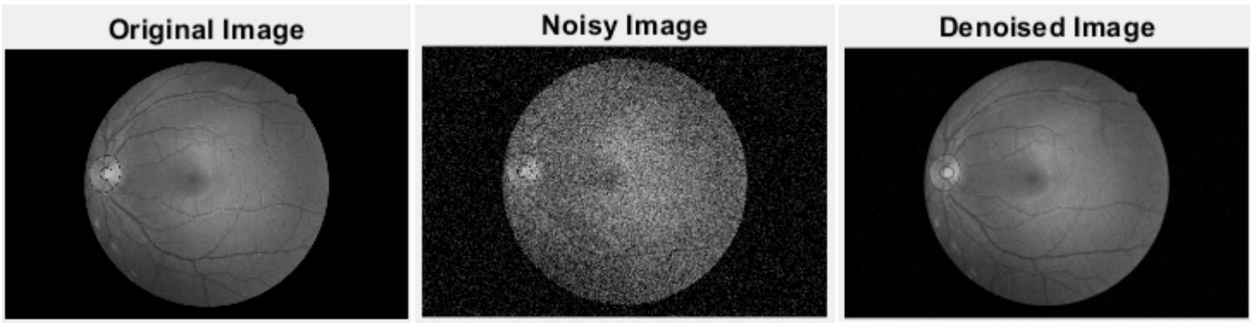

Figure 3.1.3 1: Retinal Scan

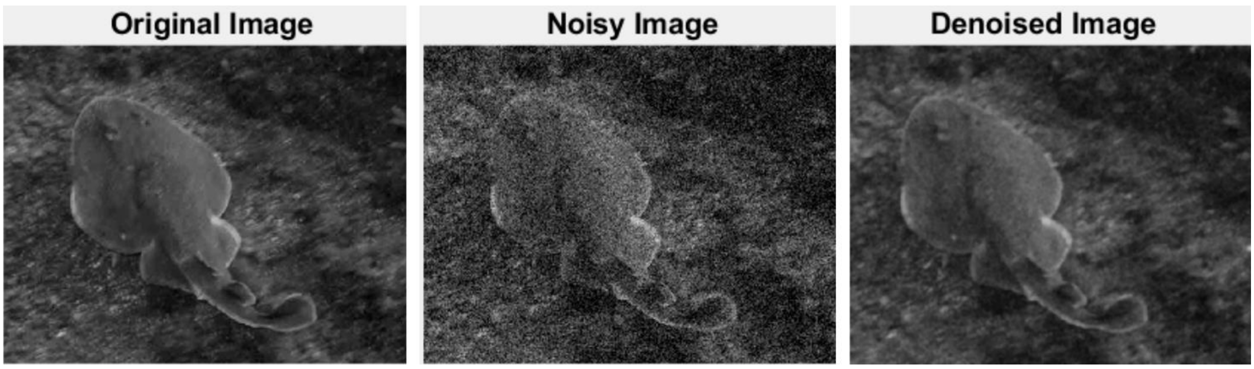

Figure 3.1.3 2: Underwater Image

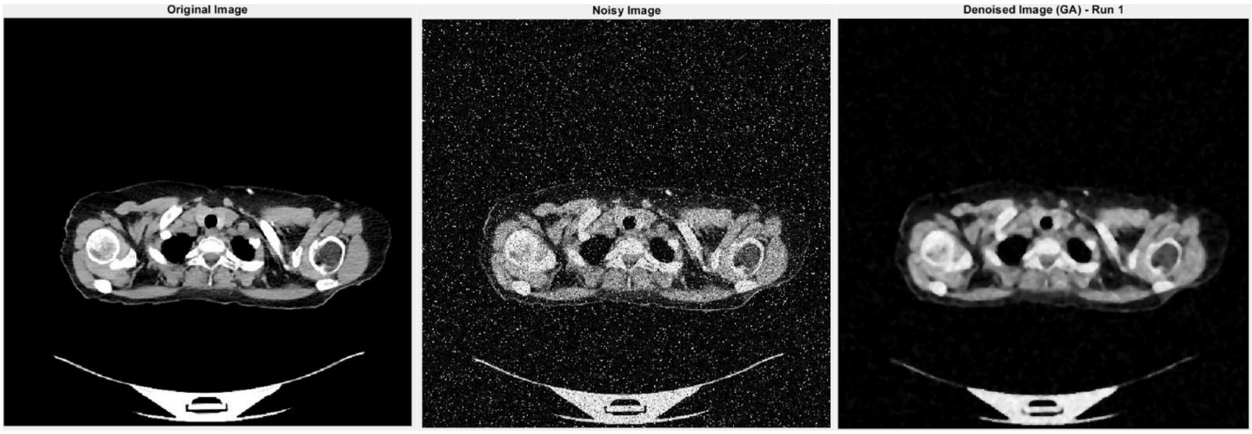

Figure 3.1.3 3: PET Image

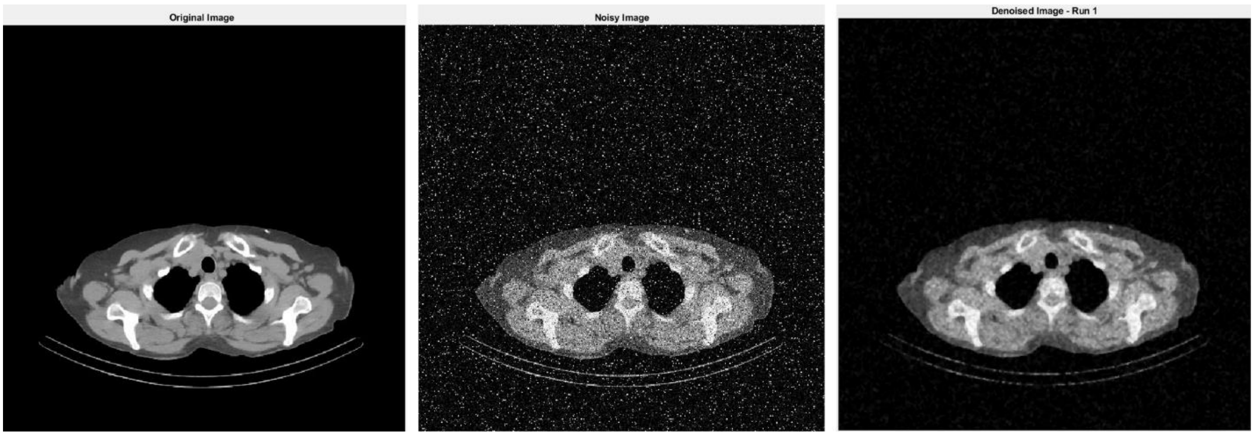

Figure 3.1.3 4: SPECT Image

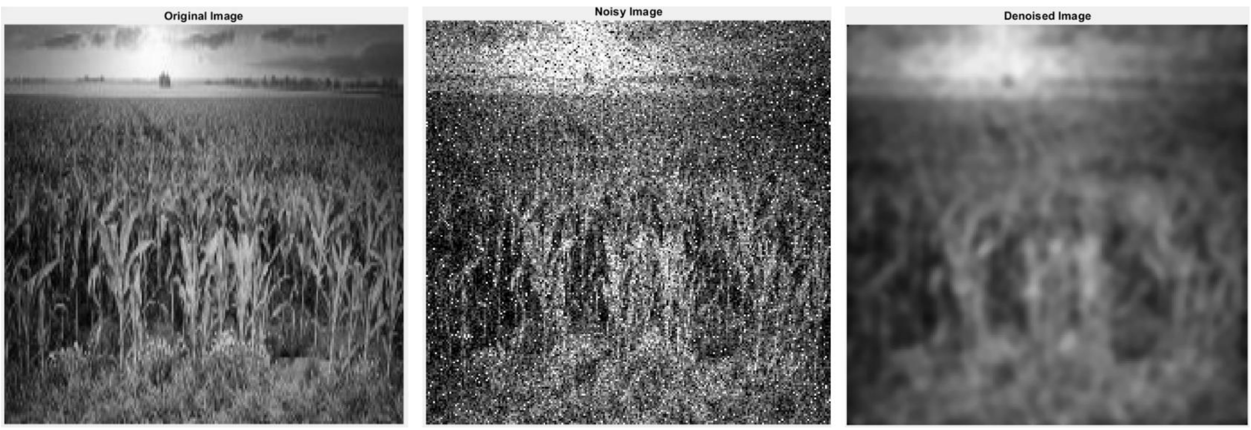

Figure 3.1.3 5: Maize Image

3.1.4 Greater Cane Rat Algorithm (GCRA):

In this section, we will look at the side by side comparison of the original image, noisy image, and the denoised image for the Greater Cane Rat Algorithm. The sequence is as follows: we have the original image read into MATLAB that has been converted into grayscale, the image corrupted by Gaussian, Salt and Pepper, Speckle, and Poisson images.

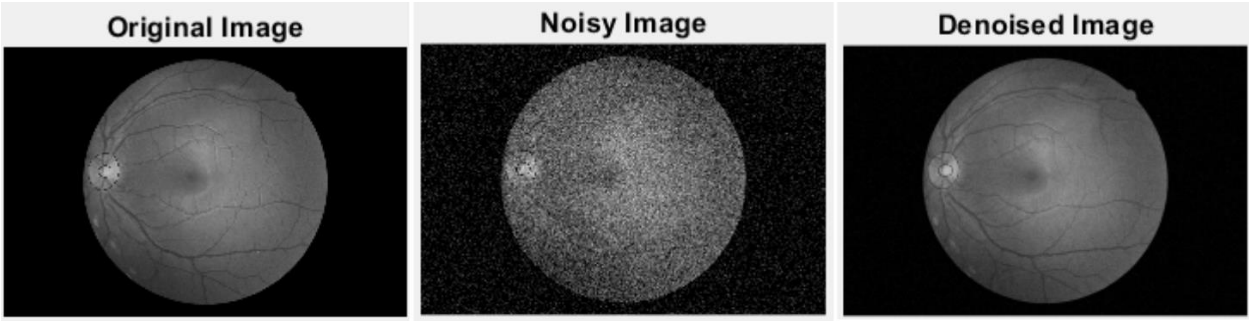

Figure 3.1.4 1: Retinal Scan

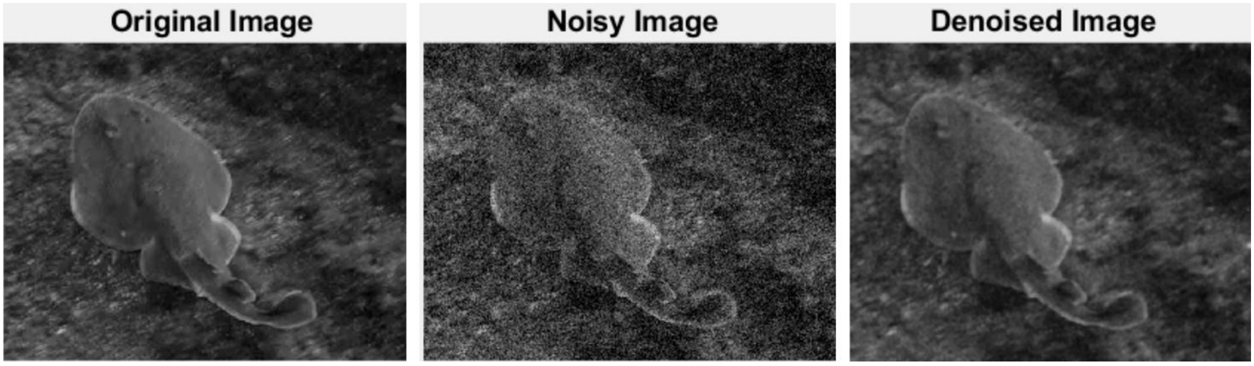

Figure 3.1.4 2: Underwater Image

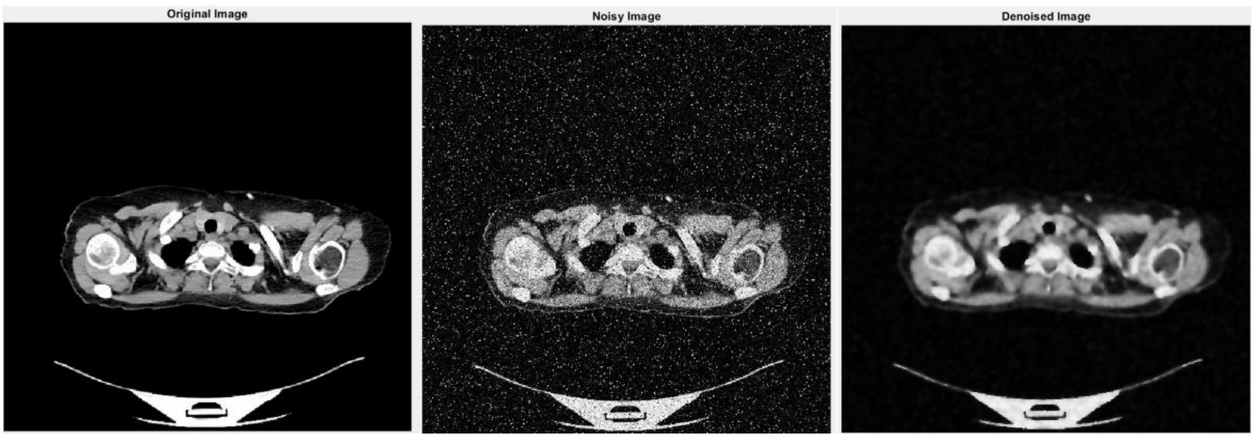

Figure 3.1.4 3: PET Image

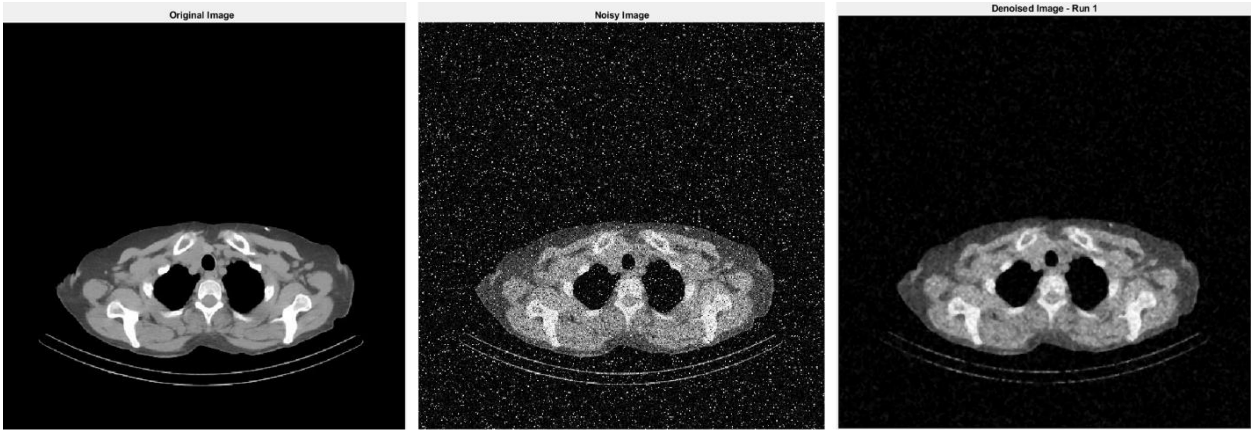

Figure 3.1.4 4: SPECT Image

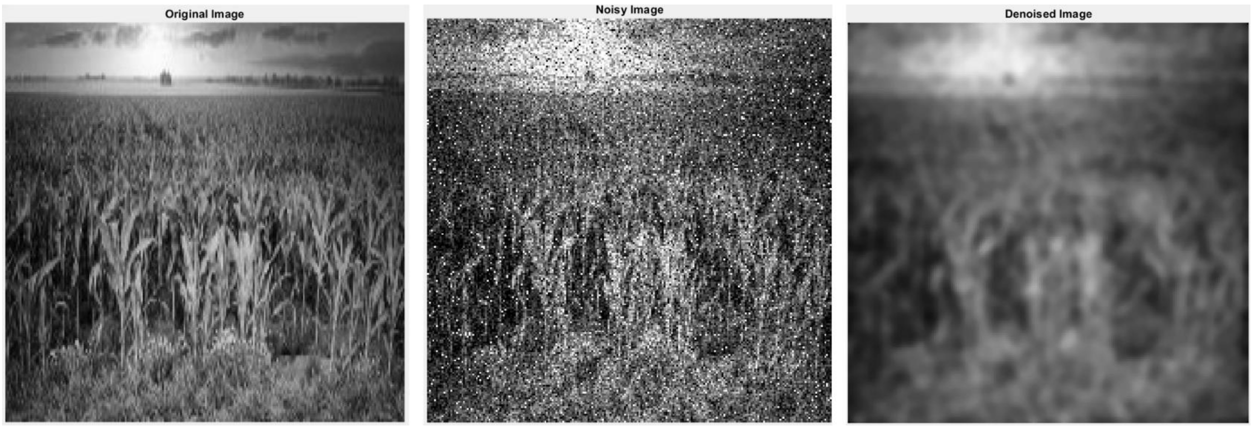

Figure 3.1.4 5: Maize Image

3.1.5 Particle Swarm Optimization Algorithm (PSO):

In this section, we will look at the side by side comparison of the original image, noisy image, and the denoised image for the Particle Swarm Optimization. The sequence is as follows: we have the original image read into MATLAB that has been converted into grayscale, the image corrupted by Gaussian, Salt and Pepper, Speckle, and Poisson images.

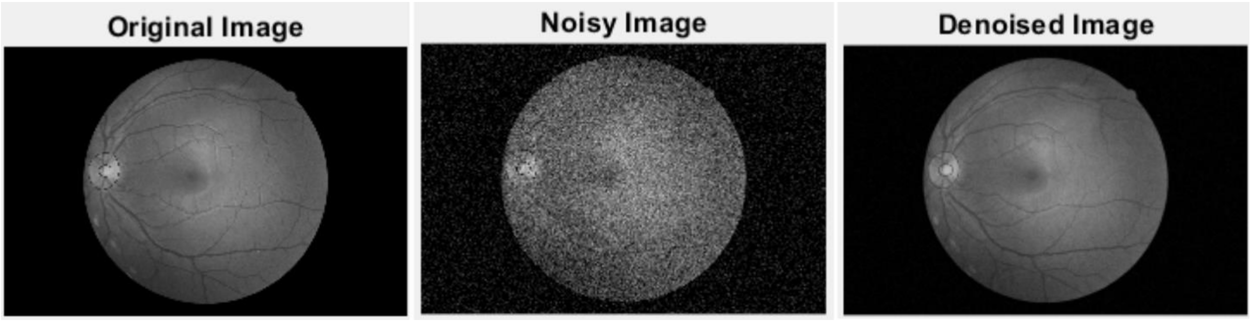

Figure 3.1.5 1: Retinal Scan

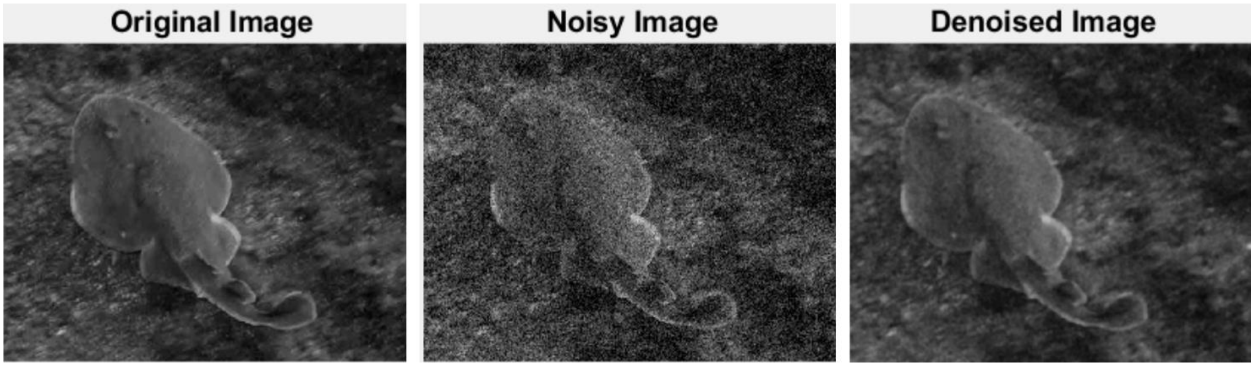

Figure 3.1.5 2: Underwater Image

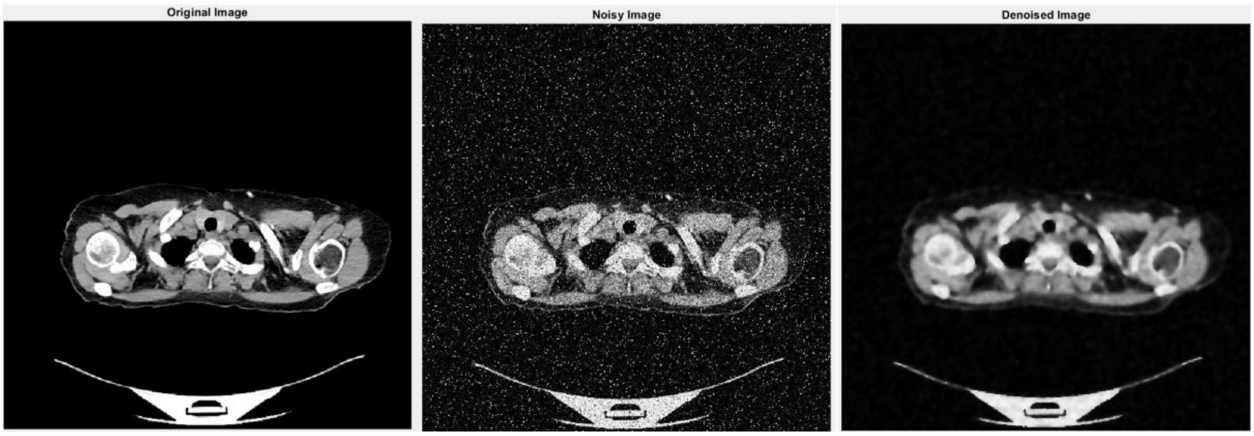

Figure 3.1.5 3: PET Image

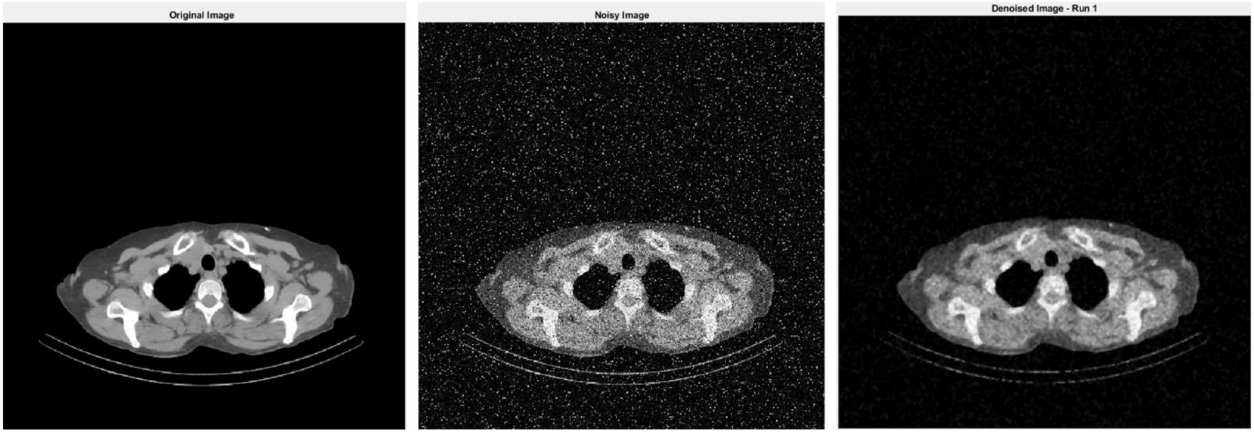

Figure 3.1.5 4: SPECT Image

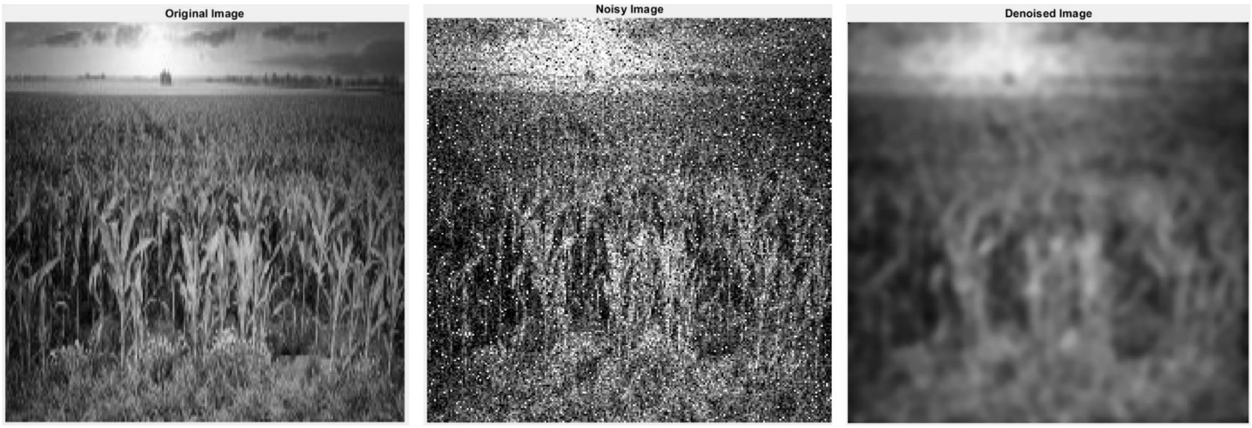

Figure 3.1.5 5: Maize Image

3.1.6 Redfox Optimization Algorithm (RFO):

In this section, we will look at the side by side comparison of the original image, noisy image, and the denoised image for the Red Fox Optimization. The sequence is as follows: we have the original image read into MATLAB that has been converted into grayscale, the image corrupted by Gaussian, Salt and Pepper, Speckle, and Poisson images.

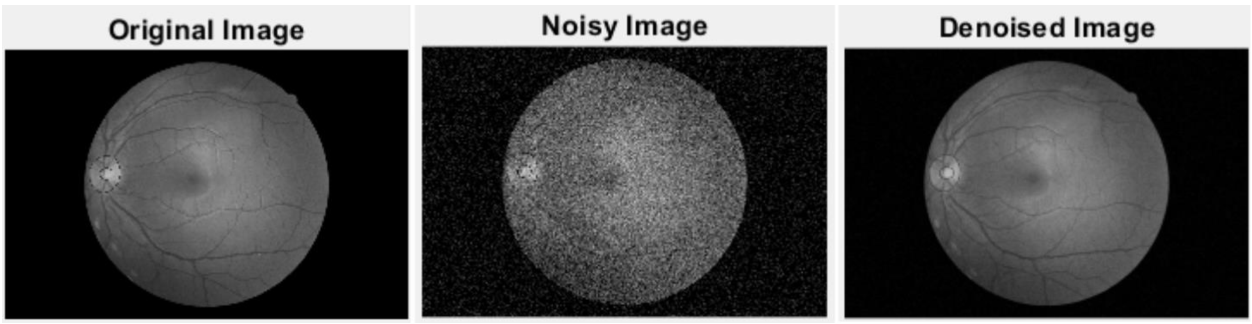

Figure 3.1.6 1: Retinal Scan

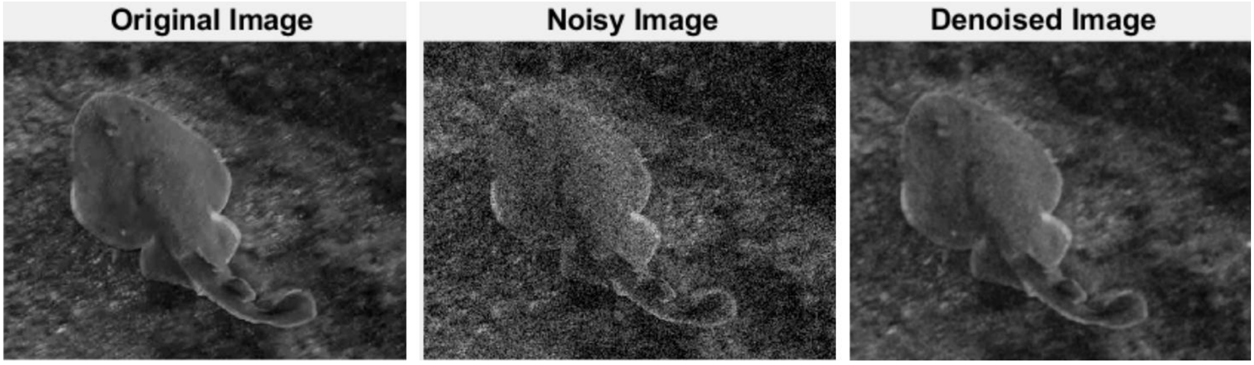

Figure 3.1.6 2: Underwater Image

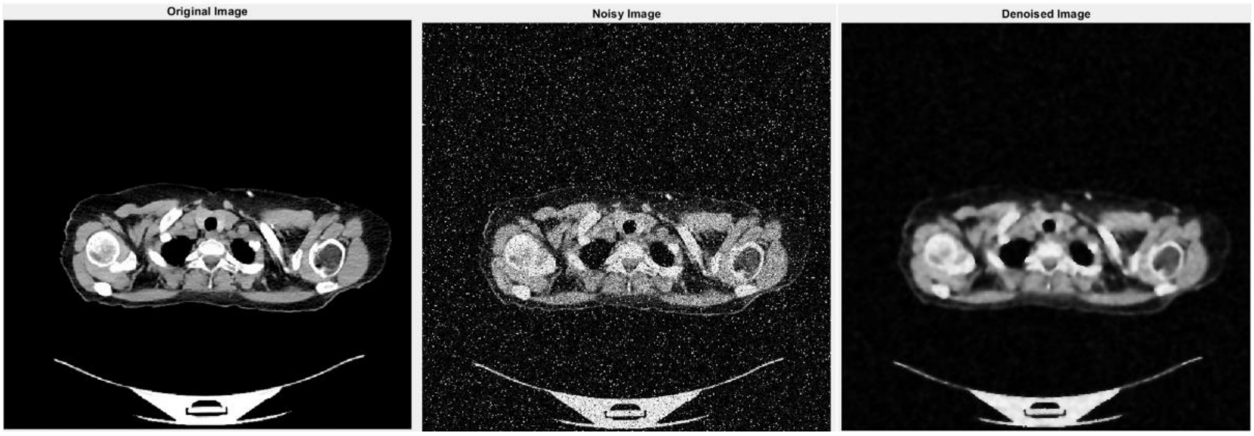

Figure 3.1.6 3: PET Image

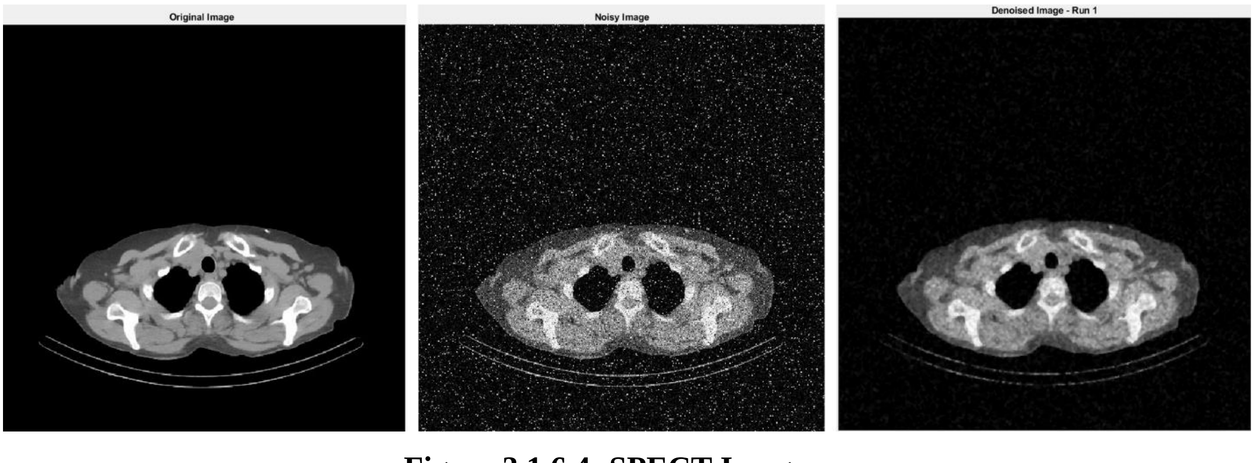

Figure 3.1.6 4: SPECT Image

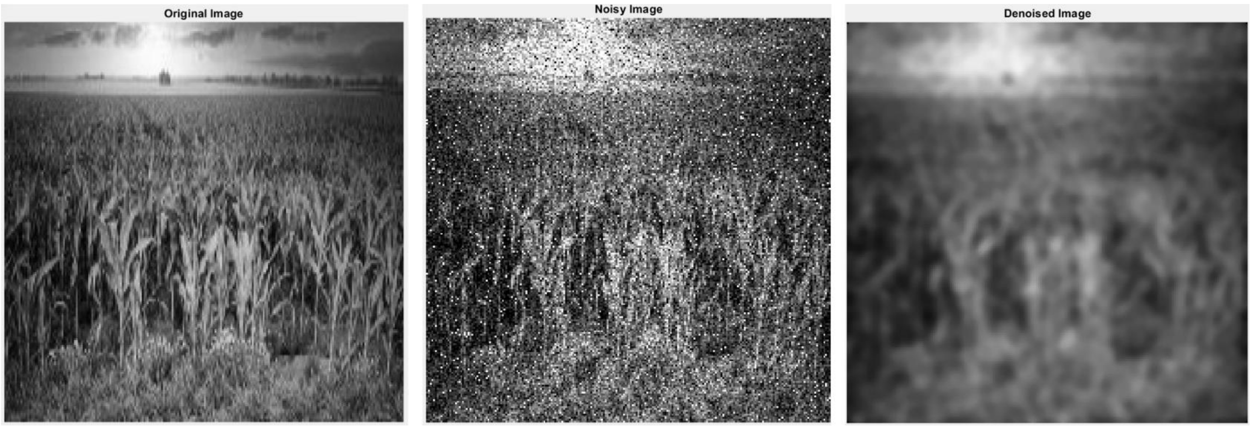

Figure 3.1.6 5: Maize Image

3.1.7 Whale Optimization Algorithm (RFO):

In this section, we will look at the side by side comparison of the original image, noisy image, and the denoised image for the Whale Optimization Algorithm. The sequence is as follows: we have the original image read into MATLAB that has been converted into grayscale, the image corrupted by Gaussian, Salt and Pepper, Speckle, and Poisson images.

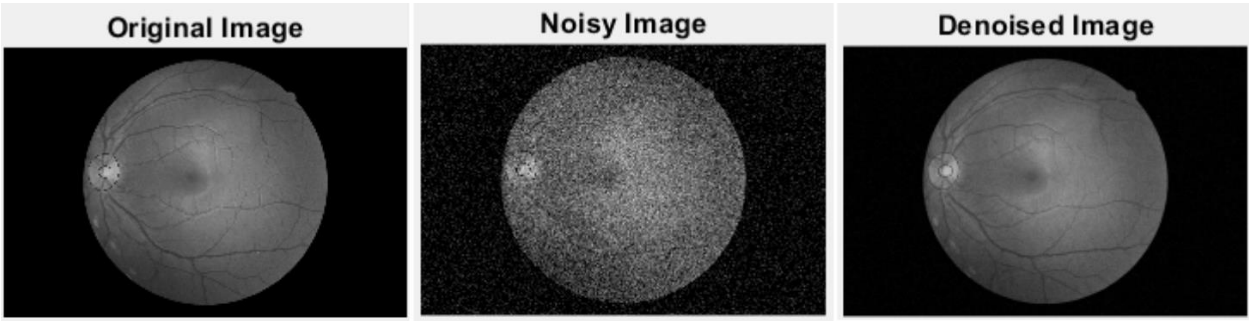

Figure 3.1.7 1: Retinal Scan

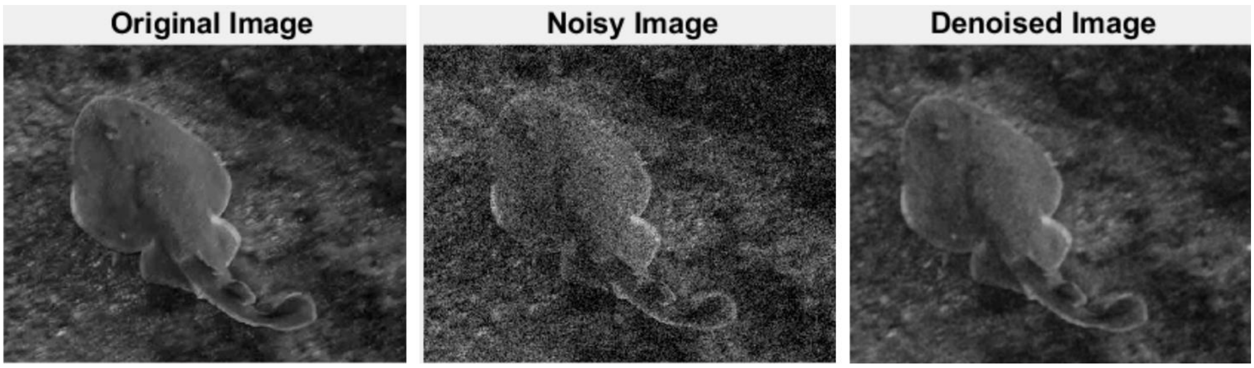

Figure 3.1.7 2: Underwater Image

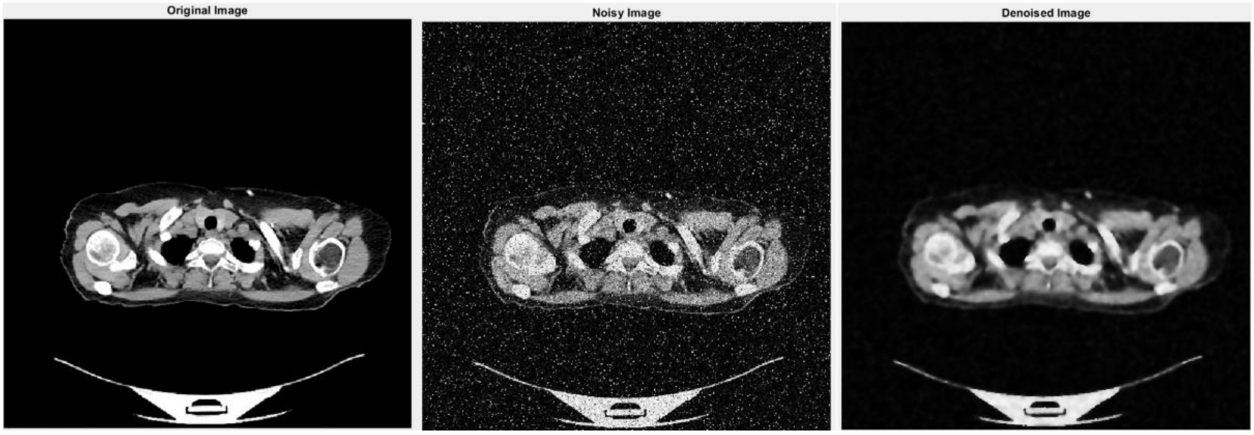

Figure 3.1.7 3: PET Image

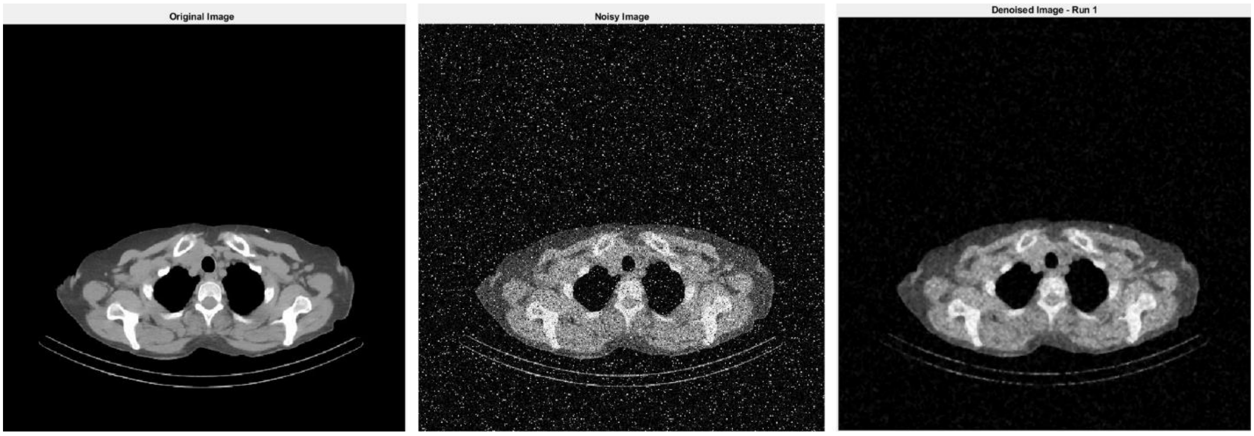

Figure 3.1.7 4: SPECT Image

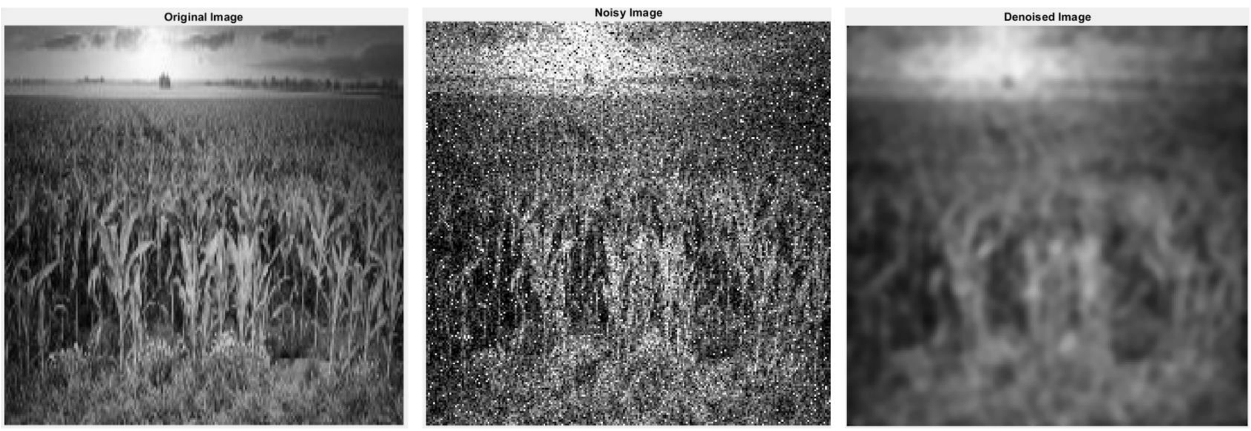

Figure 3.1.7 5: Maize Image

3.1.8 Hybrid Algorithm GA-RFO

In this section, we will look at the side by side comparison of the original image, noisy image, and the denoised image for the hybridized optimization between GA and RFO. The sequence is as follows: we have the original image read into MATLAB that has been converted into grayscale, the image corrupted by Gaussian, Salt and Pepper, Speckle, and Poisson images.

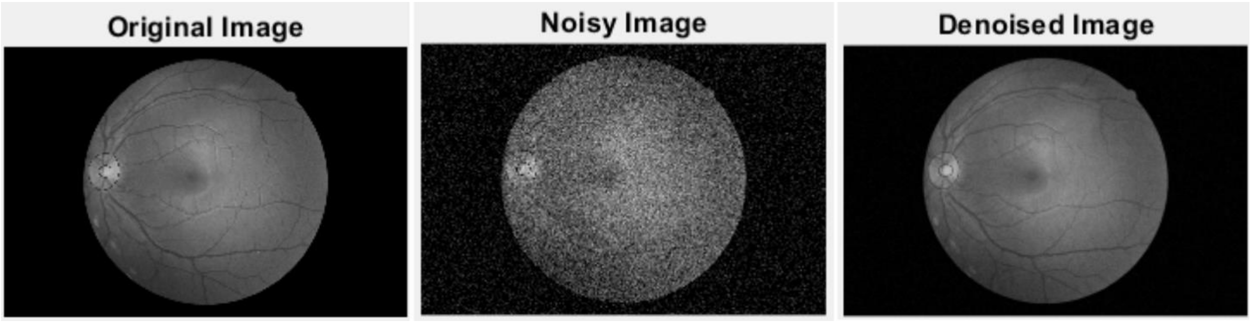

Figure 3.1.8 1: Retinal Scan

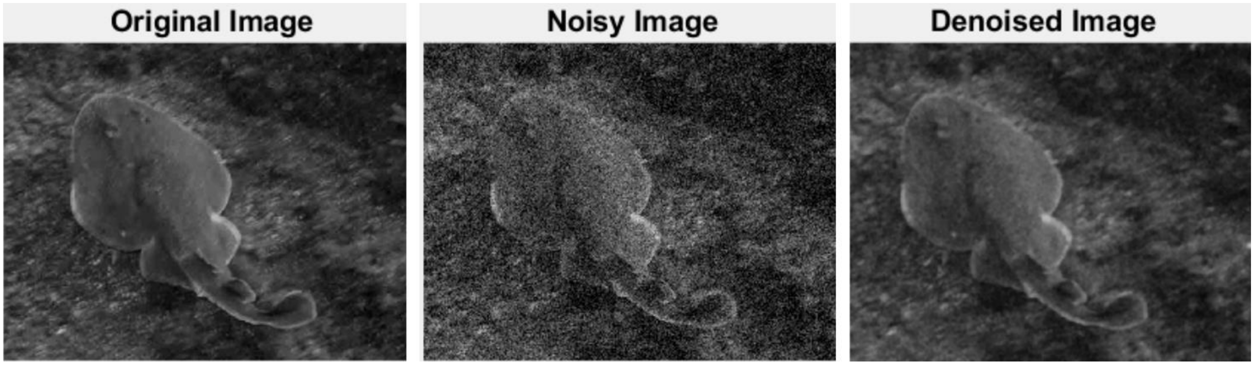

Figure 3.1.8 2: Underwater Image

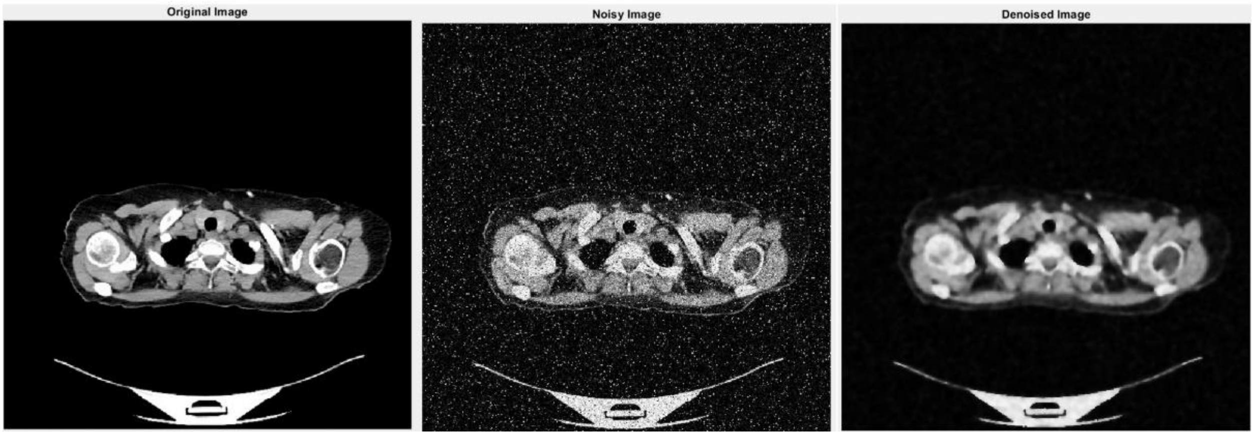

Figure 3.1.8 3: PET Image

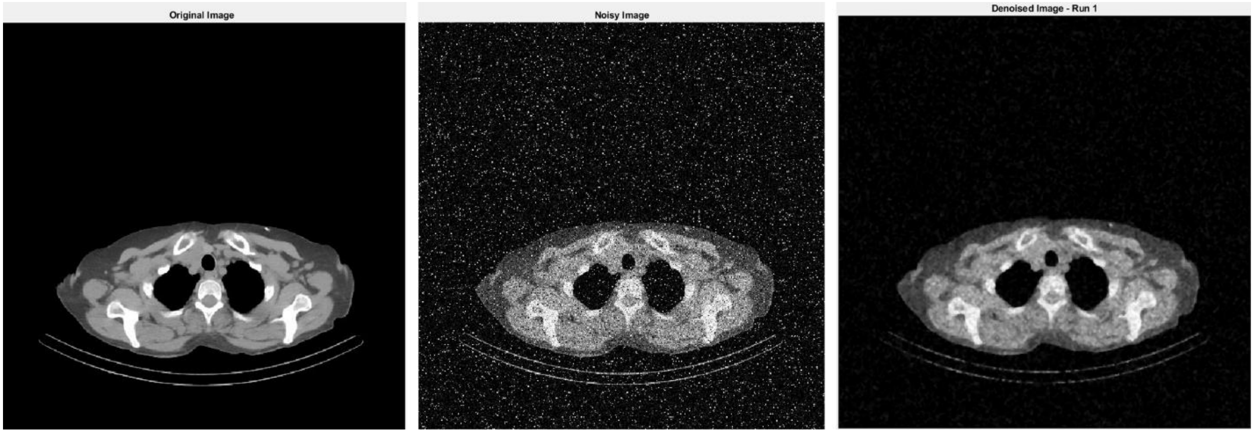

Figure 3.1.8 4: SPECT Image

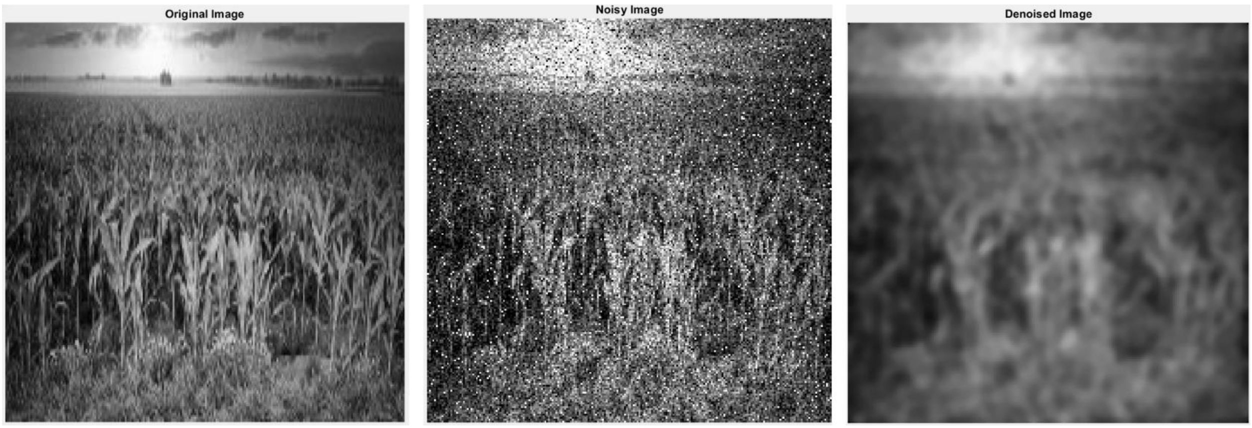

Figure 3.1.8 5: Maize Image

3.1.9 GA-PSO:

In this section, we will look at the side by side comparison of the original image, noisy image, and the denoised image for the hybridized optimization between GA and PSO. The sequence is as follows: we have the original image read into MATLAB that has been converted into grayscale, the image corrupted by Gaussian, Salt and Pepper, Speckle, and Poisson images.

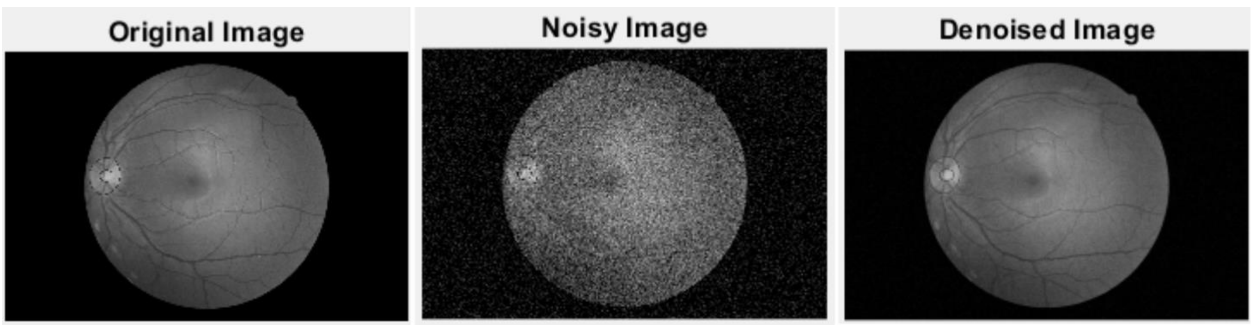

Figure 3.1.9 1: Retinal Scan

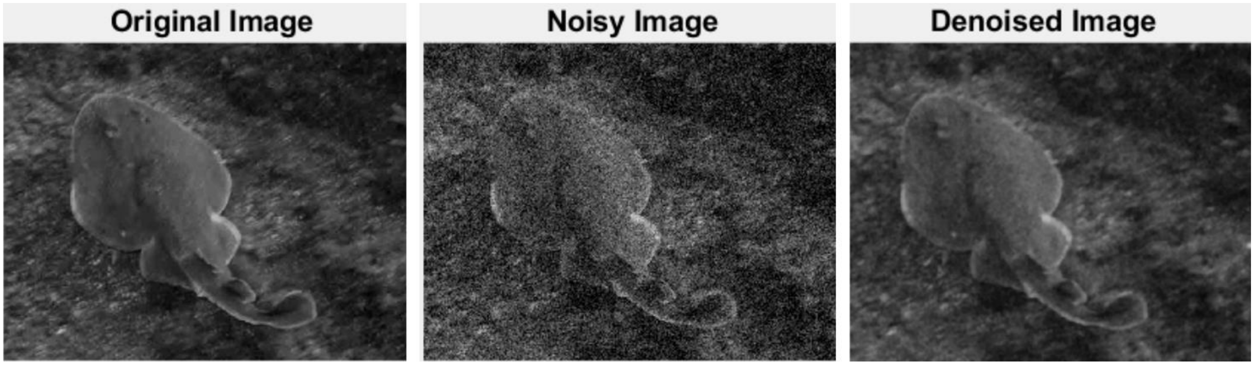

Figure 3.1.9 2: Underwater Image

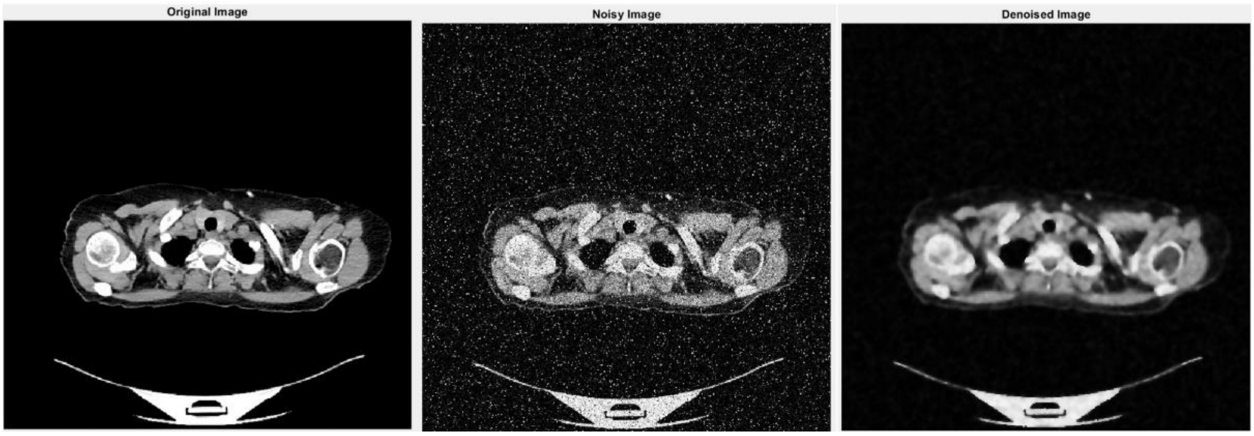

Figure 3.1.9 3: PET Image

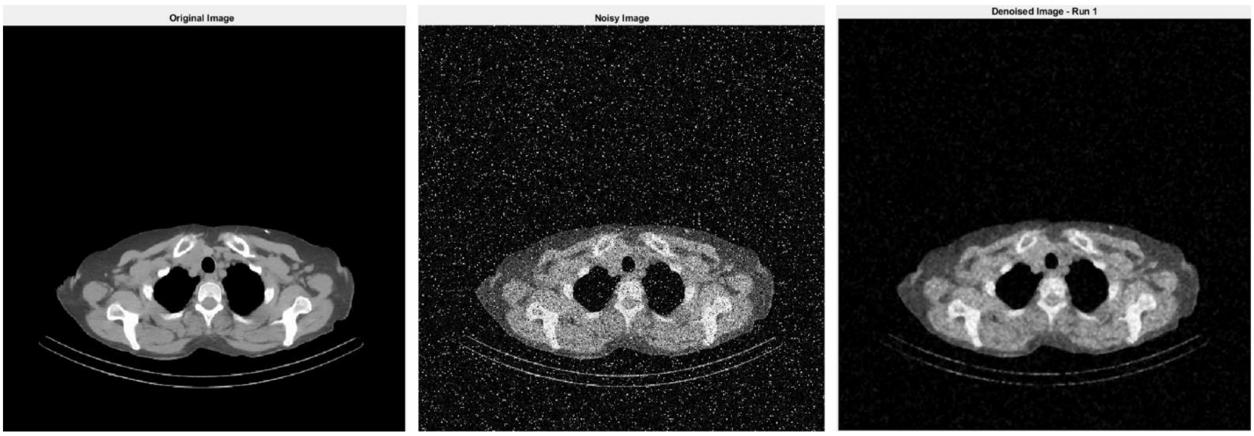

Figure 3.1.9 4: SPECT Image

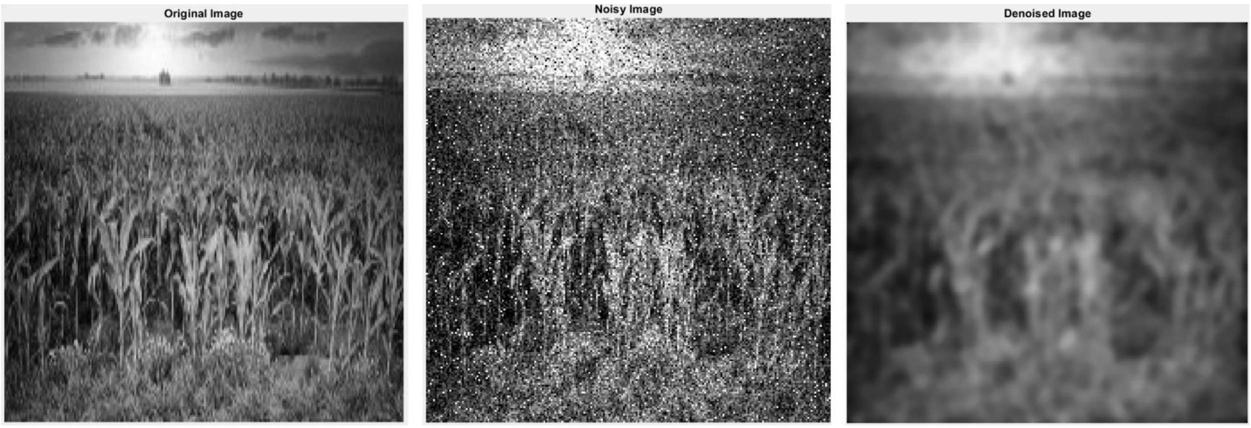

Figure 3.1.9 5: Maize Image

3.2 Quantitative Analysis of Denoising Metrics

We will now look at the quantitative analysis of how each algorithm performed for each type of images. The table will contain all the performance metrics for each algorithm, PSNR, MSE, SSIM, FSIM, Entropy of noisy image and denoised image so the performance of each algorithm can be quantified easily. We have conducted several runs for each algorithm, and then averaged to gain more reliable data. We have kept the iteration number and population size same for the sake of fairness.

Max iterations = 40 and population size = 20

Table 3.2 1 Underwater Image:

Algorithms	PSNR (dB)	MSE	SSIM	FSIM	Entropy (Noisy)	Entropy (Denoised)
EO	30.3543	0.0009	0.7705	0.9744	7.0631	6.5068
PSO	30.5902	0.0009	0.7773	0.9728	7.0627	6.4749
WOA	30.1716	0.0010	0.7631	0.9710	7.0667	6.5343
RFO	29.5371	0.0011	0.7437	0.9645	7.0615	6.5112
GCRA	28.9723	0.0013	0.7288	0.9591	7.0641	6.4584
GA	29.5092	0.0011	0.7365	0.9587	7.0653	6.4683
WHO	29.3306	0.0012	0.7362	0.9596	7.0653	6.4791
GA-RFO	29.9886	0.001	0.7562	0.9708	7.0624	6.5314
GA-PSO	30.0362	0.001	0.7616	0.9854	7.0664	6.496

Table 3.2 2 Maize Image:

Algorithms	PSNR (dB)	MSE	SSIM	FSIM	Entropy (Noisy)	Entropy (Denoised)
EO	22.1376	0.0061	0.5222	0.8831	7.632	7.2548
PSO	22.3031	0.0059	0.5310	0.8808	7.6310	7.2648
WOA	22.0111	0.0063	0.5084	0.8712	7.6357	7.3041
RFO	21.1562	0.0077	0.4165	0.8042	7.6371	7.152
GCRA	21.3612	0.0074	0.4273	0.8048	7.6345	7.1911
GA	20.5896	0.0088	0.3467	0.7465	7.6356	7.0748
WHO	20.9249	0.0081	0.3887	0.7797	7.6329	7.1209
GA-RFO	21.6298	0.0069	0.4789	0.8554	7.6373	7.2192
GA-PSO	21.9596	0.0064	0.4997	0.9704	7.6415	7.2207

Table 3.2 3 Retinal Scan:

Algorithms	PSNR (dB)	MSE	SSIM	FSIM	Entropy (Noisy)	Entropy (Denoised)
EO	34.5465	0.0004	0.7955	0.9565	6.1429	5.1471
PSO	34.0570	0.0004	0.7930	0.9485	6.1392	5.1908
WOA	34.2029	0.0004	0.7753	0.9538	6.1432	5.2641
RFO	34.1968	0.0004	0.7925	0.9537	6.1369	5.1691
GCRA	34.3057	0.0004	0.7301	0.9602	6.1387	5.2868
GA	33.6724	0.0004	0.6914	0.9579	6.1383	5.4005
WHO	34.6447	0.0003	0.7976	0.9574	6.141	5.1352
GA-RFO	34.5769	0.0003	0.8035	0.9559	6.1395	5.115
GA-PSO	33.9201	0.0004	0.7492	0.9758	6.1399	5.3109

Table 3.2 4 PET Image:

Algorithms	PSNR (dB)	MSE	SSIM	FSIM	Entropy (Noisy)	Entropy (Denoised)
EO	26.6162	0.0021	0.4742	0.9132	5.1035	4.7773
PSO	26.4809	0.0022	0.4916	0.9212	5.1181	5.1207
WOA	26.4890	0.0022	0.4806	0.9180	5.1287	5.0774
RFO	23.7107	0.0045	0.5807	0.7823	5.1131	4.6764
GCRA	23.587	0.0044	0.4527	0.7955	5.1132	4.8317
GA	23.2883	0.0047	0.5205	0.7706	5.113	4.7402
WHO	23.8682	0.0041	0.6334	0.7917	5.1149	4.6152
GA-RFO	25.1038	0.0031	0.4658	0.8756	5.1173	5.0666
GA-PSO	25.9271	0.0026	0.418	0.9804	5.1152	4.9564

Table 3.2 5 SPECT Image:

Algorithms	PSNR (dB)	MSE	SSIM	FSIM	Entropy (Noisy)	Entropy (Denoised)
EO	27.8682	0.0016	0.4577	0.8753	5.1101	4.5237
PSO	27.6952	0.0017	0.4706	0.8886	5.1124	4.8462
WOA	27.5685	0.0018	0.5279	0.8912	5.1094	4.7861
RFO	25.78	0.0026	0.5893	0.738	5.1135	4.4342
GCRA	25.4087	0.0029	0.5593	0.7291	5.11	4.5074
GA	26.0539	0.0025	0.5599	0.7709	5.1087	4.4198
WHO	26.1551	0.0024	0.609	0.7746	5.1085	4.3967
GA-RFO	26.8518	0.0021	0.5625	0.8319	5.1007	4.5779
GA-PSO	26.8865	0.0021	0.3869	0.9742	5.1042	4.8752

3.3 Algorithm Convergence curves

We will now look at the convergence curves for each algorithm, to visually understand how fast each of the algorithm converges to the optimum solution. The charts have plotted convergence for each run, and convergence curves for each of the images have been included.

3.3.1 Equilibrium Optimiser:

In this section, we will look at the convergence curves for how equilibrium optimizer performed for maize image, PET image, retinal scan image, SPECT image, and underwater image.

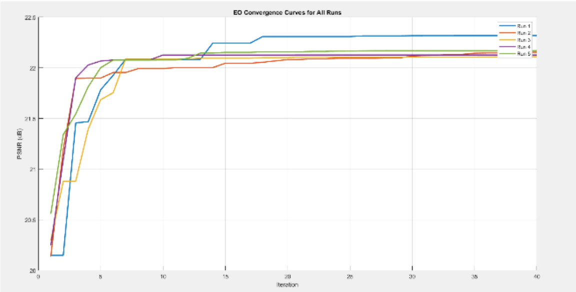

Figure 3.3 1: Maize Image

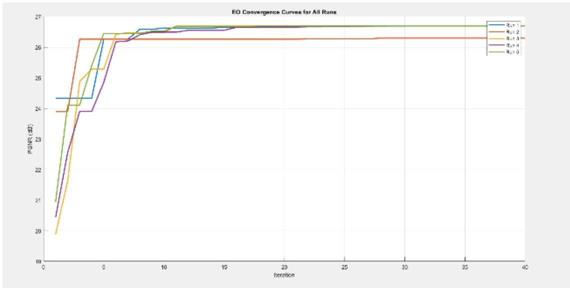

Figure 3.3 2: PET Image

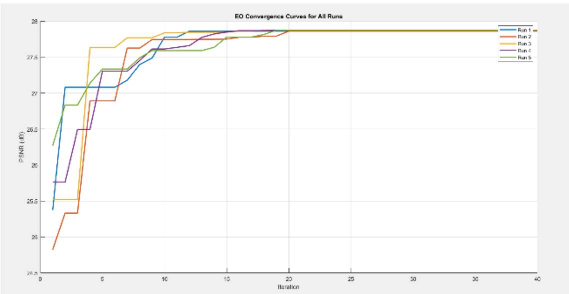

Figure 3.3 3: Retinal Scan

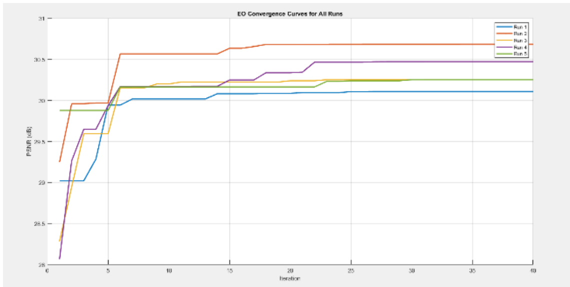

Figure 3.3 4: SPECT Image

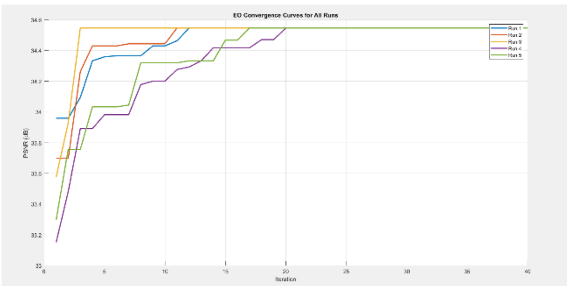

Figure 3.3 5: Underwater Image

3.3.2 *Wild Horse Optimization Algorithm:*

In this section, we will look at the convergence curves for how WHO performed for maize image, PET image, retinal scan image, SPECT image, and underwater image.

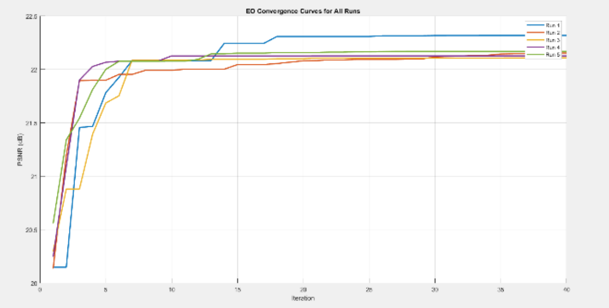

Figure 3.3 6: Maize Image

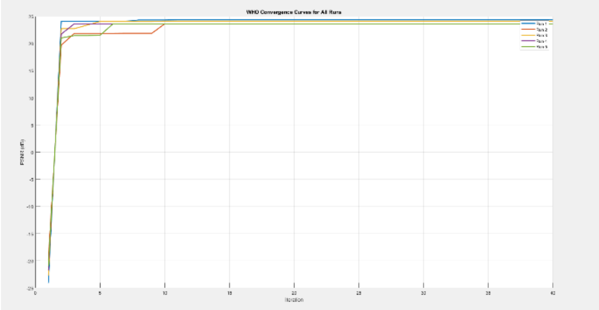

Figure 3.3 7: PET Image

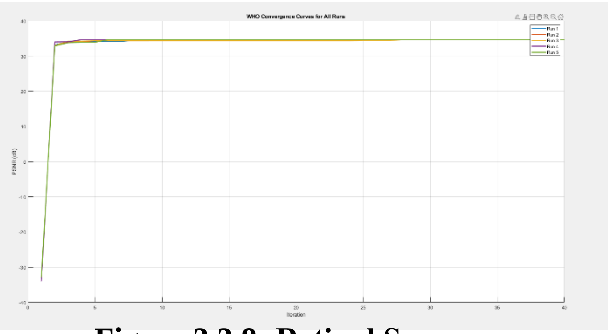

Figure 3.3 8: Retinal Scan

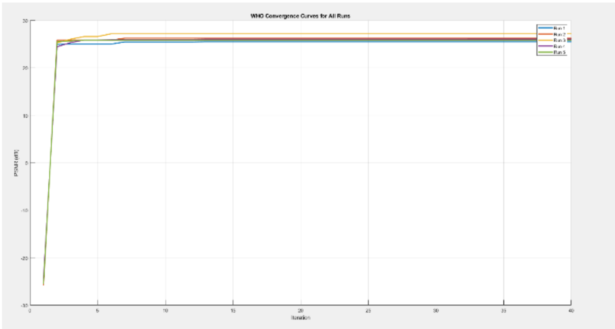

Figure 3.3 9: SPECT Image

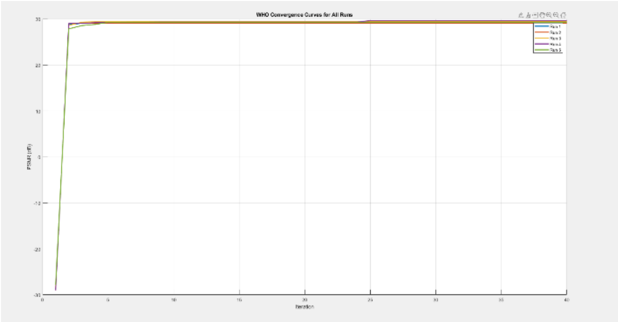

Figure 3.3 10: Underwater Image

3.3.3 *Red Fox Optimization Algorithm:*

In this section, we will look at the convergence curves for how RFO performed for maize image, PET image, retinal scan image, SPECT image, and underwater image.

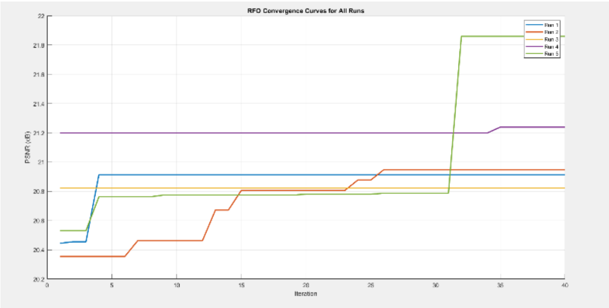

Figure 3.3 11: Maize Image

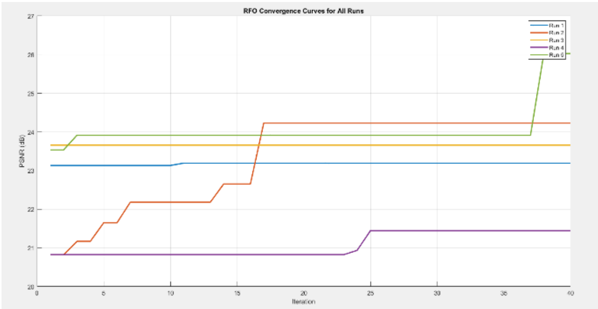

Figure 3.3 12: PET Image

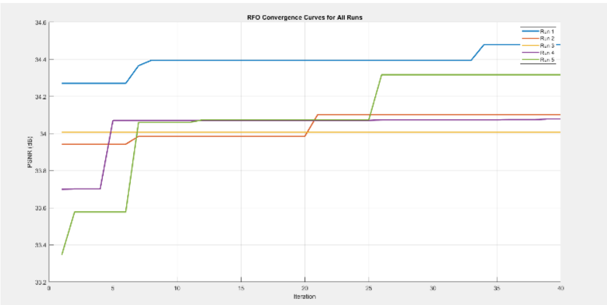

Figure 3.3 13: Retinal Scan

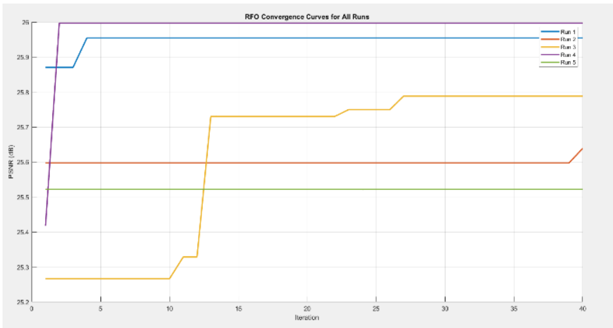

Figure 3.3 14: SPECT Image

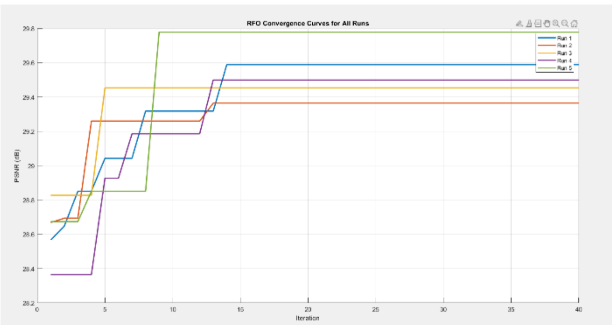

Figure 3.3 15: Underwater Image

3.3.4 *Particle Swarm Optimization Algorithm:*

In this section, we will look at the convergence curves for how PSO performed for maize image, PET image, retinal scan image, SPECT image, and underwater image.

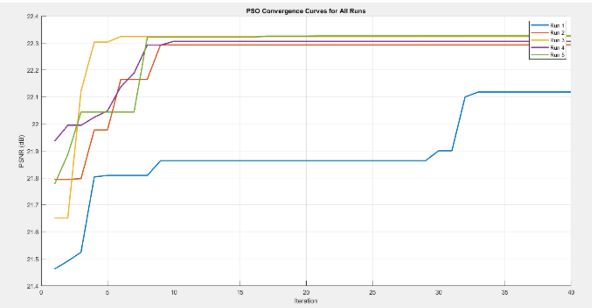

Figure 3.3 16: Maize Image

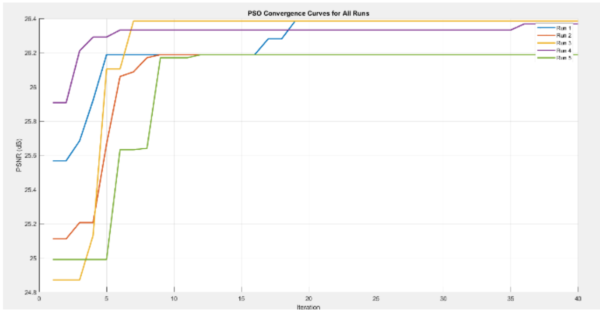

Figure 3.3 17: PET Image

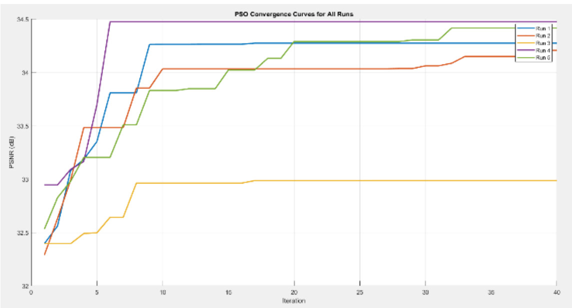

Figure 3.3 18: Retinal Scan

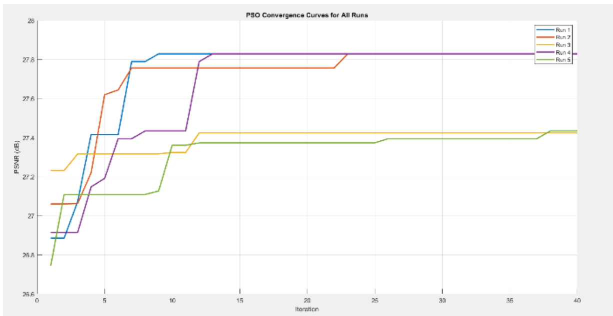

Figure 3.3 19: SPECT Image

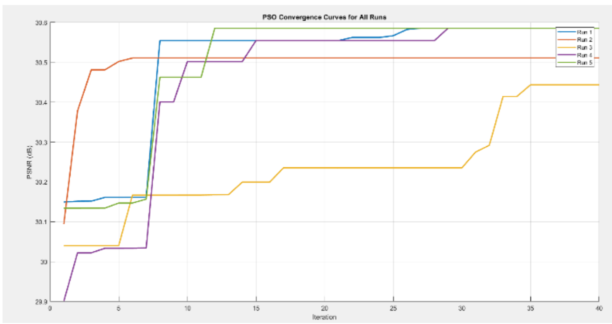

Figure 3.3 20: Underwater Image

3.3.5 Genetic Optimization Algorithm:

In this section, we will look at the convergence curves for how GA performed for maize image, PET image, retinal scan image, SPECT image, and underwater image.

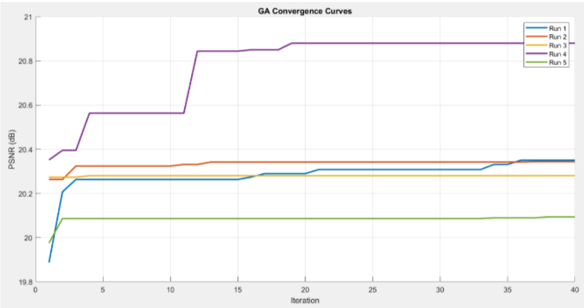

Figure 3.3 21: Maize Image

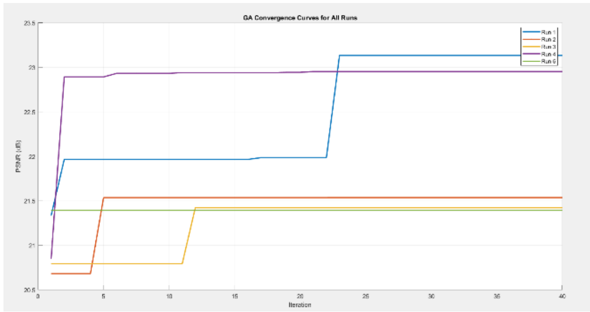

Figure 3.3 22: PET Image

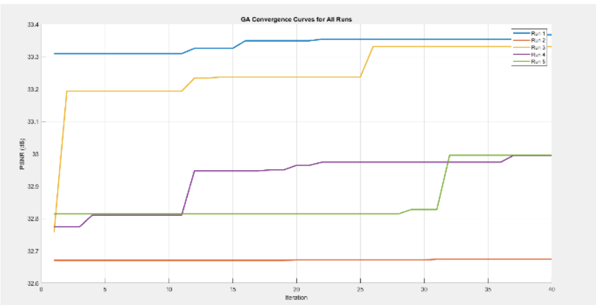

Figure 3.3 23: Retinal Scan

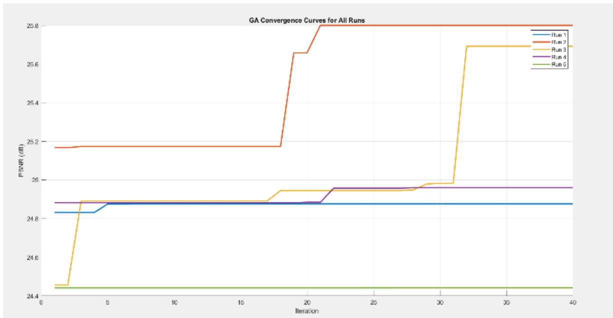

Figure 3.3 24: SPECT Image

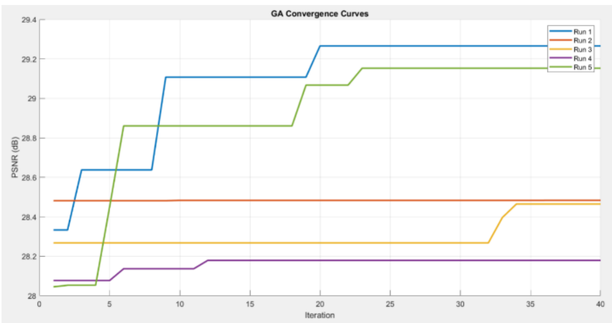

Figure 3.3 25: Underwater Image

3.3.6 *Greater Cane Rat Algorithm:*

In this section, we will look at the convergence curves for how GCRA performed for maize image, PET image, retinal scan image, SPECT image, and underwater image.

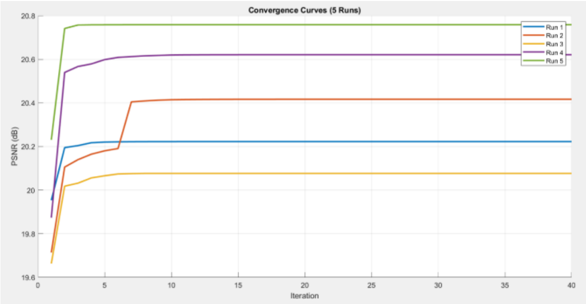

Figure 3.3 26: Maize Image

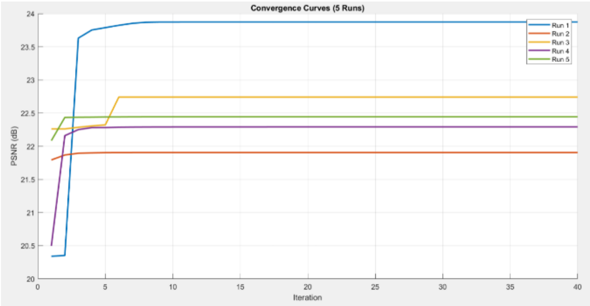

Figure 3.3 27: PET Image

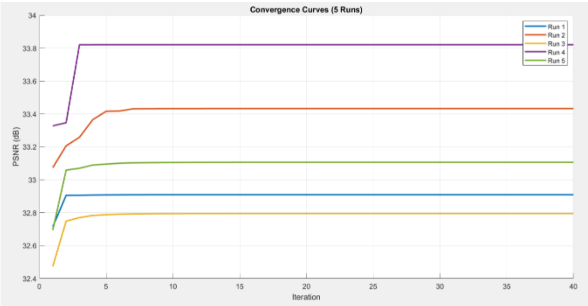

Figure 3.3 28: Retinal Scan

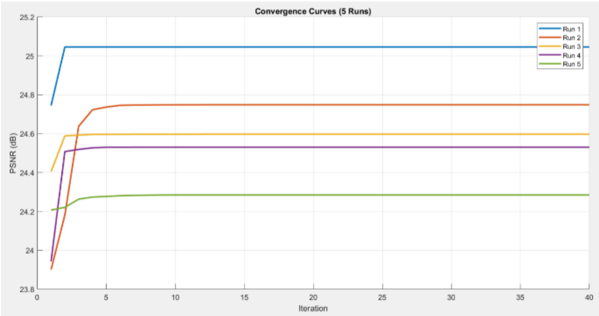

Figure 3.3 29: SPECT Image

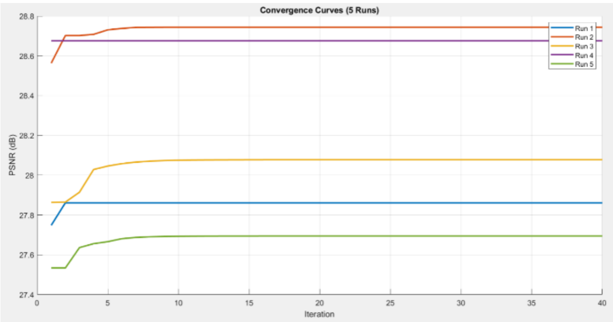

Figure 3.3 30: Underwater Image

3.3.7 *Whale Optimization Algorithm:*

In this section, we will look at the convergence curves for how WOA performed for maize image, PET image, retinal scan image, SPECT image, and underwater image.

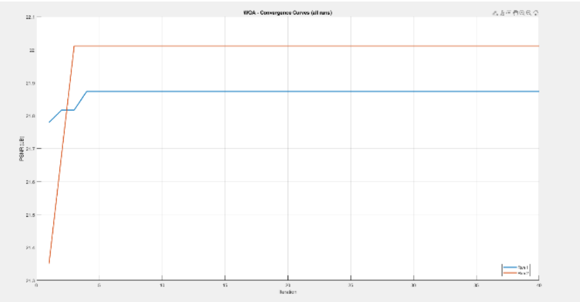

Figure 3.3 31: Maize Image

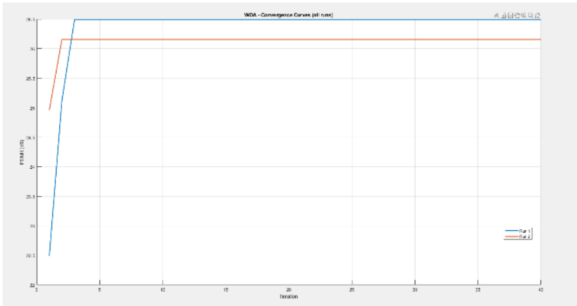

Figure 3.3 32: PET Image

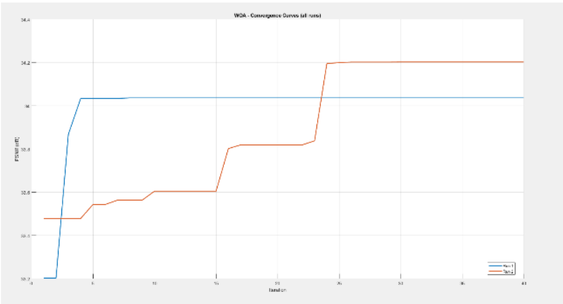

Figure 3.3 33: Retinal Scan

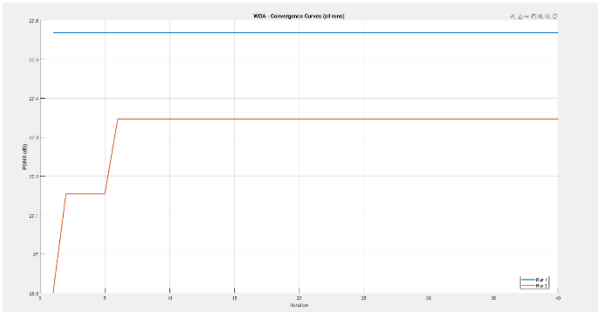

Figure 3.3 34: SPECT Image

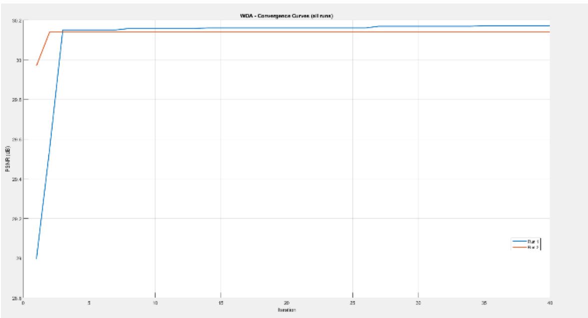

Figure 3.3 35: Underwater Image

3.3.8 Hybrid Algorithm GA-RFO:

In this section, we will look at the convergence curves for how hybridized GA-RFO performed for maize image, PET image, retinal scan image, SPECT image, and underwater image.

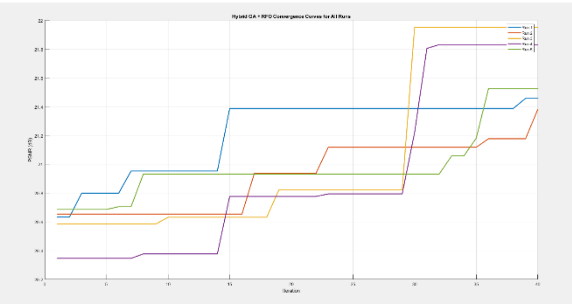

Figure 3.3 36: Maize Image

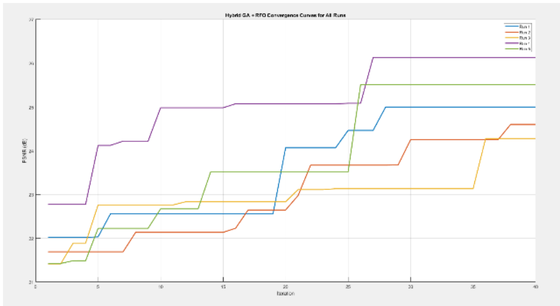

Figure 3.3 37: PET Image

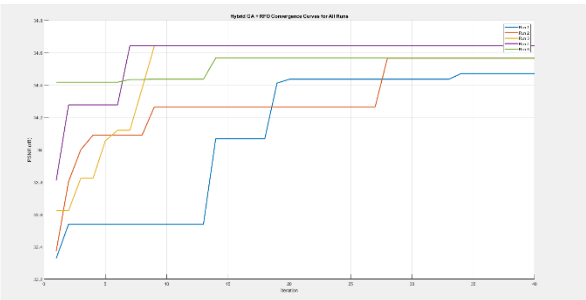

Figure 3.3 38: Retinal Scan

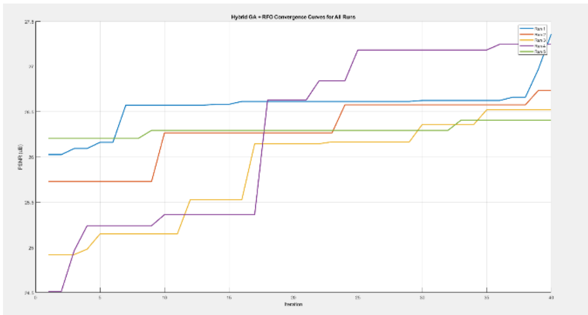

Figure 3.3 39: SPECT Image

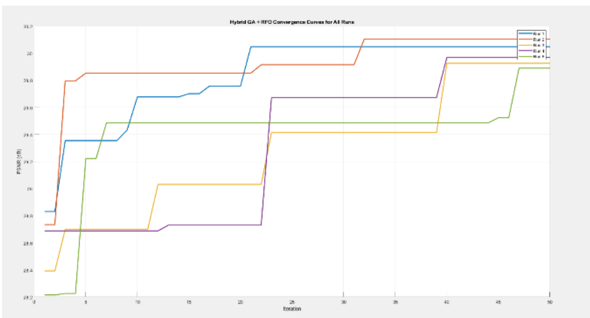

Figure 3.3 40: Underwater Image

3.3.9 GA-PSO:

In this section, we will look at the convergence curves for how hybridized GA-PSO performed for maize image, PET image, retinal scan image, SPECT image, and underwater image.

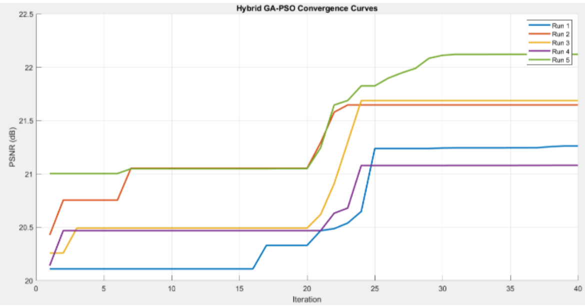

Figure 3.3 41: Maize Image

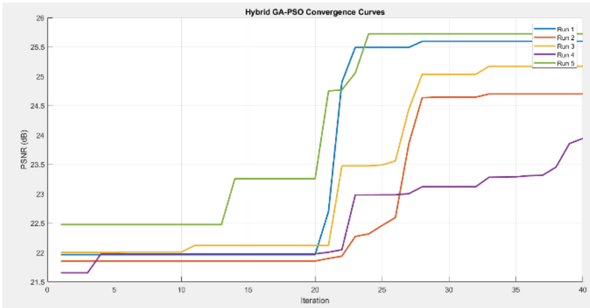

Figure 3.3 42: PET Image

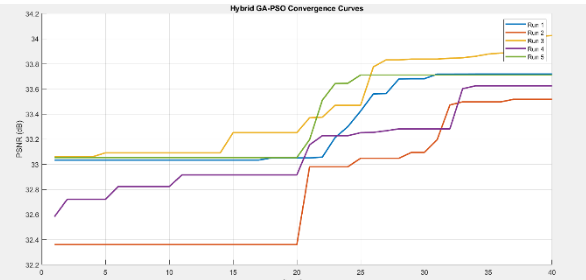

Figure 3.3 43: Retinal Scan

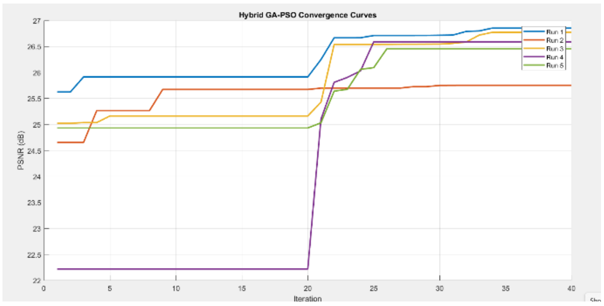

Figure 3.3 44: SPECT Image

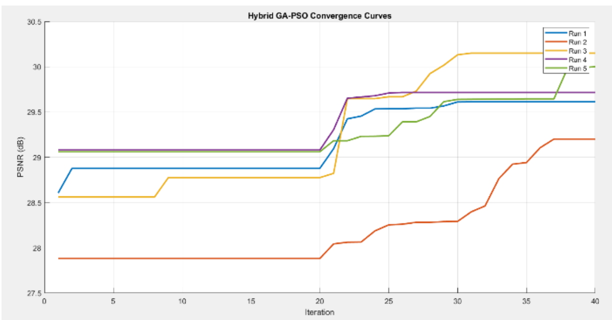

Figure 3.3 45: Underwater Image

Result Analysis

4.1.1 Overall Trends Across All Domains and Algorithms

From the numerical data presented above, it is quite clear that EO and PSO have consistently performed the best in most domains. The distinguishing aspect of the two is that EO has performed well in medical image domains, whereas PSO works better for underwater images. On the other hand, Greater Cane Rat Algorithm (GCRA) and Genetic Algorthm (GA) underperform. Wild Horse Optimization Algorithm (WHO) and Whale Optimization Algorithm (WOA) display consistent, mid to high results. RFO, while displaying moderate performance, lags.

4.1.2 Denoising Strength Analysis Based on PSNR

Equilibrium Optimizer: EO achieves superior results for medical images (Retina, PET, SPECT), confirming that it is capable of achieving good denoising performance by maintaining complex structure under heavy noise. It achieves the highest PSNR for both PET and SPECT images.

Particle Swarm Optimization: PSO does best for natural and textured images, such as underwater and maize. It achieves the highest PSNR for underwater images and maintains stability across all domains.

Whale Optimization Algorithm: This algorithm follows PSO and EO very closely across all domains, displaying reliability and efficacy. It also displays a consistent converging behavior.

Genetic Algorithm and Greater Cane Rat Algorithm: They display erratic and below average PSNR.

Red Fox Optimization Algorithm: It underperforms in medical images, which suggests that while it's good at exploitation of local bests, it doesn't perform well in finding global best.

Wild Horse Algorithm: Wild Horse Algorithm shows moderate yet consistent results across all domains, which makes it a decent option in relatively low complexity range.

4.1.3 Performance Analysis Based on Structural Similarity Index Measure (SSIM)

- WHO yields the highest SSIM for most medical images, which suggests that the edges and structures of features are preserved perfectly after denoising.
- EO and PSO lead for natural images, which means besides edge preservation, they manage to conserve textural similarity to original images. However, EO's SSIM drops in low-contrast images (e.g., PET, SPECT), implying potential over-smoothing in these domains even though it provides great PSNR.
- RFO gives average SSIM values but is more stable than GA and GRCA.

- GA consistently underperforms in SSIM, which means the edge preservation and structural consistency is low.
- WOA remains balanced, often ranking second or third, with good edge preservation

4.1.4 Performance Analysis Based on Mean Sqaured Error (MSE)

- EO and PSO have the lowest MSE values across almost all domains of datasets, confirming their ability to minimize pixel level differences effectively.
- WOA also achieves low MSE, tailing EO and PSO closely.
- GA, RFO, and GRCA show higher MSE, indicating less accurate noise suppression.
- WHO's MSE varies with the type of image, which means it's not the best for consistent results.

4.1.5 Computational Efficiency Measure Based on Runtime

- WOA is the fastest algorithm as it shows efficient convergence due to its simple mathematical operators and balanced search strategy.
- WHO and PSO are relatively fast, offering a good trade-off between performance and computation.
- EO and GA require moderate runtime, as there are complex equation and population interaction.
- GRCA is slower, and RFO is by far the slowest, taking thousands of seconds for some medical images.

4.1.6 Denoising Performance Based on Entropy

- Entropy measures texture richness. **Higher entropy** after denoising suggests more preserved details. However, higher entropy may also mean poor denoising performance.
- For Underwater and Maize images, GA and GRCA retain slightly higher entropy, but this may indicate under-filtering (residual noise).
- For medical images (Retina, PET, SPECT), WHO and EO achieve lower entropy, which means the output is less noisy.
- PSO performs inconsistently — sometimes adding entropy (over-enhancing) in low-contrast cases like PET and SPECT.
- WOA maintains moderate entropy, striking a good balance between smoothness and detail preservation.

4.1.7 Edge Preservation Based on Feature Similarity Index Measure (FSIM)

- EO and WOA achieve the highest FSIM values overall, which means they're more capable of preserving edges and important feature detail.
- Underwater & Maize: For these two images EO and PSO outperform others, with EO showing stronger feature similarity (up to 0.974).
- Retina: FSIM values are fairly close for all algorithms (~0.95–0.96), suggesting all maintain good structural integrity in high-detail medical images.
- PET & SPECT: EO, PSO, and WOA dominate again, confirming suitability for complex medical textures.
- RFO and GRCA lag behind, with weaker feature retention.

4.1.8 Performances of Hybridized Optimization Algorithm

From analyzing the numerical data derived from the hybridized optimization algorithm runs, we can conclude that:

GAPSO: We have hybridized Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to develop GAPSO. GAPSO has outperformed GA significantly, but lags slightly behind PSO in terms of PSNR. It has moderate runtime and results across all performance metrics, however, it displays significant improvement in terms of Feature Similarity Index Measure (FSIM).

GARFO: GARFO was found by hybridizing Red Fox Optimization Algorithm and Genetic Algorithm. It has outperformed both optimizers significantly in PSNR, MSE, as well as FSIM, however, it displays marginally less SSIM compared to GA and RFO individually.

Demonstration of Outcome Based Education (OBE)

5.1 Introduction

The modern engineering industry increasingly emphasizes **outcome-based approaches,** where the focus is on achieving specific competencies and applying knowledge to solve real-world problems. In the context of Electrical and Electronic Engineering (EEE), engineers are expected not only to understand theoretical concepts but also to design, implement, and evaluate practical solutions using contemporary tools and technologies.

This thesis demonstrates OBE principles by addressing practical challenges in image denoising across multiple domains, including medical imaging, agricultural images (maize crops), and underwater imagery. By applying optimization algorithms and advanced filtering techniques, the work improves image quality, supporting more accurate diagnoses, better crop monitoring, and detailed marine research. The project integrates disciplinary knowledge, problem-solving skills, and ethical considerations, highlighting the socio-cultural, environmental, and professional impacts of engineering solutions. This demonstrates how specialized engineering knowledge can be effectively applied in diverse practice areas to generate tangible, responsible, and socially beneficial outcomes.

5.2 Course Outcomes (COs) Addressed

The following table shows the COs addressed in EEE 4700 for Project and Thesis.

COs	CO Statement	POs	Put Tick (√)
CO1	Apply knowledge of electrical and electronic engineering to the solution of complex engineering problems.	PO1	√
CO2	Identify a contemporary real life problem related to electrical and electronic engineering by reviewing and analyzing existing research works.	PO2	√
CO3	Determine functional requirements of the problem considering feasibility and efficiency through analysis and synthesis of information.	PO4	√
CO4	Select a suitable solution and determine its method considering professional ethics, codes and standards.	PO8	√
CO5	Adopt modern engineering resources and tools for the solution of the problem.	PO5	√
CO6	Prepare management plan and budgetary implications for the solution of the problem.	PO11	√
CO7	Analyze the impact of the proposed solution on health, safety, culture and society.	PO6	√
CO8	Analyze the impact of the proposed solution on environment and sustainability.	PO7	√

CO9	Develop a viable solution considering health, safety, cultural, societal and environmental aspects.	PO3	√
CO10	Work effectively as an individual and as a team member for the accomplishment of the solution.	PO9	√
CO11	Prepare various technical reports, design documentation, and deliver effective presentations for demonstration of the solution.	PO10	√
CO12	Recognize the need for continuing education and participation in professional societies and meetings.	PO12	√

5.3 Aspects of Program Outcomes (POs) Addressed

The following table shows the aspects addressed for certain Program Outcomes (POs) addressed in EEE 4700 for Project and Thesis.

	Statement	Different Aspects	Put Tick (√)
PO3	**Design/development of solutions**: Design solutions for complex electrical and electronic engineering problems and design systems, components or processes that meet specified needs with appropriate consideration for public health and safety, cultural, societal, and environmental considerations.	Public health	√
		Safety	√
		Cultural	
		Societal	√
		Environmental	
PO4	**Investigation:** Conduct investigations of complex electrical and electronic engineering problems using research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of information to provide valid conclusions.	Design of experiments	√
		Analysis and interpretation of data	√
		Synthesis of information	√
PO6	**The engineer and society:** Apply reasoning informed by contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to professional engineering practice and solutions to complex electrical and electronic engineering problems.	Societal	√
		Health	√
		Safety	√
		Legal	
		Cultural	
PO7	**Environment and sustainability:** Understand and evaluate the sustainability and impact of professional engineering work in the solution of complex electrical and electronic engineering problems in societal and environmental contexts.	Societal	√
		Environmental	√
PO8	**Ethics:** Apply ethical principles embedded with religious values, professional ethics and responsibilities, and norms of electrical and electronic engineering practice.	Religious values	
		Professional ethics and responsibilities	√
		Norms	√
PO10	**Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as being able to comprehend and write effective reports and design	Comprehend and write effective reports	√
		Design documentation	√
		Make effective presentations	√

	documentation, make effective presentations, and give and receive clear instructions.	Give and receive clear instructions	√
PO11	**Project management and finance:** Demonstrate knowledge and understanding of engineering management principles and economic decision-making and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.	Engineering management principles	√
		Economic decision-making	√
		Manage projects	√
		Multidisciplinary environments	√

5.4 Knowledge Profiles (K3 – K8) Addressed

The following table shows the Knowledge Profiles (K3 – K8) addressed in EEE 4700 for Project and Thesis.

K	Knowledge Profile (Attribute)	Put Tick (√)
K3	A systematic, theory-based formulation of engineering fundamentals required in the engineering discipline	√
K4	Engineering specialist knowledge that provides theoretical frameworks and bodies of knowledge for the accepted practice areas in the engineering discipline; much is at the forefront of the discipline	√
K5	Knowledge that supports engineering design in a practice area	√
K6	Knowledge of engineering practice (technology) in the practice areas in the engineering discipline	√
K7	Comprehension of the role of engineering in society and identified issues in engineering practice in the discipline: ethics and the engineer's professional responsibility to public safety; the impacts of engineering activity; economic, social, cultural, environmental and sustainability	√
K8	Engagement with selected knowledge in the research literature of the discipline	√

The following table explains or justifies how the Knowledge Profiles (K3 – K8) have been addressed in EEE 4700/4800 (Project and Thesis).

K	Explanation/Justification
K3	The project applies theoretical knowledge of optimization algorithms and image processing fundamentals.
K4	Employs advanced frameworks of filters (Wiener, Gaussian) combined with optimization techniques for noise reduction.
K5	Applies signal processing and optimization knowledge to design an image denoising system for medical applications.
K6	Implements practical techniques in medical imaging, addressing real-world denoising problems.
K7	Examines societal impacts, including the ethical use of enhanced medical imaging for accurate diagnoses.

K8	Reviews and applies relevant research on optimization algorithms and image denoising techniques within the EEE discipline.

5.5 Use of Complex Engineering Problems

This project addresses complex engineering problems through the following steps:

- **Multi-Disciplinary Integration:** Combining image processing, optimization algorithms, and medical imaging to address noise variations in images.
- **Customized Solutions:** Adapting sequential filters and optimization algorithms to handle diverse noise patterns effectively.
- **Advanced Tools:** Utilizing computational techniques for parameter tuning and performance evaluation.
- **Stakeholder Validation:** Ensuring clinical relevance by incorporating feedback from medical professionals.

5.6 Socio-Cultural, Environmental, And Ethical Impact

Socio-Cultural Impact:

- **Improved Medical Diagnoses**

  The application of advanced imaging technologies, such as retinal, PET, and SPECT scans, enhances the accuracy and speed of medical diagnoses. These imaging methods allow for early detection of various health conditions, leading to better patient outcomes and more effective treatments.

- **Increased Healthcare Access in Low-Resource Settings**

  The adoption of AI-driven imaging solutions plays a critical role in expanding healthcare accessibility in underserved or resource-limited areas. By providing remote diagnostics and reducing reliance on specialized equipment, healthcare becomes more accessible to vulnerable populations.

- **Support for Agricultural and Food Security**

  AI-assisted image processing, particularly in analyzing maize crops, supports the agriculture sector by improving crop monitoring, pest detection, and yield prediction. This contributes significantly to food security by helping farmers make data-driven decisions to maximize crop production and ensure sustainability.

- **Aid to Marine Research and Preservation of Cultural Heritage**

  AI-powered imaging techniques applied to underwater environments assist in marine research by providing detailed and accurate imagery for the study of ecosystems and biodiversity. Additionally, these methods help preserve cultural heritage by documenting underwater archaeological sites with high precision.

Environmental Impact:

- **Biodiversity Monitoring and Marine Conservation**

  AI technology plays a pivotal role in monitoring biodiversity by enabling more efficient tracking of species and ecosystems. This data is crucial for conservation efforts, particularly in marine environments, by helping to identify endangered species and monitor the health of marine ecosystems.

- **Promotion of Sustainable Farming Practices**

  AI applications in agriculture promote sustainability by analyzing environmental factors and optimizing farming practices. These technologies can reduce the environmental impact of agriculture by promoting the use of resources more efficiently, leading to a reduction in waste and enhanced long-term sustainability.

- **Reduction of Repeated Scans, Lowering Energy and Resource Usage**

  By improving the precision of medical imaging, AI reduces the necessity for repeated scans, thereby lowering the overall consumption of energy and medical resources. This not only results in cost savings but also minimizes the environmental footprint of healthcare operations.

Ethical Impact:

- **Ensuring Patient Data Privacy and Security**

  AI technologies in healthcare prioritize the security of patient information by adhering to stringent data protection regulations. By employing advanced encryption and security protocols, patient confidentiality is maintained, fostering trust in AI-based medical systems.

- **Avoidance of Algorithmic Bias in Diagnoses**

  AI systems are designed to reduce biases that may arise from human judgment in medical diagnoses. By ensuring that algorithms are trained on diverse and representative datasets, the likelihood of biased or skewed diagnoses is minimized, promoting fairness in healthcare delivery.

- **Supporting Healthcare Professionals as Decision-Aids**

  AI systems are intended to complement healthcare professionals rather than replace them. By providing data-driven insights and assisting with diagnostic decision-making, these technologies enhance the capabilities of medical practitioners, leading to better-informed decisions without undermining their role.

Encouraging Transparency and Reproducibility in AI

Ethical AI development emphasizes the importance of transparency and reproducibility. AI systems should be designed and implemented with clear guidelines and protocols, ensuring that their actions can be understood, verified, and reproduced. This fosters accountability and trust in AI applications, particularly in sensitive fields such as healthcare.

5.7 Attributes of Ranges of Complex Engineering Problem Solving (P1 – P7) Addressed

The following table shows the attributes of ranges of Complex Engineering Problem Solving (P1 – P7) addressed in EEE 4700 for Project and Thesis.

P	**Range of Complex Engineering Problem Solving**	**Put Tick (√)**
Attribute	Complex Engineering Problems have characteristic P1 and some or all of P2 to P7:	
Depth of knowledge required	**P1:** Cannot be resolved without in-depth engineering knowledge at the level of one or more of K3, K4, K5, K6 or K8 which allows a fundamentals-based, first principles analytical approach	√
Range of conflicting requirements	**P2:** Involve wide-ranging or conflicting technical, engineering and other issues	√
Depth of analysis required	**P3:** Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models	√
Familiarity of issues	**P4:** Involve infrequently encountered issues	
Extent of applicable codes	**P5:** Are outside problems encompassed by standards and codes of practice for professional engineering	
Extent of stakeholder involvement and conflicting requirements	**P6:** Involve diverse groups of stakeholders with widely varying needs	√
Interdependence	**P7:** Are high level problems including many component parts or sub-problems	

The following table explains or justifies how the attributes of ranges of Complex Engineering Problem Solving (P1 – P7) have been addressed in EEE 4700/4800 (Project and Thesis).

P	**Explanation/Justification**
P1	Requires in-depth application of knowledge on optimization algorithms and filter design.

P2	Balances the conflicting requirements of algorithm efficiency and noise reduction quality.
P3	Demands innovative thinking in designing and fine-tuning the optimization workflow.
P4	
P5	
P6	Engages stakeholders like medical professionals to validate results and establish usability.
P7	

5.8 Attributes of Ranges of Complex Engineering Activities (A1 – A5) Addressed

The following table shows the attributes of ranges of Complex Engineering Activities (A1 – A5) addressed in EEE 4700 for Project and Thesis.

A	**Range of Complex Engineering Activities**	**Put Tick (√)**
Attribute	Complex activities means (engineering) activities or projects that have some or all of the following characteristics:	
Range of resources	**A1:** Involve the use of diverse resources (and for this purpose resources include people, money, equipment, materials, information and technologies)	√
Level of interaction	**A2:** Require resolution of significant problems arising from interactions between wide-ranging or conflicting technical, engineering or other issues	√
Innovation	**A3:** Involve creative use of engineering principles and research-based knowledge in novel ways	√
Consequences for society and the environment	**A4:** Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation	√
Familiarity	**A5:** Can extend beyond previous experiences by applying principles-based approaches	

The following table explains or justifies how the attributes of ranges of Complex Engineering Activities (A1 – A5) have been addressed in EEE 4700/4800 (Project and Thesis).

A	**Explanation/Justification**
A1	Utilizes diverse resources, including image datasets, algorithms, and computational tools.
A2	Resolves issues arising from algorithm-filter interactions to achieve optimal results.
A3	Innovates by integrating metaheuristic optimization with sequential filtering.
A4	Ensures the solution aligns with societal and environmental considerations, including medical ethics.
A5	

Conclusion

Image denoising is an important part of image preprocessing, which must be completed before further processing is performed on the image to avoid faulty analysis. Various methods of image denoising has been studied, and newer techniques that implement novel findings are being developed continually to improve denoising performance. Our work focuses on combining traditional spatial domain filtering method in conjunction with the fine tuning capabilities of metaheuristic algorithms, older and newer ones alike.

EO emerges as the most consistent and effective denoising optimizer, especially for medical imaging, because it can preserve structural details strongly and makes minimum reconstruction error. PSO ranks closely behind, performing best on natural images with complex textures. WOA offers the best balance of quality and speed, making it practical for large-scale or time-sensitive applications. WHO maintains consistent yet average performance, especially in structural similarity. GA and GRCA are less reliable, often producing erratic results with higher noise residues. RFO, while locally precise, is computationally inefficient and displays inconsistent results from image to image. GAPSO performs well yet slightly behind PSO individually. GARFO outperforms both GA and RFO in PSNR, SSIM, and MSE.

As newer optimization algorithms are being developed steadily, their performance in image denoising remains yet to be tested. The potential of hybridizing newer algorithms, as well as utilizing them in conjunction with transform domain methods are an untapped field of study. Studies that can denoise images in real time for analysis and diagnosis can be an important improvement over our work. Using naturally occurring noises instead of adding noises to image synthetically as dataset is an important progress, as naturally occurring images. In our work we have put to test traditional methods in conjunction to newer algorithms to analyze the improvement in image denoising performance, and it is clear that a singular algorithm cannot outperform across all domains, and image denoising methods, filters, as well as algorithms are often application specific.

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