IEEE 2024 5th International Conference on Circuits, Control, Communication and Computing (I4C)
4-5 October 2024

# Enhancing Medical Imaging: Denoising with Discrete Fourier Transform, Clustering, and Statistical Analysis

Bandaru Jaya Nandini
Department of Computer Science and Engineering,
Amrita School of Computing, Bengaluru,
Amrita Vishwa Vidyapeetham, India.
bl.en.u4aie22006@bl.students.amrita.edu

Mamidi Leha Sahithi
Department of Computer Science and Engineering,
Amrita School of Computing, Bengaluru,
Amrita Vishwa Vidyapeetham, India.
bl.en.u4aie22035@bl.students.amrita.edu

Siddareddy Gari Harshika
Department of Computer Science and Engineering,
Amrita School of Computing, Bengaluru,
Amrita Vishwa Vidyapeetham, India.
bl.en.u4aie22053@bl.students.amrita.edu

Sarada Jayan
Department of Mathematics,
Amrita School of Engineering, Bengaluru,
Amrita Vishwa Vidyapeetham, India.
j_sarada@blr.amrita.edu

2024 5th International Conference on Circuits, Control, Communication and Computing (I4C) | 979-8-3315-2853-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/I4C62240.2024.10748444

***Abstract*—In the complex realm of medical imaging, noise poses a significant challenge as every pixel can convey crucial information that might save lives. Various factors, including environmental noise, sensor noise, and the intrinsic constraints of imaging equipment, can cause denoising in images. This study introduces a novel image denoising approach specifically applied to the Alzheimer's dataset, which is crucial for understanding and diagnosing Alzheimer's disease. The dataset comprises five distinct classes, each representing different stages or types of the disease, making it particularly significant in the medical field. Theproposed method leverages a combination of Discrete Fourier Transform (DFT), Inverse Discrete Fourier Transform (IDFT), Butterworth low-pass filtering, and Non-local Means denoisingto enhance image quality. By employing Fourier Transform, the study performs frequency domain analysis on the image data, enabling the extraction of vital information while reducing noise. Furthermore, K-means clustering is used to categorize noisy and denoised images based on visual similarities. To validate the effectiveness of the denoising technique, statistical evaluationsare conducted through hypothesis testing, comparing noise levelsand quality metrics between noisy and denoised images. Thisstudy not only offers a comprehensive approach to addressingthe challenges of image denoising in medical imaging but alsohas significant societal benefits. By improving the clarity of images used in Alzheimer's research, the study contributes to more accurate diagnoses and better understanding of the disease, potentially leading to improved patient outcomes and advancing public health efforts in combating Alzheimer's disease.**

***Index Terms*—Image denoising, noise reduction, Discrete Fourier Transform, Butterworth low-pass filter, non-local means denoising, Alzheimer's dataset.**

## I. Introduction

Medical imaging plays a pivotal role in modern health-care, providing invaluable insights into the internal structures and functions of the human body. These images are essential diagnostic tools, allowing healthcare professionalsto see organs, tissues, and abnormalities with exceptional clarity. The accurate interpretation of these images is crucial for effective diagnosis, treatment planning, and continuous patient monitoring. However, the quality of medical images is frequently diminished by different types of noise, which can obscure critical details and make the interpretation process more challenging. Noise in medical imaging can stem from various sources, including environmental factors, sensor noise, and the inherent limitations of imaging devices. Furthermore, biological factors like patient movement or specific tissue characteristics can also introduce additional noise and artifacts. Image denoising is therefore a crucial preprocessing step in medical imaging, designed to reduce or eliminate noise while preserving the essential features of the image. Numerous techniques have been developed for image denoising over the years, each offering unique strengths and limitations. Thisstudy proposes a novel and comprehensive approach for image denoising, designed specifically for the Alzheimer's disease dataset, which includes 1,296 images divided into five distinct classes representing various stages or types of Alzheimer's disease. This dataset is particularly significant because ofits role in understanding the progression of Alzheimer's,a neurodegenerative disease impacting millions worldwide. Accurate denoising of these images is vital not just for research but also for possible clinical uses, where enhanced image clarity can result in better diagnostic outcomes.

The proposed method combines advanced techniques from both the frequency and spatial domains to effectively reduce noise while preserving essential image details. First, the images are converted into the frequency domain using the Discrete Fourier Transform (DFT), where a Butterworth low-pass filter is applied to reduce high-frequency noise components. The images are then transformed back to the spatial domain using the Inverse Discrete Fourier Transform (IDFT). This is



979-8-3315-2853-9/24/$31.00 ©2024 IEEE

followed by Non-Local Means Denoising, which improves image quality by comparing each pixel to its surrounding neighborhood and averaging similar pixels to minimize any remaining noise.

To assess the effectiveness of the denoising method, both visual and statistical evaluations are used. Visual comparisons are conducted with plots generated by the Matplotlib Python library, where the original, noisy, and denoised images are placed side by side. Additionally, K-means clustering is introduced as an innovative method to evaluate the effectiveness of the denoising process by grouping images based on visual similarities. This provides insights into how well the noise has been separated from the actual image content. Moreover, hypothesis testing is performed to statistically assess the noise levels and quality metrics of the denoised images in comparison to their noisy counterparts.

The contributions of this study are both significant and diverse. First, the integration of frequency and spatial domain techniques creates a hybrid approach that capitalizes on the strengths of both domains, offering an effective solution for noise reduction while maintaining critical image details. Second, applying the denoising methodology to the Alzheimer's dataset addresses the unique challenges of this complex and clinically significant dataset. Third, the introduction of K-means clustering as a tool for evaluating the denoising process provides a new perspective on image quality assessment, enhancing the reliability of the validation methods. Finally, by improving the quality of images used in Alzheimer's research, this study has the potential to significantly impact public health efforts aimed at combating Alzheimer's disease, leading to more accurate diagnoses, a better understanding of the disease, and ultimately, improved outcomes for patients.

In conclusion, this study presents a comprehensive approach to image denoising in the context of medical imaging, with a particular focus on the Alzheimer's dataset. The combination of sophisticated denoising algorithms and strict validation protocols shows how this technology can improve image quality and help improve clinical and research outcomes. The societal benefits of this work are profound, as it contributes to the ongoing fight against Alzheimer's disease by improving the tools available for its study and diagnosis.

## II. LITERATURE SURVEY

Z. Li's study [1] emphasizes the use of 2D DFT for edge detection and denoising of images, providing a detailed introduction to Fourier theory and explaining how images are converted from the spatial domain to the frequency domain for processing using high-pass and low-pass filters. A limitation of this approach is that it relies on a fixed filtering mechanism that may not adapt well to varying image characteristics, potentially resulting in a loss of important details during noise reduction.

Alexey et al. [2] introduce a 2D DFT with variable parameters (2D DFT-VP) to accelerate computations, using separability properties of one-dimensional parametric DFTs, parametric FFTs, and vector-based 2D FFT methods. This approach significantly reduces computation time, making it beneficial for fields like tomography and medical imaging. However, the primary limitation is the complexity involved in implementing variable parameters, which can complicate the algorithm and require more sophisticated computational resources.

J. Lee's work [3] explores the use of alternative filterssuch as Gaussian, Boxcar, and trigonometric filters to improvedigital image quality, as well as unconventional techniquesfor translating data back from the frequency domain into the image domain. While these filters can offer improvements in image quality, a notable drawback is that each filter type may introduce specific artifacts, such as blurring or ringing, and may not universally suit all image types. The performance of these filters heavily depends on the image's nature and the type of noise, making it difficult to generalize the approach across different image processing scenarios.

Kumari et al. [4] propose using fractional Fourier transforms (FrFT) for image denoising, employing a set of parallel filters in the FrFT domain to selectively affect certain frequency components. This approach allows for noise reduction while preserving edge sharpness, but selecting optimal filter cutoff frequencies is challenging and requires either prior knowl- edge or extensive tuning. This tuning process can be time-consuming and limits the technique's applicability in real-time or automated processing systems.

Alexey et al. [5] detail the evolution of DFTs from one-dimensional to two-dimensional transforms, focusing on the development of DFTs with variable parameters to meet the changing needs of signal processing. While this work expands the theoretical understanding of DFTs, a key limitation is that the practical implementation of these advanced transforms, especially in real-time applications, remains complex and resource-intensive.

Ponomareva et al. [6] introduce novel discrete Fourier transforms with variable parameters to reduce constraints in processing 2D signals like images. Their approach partitions the Fourier matrix into smaller sections for easier processing, helping mitigate unwanted effects and reduce computation costs. However, the new transforms' effectiveness may be limited by the specific conditions under which they are applied, such as particular types of image noise or signal characteristics.

Shafique et al. [7] developed a dynamic denoising method tailored for 2D medical images affected by periodic noise, using Fourier domain transformations and mirroring to automatically detect and correct noisy spikes. Although effective in restoring image quality, especially in ultrasound images with higher noise levels, the technique is primarily suited to periodic noise and may not effectively address other noise types, such as random or impulsive noise.

Karmakar et al. [8] explored image compression using the Fast Fourier Transform (FFT), achieving compression by discarding high-frequency components. While the method effectively reduces file size, it is highly sensitive to noise and may introduce blocking effects, which degrade image quality.

This sensitivity to noise makes it less suitable for imageswhere maintaining high fidelity is critical, such as in medical imaging or scientific analysis. The trade-off between compres-sion ratio and image quality poses a significant limitation, particularly for applications requiring both high compression efficiency and minimal distortion.

John et al. [9] present an in-depth analysis of Fourier Transform (FT) as applied to image processing, focusing on its application to signal analysis and reconstruction.

Chen et al. [10] present a Fourier Transform-based approach to image deblurring, addressing issues of motion and jitter. Although effective in tackling blur artifacts, the technique's success is heavily dependent on the accurate modeling of motion blur, which may not always be feasible in real-world scenarios where motion paths are unpredictable or complex. Nahhal et al. [11] present a fast, accurate, and separable method for fitting Gaussian functions, which significantly enhances processing speed and precision in various signal processing applications. A key limitation of this method is its sensitivity to initial parameter estimates; inaccurate starting points can lead to convergence issues or suboptimal fits.

Basu et al. [12] investigate the effects of order and cutoff frequency of Butterworth low-pass filters on ECG signal denoising. Their comparative study highlights how different configurations can effectively reduce noise in ECG signals.

Mogheer et al. [13] propose methods to reduce signal overshooting caused by cutoff frequency changes in controlled digital Butterworth low-pass filters. While the approach effectively minimizes overshooting, a significant limitation is the increased complexity of the filter control mechanism, which may complicate real-time applications or require more advanced computational resources. Soora et al. [14] explore various filtering techniques to remove noise from images, including spatial and frequency domain filters.

Huang et al. [15] develop an adaptive non-local means algorithm for image denoising that leverages both spatial and intensity information to preserve edges while reducing noise. Feng et al. [16] propose an image denoising algorithm that combines improved wavelet thresholding with non-local mean filtering to enhance noise reduction while preserving image details. Although effective, the dual filtering approach can be computationally demanding, making it less suitable for applications requiring real-time performance. Yu et al. [17] apply non-local means denoising techniques to solar images, focusing on maintaining image integrity while reducing noise.

Sridhar et al. [21] propose improved methods for noise estimation in images, which are crucial for applications in computer vision and pattern recognition. Their techniques outperform existing methods in estimating noise standard deviation, particularly in cartoon-related images. However, the approach is highly specialized and may not generalize well to other types of images or noise conditions.

# III. METHODOLOGY

Using a variety of methods, noise in photos is reduced by following the process as shown in Fig 1. Discrete Fourier Transform (DFT) is first used to convert pictures into the frequency domain. After removing high-frequency noise with a Butterworth filter, inverse DFT is used to return the pictures to the spatial domain. Non-Local Means Denoising is employed to achieve additional noise reduction. The efficiency of these techniques is assessed by using Matplotlib to visualize the data and statistically verifying the noise reduction through hypothesis testing.

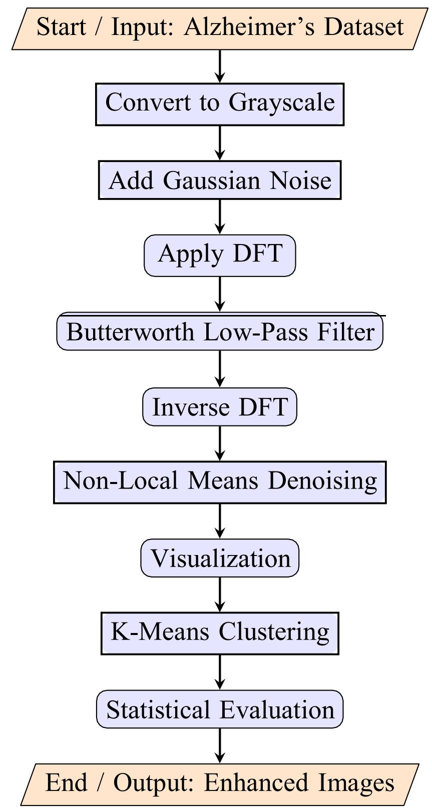


Fig. 1. Proposed Method of Image Noise Reduction

## *A. Data Preparation and Processing*

The Alzheimer's disease dataset consists of 1296 images classified into 5 groups. These images are converted to grayscale using OpenCV for consistent processing. Gaussian noise is introduced to mimic real-world conditions. The images with noise are then transformed from their original form to a different representation called the frequency domain using the Discrete Fourier Transform (DFT). This transformation helps to identify different frequency components like noiseand image features. By analyzing the magnitude spectrumof the transformed images, the intensity of each frequency component is determined, allowing for the separation of high- frequency noise from low-frequency image features.

## *B. Butterworth Low-Pass Filter for Noise Reduction*

The purpose of a Butterworth low-pass filter is to attenuate high-frequency noise components while permitting low-frequency components to flow through. The DFT image is subjected to this filter, which greatly reduces overall noise while maintaining important image details.

The image is then brought back to its original form using the inverse DFT, resulting in a less noisy reconstruction. Non-Local Means Denoising further reduces noise by averaging similar pixels while keeping important details. It compares patches in the image to find similar regions and averages them, preserving important features. This helps clean any remaining noise after applying other denoising techniques.

### *C. Non- Local Means Denoising*

Non-Local Means Denoising is a method used to further reduce noise in an image by averaging similar pixels while preserving important details. Non-Local Means Denoising operates by comparing patches in an image to find similar regions and then averaging them to reduce noise while preserving important image features. This process helps to further clean any remaining noise after applying other denoising techniques.

### *D. Visualization and Comparison*

Matplotlib helps to plot and compare the original, noisy, DFT, and final denoised images. This visual comparison makes it easier to see how well each step of denoising works.

### *E. K Means Clustering*

K-means clustering is used to group noisy and denoised images based on their visual similarities. Features are extracted using Gabor filters and Histogram of Oriented Gradients (HOG), combined into feature vectors. Images are resized, and Principal Component Analysis (PCA) reduces their dimensionality. The optimal number of clusters is determined using the Elbow Method and Silhouette Score. K-means clustering is then applied to the reduced feature vectors, and images are visualized to check if they are grouped correctly.

### *F. Statistical Evaluation*

For hypothesis testing, the noise level, measured as the standard deviation of pixel values, was compared between the original noisy images and their denoised versions. A paired t-test was conducted to determine if there was a significant difference in noise levels. Additionally, the PSNR, which assesses image quality, was calculated for each pair of noisy and denoised images. The mean PSNR was then analyzed to determine if there was a significant enhancement in image quality post-denoising.

## IV. IMPLEMENTATION

The Alzheimer's dataset images are loaded first, and Gaussian noise is added to replicate noisy environments, before denoising is applied. The noisy images are then transformed into the frequency domain using a Discrete Fourier Transform (DFT), which helps extract important characteristics while reducing noise. Next, to efficiently suppress high-frequency noise components in the DFT-transformed pictures, a Butterworth low-pass filter is built and applied. The filtered images are returned to the spatial domain after the first denoising step, producing partially denoised images. Non-Local Means Denoising (NLMD) is used to further improve the denoising process and raise the quality of the denoised images. During this procedure, different images are methodically saved into distinct folders for noisy images, DFT-transformed images, filtered images, and final denoised images as shown in Fig 2.

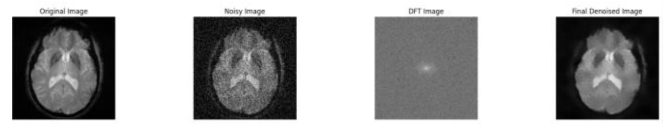


Fig. 2. Results of Image Denoising

Clustering the noisy and the denoised images into different clusters is implemented using K Means. Features from the images are extracted using Gabor filters and the Histogram of Oriented Gradients (HOG), which captures the necessary texture and edge information. Thereafter, there is the employment of several dimensionality reduction techniques, among which is the Principal Component Analysis that further smoothes the clustering process. The optimum number of clusters is calculated using the Elbow Method and Silhouette Scores,after which the feature vectors are subjected to K-means clustering for grouping of images.

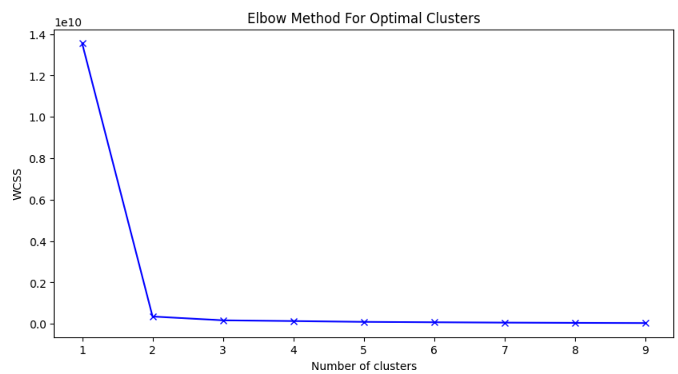


Fig. 3. Elbow Technique to find optimal number of clusters

The elbow point is typically where the curve starts to flatten. As shown in the plot 3, the elbow appears to be at k=2. This is where the rate of decrease in WCSS significantly reduces, indicating that adding more clusters beyond this point does not significantly improve the clustering.

The optimal number of clusters is typically at the highest point on the silhouette score plot. In the given plot 4, the silhouette score is highest at k=2. After k=2, the silhouette score decreases, indicating that clustering quality diminishes with more clusters.

The amount of denoising done in each image is determined by this, which is expressed by the measured standard deviation of the pixel values and so on the measure of the noise level of the noisy and the denoised image. This quantification will give an idea about the extent of noise reduction. The noise levels are analyzed statistically in order to check whether


Fig. 4. Silhouette Score to find optimal number of clusters


Fig. 5. K Means Clustering analysis

there is a reduction of very high significance in the process of denoising through the paired t test. The denoising efficiency is further checked with the quality of denoising through the computation of PSNR between the noisy and the denoised images. The noise in the image becomes smaller with the increase in the PSNR, and the denoised image is of good quality. Improvement in mean PSNR on quality after denoising is checked.

Overall, In order to reduce noise in the frequency domain, Discrete Fourier Transform (DFT) and a Butterworth low-pass filter are applied after Gaussian noise has been introduced to images from the Alzheimer's dataset. The filtered pictures are then reverted to the spatial domain, Non-Local Means Denoising (NLMD) is applied for additional refinement, and intermediate images are methodically saved for study. K-means clustering groups images into clusters according to similarity by using features that are retrieved using Gaborfilters and Histogram of Oriented Gradients (HOG). Statistical analysis, such as paired t-tests and PSNR computation, assesses the efficacy of denoising and offers insights intoreducing noise and improving image quality.

## V. RESULTS AND ANALYSIS

The denoising process effectively transformed the noisy images from the Alzheimer's dataset into clearer representations, making them easier to comprehend. Initially, Gaussian noise was introduced to replicate real-world conditions. Subsequently, noise in the frequency domain underwent reduction through the application of Discrete Fourier Transform (DFT) combined with a Butterworth low-pass filter,Inverse Discrete Fourier Transform (IDFT), Non-Local Means Denoising. That approach ensures a gradual removal of noise without compromising the fundamental features of the images.

In addition, with the capability of producing similarity within the images, K-means clustering was suitable in theseparation of the noisy and denoised images into separategroups. It was good at extracting features from the images using the Gabor filters and HOG and aggregating them to formfeature vectors.

To lower the dimensionality of the feature vectors af- ter scaling the images into a common shape, the Principal Component Analysis was used. To come up with an ideal number of clusters, the Elbow Method and the Silhouette Score were used. The images are then plotted accurately to their respective clusters following an efficient application of K-means clustering to the reduced feature vectors.

In the Fig 5 , clusters are effectively separated because of the combination of feature extraction, PCA, and K-means clustering. The K-means algorithm captures and visualizes the most significant differences in the images. The distinct clusters in the PC1-PC2 space indicate that the images within each cluster share similar characteristics, while those in different clusters have different characteristics. This process works well for distinguishing noisy images from denoised images.

The denoising technique was successful in improving image clarity, as seen by the considerable drop in noise levels between the original noisy images and the denoised ones.

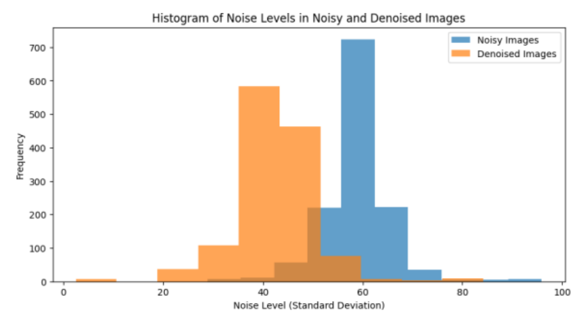


Fig. 6. Histogram of Noise levels in Noisy and Denoised Images

The histogram plotted in the figure 6 illustrates the distribution of noise levels in both the noisy and denoised images. It shows that the denoised images tend to have lower noise levels overall compared to the noisy images.

In order to verify that the image quality increased following noise removal, the Peak Signal-to-Noise Ratio (PSNR) was also measured between the pairs of noisy and denoised images.

## VI. CONCLUSION AND FUTURE SCOPE

In conclusion, the noise reduction methodology effectively improved image quality using Non-Local Means Denoising, Butterworth low-pass filtering, and Discrete Fourier Transform (DFT). Both analytical results and visual assessments confirmed a substantial decrease in noise, validating the effectiveness of the employed techniques. Cluster analysis, supported by dimensionality reduction methods like Principal Component Analysis (PCA) and evaluation techniques such as the Elbow Method and Silhouette Scores, demonstrated successful differentiation between noisy and denoised images, reflecting the method's ability to accurately categorize image states. The statistical analysis further reinforced these findings, with a t-statistic of 56.98 and a p-value of 0.0, leading to the rejection of the null hypothesis. This result indicates a significant difference in noise levels, with mean noise levels decreasing from 58.89 in noisy images to 42.29 in denoised images. Additionally, a mean Peak Signal-to-Noise Ratio (PSNR) of 27.86 supports the effectiveness of noise reduction, as higher PSNR values correspond to better image quality. Looking ahead, future work should investigate advanced denoising algorithms, including deep learning approaches, and adaptive filtering techniques to manage varying noise levels. Expanding the methodology to accommodate different types of noise and exploring real-time denoising applications could further enhance its practical applicability and robustness in real-world scenarios.

## REFERENCES


[1] Z. Li, "Analysis and Applications of 2D Discrete Fourier Trans- form in Image Denoising and Edge Detection," 2023 4th Interna- tional Conference on Computer Engineering and Intelligent Control(ICCEIC), Guangzhou, China, 2023, pp. 120-129, doi: 10.1109/ICCEIC60201.2023.10426668.

[2] P. Alexey, P. Olga and S. Natalia, "2D Discrete Fast Fourier Transform with variable parameters," 2022 24th International Conference on Digital Signal Processing and its Applications (DSPA), Moscow, Russian Federation, 2022, pp. 1-8, doi: 10.1109/DSPA53304.2022.9790753.

[3] J. Lee, "Development of Alternative Filters to Enhance the Qual- ity of Digital Images," 2023 International Conference on Modeling & E-Information Research, Artificial Learning and Digital Applica- tions (ICMERALDA), Karawang, Indonesia, 2023, pp. 122-126, doi: 10.1109/ICMERALDA60125.2023.10458204.

[4] R. Kumari and A. Mustafi, "Denoising of Images using Fractional Fourier Transform," 2022 2nd International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET), Patna, India, 2022, pp. 1-6, doi: 10.1109/ICEFEET51821.2022.9848244.

[5] P. Alexey, P. Olga and S. Natalia, "Evolution of One-Dimensionaland Two-Dimensional Discrete Fourier Transform," 2022 24th International Conference on Digital Signal Processing and its Appli- cations (DSPA), Moscow, Russian Federation, 2022, pp. 1-6, doi: 10.1109/DSPA53304.2022.9790768

[6] O. Ponomareva, A. Ponomarev and N. Smirnova, "Two-Dimensional Discrete Fourier Transform with Variable Parameter in the Spatial-Frequency Domain," 2021 23rd International Conference on Digital Signal Processing and its Applications (DSPA), Moscow, Russian Federation, 2021, pp. 1-4, doi: 10.1109/DSPA51283.2021.9535997.

[7] U. Shafique, F. Majeed, S. Naz, M. Amara, I. U. Mustafa and H. U. Zia, "Dynamic Denoising Mirroring Filter for Periodic Noise Removal from 2D Medical Images," 2023 International Conference on Energy, Power, Environment, Control, and Computing (ICEPECC), Gujrat, Pakistan, 2023, pp. 1-5, doi: 10.1109/ICEPECC57281.2023.10209516.

[8] Karmakar, Samit and Mondal, Mrinmoy and Roy, Debjit and Mitra, Soham and Paul, Pratyay and Pal, Tanmoy and Biswas, Aparna and Chakraborty, Arindam , "Image Compression and Decompression based on FFT algorithm," 2023 7th International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech), Kolkata, India, 2023, pp. 1-6, doi: 10.1109/IEMENTech60402.2023.10423491.

[9] A. M. John, K. Khanna, R. R. Prasad and L. G. Pillai, "A Review on Application of Fourier Transform in Image Restoration," 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India, 2020, pp. 389-397, doi: 10.1109/I-SMAC49090.2020.9243510.

[10] M. Chen, X. Zhang, M. Feng and W. Xing, "Image Deblurring Method Based on Fourier Transform," 2019 6th International Conference on Systems and Informatics (ICSAI), Shanghai, China, 2019, pp. 1285-1289, doi: 10.1109/ICSAI48974.2019.9010430.

[11] I. Al-Nahhal, O. A. Dobre, E. Basar, C. Moloney and S. Ikki, "A Fast, Accurate, and Separable Method for Fitting a Gaussian Function [Tips & Tricks]," in IEEE Signal Processing Magazine, vol. 36, no. 6, pp. 157-163, Nov. 2019, doi: 10.1109/MSP.2019.2927685.

[12] S. Basu and S. Mamud, "Comparative Study on the Effect of Order and Cut off Frequency of Butterworth Low Pass Filter for Removal of Noise in ECG Signal," 2020 IEEE 1st International Conference for Convergence in Engineering (ICCE), Kolkata, India, 2020, pp. 156-160, doi: 10.1109/ICCE50343.2020.9290646.

[13] H. S. Mogheer and I. I. Turulin, "Reduction of Signal Over-shooting Caused by Cutoff Frequency Changing in the Controlled Digital Butterworth Low Pass Filter," 2022 International Confer- ence on Industrial Engineering, Applications and Manufacturing (ICIEAM), Sochi, Russian Federation, 2022, pp. 783-788, doi: 10.1109/ICIEAM54945.2022.9787099.

[14] N. R. Soora, S. Vodithala and J. S. H. Badam, "Filtering Tech- niques to remove Noises from an Image," 2022 International Con- ference on Advances in Computing, Communication and Applied In- formatics (ACCAI), Chennai, India, 2022, pp. 1-9, doi: 10.1109/ACCAI53970.2022.9752476.

[15] Z. Huang, D. Li, Y. Feng, X. Jiang and L. Wang, "An Adaptive Non Local Means Image Denoising Algorithm," 2020 IEEE 5th International Conference on Signal and Image Processing (ICSIP), Nanjing, China, 2020, pp. 169-174, doi: 10.1109/ICSIP49896.2020.9339453.

[16] L. Feng and J. Wang, "Research on Image Denoising Algorithm Based on Improved Wavelet Threshold and Non-local Mean Filtering," 2021 IEEE 6th International Conference on Signal and Image Pro- cessing (ICSIP), Nanjing, China, 2021, pp. 493-497, doi: 10.1109/ICSIP52628.2021.9688900.

[17] L. Yu and S. Feng, "Solar Image Denoising Using Non-Local Means Method," 2023 International Conference on Computer Science and Automation Technology (CSAT), Shanghai, China, 2023, pp. 593-597, doi: 10.1109/CSAT61646.2023.00159.

[18] Y. Wei, C. Niu, H. Wang and D. Liu, "The Hyperspectral Image Clustering Based on Spatial Information and Spectral Clustering," 2019 IEEE 4th International Conference on Signal and Image Process- ing (ICSIP), Wuxi, China, 2019, pp. 127-131, doi: 10.1109/SIPROCESS.2019.8868487.

[19] P.Santhi, G.Mahalakshmi, "K-MEANS Clustering Algorithm Combined With Nearest Neighbor Classification And Binary Search Tree Data Structures For Heart Disease Diagnosis", Paideuma Journal of Research, Vol.12, No.12, 2019. (IF:1.07)

[20] L. Thanmayi A. V., Reddy, S. Dharahas, and Dr. Sreeja Kochuvila, "Detection of Leukemia using K-means Clustering and Machine Learning", in 4th EAI International Conference on Ubiquitous Communications and Network Computing (UBICNET), Department of ECE, Amrita School of Engineering, Bengaluru., 2021.

[21] P. Sridhar and Sathiya, R. R., "Noise standard deviation estimation for additive white gaussian noise corrupted images using SVD domain", International Journal of Innovative Technology and Exploring Engineering (IJITEE),vol.8,2019.

[22] Surekha Paneerselvam and Ramakotti, Raksha, "A Deep Learning Implementation of End-to-End Image Denoising Steganography Model." In Proceedings of Third International Conference on Communication, Computing and Electronics Systems, pp. 139-151. Springer, Singapore,2022.

[23] H.Gupta, H. Singh, A. Kumar and L.K. Balyan, "Pixel Corrected Adaptive Conductance Function based Diffusion Filter and Image Denoising using Bi-dimensional Empirical Mode Decomposition" IEEE International Conference on Control, Automation, Power and Signal Processing, Jabalpur, India,pp.1-5,2021.

[24] H. Singh, S.V.R. Kommuri, A. Kumar and V Bajaj, "A newtechnique for Guided Filter based Image Denoising using Mod- ified Cuckoo Search Optimization,"Expert Systems With Applications(Elsevier),vol.176, 114884, 2021 [Impact Factor:8.5]

[25] Pramod C. P., Pillai G. N. (2021), K-Means clustering based Extreme Learning ANFIS with improved interpretability for regression problems. Knowledge-Based Systems.