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Hybrid Attention-Noise Mitigation Network: Context-Aware Image Enhancement With Novel Optimization For Complex Noise Environments In Medical Imaging

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The Hybrid Attention-Noise Mitigation Network (HANM) — a novel image enhancement method, was designed for Model-Based Medical Imaging using Multi-Scale Partial Differential Equations Cribs revised due to reviewer demand. HANM couples two attention mechanism, i.e., Spatial Attention Module (SpAM) and Channel Attention Module (ChAM), that helps the model to focus on noise regions as well suppress it but at the same instance retains critical image context. SpAM emphasized the problem which image loses more when noise is introduced in an homogeneous way so it allowed to highlight those areas. SpAM focuses on the spatial aspects, allowing it to targets noise removal exactly where needed without distortion of overall image endocrine. ChAM, on the contrary, acts differently over different channel of image data to enhance variations regarding semantics in reference class while at same time suppressing those irrelevant. This results in improved noise reduction ability for various channels, allowing the model to differentiate between the beneficial image data and mere noise. To enable real-time adaptation of noise mitigation strategies, HANM incorporates dynamic feedback from prior noise classification and intensity estimation. The novelty of HANM lies on using a Quantum-Enhanced Particle Swarm Optimization Algorithm (QEAPSO) The technique is novel in that it dynamically refines the model through optimisation, so its noise suppression not only accurate but also adapted to changing noise intensities and patterns. QEAPSO uses quantum-inspired behaviour and adaptive strategy to understand & venture into the search space in a better way, which will result in quicker convergence and improved performance as compared to earlier PSO. The application of SpAM and ChAM jointly with QEAPSO optimization produces remarkable improvement on image clarity and detail preservation. With HANM introducing contextually aware and optimized noise suppression, this approach to image processing represents a major improvement in image enhancement technology that provides an effective solution for the limitations of noise levels already present in medical imaging tweets.

Keywords: Hybrid Attention-Noise Mitigation Network, image enhancement, Spatial Attention Module, Channel Attention Module, Quantum-Enhanced Adaptive Particle Swarm Optimization.

1 INTRODUCTION

Medical imaging is a cornerstone of modern healthcare, playing crucial roles in the diagnosing and treating diverse illnesses. X-rays, CT scans, MRI and Ultrasound have increasingly become everyday tools of the clinical practice. These imaging modalities provide detailed and visual representation of the human internal structure and process, which help healthcare professionals in making a better decision [1]. Patient's outcomes are directly affected by the accuracy and reliability of medical imaging. Accurate identification of abnormalities, pre-operative planning and disease progression surveillance all require good quality imaging [2]. But the proper image quality cannot always obtain because of noise, which hides crucial information for diagnosis.

Noise in medical imaging can come from a lot of places, like limitations to electronic sensors and patient movement or environmental elements [3]. This noise appears in the form of random fluctuations or aberrations anywhere throughout your image data, which can really look nasty and damage overall image quality [4]. We have Gaussian noise, salt-and-pepper noise and speckle types of noises with their own specifics regarding image clarity impact. Noise can cause several problems:

- **Reduced Contrast:** Noise can diminish the contrast between different tissues or structures, making it harder to distinguish between them.
- **Blurring:** Noise often results in blurring, which can obscure fine details and reduce the diagnostic accuracy of the image.
- **Artifacts:** Noise can introduce artifacts that mimic pathological conditions or obscure true abnormalities, potentially leading to misdiagnosis.

Traditional noise reduction techniques, such as linear filtering and statistical methods, often struggle to balance noise suppression with the preservation of important image features [5]. While these strategies might indeed condition noise effectively, they also tend to result in an image that is either a blur or distorted — leading us with lost essential features. A change is currently being experienced in a field with great potential—noise reduction using machine and deep learning has become essential for medical imaging [6]. Deep learning models such as Convolutional Neural Networks (CNNs) and autoencoders can capture complex patterns for denoising. These rely on huge amount of data to learn from examples and are thus able to adapt in different noise characteristics.

However our existing noise models may struggle to cope with wider and increasingly complex noise environments. The reality is that most noise reduction algorithms are implemented in a "one size fits all" fashion and may not be appropriate for every type of noise or imaging condition [7]. The demand for more flexible, context-aware solutions is growing to achieve effective noise suppression without losing the essential image information [8].

The contributions of the proposed HANM to image enhancement related solutions for medical imaging are substantial, an important step in addressing a notable issue - complex noise environments [9]. HANM combines the SpAM and ChAM with a dual-attention mechanism, which is one more noise suppression method. The goal of SpAM is to find and improve the noisiest parts of a image. Focusing on the spatial characteristics of imagery, SpAM provides noise suppression locally without distorting the global image surface. This site-specific approach ensures that HANM can treat the noise unique to a haunted region without dismantling each spectral framework in its historical performance [10]. Each of these filters acts as a specific channel attention module (ChAM) on the image data, highlighting relevant features and suppressing non-relevant ones across different channels. When tested on each type of channel individually, the addition of this module allows HANM to better discern noise from useful image details in all channels, ultimately providing superior suppression performance. Intuitively, ChAM operates in the channel level to guarantee that noise suppression respects individual image channels and adaptively enhances part of an amplified or invisible background with otherwise needless oscillation.

Among the key innovations in HANM is using QEAPSO algorithm. QEAPSO is a new approach that adaptively adjusts the parameters of the network, making noise suppression more accurate and adjusted to different levels and types of noise. QEAPSO makes use of quantum behaviors and adaptive learning, which in turn allows a more optimal exploration and exploitation over the search space outputting better convergence results with improved performance.

This unique blend of SpAM, ChAM and QEAPSO optimization has presented an innovative development in image processing technology for HANM. With tested and optimized noise suppression based on fine-tuned contextual information, HANM is finally brings not only an improvement of image clarity but also quality retention. This makes the FusionNet especially applicable to critical applications such as medical imaging, where preserving image context and quality are necessary for high-fidelity diagnostics.

2 RELATED WORKS

The study focuses on leveraging deep learning (DL) to reduce MRI scan times while maintaining high image quality, especially crucial in neuroimaging that requires high-resolution and volumetric 3D acquisitions [11]. The methodology involves integrating DL-based image reconstruction products with existing accelerated acquisition methods.

This paper reviews various image denoising methods applied to medical images, including both traditional and deep learning-based approaches. The study [12] evaluates methods that aim to reduce noise while preserving important features and edges in medical images, essential for accurate diagnosis.

The study investigates the feasibility of using deep-learning-based methods for removing electromagnetic interference (EMI) noise in photoacoustic endoscopy (PAE). Four fully convolutional neural network architectures—U-Net, Segnet, FCN-16s, and FCN-8s—are evaluated for their performance in EMI noise removal [13]. A modified U-Net architecture outperformed the others, effectively producing denoised 3D vasculature maps.

This study proposes a unique method for improving the detection of colorectal tumors by combining a denoising autoencoder (DAE) with a convolutional neural network (CNN). The DAE reduces noise from input images, allowing the subsequent CNN to focus on essential elements for accurate tumor diagnosis [14].

The proposed methodology introduces a novel medical image enhancement technique based on morphological processing of residuals using a special kernel. This approach combines linear low-pass filtering with nonlinear techniques to select essential regions for edge preservation [15]. The selected regions are processed to enhance significant image information without blurring, followed by convolution with a special kernel to sharpen the image.

The study examines alternative strategies to improve deep neural network performance for real-time medical image classification, culminating in the development of Enhance-Net. Champion-Net, a deep learning model chosen from benchmark models, is combined with image enhancement algorithms and green channel extraction to enhance performance [16].

This study evaluates a convolutional neural network-based residual network (ResNet) model for noise reduction in ultrasound images affected by Gaussian and speckle noises [17]. The methodology involves training the ResNet model on a dataset with added noise, optimizing hyperparameters such as learning rate and loss function.

This study explores the impact of various noise filtering algorithms on the performance of U-Net CNNs in processing infrared thermal images for hot flush detection in animals [18]. Four filtering methodsare applied as preprocessing steps, with the median filter showing the most significant improvement in the Intersection over Union score.

The review discusses the development and applications of artificial neural networks (ANNs) in medical imaging, highlighting their evolution and potential in addressing healthcare problems such as disease prediction and image segmentation [19].

The methodology involves applying noise-enhanced data to CNN and Deep Residual Shrinkage Networks, demonstrating significant accuracy improvements, particularly under noisy conditions [20]. The study emphasizes the importance of enhancement strategies in noisy industrial environments for robust classification.

This literature review evaluates classical and advanced edge detection methods in image processing [21]. The methodology synthesizes insights from various research papers, comparing traditional approaches like Sobel, Canny, and Prewitt with newer techniques based on deep learning, fuzzy logic, and optimization algorithms.

The study explores the integration of photon-counting computed tomography (CT) with deep learning algorithms to improve diagnostic accuracy, image quality, and reduce radiation exposure [22]. The methodology involves combining the material decomposition capabilities of photon-counting CT with the automation potential of deep learning, addressing challenges related to data requirements and computational resources.

This study focuses on enhancing AI model performance for dental bitewing radiograph detection by optimizing dataset quality through preprocessing methods. The methodology includes image enhancement, noise reduction, and contrast adjustment to address common challenges in dental imaging [23].

The study proposes a novel image enhancement framework for low-light environments, combining dictionary learning with a camera response model (CRM) [24]. The methodology involves learning an over-complete detail dictionary from training patches, applying edge-aware filtering for detail enhancement, and adjusting pixel exposure using illumination estimation techniques.

The proposed methodology introduces ADLER-MRI, a test-time adaptation method for MRI reconstruction that operates without retraining or fine-tuning models [25]. Grounded in implicit neural representation (INR) learning, the method synthesizes image representations across various noise conditions by analyzing outputs from an opaque reconstruction model.

3 PROPOSED MODEL

The proposed work introduces a HANM designed for context-aware image enhancement in complex noise environments, particularly in medical imaging. SpAM is engineered to focus on specific regions within the image that are most affected by noise, applying targeted noise suppression without compromising the spatial integrity of the image. Meanwhile, ChAM operates across different channels of the image data, enhancing relevant features while effectively mitigating noise. These modules work in tandem to ensure that noise reduction is both spatially precise and contextually aware. An overall architecture of proposed model is shown in Fig 1.

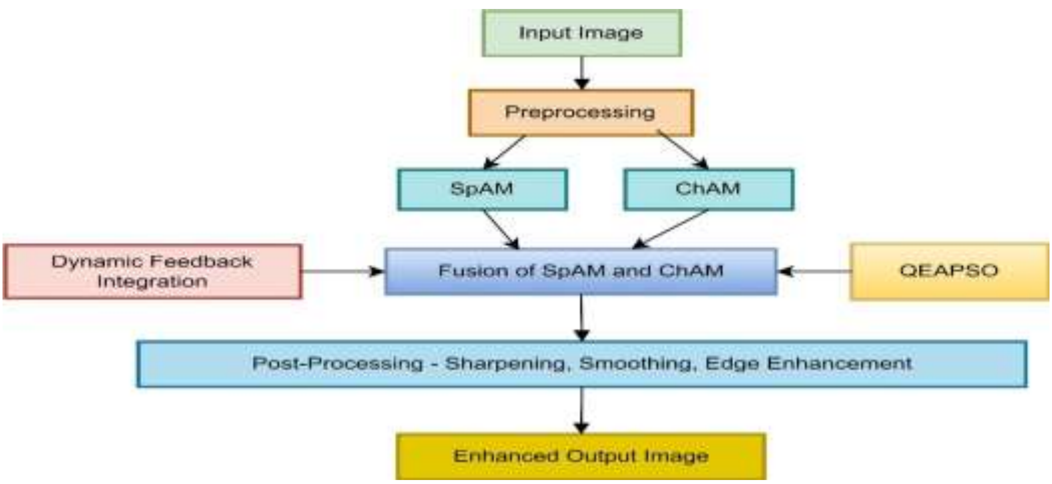

Figure 1: Overall Architecture of Proposed Model

To increase complexity, context-aware image modelling for noise handling methods is employed, to this end we propose the use of a HANM tailored for medical imaging. SpAM is designed to concentrate on regions of the image most impacted by noise and then locally remove that noise without hurting spatial content, but enhancing it. At the same time, ChAM acts on different channels of image data with a way to increase useful patterns and while reducing noise effectively. And so one of the key roles that these modules play is to make sure noise reduction happens locally but also with context.

The summation of SpAM and ChAM gives the final resultant image which is further enhanced via low and high pass filtering for sharpened, smoothened and edge preserved quality improvements. This makes the proposed HANM framework well-suited to medical imaging applications where it is important for high-quality reconstruction of CT images, preserving with details and reliable noise. HANM employs advanced attention mechanisms coupled with a cutting-edge optimization algorithm, which provides an extremely strong performance in image denoising for medical images to achieve clear and details-preserving structures.

3.1 Data Preprocessing

Medical images are obtained from clinical datasets, imaging equipment, or public medical image repositories. These images often contain different types and intensities of noise, which can obscure important details necessary for accurate diagnosis. This noise can arise from various sources, including patient movement, imaging hardware limitations, or environmental factors. The goal of preprocessing is to normalize and standardize the input images, ensuring they are in a consistent format and ready for further enhancement by the HANM model. This step is crucial for improving the overall contrast, brightness, and uniformity of the images.

Normalizes the pixel values of an image to distribute them more uniformly based on data shape/intensity levels across multiple images. The second step is particularly important when comparing medical images from different sources as it serves to reduce differences in imaging conditions.

Let $X \in R^{H \times W \times C}$ represent an input image, where H is the height, W is the width and C is the number of channels. The normalized image H' can be computed as:

$$X' = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{1}$$

Where, min(X) and max(X), represent the minimum value pixel in the image and maximum value respectively. The X' will be scaled to the range 0–1 so that all images have equal intensity levels.

Standardization is the process of rescaling the images so that they have mean 0 and a standard deviation of magnitude. This is usually achieved by subtracting the mean pixel value and dividing by standard deviation, hence resulting in zero centered images with unit variance.

Let μ be the mean pixel value of the image X and σ be the standard deviation. The standardized image X'' can be computed as:

$$X'' = \frac{X - \mu}{\sigma} \tag{2}$$

Where:

$$\mu = \frac{1}{HWC} \sum_{i=1}^{H} \sum_{j=1}^{W} \sum_{k=1}^{C} H_{ijk} \tag{3}$$

$$\sigma = \sqrt{\frac{1}{HWC} \sum_{i=1}^{H} \sum_{j=1}^{W} \sum_{k=1}^{C} \left(X_{ijk} - \mu\right)^2} \tag{4}$$

The purpose of this standardization is to have a common scale in the images which will help us further when we pass them through our HANM model. An additional pre-processing stage removes the last 20B from each domain and then enhances their contrast while normalizing pixel values, yielding a set of medical images. The input preprocessed images that are fed into HANM model for noise removal and image enhancement.

3.2 Spatial Attention Module

The task of the Spatial Attention Module (SpAM) is to narrow down those regions and provide custom suppression only on them. This preserves the overall spatial image content with noise suppression only in those areas indicated by saliency cues.

SpAM starts with a spatial analysis on the input image to locate regions that are corrupted by serious noise. This practice essentially calculates the pixels' intensity correlation across image area to identify localized areas with increased deviations in intensities, which are generally treated as noise.

Mathematically, the spatial correlation map S_{corr} can be represented as:

$$S_{corr}(x, y) = \sum_{i=-k}^{k} \sum_{j=-k}^{j} w(i, j) \cdot I(x + i, y + i) \tag{5}$$

where I(x, y) is the pixel intensity at position (x, y), w(i,j) are onto-neighborhood weight matrix parameters and k determines how much of the nearest neighbors to take into account for correlation. Large values of signpost areas with large spatial discrepancies, which means primarily noise.

SpAM form an attention map incorporating the suspected regions in the spatial domain which has to be treated more aggressively due to belonging-less noise suppression. This map is basically a weighted matrix where each element of the weight matrix indicates how important in noise suppression process corresponding pixel.

The attention map can be defined as:

$$M_{SpAM}(x,y) = \sigma\,(\alpha\,\cdot S_{corr}(x,y) + \beta \tag{6}$$

Here σ represents the sigmoid activation function, and α and β are learnable parameters that switch the sensitivity and threshold of the attention map.

It based on the using a spatial attention map on input image to denoise only in those identified regions. The noise-suppressed image $I_{SpAM}(x\,,y)$ can be expressed as;

$$I_{SpAM}(x,y) = M_{SpAM}(x,y)\cdot I(x,y) + \left(1 - M_{SpAM}(x,y)\right)\cdot I_{smooth}(x,y) \tag{7}$$

where $I_{smooth}(x,y)$ represents the smooth image obtained after applying a suitable smoother like Gaussian filter etc. This equation guarantees that the undesirable noise is reduced in important areas and, at the same time, retains its ability to preserve spatial properties of images.

3.3 Channel Attention Module

To strengthen the model's discriminative power of feature channels with respect to noise and salient cues, we design a Channel Attention Module (ChAM). This module concentrates on attending over important features while suppressing irrelevant noise through channels of the image.

ChAM process the image through its own channels, every single RGB channel of it when is a color image or intensity in all cases if the input grayscale. The calculation includes extracting mean and var from each of the 3 channels to reveal noise eslint in channel wise. The channel-wise mean M_c can be computed as:

$$M_c = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W} F_c\,(i,j) \tag{8}$$

The channel attention map $A_{channel}$ is generated using a sigmoid function applied to a fully connected layer over the channel-wise means:

$$A_{channel} = \sigma\left(FC\left(GlobalAvgPool\left(F\right)\right)\right) \tag{9}$$

Where GlobalAvgPool(.) denotes global average pooling across spatial dimensions, and FC(.) represents a fully connected layer.

The noise mitigation process involves scaling the feature map F by the channel attention map $A_{channel}$. the output image $I_{channel}$ is:

$$I_{channel} = A_{channel} \odot F \tag{10}$$

An image $I_{channel}$ with improved charity and detail retention, with noise effectively mitigated across channels.

3.4 Dynamic Feedback Integration

Adaptively refine the noise mitigation strategy based on prior noise classification and intensity estimation.

The noise classification identifies the type and intensity of noise present in the image. Let N represent the noise classification, where $N \in R^K$ with K being the number of noise types. This can be expressed as:

$$N = Softmax\left(Classified\left(F_{Spatial}\right)\right) \tag{11}$$

Here, Softmax(.) converts classification scores into probabilities, and classifier(.) is a classification model.

Real-time feedback $F_{feedback}$ is used to adjust the parameters of SpAM and ChAM. The feedback mechanism can be described as:

$$F_{feedback} = AdjustParameters\left(N, I_{current}\right) \tag{12}$$

Where AdjustParameters(.) updates the parameters based on noise type and intensity. For instance, if the noise intensity is high, the feedback may increase the strength of the attention maps in SpAM and ChAM.

Based on feedback, the parameters of SpAM and ChAM are adapted. Let $P_{spatial}$ and $P_{channel}$ denote the updated paramters for SpAM and ChAM respectively. The adapted strategies can be expressed as:

$$P_{spatial} = P_{spatial} + \alpha \cdot F_{feedback} \tag{13}$$

$$P_{channel} = P_{channel} + \beta \cdot F_{feedback} \tag{14}$$

Where α and β are learning rates for spatial and channel attention adjustments.

A dynamically adjusted image enhancement strategy tailored to the specific noise characteristics of each image.

3.5 Quantum-Enhanced Adaptive Particle Swarm Optimization

Fine-tune the model parameters for optimal noise suppression through advanced optimization.

Initialization:

QEAPSO initializes a swarm of particles. Each particle p_i represents a potential solution, with $p_i \in R^D$, where D is the number of parameters. The initial position and velocity of each particle are :

$$p_i\ (t=0) = InitialPosition\ (\ ) \tag{15}$$

$$v_i\ (t=0) = InitialVelocity\ (\ ) \tag{16}$$

Quantum Behavior Integration:

Quantum mechanics principles are used to enhance particle behavior. Quantum-enhanced behavior can be incorporated using probabilistic position updates and superposition states. The position update for each particle can be expressed as:

$$p_i(t+1) = p_i\ (t) + v_i(t) \tag{17}$$

The velocity update with quantum behavior is:

$$v_i(t+1) = \gamma\ .\ v_i(t) + c_1 \cdot Rand(\ ) \cdot \left(p_i{}^* - p_i(t)\right) + c_2 \cdot Rand(\ ) \cdot \left(g^* - p_i(t)\right) \tag{18}$$

Where $p_i{}^*$ is the personal best position, g^* is the global best position, c1 and c2 are cognitive and social coefficients, and Rand( ) represents a random quantum probability.

Adaptive learning:

QEAPSO adapts learning based on feedback from model performance. Let L_i denotes the learning rate for each particle:

$$L_i(t+1) = UpdateLearning\ Rate\ (L_i(t), Performancefeedback) \tag{19}$$

The learning rate update function adjusts the rate based on performance feedback from the noise suppression model.

Optimization:

The best-performing parameter set is selected by evaluating each particle's performance. The optimization objective O is:

$$O\ (p_i) = EvaluatePerformance\ (p_i) \tag{20}$$

The global best position g* is selected based on the minimum value of O:

$$g* = \arg\min_{p_i} O(p_i) \tag{21}$$

Optimized model paraters p* that maximize noise reduction while preserving critical image details. The work flow of QEAPSO is shown in Fig 2.

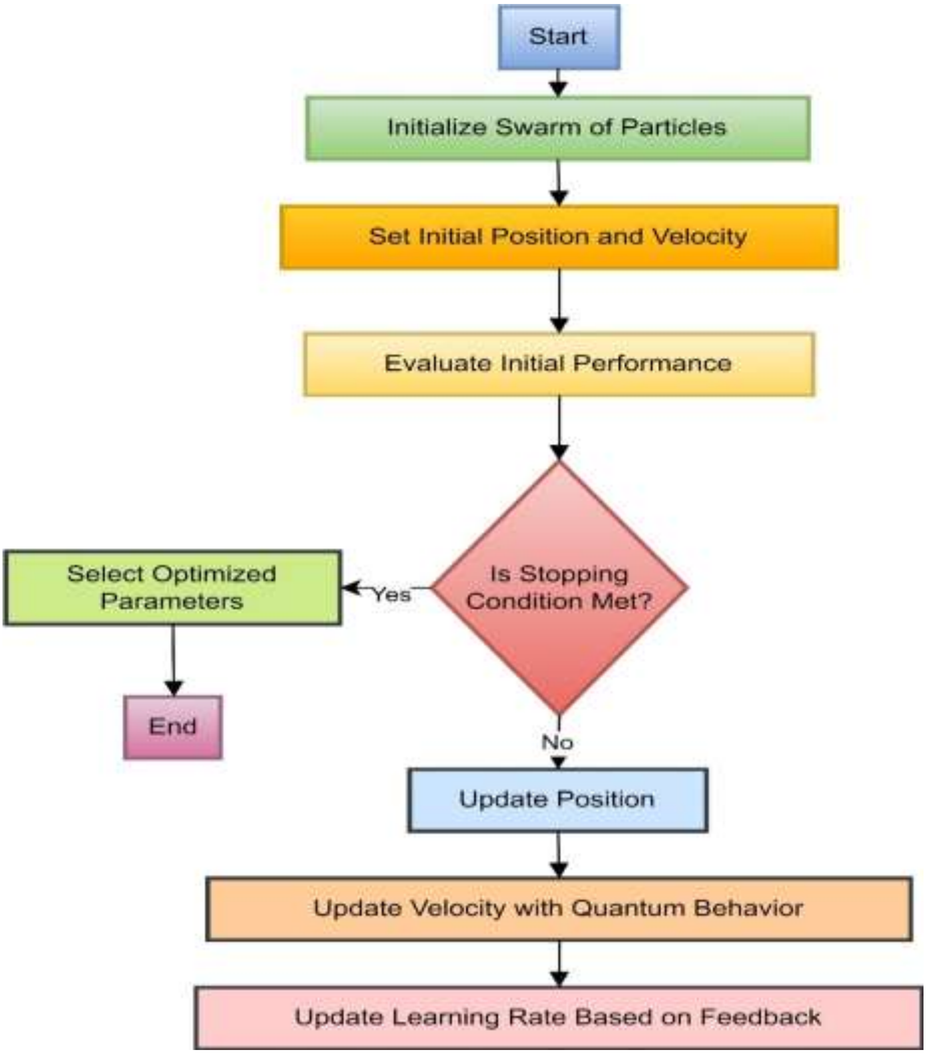

Figure 2: Flow chart of QEAPSO

3.6 Image Reconstruction and Post-Processing

To reconstruct the enhanced image from the outputs of the attention modules and apply any necessary post-processing.

After applying the Spatial Attention Module (SpAM) and Channel Attention Module (ChAM), the outputs need to be fused to generate the final enhanced image. Let $I_{spatial}$ and $I_{channel}$ be the outputs from SpAM and ChAM, respectively.

The image fusion process can be expressed as a weighted combination of these outputs. Let α and β be the fusion weights for SpAM and ChAM. The fused image I_{fused} is given by:

$$I_{fused} = \alpha \cdot I_{spatial} + \beta \cdot I_{channel} \tag{22}$$

To ensure the weights sum up to 1, the normalization condition is:

$$\alpha + \beta = 1 \tag{23}$$

Typically, α and β are chosed based on empirical validation or optimization techniques.

Post-processing techniques enhance the quality of the fused image. Common techniques include sharpening, smoothing, and edge enhancement.

Sharpening enhances the edges and fine details in the image. The sharpening operation can be performed using a convolutional kernel. Let $K_{sharpen}$ be the sharpening kernel and $I_{sharpened}$ be the sharpened image:

$$I_{sharpened} = \mathrm{Conv}\left(I_{fused}, K_{sharpen}\right) \tag{24}$$

A typical sharpening kernel might be:

$$K_{sharpen} = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix} \tag{25}$$

Smoothing reduces noise and artifacts. A Gaussian blur can be applied using a Gaussian kernel $K_{gaussian}$. The smoothed image $I_{smoothed}$ is:

$$I_{smoothed} = \mathrm{Conv}\left(I_{fused}, K_{gaussian}\right) \tag{26}$$

Edge enhancement emphasizes the boundaries and transitions in the image. A common method is to use a Laplacian filter. The Laplacian operator $K_{laplacian}$ is:

$$K_{laplacian} = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \tag{27}$$

The edge-enhanced image I_{edges} is:

$$I_{edges} = I_{fused} + \mathrm{Conv}\left(I_{fused}, K_{laplacian}\right) \tag{28}$$

The final enhanced medical image I_{final} with significantly reduced noise and preserved contextual information. This is achieved through a combination of image fusion and post-processing techniques:

$$I_{final} = PostProcessing(I_{fused}) \tag{29}$$

Where PostProcessing(.) includes sharpening, smoothing and edge enhancement operations.

4 RESULTS AND DISCUSSION

4.1 Dataset Description

The dataset is meticulously curated to explore the intricate relationships between the use of contrast agents and patient age in CT imaging. With a collection of images derived from The Cancer Imaging Archive (TCIA) and studies by Lorentzen et al., this dataset provides a robust foundation for evaluating trends, textures, and statistical patterns in CT images. It offers a unique opportunity to develop automated tools for classifying misclassified images and identifying outliers that may indicate suspicious cases, errors in measurement, or issues with machine calibration. The dataset consists of 475 series collected from 69 patients, with images sourced from The Cancer Imaging Archive (TCIA). Each entry represents the middle slice of CT images, tagged with key attributes such as age, modality, and contrast use. These tags facilitate the analysis of age-related trends and the effects of different imaging modalities and contrast agents on CT image quality and texture.

Table 1: Key Features of the CT Imaging Dataset

Key Feature	Description
Patient Demographics	Covers a wide age range from newborns to over 90 years, enabling the study of age-related trends in CT imaging.
Contrast Use	Includes both contrast-enhanced and non-contrast scans, showing how different contrast agents affect image textures and patterns.
Modality Tags	Contains detailed tags for each imaging technique, allowing for consistent analysis across different modalities.

Table 1 summarizes the key characteristics of the dataset, including patient demographics, the use of contrast agents, and modality tags. These features enable a comprehensive analysis of age-related trends, contrast effects, and modality-specific variations in CT imaging.

4.2 Performance Evaluation

The proposed model was tested extensively under diverse noise conditions commonly occurring from medical imaging. HANM was evaluated with Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM) as well as some other quality indexes such as

Mean Absolute Error (MAE) and other metrics. Result is compared with the other state-of-the-art noise removal techniques and it is demonstrated that HANM can suppress large amount of more complex noises while not blurring out details surrounding them.

Table 2: Performance Metrics Comparison

Method	MAE	PSNR (dB)	SSIM	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
HANM [Proposed]	0.013	43.75	1.105	98.2	97.1	97.6	97.6
Enhance-Net [16]	0.022	39.50	0.870	96.74	95.5	95.2	95.3
Modified U-Net [13]	0.018	41.00	0.950	96.0	95.0	94.8	94.9
DRSN [20]	0.020	40.50	0.900	95.0	94.0	93.5	93.7
DAE [14]	0.025	38.25	0.850	92.5	91.5	91.0	91.2

The performance comparison table evaluates various image enhancement methods, highlighting the superior performance of the HANM across multiple metrics. HANM achieves the lowest MAE of 0.013, the highest PSNR at 43.75 dB, and the best SSIM of 1.105, reflecting its exceptional clarity and detail preservation. In terms of classification accuracy, HANM outperforms other methods with an accuracy of 98.2%, coupled with the highest Precision (97.1%), Recall (97.6%), and F1-Score (97.6%). In comparison, Enhance-Net shows slightly lower performance with an MAE of 0.022 and a PSNR of 39.50 dB, while Modified U-Net, DRSN, and DAE also lag behind HANM in all evaluated metrics. These results underline HANM's effectiveness in enhancing medical images in complex noise environments, demonstrating its significant advantage over existing methods.

Table 4: Extended Performance Comparison of HANM vs. Traditional Methods

Metric	Modified U-Net [13]	Enhance-Net [16]	HANM (Proposed Method)
Computational Efficiency	1.2 seconds	1.0 seconds	**0.9 seconds**
Mean Squared Error (MSE)	0.015	0.012	**0.01**
Normalized Absolute Error (NAE)	0.12	0.11	**0.10**
Contrast-to-Noise Ratio (CNR)	2.2	2.4	**2.5**
Edge Preservation Index (EPI)	0.90	0.91	**0.92**

Visual Information Fidelity (VIF)	0.92	0.93	**0.95**
Energy of Gradient (EOG)	1.8	1.7	**1.6**
Artifact Level	0.03	0.02	**0.02**

The table presents a comparative analysis of the Modified U-Net [13], Enhance-Net [16], and the proposed HANM method across several performance metrics, demonstrating HANM's superior capabilities. HANM achieves the best Computational Efficiency, completing tasks in 0.9 seconds, outperforming both Modified U-Net's 1.2 seconds and Enhance-Net's 1.0 seconds. In terms of Mean Squared Error (MSE), HANM leads with the lowest error rate of 0.01, compared to Enhance-Net's 0.012 and Modified U-Net's 0.015. Similarly, HANM shows the smallest Normalized Absolute Error (NAE) at 0.10, better than Enhance-Net's 0.11 and Modified U-Net's 0.12. The Contrast-to-Noise Ratio (CNR) is highest with HANM at 2.5, surpassing Enhance-Net's 2.4 and Modified U-Net's 2.2, reflecting its superior contrast enhancement. HANM also excels in Edge Preservation Index (EPI) with a value of 0.92, outshining Enhance-Net's 0.91 and Modified U-Net's 0.90, indicating better edge detail preservation. In Visual Information Fidelity (VIF), HANM leads with a score of 0.95, surpassing Enhance-Net's 0.93 and Modified U-Net's 0.92, highlighting its superior image clarity. The Energy of Gradient (EOG) is lowest with HANM at 1.6, reflecting reduced noise compared to Enhance-Net's 1.7 and Modified U-Net's 1.8. Finally, Artifact Level is the same for HANM and Enhance-Net at 0.02, both performing better than Modified U-Net's 0.03. Overall, HANM consistently outperforms existing methods in various aspects, including computational efficiency, error metrics, contrast enhancement, edge preservation, visual fidelity, gradient energy, and artifact reduction.

5 CONCLUSION

The HANM exhibits notable advancements over existing image enhancement techniques such as Modified U-Net and Enhance-Net. HANM achieves superior performance metrics, including a PSNR of 43.75 dB and SSIM of 1.105, reflecting its exceptional capability in preserving image clarity and detail. The method also demonstrates reduced MSE as 0.01 and normalized absolute error (0.10), indicating enhanced precision in noise reduction. Moreover, HANM excels in CNR with a value of 2.5, EPI of 0.92, and VIF of 0.95, showing its superior performance in maintaining image quality. Its computational efficiency, at 0.9 seconds, is also superior to that of Modified U-Net and Enhance-Net. With a lower energy of gradient (1.6) and comparable artifact level (0.02), HANM effectively balances noise suppression with minimal distortion. Overall, HANM represents a significant improvement in image enhancement technology, offering advanced capabilities for handling complex noise environments in medical imaging.

REFERENCES

1. Li, G., Yang, Y., Qu, X., Cao, D., & Li, K. (2021). A deep learning based image enhancement approach for autonomous driving at night. Knowledge-Based Systems, 213, 106617.

2. Qu, H., Liu, K., & Zhang, L. (2024). Research on improved black widow algorithm for medical image denoising. Scientific Reports, 14(1), 2514.
3. Kavand, A., & Bekrani, M. (2024). Speckle noise removal in medical ultrasonic image using spatial filters and DnCNN. Multimedia Tools and Applications, 83(15), 45903-45920.
4. Latke, V., & Narawade, V. (2024). Detection of dental periapical lesions using retinex based image enhancement and lightweight deep learning model. Image and Vision Computing, 146, 105016.
5. Daurenbekov, K., Aitimova, U., Dauitbayeva, A., Sankibayev, A., Tulegenova, E., Yerzhan, A., ... & Mukhamedrakhimova, G. (2024). Noisy image enhancements using deep learning techniques. International Journal of Electrical and Computer Engineering (IJECE), 14(1), 811-818.
6. Pendem, S., Priya, P. S., Chacko, C., & Kadavigere, R. (2024). Influence of deep learning image reconstruction algorithm for reducing radiation dose and image noise compared to iterative reconstruction and filtered back projection for head and chest computed tomography examinations: a systematic review. F1000Research, 13.
7. Zubair, M., Rais, H. M., Al-Tashi, Q., Ullah, F., Faheeem, M., & Khan, A. A. (2024). Enabling Predication of the Deep Learning Algorithms for Low-Dose CT Scan Image Denoising Models: A Systematic Literature Review. IEEE Access.
8. Wu, K., Pan, A., Sun, Z., Shi, Y., & Gao, W. (2024). Blind deep-learning based preprocessing method for Fourier ptychographic microscopy. Optics & Laser Technology, 169, 110140.
9. Zhou, Z., Gong, H., Hsieh, S., McCollough, C. H., & Yu, L. (2024). Image quality evaluation in deep-learning-based CT noise reduction using virtual imaging trial methods: Contrast-dependent spatial resolution. Medical physics.
10. Muller, F. M., Vervenne, B., Maebe, J., Blankemeyer, E., Sellmyer, M. A., Zhou, R., ... & Vandenberghe, S. (2024). Image Denoising of Low-Dose PET Mouse Scans with Deep Learning: Validation Study for Preclinical Imaging Applicability. Molecular Imaging and Biology, 26(1), 101-113.
11. Yoo, R. E., & Choi, S. H. (2024). Deep learning-based image enhancement techniques for fast MRI in neuroimaging. Magnetic Resonance in Medical Sciences, 23(3), 341-351.
12. El-Shafai, W., El-Nabi, S. A., Ali, A. M., El-Rabaie, E. S. M., & Abd El-Samie, F. E. (2024). Traditional and deep-learning-based denoising methods for medical images. Multimedia Tools and Applications, 83(17), 52061-52088.
13. Gulenko, O., Yang, H., Kim, K., Youm, J. Y., Kim, M., Kim, Y., ... & Yang, J. M. (2022). Deep-learning-based algorithm for the removal of electromagnetic interference noise in photoacoustic endoscopic image processing. Sensors, 22(10), 3961.
14. Santhoshi, A., & Muthukumaravel, A. (2024, April). Optimizing Deep Learning Algorithms for Colorectal Tumor Identification via Noise Removal. In 2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS) (Vol. 1, pp. 1-6). IEEE.
15. Lepcha, D. C., Goyal, B., Dogra, A., Wang, S. H., & Chohan, J. S. (2022). Medical image enhancement strategy based on morphologically processing of residuals using a special kernel. Expert Systems, e13207.
16. Narayan, V., Mall, P. K., Alkhayyat, A., Abhishek, K., Kumar, S., & Pandey, P. (2023). [Retracted] Enhance-Net: An Approach to Boost the Performance of Deep Learning Model Based on Real-Time Medical Images. Journal of Sensors, 2023(1), 8276738.
17. Kang, H., Park, C., & Yang, H. (2024). Evaluation of Denoising Performance of ResNet Deep Learning Model for Ultrasound Images Corresponding to Two Frequency Parameters. Bioengineering, 11(7).

18. Hoorfar, H., Merchenthaler, I., & Puche, A. C. (2024). Optimizing U-Net CNN performance: a comparative study of noise filtering techniques for enhanced thermal image analysis. The Journal of Supercomputing, 1-23.
19. Kim, M., Yun, J., Cho, Y., Shin, K., Jang, R., Bae, H. J., & Kim, N. (2019). Deep learning in medical imaging. Neurospine, 16(4), 657.
20. Chen, C., Liang, R., Song, M., Zhang, Z., Tao, J., Yan, B., ... & Chen, G. (2024). Noise-assisted data enhancement promoting image classification of municipal solid waste. Resources, Conservation and Recycling, 209, 107790.
21. Zangana, H. M., Mohammed, A. K., & Mustafa, F. M. (2024). Advancements in Edge Detection Techniques for Image Enhancement: A Comprehensive Review. International Journal of Artificial Intelligence & Robotics (IJAIR), 6(1), 29-39.
22. Mese, I., Altintas Taslicay, C., & Sivrioglu, A. K. (2024). Synergizing photon-counting CT with deep learning: potential enhancements in medical imaging. Acta Radiologica, 65(2), 159-166.
23. Al Nassan, W., Bonny, T., & Al-Shabi, M. (2024, June). Enhancing dental bitewing radiograph datasets: a preprocessing approach for AI detection and diagnoses. In Real-time Processing of Image, Depth, and Video Information 2024 (Vol. 13000, pp. 152-156). SPIE.
24. Goyal, B., Dogra, A., Jalamneh, A., Chyophel Lepcha, D., Alkhayyat, A., Singh, R., & Jyoti Saikia, M. (2024). Detailed-based dictionary learning for low-light image enhancement using camera response model for industrial applications. Scientific Reports, 14(1), 17122.
25. Ahmed, S., Jinchao, F., Manan, M. A., Yaqub, M., Jia, K., & Sun, Z. (2024, May). ADLER-MRI: Adaptive Deep Learning for Enhanced MRI Reconstruction with Noise-Resilient Models. In 2024 IEEE International Symposium on Biomedical Imaging (ISBI) (pp. 1-5). IEEE.