APTISI Transactions on Technopreneurship (ATT)
Vol. 7, No. 3, November 2025, pp. 713−725
E-ISSN: 2656-8888 | P-ISSN: 2655-8807, DOI:10.34306

Technopreneurial Filtering Technique for Speckle Noise Reduction in Ultrasound Imaging of Polycystic Ovary Syndrome

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Article Info

Article history:

Submission June 15, 2025
Revised July 4, 2025
Accepted September 7, 2025
Published September 24, 2025

Keywords:

Attention Module
Speckle Noise
Noise Reduction
Polycystic Ovary Syndrome

ABSTRACT

Polycystic Ovary Syndrome (PCOS) is a common endocrine disorder in women that is frequently diagnosed by ultrasound imaging by examining ovarian abnormality. Ultrasound images, though, are normally contaminated with speckle noise that degrades image quality and poses difficulties for diagnosis. **Conventional denoising methods** like mean and median filtering are unable to eliminate noise properly while maintaining fine details. To solve this problem, this paper introduces a new Attention-based Autoencoder (AAE) for denoising PCOS ultrasound images. The model uses an attention mechanism to selectively amplify significant image areas and suppress noise, enhancing image quality for diagnosis. The introduced method was tested on a publicly available ultrasound dataset with synthetic speckle noise at various levels (variance 0.5, 0.02, and 0.001). Experimental results prove that the suggested method performs better than conventional denoising methods, with peak signal-to-noise ratio (PSNR) values of 31.33, 34.25, and 36.23, respectively. The structural similarity index measure (SSIM) also reveals notable improvements and corresponding scores of 85.21, 92.33, and 99.25. Beyond technical performance, this work supports the development of scalable, AI-driven PCOS diagnostic tools within a technopreneurship incubator model. These **results** indicate that AAEs can improve ultrasound image quality, facilitating more accurate PCOS diagnosis.

DOI: https://doi.org/10.34306/att.v7i3.767

1. INTRODUCTION

The World Health Organization (WHO) reports that Polycystic Ovary Syndrome (PCOS) affects around 8–13% of women around the world, making it a common health problem for women [1, 2]. There are different symptoms that occur during PCOS, such as trouble getting pregnant, irregular periods, and excess hair growth, etc. This is caused by small cysts in the ovaries, high testosterone levels, and insulin problems, which can disrupt normal ovulation and overall health. It also affects other health-related conditions and causes different diseases like heart disease, diabetes, and some types of cancer. So early identification of this disease is mainly mandatory to prevent severe complications [3, 4].

For effective detection of this disease, all depends upon various methods such as blood tests, patient physical body examinations, Magnetic Resonance Imaging (MRI), and ultrasound methods. Among all these, ultrasound methods have become more popular for their non-invasive nature and accurately detecting key components from ovaries. But many times, these images are prone to different types of noise, such as shadow, Gaussian, and speckle noise, which can make it challenging to accurately identify the disease from ovarian ultrasound images [5–7]. By the shadow noise, it looks like dark areas that block certain regions of the data. In contrast, Gaussian noise compromised the clarity of the image due to its blurry effect, and lastly, speckle noise creates a smaller pattern of noise, which makes it difficult to differentiate small structures like cysts from noise. These interferences lead to lowering the performance of the predicting models [8].

In recent years, many methods have been proposed for filtering ultrasound images, such as mean, median, Gaussian, and adaptive filtering [9]. Although these methods remove the noise, they also remove important features from the image, and these methods face difficulties in high levels of noise scenarios. As these methods are heavily based on their parameters like kernel function, filter types, number of levels, etc., which leads to difficulty removing noise from the image effectively [10–12]. The Gaussian-based filtering method is often used for smoothing the image, and sometimes it removes important components from the image, and adaptive filtering is not so much used in practical applications as it does not effectively utilize higher-order statistics from the input data. So, these methods have their own limitations, which affect the effectiveness of filtering the ultrasound image accurately [13–16]. Also, another researchers [17] suggested a self-supervised approach for eliminating noise from the ultrasound image.

There is a need for scalable, intelligent solutions that can improve medical imaging pipelines due to the expanding convergence of AI and healthcare innovation, particularly under the purview of technopreneurship incubator models [18]. This goal is supported by the proposed work, which provides a flexible framework that can be incorporated into clinical decision-support tools and diagnostic startup ecosystems.

This paper addresses these problems that occur in the current methods by proposing an Attention-based Autoencoder (AAE) framework [19, 20]. This framework effectively eliminates noise by preserving the essential features of images. In this, the model is trained with different noise levels, which makes it more robust and generalized in the context of noise elimination from ultrasound images. In this, the attention module gives flexibility to pay attention to the most relevant features during noise elimination, which makes the denoised version of the image more useful. The primary objective of this research is to develop an AAE for denoising PCOS ultrasound images, ensuring improved image quality and diagnostic accuracy. The key goals of this study are [21, 22]:

- Develop an autoencoder framework with attention mechanisms to effectively remove speckle noise from PCOS ultrasound images [23].
- Ensure that critical anatomical features, such as ovarian cysts and follicular structures, remain intact after noise removal [24].
- Assess the proposed model's robustness by applying synthetic speckle noise at different variance levels (0.5, 0.02, and 0.001) and comparing results with traditional denoising methods [25].

The rest of this paper is organized as follows: Section 2. presents a recent study on different filtering techniques. Section 3. details the methodology, including the proposed method. Section 4. discusses the experimental results of denoising models. Finally, Section 6. offers concluding remarks on the paper's findings.

2. LITERATURE REVIEW

Research on PCOS ultrasound images often focuses more on classification than on noise elimination [26]. However, noise, particularly speckle noise, is a significant issue in ultrasound imaging, and few studies have tackled this specific challenge [27–29]. Many recent studies only focus on additive Gaussian noise, but for speckle noise, there are few studies. There are many studies that define a new novel method to denoise the ultrasound images [30]. For additive noise, developed the Non-Local Means (NLM) filtering method [31], which is widely used for additive noise removal in MRI and CT imaging. While NLM is effective for Gaussian noise, it struggles with speckle noise due to its different statistical properties. Consequently, various NLM adaptations [32, 33] have emerged to better target speckle noise. Another study [34] proposed refining NLM weights within a low-dimensional PCA subspace for improved speckle reduction. Although this strategy enhances noise targeting, PCA's processing complexity may limit its efficiency in real-time applications.

The Optimized Bayesian Non-Local Means (OBNLM) filter [35] was invented to tackle patch similarity in noisy conditions. This method uses a Bayesian framework for improving patch matching by replacing the traditional Euclidean distance with a Pearson distance. Although its effectiveness, this technique is computationally demanding for high-resolution photos. [36] introduced a hybrid methodology that fused local statistical characteristics and NLM. This strategy tries to enhance accuracy in difficult noise situations by integrating local and global information. However, integrating numerous details may inadvertently increase the risk of over-smoothing intricate visual elements. Another studied non-local Total Variation (TV) method utilizing NLM to address nonlinear noise. In contrast to traditional television approaches, these non-local television methods enhance retention of image attributes. Nonetheless, television systems occasionally fail to accurately capture intricate details in textured regions, perhaps leading to the omission of sensitive characteristics [37, 38].

[39] introduced an intelligent classification approach for ovarian detection that integrates texture and intensity characteristics. They used autocorrelation, and sum variance from the Grey-Level Co-Occurrence Matrix (GLCM), along with intensity from k-means clustering, to train a backpropagation neural network for detecting ovarian issues. Despite its potential, the method's dependence on manually crafted characteristics restricts its applicability to alternative ultrasound scenarios. [40] concentrated on generating noise-free photos by customizing filters for particular noise categories. A median filter was employed for salt-and-pepper noise, while an adaptive Wiener filter was utilized for Gaussian noise, resulting in significant enhancements in Mean Squared Error (MSE). However, this method might not work well in situations with different types of noise mixed together, and needing to manually identify the types of noise could make it harder to use automatically. [41] used OBNLM filtering with Convolutional Neural Networks (CNNs) to eliminate noise from ultrasound pictures. Here, the OBNLM filter first cleans the image, and the CNN further refines the denoising, offering effective denoising. However, using two distinct models (OBNLM and CNN) may increase computational demands, impacting real-time applications. [42] used the Two-Dimensional Fractional Fourier Transform (2D-FrFT) to denoise ultrasound images. To optimize a parameter, they employed a transfer learning-based VGG-16 model. While this method targets specific artifact types and adapts to various noise angles, [42] study tested the model on only 10 images, limiting generalizability and raising concerns about real-world scalability. Some recent studies [43, 44] focused on mobile application in medical image analysis for more convenience. [43] developed mobile application called Halodoc enhancing patient-doctor consultations while ensuring data privacy and efficiency. Whereas [44] explored gradient centralization in conjunction for enhanced performance.

Recent studies [44–47] focused on technopreneurial innovation in the healthcare sector. The developments in healthcare [45–47] suggested the technopreneurial innovation through AI involvement to enhance healthcare quality and sustainability and emphasized the importance of entrepreneurship for business growth. Whereas [47, 48] suggested business models and stakeholder roles for digital health entrepreneurship and emphasized the need to understand the industry's business strategies and regulatory environment.

3. MATERIALS AND METHODS

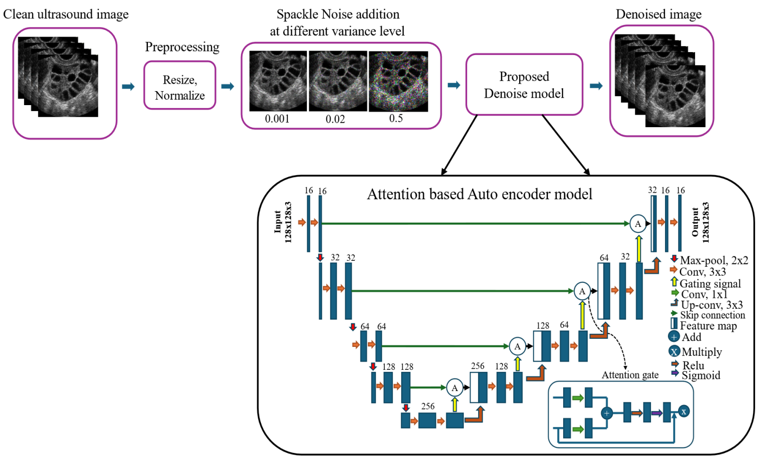

Figure 1. Block Diagram of Proposed Denoise Method

In the above Figure 1 shows the block diagram of the proposed denoised model. Here the ultrasound images are first pre-processed to maintain consistency, and after that, the speckle noise is added with different levels (0.001, 0.02, and 0.5) to demonstrate the proposed method's performance. After that, the noisy image is input to the proposed denoising model. The proposed method preserves relevant details for a precise diagnosis by producing a denoised image with less speckle noise. The attention mechanism of this architecture, which is detailed in the block, allows the model to prioritize important features, improving its denoising performance at various noise levels. Each step is explained in detail in the following subsections [49, 50].

3.1. Dataset Description and Noise Addition

A publicly accessible dataset of ultrasound images associated with PCOS was used in this paper. The dataset includes 3,856 samples in total, each of which represents ultrasound images taken for PCOS analysis and diagnosis. These photos offer vital visual information that helps detect cysts and other anomalies linked to illness. Machine learning and image processing tasks benefit greatly from the dataset's diversity, which includes a wide range of patient profiles and variations in PCOS manifestation.

Even though the original ultrasound image dataset is clean, synthetic speckle noise was added for this study to mimic real-world imperfections and improve the model's resilience. Different noise intensities were produced by adding speckle noise, a granular noise frequently seen in medical ultrasound imaging, at different variance levels. For the suggested model to successfully remove noise from the photos, this step was essential for training. Applying the model to real-world noisy ultrasound images allowed it to generalize better because it was exposed to a wide range of scenarios through the simulation of noise at varying intensities. A mathematical representation of the addition of speckle noise to a clear ultrasound image X is as follows:

$$X_{\text{noisy}} = X + X \odot N \tag{1}$$

Where X_{noisy} is the noisy image, X is the clean image, $N \sim \mathcal{N}(0, \sigma^2)$ is the noise matrix sampled from a Gaussian distribution with mean 0 and σ^2, and $\odot$ represents element-wise multiplication. The variance σ^2 is varied to simulate different levels of noise intensity, enabling the model to handle diverse noise conditions. The Figure 2 below illustrates a clean ultrasound image alongside versions with varying levels of added noise.

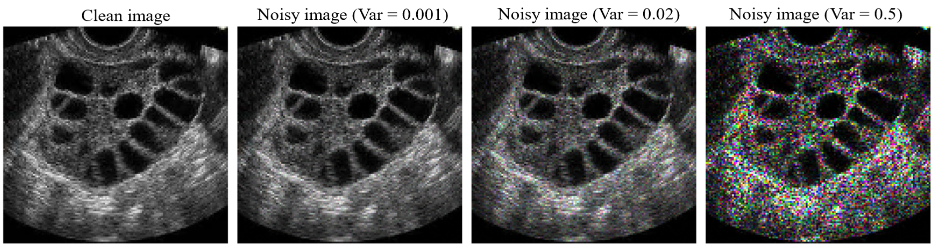

Figure 2. Clean Ultrasound with Noise Image with Varying Levels of Variance

3.2. Pre-Processing

In this, different preprocessing techniques are employed to enhance the quality of the image before inputting it into the proposed method. As the image size varies so to make constant take a uniform size (128128x3) for every image. To bring all image values in certain ranges, we used normalization techniques. also used image smoothing to remove small artifacts while maintaining important features to improve performance. By enhancing the consistency and quality of the input data, these procedures optimize the deep learning model's performance.

3.3. Filtering Method

To effectively eliminate noise from the ultrasound images, we employed an AAE as our filtering method. Autoencoders contain mainly two parts: an encoder that converts the input image into a low-dimensional latent space and a decoder that reconstructs the image from this latent representation. In our case, we extended this architecture by integrating an attention mechanism, allowing the model to focus on the most relevant features in the image, thereby improving noise removal performance.

The attention mechanism plays a crucial role in enhancing the performance of the proposed AAE by selectively focusing on important image regions while suppressing noise. Traditional autoencoders compress the input into a latent representation and reconstruct the image, but they often fail to differentiate between important structures (e.g., ovarian cysts) and unwanted noise patterns (e.g., speckle noise). To address this issue, an attention gate network is incorporated, which dynamically adjusts the feature representation by highlighting relevant information and down-weighing less significant regions.

Mathematically, for a given input image $X_{\text{noisy}} \in \mathbb{R}^{h \times w}$, where h and w represent the height and width of the noisy image, the encoder function $f_{\text{encoder}}(\cdot)$ projects X_{noisy} into a latent space $Z \in \mathbb{R}^{h' \times w' \times d}$, where the number of channels is represented by d, and h', w' are the dimensions of the compressed representation. This can be represented as:

$$Z = f_{\text{encoder}}(X_{\text{noisy}}) \tag{2}$$

Next, the attention mechanism computes an attention map $A \in \mathbb{R}^{h' \times w' \times d}$, which assigns weights to different regions of the latent space. The attention map is derived as:

$$A = \sigma(W_a \cdot Z + b_b) \tag{3}$$

Where W_a and b_b are learnable weights and biases of the attention network, and $\sigma(\cdot)$ represents the softmax function, ensuring that the attention weights sum to 1 across spatial dimensions, emphasizing the most important regions of the feature map. The attention map is then applied elementwise to the latent representation Z using the Hadamard product (element-wise multiplication):

$$\tilde{Z} = A \odot Z \tag{4}$$

Here, $\tilde{Z} \in \mathbb{R}^{h' \times w' \times d}$ is the attended latent representation, which retains important features while down-weighting noise. This attended latent space is then passed to the decoder $f_{\text{decoder}}(\cdot)$ to reconstruct the denoised image $\hat{X}$:

$$\hat{X} = f_{\text{decoder}}(\tilde{Z}) \tag{5}$$

The objective is to minimize the difference between the original clean image X and the reconstructed denoised image $\hat{X}$. The loss function used to train the model is the mean squared error (MSE) between the clean image and the denoised image, defined as:

$$L_{mse} = \frac{1}{n} \sum_{i=1}^{n} (X_i - \hat{X}_i)^2 \tag{6}$$

After that, to enhance the attention mechanism's ability to focus on relevant regions of the image, we introduce an attention regularization term. This term penalizes the attention map when it becomes overly diffuse, ensuring that the model focuses on the most critical areas. The regularization is based on the L1 norm of the attention map, defined as:

$$L_{att} = \frac{1}{n} \sum_{i=1}^{n} \|A_i\|_1 \tag{7}$$

Where $\|A_i\|_1$ is the L1 norm of the attention map for the i-th sample, encouraging sparsity in the attention weights. The final loss function used to train the model combines the reconstruction loss (mean squared error) and the attention regularization:

$$L = L_{mse} + \lambda L_{att} \tag{8}$$

In here, λ is a hyperparameter of regularization that governs the trade-off between the reconstruction of the clean image and the sparsity of the attention map. The autoencoder with attention is trained to minimize this compound loss, learning to remove noise from ultrasound images, preserving relevant anatomical structures while eliminating real and synthetic speckle noise. This is a significant contribution to our work since the regularization-driven attention mechanism enables the model to better separate noise from informative features, leading to improved denoising. The attention mechanism of the proposed AAE model is improving the denoising ability of PCOS ultrasound images by selectively enhancing notable areas of images and suppressing noise. Unlike traditional filtering methods where uniform noise removal is enforced globally on the entire image, attention adapts the network to selectively concentrate on diagnostically significant areas such as ovarian cysts and follicular patterns while resisting the speckle noise minimally. Through this selective attention, it ensures that such critical anatomical data is properly retained to prevent being lost from the fine structures needed in a correct PCOS diagnosis. Further, through dynamic feature weighing with the attention gate network, the model learns to differentiate noise from useful patterns and is hence less likely to over-smooth. This results in higher image sharpness and improved diagnostic readability. Furthermore, the attention mechanism enhances the model's generalizability by being able to handle different levels of noise efficiently and thus being trustworthy under different imaging conditions.

3.4. Approach to Denoising Raw PCOS Images

In this case, an AAE model is utilized for the denoising of ultrasound images. With the help of the attention mechanism, the model can effectively remove the noise while preserving the important features, which are helpful for PCOS detection. Compared to existing methods, these methods allow the use of adaptively learning the noise pattern to improve denoising for images. Subsequently, the various steps are elucidated for noise removal:

- Step 1: Firstly, collect all the ultrasound images and perform some preprocessing operations, namely smoothing, normalization, and resizing, to help make the images clearer and better visuals. Then, speckle noise, at several different levels, is added to the database for further evaluation.
- Step 2: After this, these noisy images are entered into the proposed model to begin the training. Since the model is exposed to several different noise levels, the model can learn to separate noise from useful features in the image.
- Step 3: Utilize attention to obtain the important parts of the image for feature extraction to enhance the noise filtering while keeping the important details.
- Step 4: To measure how effectively the image has been denoised, this paper compares it with state-of-the-art methods, using quality measures such as the Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR).

4. RESULT AND DISCUSSION

This section describes the experimental procedure, including dataset preparation, noise addition, model training, and evaluation using various performance metrics, along with a comparative analysis of results.

4.1. Experimental Setup

This research assesses the performance of a particular denoising technique against a publicly available dataset of 3,356 PCOS ultrasound images. These images contain speckle noise at three levels: 0.001, 0.02, and 0.5. The dataset consists of 2,685 training images and 671 testing images. Training the model on each specific noise level makes the model more robust to various kinds of noise. Such a strategy methodically evaluates the model's performance with regard to removing noise and correctly identifying data at different noise levels to confirm good performance in practical scenarios.

4.2. System and Hyperparameter Specifications

The model was trained on an Intel® Xeon® Silver 4216 CPU, 128 GB RAM, and Nvidia® RTX A4000 GPU with 16 GB VRAM. A loss function, Mean Squared Error (MSE), was used, and an optimizer function to train the denoise model was Adaptive Moment Estimation (Adam), which utilizes momentum and adaptive learning rate for faster convergence. The batch size is set at 64, and the learning rate is 0.0001 to strike an equilibrium between stability and efficiency. The model was trained on 2,000 epochs so that the model learns from the noise dataset and adjusts to different noise levels, which improves generalization for real-world scenarios. The proposed model tuning process for ultrasound image denoising was configured with specific performance parameters, resulting in optimal performance during the tuning process. The model was trained with an input and output size of 128x128x3. A learning rate of [0.01, 0.001, 0.00005] was initially used to find the most stable setting.

Higher learning rates, such as 0.01, led to unstable convergence, while excessively low values, such as 0.00005, resulted in slow learning. The chosen learning rate of 0.001 ensured smooth and stable convergence. For the optimizer, three options SGD, RMSprop, and Adam were evaluated. SGD led to slow convergence and difficulty escaping local minimums, while RMSprop exhibited fluctuating validation loss. Adam was selected as the final optimizer due to his ability to balance momentum and adaptive learning rates, leading to stable and efficient training. Batch size selection involved testing 32 and 64, where smaller batch sizes introduced high variance, while larger batch sizes increased memory consumption and slowed convergence. The optimal batch size of 64 offered the best balance between stability and training efficiency. Regarding the number of epochs, the model was initially trained for 2000 epochs, with performance monitored throughout. Loss stabilization was observed after 1500 epochs, indicating potential for early stopping around 1800 epochs in practical applications. These hyperparameter choices were made to ensure the model effectively removed noise while preserving key anatomical structures in ultrasound images.

4.3. Performance Evaluation Metrics

In this paper two useful matrices are used to evaluate the model performance: PSNR and SSIM. PSNR provides a quantitative evaluation of image quality following denoising by calculating the relationship between the maximum power of an image and the power of corrupting noise. It is computed as:

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{9}$$

Where MAX_I^2 is the maximum pixel value, and MSE represents the Mean Squared Error between the denoised and clean ultrasound images. A high PSNR value gives better denoising performance and closer to the original image.

SSIM, on the other hand, evaluates structural similarity between images by considering luminance, contrast, and structural information. It ranges from -1 to 1, with values closer to 1 indicating higher similarity. The SSIM is given by:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{10}$$

Where μ_x and μ_y are the means, σ_x^2 and σ_y^2 are variances, σ_{xy} is the covariance of images x and y, while C_1 and C_2 are constants. Together PSNR and SSIM provide a comprehensive evaluation of the denoising models' performance in preserving image fidelity and structural details.

4.4. Experimental Results for Denoising

The proposed attention model was applied to noisy ultrasound images, effectively producing denoised outputs. This approach, illustrated in Figure 3, was quantitatively assessed using PSNR and SSIM, with results detailed in Table 1. The model's performance was compared against five state-of-the-art denoising techniques, including mean filter, Laplacian filter, bilateral filter, two-stage image denoising, and the OBNLM filter. Each method contributes unique noise-reduction characteristics: the mean filter averages pixel values for smoothing, the Laplacian filter enhances edges, and the bilateral filter preserves edges while removing noise. The Two-Stage Image Denoising method employs Discrete Wavelet Transform (DWT) for decomposing and thresholding wavelets, with noise patterns classified through a neural network to apply adaptive filters. The OBNLM filter, combined with a CNN, efficiently removes speckle noise, yielding a refined, denoised output. Together, these methods provide a comprehensive framework for denoising ultrasound images.

Table 1. Performance Evaluation of Proposed Denoise Method with State of Art Methods.

	Performance after denoise					
Performance before denoise	0.5		0.02		0.001	
Performance metric	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Mean filter [39]	28.31	15.63	28.40	45.91	28.52	54.28
Laplacian filter [40]	28.35	18.23	28.49	55.25	28.46	60.80
Bilateral [35]	29.32	30.23	29.65	60.25	29.74	72.19
Two-Stage Denoising [42]	29.35	48.52	29.72	67.32	29.83	78.54
OBNLM Filter [41]	29.40	60.80	30.98	88.24	31.22	89.76
Proposed Method	**31.33**	**85.21**	**34.25**	**92.33**	**36.23**	**99.25**

The above Table 1 compares the denoising performance of various methods across different noise variance levels (0.5, 0.02, and 0.001) using PSNR and SSIM metrics. At a high variance level of 0.5, the proposed method achieves a PSNR of 31.33, which is significantly higher than other methods, with a 7% improvement over the second bilateral filter (29.32 PSNR). At a lower variance of 0.02, the proposed method reaches a PSNR of 34.25 and an SSIM of 92.33, showing a 7.5% PSNR improvement over the next-best OBNLM filter (30.98 PSNR). For the lowest noise variance (0.001), the proposed method yields a PSNR of 36.23 and an impressive SSIM of 99.25, indicating a major SSIM enhancement compared to the OBNLM filter, which achieved 89.76 SSIM.

The proposed method gives better results as it uses an AAE structure, which effectively identifies and preserves fine image details while focusing on regions needing denoising. In contrast, traditional methods such as the mean and Laplacian filters struggle due to their simplistic operations; the mean filter blurs important details by averaging pixel values, while the Laplacian filter, designed primarily for edge detection, amplifies noise. The bilateral filter maintains edges reasonably well but cannot handle high noise levels as effectively. The two-stage image denoising approach often over-smooths, sacrificing detail for noise reduction. Unlike these methods, the proposed AAE adaptively enhances image quality, demonstrating clear advantages across all tested noise levels.

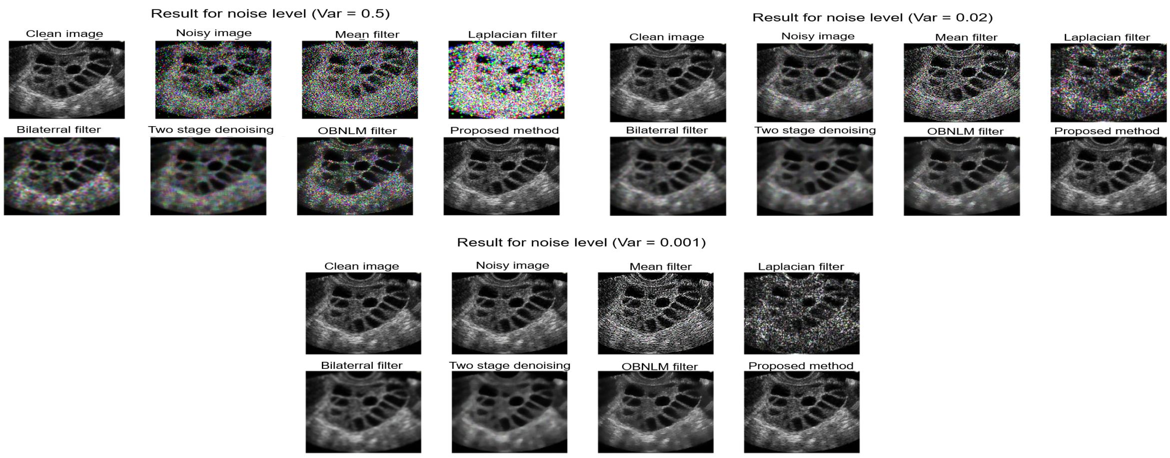

Figure 3. Qualitative Result of Denoise Ultrasound Image on Varying Noise Levels

The above Figure 3 shows the performance of various denoising methods on an ultrasound image with different noise variances levels: 0.5, 0.02, and 0.001. At the highest noise level (variance = 0.5), the noisy image is extremely grainy, making it challenging to discern structural details. While some filters like the mean and bilateral filters manage to reduce noise, they often blur essential features. The Laplacian filter emphasizes edges but fails to address noise effectively at this high level. The OBNLM filter and the two-stage image denoising approach achieve moderate noise reduction, but only the proposed method effectively removes most of the noise while preserving image details, resulting in the clearest output in this challenging noise condition.

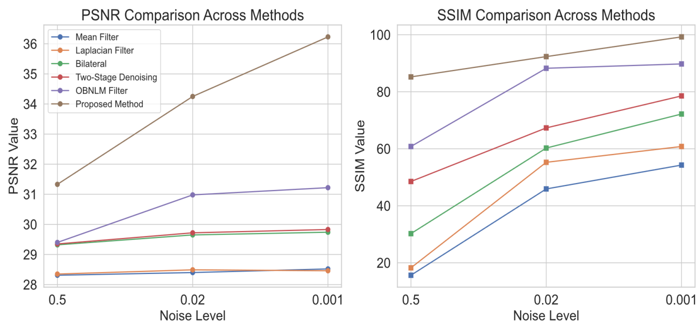

Figure 4. Line chart Comparison of Denoising Methods Based on PSNR and SSIM Across Different Noise Levels

As the noise variance decreases to 0.02 and then 0.001, all methods show improved results, with more structural details becoming visible in the images. At variance 0.02, filters like the OBNLM and bilateral filters maintain more clarity while reducing noise, but minor artifacts or blurring persist. By the time the noise is minimal (variance = 0.001), the denoising methods produce images that are quite close to the original. The proposed method continues to outperform others across all levels of noise, consistently delivering the cleanest images with the highest structural fidelity, indicating its robustness and adaptability across different noise conditions.

The above Figure 4 compares the performance of various image denoising methods at different noise levels, showing their effectiveness in terms of PSNR on the left and SSIM on the right. In both plots, the horizontal axis represents noise levels, with lower values indicating less noise, and the vertical axis represents PSNR and SSIM values, respectively. Higher PSNR and SSIM values mean better image quality after denoising. The Proposed Method outperforms the others across all noise levels, achieving the highest PSNR and SSIM values, indicating it preserves image quality better than traditional methods like the Mean Filter, Laplacian Filter, Bilateral Filter, Two-Stage Denoising, and OBNLM Filter. The other methods show moderate improvements as noise levels decrease, but they are generally less effective than the Proposed Method.

The below Figure 5 illustrates the performance of various denoising techniques on various levels of noise. There is an axis for each noise level (0.5, 0.02, and 0.001), with the higher value on each axis representing improved performance in retaining image quality upon denoising. The Proposed Method performs better than other methods for all levels of noise, in terms of both PSNR and SSIM, as indicated by its broader spread towards the corners of the chart. There are other techniques, including the Mean Filter, Laplacian Filter, Bilateral Filter, Two-Stage Denoising, and OBNLM Filter, with lesser spreads, revealing lower PSNR and SSIM values and hence less efficient denoising. The radar chart clearly demonstrates superior performance of the Proposed Method in achieving both structural similarity and signal-to-noise ratio for various intensities of noise.

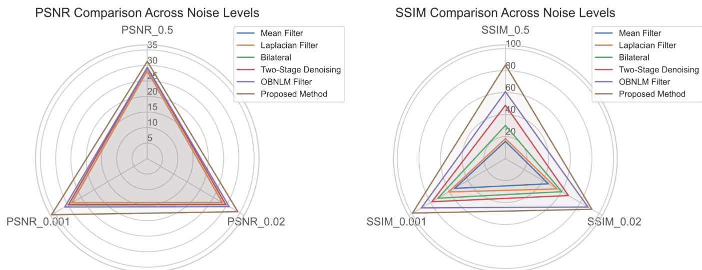

Figure 5. Radar Chart Comparing Denoising Methods Based on PSNR and SSIM Across Different Noise Levels

4.5. Discussion

This paper presents an AAE model for PCOS ultrasound image denoising that performs well across noise levels. Despite promising quantitative and qualitative outcomes, the model has numerous drawbacks. First, the dataset uses synthetic speckle noise rather than clinical noise, which may limit generalizability to uncontrolled clinical situations. Second, the model was trained and evaluated on a single public dataset without multi-institutional validation, which may impair its adaptability to different imaging settings. Finally, while the suggested approach enhances denoising efficiency, resource-constrained devices like handheld ultrasound scanners were not tested for real-time performance.

This technopreneurial work shows how AI-driven diagnostic tools might improve reproductive health imaging. Policy measures are needed to apply these findings. Educational institutions should teach AI and biological imaging to prepare technopreneurs. AI-enabled women's health diagnostics firms can receive government grants or subsidies. Incubators and health-tech accelerators can also help clinicians and developers collaborate on clinically relevant and economically feasible AI advances. These suggestions enable digital transformation and medical AI adoption in entrepreneurial ecosystems. Additionally The suggested AI-based denoising model makes it easier to diagnose Polycystic Ovary Syndrome (PCOS) early on, which is a direct contribution to SDG 3 (Good Health and Well-being). It fits with SDG 9 (Industry, Innovation, and Infrastructure) since it encourages AI innovation in ultrasound imaging. Also, its possible use in health tech incubators and digital education platforms fits with SDG 4 (Quality Education) by giving future healthcare technopreneurs and physicians AI capabilities to help them make better diagnoses.

5. MANAGERIAL IMPLICATIONS

The findings of this study offer significant implications for healthcare management, particularly in hospitals, clinics, and diagnostic centers. The adoption of the proposed Attention-based Autoencoder (AAE) model has the potential to enhance the quality of ultrasound imaging for PCOS diagnosis, thereby improving clinical decision-making processes. From a managerial perspective, integrating such AI-based approaches could contribute to reducing diagnostic errors, strengthening institutional credibility, and ensuring the provision of higher-quality reproductive health services.

For health technology companies and emerging diagnostic startups, the study provides valuable insights into the commercialization of AI-driven medical imaging solutions. The proposed model can serve as a foundation for developing automated diagnostic applications that may be incorporated into portable ultrasound devices or telemedicine platforms. This innovation can expand patient access to reliable diagnostic tools, enhance market competitiveness, and foster the development of sustainable business models in the digital healthcare ecosystem.

Furthermore, the study underscores the importance of aligning technological implementation with regulatory frameworks, ethical standards, and patient data protection. Managers are required to ensure that the deployment of AI-based diagnostic tools adheres to privacy regulations and clinical governance practices. In this regard, the managerial implications extend beyond operational improvements and financial outcomes, encompassing sustainability, trust-building among stakeholders, and contributions to SDG 3 (Good Health and Well-being) and SDG 9 (Industry, Innovation, and Infrastructure).

6. CONCLUSION

This paper offers a new AAE model for speckle noise removal in ultrasound images, with a focus on PCOS detection. The presented method well removes noise while retaining important anatomy information, showing prominent improvement over the conventional denoising approach. By utilizing an attention mechanism, the model conducts selective enhancement of key regions of the image, achieving greater PSNR (31.33, 34.25, 36.23) and SSIM (85.21, 92.33, 99.25) values under varying amounts of noise. Comparative analysis with current methods, such as mean filtering, bilateral filtering, and OBNLM filtering, illustrates the better performance of the proposed method. These findings show the potential clinical value of using deep learning-based denoising in ultrasound imaging to improve diagnostic accuracy for PCOS. Future studies may investigate multi-scale attention mechanisms or hybrid models that integrate CNNs and transformers to further enhance noise removal and image quality. In addition, applying the same concept to other medical imaging fields, such as thyroid, liver, and kidney ultrasound scanning, might also extend its reach in the field of medicine. The use of ultrasound imaging in diagnosing PCOS is made easier by the proposed AAE, which greatly enhances image quality while effectively eliminating speckle noise. This research aids in the wider application of artificial intelligence in health systems, particularly concerning digital diagnostic devices. Later studies may investigate attention mechanisms using transformers and adapt the technique to other branches of medical imaging for more significant clinical influence.

7. DECLARATIONS

7.1. About Authors

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7.2. Author Contributions

Conceptualization: PP; Methodology: SC; Validation: PP and SC;; Writing Original Draft Preparation: PP and SC; Writing Review and Editing: SC and XN; Visualization: SC; All authors, PP, SC, and XN, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.4. Funding

This work was supported by a grant from the Hubei Key Laboratory of Intelligent Robot of China (Grant No. HBIRL202009).

7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] E. Stener-Victorin, H. Teede, R. J. Norman, R. Legro, M. O. Goodarzi, A. Dokras, J. Laven, K. Hoeger, and T. T. Piltonen, "Polycystic ovary syndrome," *Nature Reviews Disease Primers*, vol. 10, no. 1, p. 27, 2024.

[2] H. Singh, A. S. Ahmed, F. Melandsø, and A. Habib, "Ultrasonic image denoising using machine learning in point contact excitation and detection method," *Ultrasonics*, vol. 127, p. 106834, 2023.

[3] A. Chaudhuri, "Polycystic ovary syndrome: Causes, symptoms, pathophysiology, and remedies," *Obesity Medicine*, vol. 39, p. 100480, 2023.

[4] R. Saranya and R. Sridevi, "Design of automatic follicle detection and ovarian classification system for ultrasound ovarian images," *Multimedia Tools and Applications*, pp. 1–27, 2024.

[5] K. M. Hoeger, A. Dokras, and T. Piltonen, "Update on pcos: consequences, challenges, and guiding treatment," *The Journal of Clinical Endocrinology & Metabolism*, vol. 106, no. 3, pp. e1071–e1083, 2021.

[6] D. Jonas, H. D. Purnomo, A. Iriani, I. Sembiring, D. P. Kristiadi, and Z. Nanle, "Iot-based community smart health service model: Empowering entrepreneurs in health innovation," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 1, pp. 61–71, 2025.

[7] T. Pujiati, H. Setiyowati, B. Rawat, N. P. L. Santoso, and M. G. Ilham, "Exploring the role of artificial intelligence in enhancing environmental health: Utaut2 analysis," *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 1, pp. 37–46, 2025.

[8] L. P. Dewanti, L. Sitoayu, and A. Idarto, "Digital tele-counseling for sustainable maternal health services in indonesia focus on telelactation," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 1, pp. 10–20, 2024.

[9] S. Ahmed, M. S. Rahman, I. Jahan, M. S. Kaiser, A. S. Hosen, D. Ghimire, and S.-H. Kim, "A review on the detection techniques of polycystic ovary syndrome using machine learning," *IEEE Access*, vol. 11, pp. 86 522–86 543, 2023.

[10] S. A. Suha and M. N. Islam, "An extended machine learning technique for polycystic ovary syndrome detection using ovary ultrasound image," *Scientific Reports*, vol. 12, no. 1, p. 17123, 2022.

[11] W. M. H. W. Mahmud, A. Huong, and N. A. Jumadi, "Preliminary analysis of ultrasound features for detection of polycystic ovary syndrome (pcos) in women," in *Biomedical Engineering: AI and Technological Innovations*. Springer, 2025, pp. 137–151.

[12] A. Nazarudin, N. Zulkarnain, S. S. Mokri, W. M. D. W. Zaki, A. Hussain, M. F. Ahmad, and I. N. A. M. Nordin, "Performance analysis of a novel hybrid segmentation method for polycystic ovarian syndrome monitoring," *Diagnostics*, vol. 13, no. 4, p. 750, 2023.

[13] R. Yang, Y. Zou, L. Li, W. V. Liu, C. Liu, Z. Wen, and Y. Zha, "Enhancing repeatability of follicle counting with deep learning reconstruction high-resolution mri in pcos patients," *Scientific Reports*, vol. 15, no. 1, p. 1241, 2025.

[14] A. M. Rahmat, N. N. Noor, I. L. Maria, and G. Davies, "Risk factors for the incidence of drug-resistant tuberculosis in the labuang baji hospital: A healthpreneur perspective," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 3, pp. 468–480, 2024.

[15] J. L. Willson, A. Nuche, and R. Widayanti, "Ethical considerations in the development of ai-powered healthcare assistants," *International Transactions on Education Technology (ITEE)*, vol. 2, no. 2, pp. 109–119, 2024.

[16] A. S. Rafika, A. Faturahman, B. N. Henry, F. D. Yulian, and M. Hassan, "Ai-driven big data solutions for personalized healthcare: Analyzing patient data to improve treatment outcomes," *Journal of Computer Science and Technology Application*, vol. 2, no. 1, pp. 36–45, 2025.

[17] C. Yu, F. Ren, S. Bao, Y. Yang, and X. Xu, "Self-supervised ultrasound image denoising based on weighted joint loss," *Digital Signal Processing*, vol. 162, p. 105151, 2025.

[18] Y.-H. Li, Y.-L. Li, M.-Y. Wei, and G.-Y. Li, "Innovation and challenges of artificial intelligence technology in personalized healthcare," *Scientific reports*, vol. 14, no. 1, p. 18994, 2024.

[19] L. Wang, X. Wang, A. Vizziello, and P. Gamba, "Rsaae: Residual self-attention-based autoencoder for hyperspectral anomaly detection," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–14, 2023.

[20] P. Singh and A. Sharma, "Attention-based convolutional denoising autoencoder for two-lead ecg denoising and arrhythmia classification," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–10, 2022.

[21] G. Govindharajan, S. Subramanian, M. Doraipandian, and S. Rajendran, "Innovative ai-driven models for predicting polycystic ovarian syndrome: An extensive review of machine learning and deep learning frameworks," *Archives of Computational Methods in Engineering*, pp. 1–26, 2025.

[22] K. van der Ham, F. Barbagallo, E. van Schilfgaarde, M. E. Lujan, J. S. Laven, and Y. V. Louwers, "The additional value of ultrasound markers in the diagnosis of polycystic ovary syndrome," *Fertility and Sterility*, vol. 123, no. 2, pp. 342–349, 2025.

[23] B. Karthik and K. R. CV, "Speckle noise removal from biomedical mri images and classification by msvm," in *Green AI-Powered Intelligent Systems for Disease Prognosis*. IGI Global, 2024, pp. 261–278.

[24] S. Reka, T. S. Praba, M. Prasanna, V. N. N. Reddy, and R. Amirtharajan, "Automated high precision pcos detection through a segment anything model on super resolution ultrasound ovary images," *Scientific Reports*, vol. 15, no. 1, p. 16832, 2025.

[25] N. A. El-Hag, H. M. El-Hoseny, and F. Harby, "Dnn-driven hybrid denoising: advancements in speckle noise reduction," *Journal of Optics*, pp. 1–10, 2024.

[26] P. Sharmila, P. Sivasakthi *et al.*, "Classification of pcos in ultrasound images using deep learning methods," in *2024 International Conference on IoT, Communication and Automation Technology (ICICAT)*. IEEE, 2024, pp. 1089–1092.

[27] S. Sowmiya, S. Umapathy, O. Alhajlah, F. Almutairi, S. Aslam, and R. Ahalya, "F-net: Follicles net an efficient tool for the diagnosis of polycystic ovarian syndrome using deep learning techniques," *Plos one*, vol. 19, no. 8, p. e0307571, 2024.

[28] P. Bedi, S. Goyal, A. S. Rajawat, and M. Kumar, "An integrated adaptive bilateral filter-based framework and attention residual u-net for detecting polycystic ovary syndrome," *Decision Analytics Journal*, vol. 10, p. 100366, 2024.

[29] M. Harada, "Pathophysiology of polycystic ovary syndrome revisited: Current understanding and perspectives regarding future research," *Reproductive medicine and biology*, vol. 21, no. 1, p. e12487, 2022.

[30] S. Cammarasana, P. Nicolardi, and G. Patanè, "Real-time denoising of ultrasound images based on deep learning," *Medical & Biological Engineering & Computing*, vol. 60, no. 8, pp. 2229–2244, 2022.

[31] X. Zhang, "Two-step non-local means method for image denoising," *Multidimensional Systems and Signal Processing*, vol. 33, no. 2, pp. 341–366, 2022.

[32] A. Kaur and G. Dong, "A complete review on image denoising techniques for medical images," *Neural Processing Letters*, vol. 55, no. 6, pp. 7807–7850, 2023.

[33] B. Rawat, A. S. Bist, D. Supriyanti, V. Elmanda, and S. N. Sari, "Ai and nanotechnology for healthcare: A survey," *APTISI Transactions on Management*, vol. 7, no. 1, pp. 86–91, 2023.

[34] M. Kuswari, R. Gantino, and J. Maratis, "Maximizing healthcare service information system: Understanding the influence of integration on efficiency," *ADI Journal on Recent Innovation*, vol. 6, no. 2, pp. 108–117, 2025.

[35] P. Coupé, P. Hellier, C. Kervrann, and C. Barillot, "Nonlocal means-based speckle filtering for ultrasound images," *IEEE transactions on image processing*, vol. 18, no. 10, pp. 2221–2229, 2009.

[36] Y. Zhan, M. Ding, L. Wu, and X. Zhang, "Nonlocal means method using weight refining for despeckling of ultrasound images," *Signal Processing*, vol. 103, pp. 201–213, 2014.

[37] L. Kask, N. Bloom, and R. Porta, "Health informatics: Utilization of information technology in health

care and patient management," *International Journal of Cyber and IT Service Management*, vol. 4, no. 1, pp. 53–58, 2024.

[38] A. K. Bedi and R. K. Sunkaria, "Ultrasound speckle reduction using adaptive wavelet thresholding," *Multidimensional Systems and Signal Processing*, vol. 33, no. 2, pp. 275–300, 2022.

[39] V. Kiruthika, S. Sathiya, and M. Ramya, "Machine learning based ovarian detection in ultrasound images," *International Journal of Advanced Mechatronic Systems*, vol. 8, no. 2-3, pp. 75–85, 2020.

[40] S. B. Choubey, A. Choubey, D. Nandan, and A. Mahajan, "Polycystic ovarian syndrome detection by using two-stage image denoising." *Traitement du signal*, vol. 38, no. 4, 2021.

[41] G. Vasavi and S. Jyothi, "Noise reduction using obnlm filter and deep learning for polycystic ovary syndrome ultrasound images," in *International Conference On Computational And Bio Engineering*. Springer, 2021, pp. 203–212.

[42] M. Jha, R. Gupta, and R. Saxena, "Noise cancellation of polycystic ovarian syndrome ultrasound images using robust two-dimensional fractional fourier transform filter and vgg-16 model," *International Journal of Information Technology*, vol. 16, no. 4, pp. 2497–2504, 2024.

[43] R. K. Hudiono and S. Watini, "Remote medical applications of artificial intelligence," *International Transactions on Artificial Intelligence*, vol. 1, no. 2, pp. 182–187, 2023.

[44] V. Agarwal, M. Lohani, and A. S. Bist, "A novel deep learning technique for medical image analysis using improved optimizer," *Health Informatics Journal*, vol. 30, no. 2, p. 14604582241255584, 2024.

[45] U. Rahardja, P. A. Sunarya, Q. Aini, S. Millah, and S. Maulana, "Technopreneurship in healthcare: Evaluating user satisfaction and trust in ai-driven safe entry stations," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 3, pp. 404–417, 2024.

[46] L. Patru, F.-A. Birchi, and C. L. Patru, "The relationship between digital technology and the development of the entrepreneurial competencies of young people in the medical field," *Electronics*, vol. 12, no. 8, p. 1796, 2023.

[47] A. V. Samrot, M. Bavanilatha *et al.*, "Medical biotechnology-approaches to become an entrepreneur in medical biotechnology," in *Opportunities for Biotechnology Research and Entrepreneurship*. Bentham Science Publishers, 2024, pp. 291–308.

[48] S. N. Weimar, R. S. Martjan, and O. Terzidis, "Conceptualizing the landscape of digital health entrepreneurship: a systematic review and research agenda," *Management Review Quarterly*, vol. 75, no. 2, pp. 1619–1667, 2025.

[49] A. E. Ilesanmi and T. O. Ilesanmi, "Methods for image denoising using convolutional neural network: a review," *Complex & Intelligent Systems*, vol. 7, no. 5, pp. 2179–2198, 2021.

[50] H. Thanganadar, S. M. Yaseen, S. K. Shukla, A. S. Bist, S. N. Shavkatovich, and P. Vijayakumar, "6g wireless communication cyber physical system based smart healthcare using quantum optimization with machine learning," *Wireless Personal Communications*, pp. 1–20, 2024.