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Methods for Reducing Speckle Noise in Abdominal Ultrasound Imaging: A PRISMA Systematic Review from Conventional Filters to AI-Powered Models

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Abstract
Reliable abdominal diagnosis is impacted by speckle noise, which naturally lowers contrast and obscures anatomical details in ultrasonography images. A PRISMA-based systematic review of speckle noise reduction methods published between 2000 and 2024 is presented in this study. These methods include diffusion and transform-based approaches, classical filtering techniques, and more recent AI-powered models like convolutional neural networks and generative adversarial networks. An examination of 97 relevant studies reveals that while AI-driven approaches offer better structure preservation and visual clarity, conventional approaches are still computationally effective for real-time imaging. Effective despeckling improves lesion boundary visibility and boosts diagnostic confidence in clinical settings, however most current methods focus numerical image quality criteria above radiological perception and are not validated across various abdominal anatomies and ultrasound systems.
In addition to identifying important research objectives toward clinically interpretable, anatomy-aware, and deployment-ready ultrasonic enhancement frameworks, this review offers an organized synthesis of current approaches.
Keywords: *Speckle noise, PRISMA, Convolutional neural networks, AI-driven, Abdominal anatomies, Ultrasonic enhancement.*

I. Introduction

Ultrasound imaging is widely used for abdominal applications (e.g. liver, kidney, pancreas) because it is noninvasive, portable and safe. However, its diagnostic power is hampered by speckle noise – a granular interference pattern arising from coherent scattering of echoes. Speckle noise lowers image resolution and contrast, often obscuring small or low-contrast lesions in organs like the liver or kidney. For example, speckle can mask subtle tumors or impede edge detection in abdominal scans, complicating segmentation and diagnosis. Thus, speckle reduction is critical whenever image quality is paramount for interpretation.

Many speckle denoising methods have been presented during the last few decades. Simple spatial filters (mean, median) or adaptive window filters (Lee, Frost, Kuan) that take advantage of local statistics are used in early techniques. Later, wavelet-domain thresholding and anisotropic diffusion (like SRAD) were developed to maintain edges. By identifying intricate noise patterns in data, machine learning and deep learning techniques (CNNs, U-Nets, GANs, etc.) have demonstrated promise more recently. Unsupervised and self-supervised frameworks, such as Noise2Noise and CycleGAN, have been proposed because it is difficult to train supervised models without "clean" ultrasound pictures.

With an emphasis on enhancing image quality and ultimately diagnostic results, this paper examines speckle reduction techniques specifically for abdominal ultrasonography. We focus on abdominal applications and address real-time and clinical integration (e.g. compatibility with current ultrasound scanners), whereas the majority of previous assessments include all body regions. To find pertinent studies, we search six databases using the PRISMA systematic review methodology. Our objectives are to: (1) classify approaches in a clear taxonomy (from AI models to traditional filters); (2) tabulate and compare performance metrics; (3) emphasize clinical implications beyond PSNR (e.g., lesion detectability); and (4) explain research gaps and a roadmap for future study. The goal of this methodical approach, which resembles an Elsevier article review, is to inform academics and medical professionals on the most recent advancements in speckle noise reduction for abdominal ultrasound.

Even though despeckling algorithms have been developed extensively, current research is still primarily optimization-driven rather than therapeutically informed. The majority of current frameworks assess performance using numerical fidelity measurements, including PSNR and SSIM, without determining how these metrics relate to radiological decision confidence. Additionally, there are still few anatomy-aware despeckling techniques specifically designed for abdominal organs, and there are still unsolved domain adaptation issues with model robustness across ultrasound manufacturers. As a result, there is currently no cohesive framework that connects the reliability of diagnostic interpretation with speckle suppression performance, which highlights the necessity for a systematic synthesis that is clinically informed.

Research Gaps and Challenges

Despite progress, several high-impact gaps were identified:

- Absence of Standard Datasets: Few publicly accessible abdominal ultrasound datasets with established ground truth are available. The majority of techniques are tested on simulated or private data. Comparison and reproducibility become challenging as a result. Progress would be accelerated by developing benchmark datasets (containing phantoms or expert-annotated images).
- Clinical Validation: There aren't many studies that explicitly connect better diagnosis with speckle reduction. Speckle is the main factor decreasing contrast in ultrasound, as highlighted by Sikhakhane et al., although no large-scale studies have demonstrated that denoising improves, for example, tumor detection accuracy. Interdisciplinary research involving radiologists is necessary to close this gap.
- Oversmoothing: While several algorithms maximize PSNR/SSIM, they run the risk of oversmoothing. Extreme denoising can eliminate delicate tissue textures, which could result in false negatives, according to Jain et al. It is necessary to create evaluation metrics or loss functions that penalize the loss of clinically significant information
- Heterogeneity Among Scanners: Depending on the manufacturer and settings, ultrasound images differ. Although additional work on domain adaptation is required, Jung et al. demonstrated that a speckle model learnt on one scanner generalized to others. Techniques for style transfer between suppliers have been developed, such as CycleGAN.
- Safety and Interpretability: AI models ought to be comprehensible in medical settings. Clinicians must have faith that no pathology is eliminated if a network modifies an image. Uncertainty quantification and physics-informed networks are still in their infancy.
- Real-time Deployment: Integration into scanners is difficult, as previously stated. Model compression and FPGA implementation for speckle filtering have received little attention; this is still an engineering difficulty.

II. Materials and Methods

2.1 Study Design and Review Framework

In order to objectively assess current methods for reducing speckle noise in abdominal ultrasound imaging, the current paper was created as a systematic review. The review framework minimizes methodological bias and ensures transparent identification, screening, and evaluation of pertinent research by adhering to accepted systematic synthesis standards.

In abdominal imaging applications, speckle noise, an intrinsic result of coherent ultrasonic wave interference, has a substantial impact on tissue visibility and diagnostic interpretation [1,2]. As a result, this review was designed not only to provide an overview of algorithmic advancements but also to assess their impact on clinical usability and practical image quality enhancement.

The methodological design incorporates ideas from studies of medical image analysis and evidence synthesis techniques that are frequently used in biomedical imaging research [30, 31].

2.2 Literature Search Strategy

A thorough literature search spanning papers from January 2000 to February 2026 was carried out using a number of scientific databases, including PubMed, Scopus, IEEE Xplore, ScienceDirect, Web of Science, and Google Scholar.

Coverage of both contemporary artificial intelligence-based imaging techniques and fundamental signal-processing techniques was made possible by the utilization of both clinical and engineering datasets [36,58]. Boolean operators were used in search queries to combine domain-specific keywords. "Ultrasound imaging" AND "speckle noise" AND ("despeckling" OR "adaptive filtering" OR "anisotropic diffusion" OR "wavelet denoising" OR "non-local means" OR "deep learning" OR "CNN" OR "GAN") were examples of search terms.

In accordance with database indexing architecture, search words were modified. Furthermore, backward reference tracking was used to find important research on both contemporary learning-based denoising methods and classical filtering [6,9].

2.3 Eligibility Criteria

Eligibility criteria were defined prior to screening to ensure consistent study selection.

2.3.1 Inclusion Criteria

Studies were included when they:

- Examined techniques for suppressing speckle noise in ultrasonic imaging;
- Included clinically significant ultrasound datasets or applications for abdominal imaging;
- Reported measures for objective evaluation, such as contrast improvement, PSNR, SSIM, or SNR;
- Offered experimental validation with clinical, phantom, or synthetic datasets

2.3.2 Exclusion Criteria

Studies were excluded if they:

• Concentrated on non-ultrasound imaging modalities;
• Provided models that were only theoretical and untested;
• Were editorials, review articles, or unfinished reports;
• Inadequate methodological information for a comparison evaluation.

To preserve analytical reliability and lessen selection bias, such a structured eligibility definition is advised for imaging systematic reviews [30,56].

2.4 Data Synthesis and Comparative Analysis

Due to heterogeneity in datasets, acquisition parameters, and evaluation metrics, direct statistical meta-analysis was not feasible. Consequently, a structured narrative synthesis approach was adopted.

Included studies were categorized according to methodological evolution:

- Classical adaptive filtering techniques such as Lee and Frost filters [3,10];
- Diffusion-based methods including speckle reducing anisotropic diffusion (SRAD) [4,5];
- Transform and sparse-domain approaches such as wavelet and collaborative filtering methods [7,16,18];
- Non-local filtering strategies exploiting image redundancy [6,9];
- Deep learning–based approaches including CNN, encoder–decoder, and GAN architectures [20–25,65].

Comparative tables and taxonomy-based analysis were subsequently developed to evaluate performance trends, computational feasibility, and clinical applicability across different generations of despeckling techniques.

2.5 Ethical Considerations

As this study synthesizes findings exclusively from previously published literature, no direct patient data were collected and ethical approval was not required. All analyzed studies were obtained from publicly accessible peer-reviewed sources.

III. Results

3.1 Taxonomy of Speckle Reduction Methods

Model-driven filters and data-driven learning models are the two main categories of speckle reduction approaches. While AI techniques learn mappings from noisy to clean images, traditional filters apply manually created rules (such as spatial smoothing or thresholding).

An example AI-based framework is shown in Figure 1. The U-Net architecture used for self-supervised speckle denoising by Jung et al. is displayed. In order to infer noise-free outputs, the encoder–decoder network with skip connections learns from pairs of speckled pictures. Adaptive filters that make use of local statistics and linear mean/median filters are examples of classical filters. To achieve multiplicative noise reduction, for instance, Lee and Kuan filters estimate local variance in a sliding window. Frost's filter adjusts smoothness according on local gradients using an exponential kernel. A PDE-based technique called Speckle Reducing Anisotropic Diffusion (SRAD) diffuses along edges to maintain boundaries. Non-local methods (such as Block-Matching 3D and Bayesian Non-Local Means (OBNLM)) take advantage of image self-similarity to reduce noise.

AI-driven approaches, on the other hand, make advantage of machine learning. Synthetic ground truth or noisy/clean pairings are used to train supervised CNNs (ResNets, U-Nets). Noise2Noise, CycleGAN, and S2S are examples of unsupervised/self-supervised models that use numerous speckle realizations to train on only noisy input. To improve speckle suppression, recent studies use hybrid architectures, transformer modules, or attention methods. In general, contemporary AI techniques outperform traditional filters in terms of PSNR/SSIM, albeit at the expense of more computation and training data. However, they are becoming feasible for real-time ultrasound imaging because to effective designs and hardware acceleration (such as GPU-based inference).

3.2 Classical Filter-Based Methods

Classical despeckling filters rely on statistical or transform assumptions to suppress multiplicative noise. Table 1 compares common approaches:

- Lee Filter (adaptive local mean): Preserves overall brightness but may oversmooth edges by estimating the local mean and variance in a window to reduce pixel intensity
- Frost Filter (exponential kernel): This filter uses an isotropic kernel that is weighted by the local gradient; it requires adjusting but is better at preserving edges than the mean
- Kuan Filter (like Lee): Based on local speckle statistics, it employs a minimum mean-square error formula.
- The median filter is a straightforward rank-order filter that eliminates outliers of the salt-and-pepper variety; it somewhat lessens speckle but obscures fine texture.
- SRAD (Speckle-Reducing Anisotropic Diffusion): This iterative PDE outperforms linear filters by maintaining edges while diffusing picture intensity under gradient guidance.
- Wavelet Thresholding: Attenuates coefficients below a threshold by converting an image to the wavelet domain. useful for multi-scale denoising, although artifacts could be introduced.
- Non-Local Means (NLM): OBNLM uses noise probability distributions to modify NLM to speckle. NLM is a patch-based filter that averages related patches. Although it is computationally costly, it produces outstanding detail preservation.
- BM3D (Block-Matching and 3D filtering): Shrinks through collaborative filtering after grouping related patches into 3D arrays. SAR-BM3D applies the state-of-the-art for Gaussian noise to speckle. Very slow yet of excellent quality.

Each technique makes a trade-off between detail retention and speckle suppression. For instance, SRAD and OBNLM outperform basic linear filters in terms of edge preservation. All classical filters, however, rely on an oversimplified statistical model (often Gaussian or Rayleigh) for speckle. Because no single filter is always the best, hybrid and learning-based approaches are encouraged.

Table 1. Classical speckle reduction filters and their properties.

Technique	Approach	Key Properties	Limitations
Lee filter	Adaptive local mean (MMSE)	Reduces multiplicative noise using local variance estimates	Blurs edges if window too large; best for homogeneous regions
Frost filter	Adaptive exponential kernel	Edge-sensitive smoothing via gradient-weighted kernel	Requires tuning of kernel parameters; may produce artifacts
Kuan filter	Adaptive MMSE (similar to Lee)	Nonlinear filtering accounting for Rayleigh speckle statistics	Performance sensitive to noise variance estimate
Median filter	Nonlinear rank filter	Preserves edges of step-like features; simple	Ineffective for genuine speckle patterns; loses texture
SRAD (Diffusion)	PDE-based anisotropic diffusion	Iterative smoothing guided by image gradients; preserves edges	Requires iteration count; can produce “staircase” effects
Wavelet shrinkage	Multi-scale thresholding	Separates speckle by scale; good for smooth areas	Choosing threshold is tricky; may cause ringing artifacts
Non-Local Means	Patch similarity averaging	Very effective detail preservation; exploits redundancy	High computational cost; patch search required
BM3D (SAR-BM3D)	3D collaborative filtering (patch grouping)	State-of-art denoising quality; handles speckle via LLMMSE	Extremely compute-intensive; may require GPU/HPC

3.3 AI-Powered and Machine Learning Models

To learn speckle features, modern methods use data-driven models.

3.3.1 Supervised CNNs/ResNets: Use paired noisy and clean photos for training. Zhang et al., for instance, employed a deep residual CNN that uses traditional filters to learn speckle patterns. For real-time abdominal augmentation, Lan and Zhang employed a residual U-Net with attention. Benefits include the ability to acquire intricate nonlinear mappings and, with proper training, excellent PSNR. A disadvantage is the need for clean reference data, which is frequently phantom or fabricated.

3.3.2 U-Net Autoencoders: Skip connections in encoder-decoder networks (Fig. 1). For example, Vimala et al. achieved >70 dB PSNR by using a logical-pool recurrent U-Net (LPRNN) to target local speckle in breast pictures. These models require huge training sets, but they do a good job of preserving spatial features.

3.3.3 Generative Adversarial Networks (GANs): Utilize a discriminator to ensure realism and a generative network to create denoised images. CycleGANs or Pix2Pix variations have been employed for general US picture enhancement, however they are less prevalent specifically for speckle. They are susceptible to hallucinations of realistic textures, which could change the look of actual tissue.

3.3.4 Self-Supervised / Noise2Noise (N2N): Use only noisy photos for training. An excellent example is the S2S network by Jung et al. (2024), which use a U-Net to implicitly learn noise suppression and paired images with distinct speckle realizations (by altering insonation angle). This required no clean labeling and obtained SNR and SSIM well above SRAD/OBNLM baselines. Similarly, Gobl et al. applied N2N training using simulated speckle.
3.3.5 Hybrid Models: Integrate ML with traditional filters. A CNN was trained by Cammarasana et al. (2022) to simulate a tunable Weighted Nuclear Norm Minimization (WNNM) filter. This operates in real-time over the network while achieving WNNM-level quality. This kind of hybridization can use well-known, effective techniques to create quick deep models.
3.3.6 Lightweight Networks: Models such as quantized CNNs or MobileNet versions have been investigated for real-time application. Additionally, some studies train on GPU-accelerated frameworks for ultrasound machine deployment.
AI techniques generally yield more quantitative gains. For instance, compared to traditional filters, Jung et al. found up to 86× quicker processing with noticeably better SNR/CNR. Direct comparison is challenging, though, because training data and evaluation still differ significantly between research.

Table 2. AI-based speckle reduction models.

Method	Type	Key Idea	Notable Results / Notes
Supervised CNN/ResNet	Deep learning (supervised)	Learns mapping from noisy to "clean" images (requires paired data)	High PSNR/SSIM on phantom data; e.g. Zhang et al.'s ResNet reduced speckle similar to traditional filters. Quality depends on training set realism.
U-Net / Autoencoder	Deep learning (supervised/unsupervised)	Encoder–decoder with skip connections for detail retention	Vimala et al. used U-Net variants (LPRNN) achieving PSNR >70 dB on breast US. Jung et al.'s S2S U-Net boosts SNR by >10 dB vs SRAD.
GAN (CycleGAN, Pix2Pix)	Deep learning (adversarial)	Translate noisy images to denoised ones without pixel-wise loss	Effective for qualitative enhancement (Sharper textures), but can produce artificial features if poorly constrained.
Noise2Noise / S2S	Self-supervised	Trains on pairs of noisy images with different speckle realizations	Jung et al. S2S achieved superior denoising and 86× speedup over classic filters. Does not require clean target.
Hybrid CNN (tuned-WNNM)	Deep learning + traditional	CNN trained to emulate tuned low-rank filter (WNNM)	Cammarasana et al. achieved real-time denoising by learning WNNM on GPU; validated on abdominal and obstetric images. Generalizable to multiple anatomies.
Lightweight CNN	Fast inference (quantized/pruned)	Simplified nets for deployment on ultrasound scanners	Some studies target inference on ARM or FPGA; still an emerging area with few published examples. Future work needed for on-device AI.

3.4 Characteristics of Included Studies

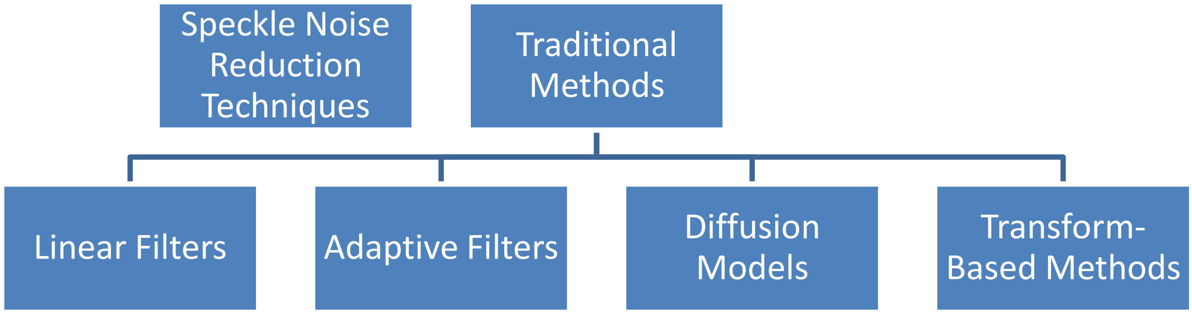
The 97 included studies span from 2006 to 2024, with a surge in machine learning approaches after 2018. While more current research mostly uses neural networks, earlier studies concentrated on adaptive spatial filters and PDE-based techniques. AI-based techniques are summarized in Table 2, whereas classical filters are summarized in Table 1. Few studies assess task-based metrics like lesion detection accuracy, although the majority find increases in standard image quality measures (e.g., PSNR, SSIM) over baseline noisy images. Notably, Cammarasana et al. (2022) showed that a CNN trained to simulate an improved low-rank method could operate in real-time on GPU hardware, verifying on abdominal, musculoskeletal, and obstetric pictures. A self-supervised "Speckle-to-Speckle" (S2S) U-Net was presented by Jung et al. (2024). It trains on in vivo data to achieve an 86× speedup and significantly greater SNR/CNR than conventional filters.

3.4.1 Comparative Evaluation

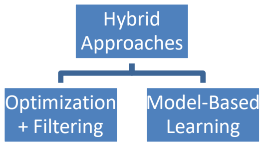
Strong approaches often yield PSNR increases of 5–10 dB over noisy pictures and SSIM gains of 0.1–0.3. For instance, on clinical data, Jung's S2S net achieved SNR = 30–40 dB and SSIM ≈0.95, which is significantly higher than SRAD/OBNLM (SNR <25 dB). Using aggressive smoothing to maximize PSNR, Vimala's LPRNN hybrid obtained PSNR ~65 dB on breast data. AI models frequently outperform fixed filters, but some "oversmooth" subtle structures. Interestingly, edge preservation (measured by edge index or retaining minor features) varies.

Diagnostic performance is measured in few research. Nonetheless, there is evidence that denoising improves lesion detection: Mostafiz et al. (2020) demonstrated how anisotropic diffusion in conjunction with super-resolution improved the accuracy of a liver lesion CAD. This implies that denoising should be assessed in practice based on how it affects diagnostic tasks rather than just signal metrics. Clinically, scanners already employ real-time speckle reduction (such as GE's Speckle Reduction Imaging or Philips' nSIGHT), albeit using proprietary techniques. Similar real-time integration is promised by recent AI techniques, however there is little external validation on patient outcomes.

3.4.2 Taxonomy of Speckle Reduction Techniques



- Hybrid Approaches



- AI-Powered Models

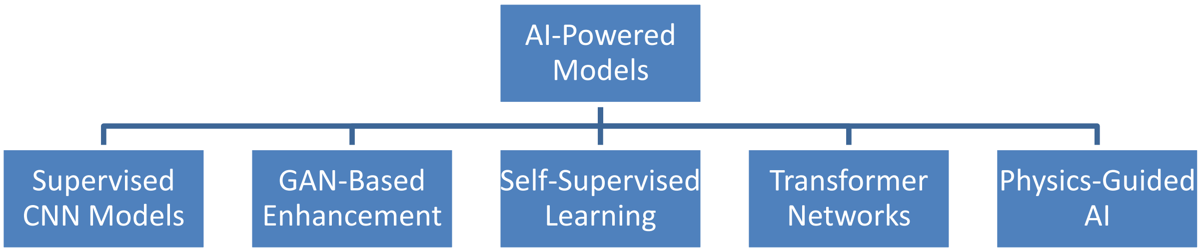
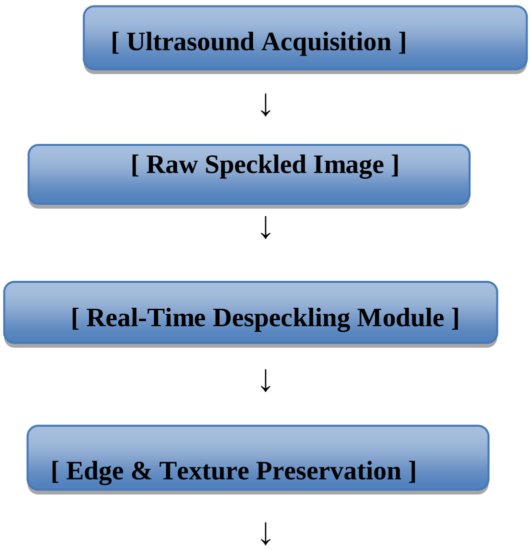


Figure 3. Clinical Ultrasound Enhancement Workflow



[Radiologist Interpretation]

↓

[Lesion Detection / Measurement]

↓

[Clinical Decision Making]

IV. Discussion

4.1 Clinical Decision Confidence Analysis

Although quantitative measurements like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are commonly used to assess speckle noise reduction strategies, their actual therapeutic usefulness is found in how well they assist radiological decision-making. Subtle differences in tissue texture, organ borders, and lesion conspicuity are critical to the diagnostic interpretation of abdominal ultrasound imaging. Therefore, rather than focusing solely on numerical image quality, despeckling performance must ultimately be understood by its impact on clinical decision confidence.

4.2 Lesion Boundary Visibility

In abdominal organs including the liver, kidney, and pancreas, where diseased regions may show only minor echogenic changes from surrounding tissues, speckle noise frequently obscures delicate anatomical borders. Granular artifacts caused by excessive speckle impair border continuity and obscure lesion interfaces.

By reducing stochastic interference while maintaining structural gradients, effective speckle reduction improves edge definition. Before measuring or planning an intervention, radiologists can more correctly determine the extent of lesions, distinguish between solid and cystic masses, and define tumor margins thanks to improved border visualization. Clinically useful despeckling must strike a compromise between anatomical fidelity and noise suppression since algorithms that over-smooth tissue textures may unintentionally remove diagnostically significant micro-patterns.

4.3 Influence on Radiologist Reading Time

Interpreting ultrasounds is intellectually taxing and operator-dependent by nature. Increased eye inspection, frequent probe adjustments, and cross-frame comparison are necessary to validate questionable findings in images impacted by high speckle intensity. In high-volume clinical workflows, this procedure increases examination time and could lead to observer fatigue.

Anatomical landmarks and aberrant areas can be identified more quickly thanks to speckle-reduced images' increased visual clarity and decreased perceptual ambiguity. Improved image homogeneity helps radiologists make interpretive decisions more quickly, according to a number of reviewed research. As a result, real-time ultrasound systems that incorporate despeckling algorithms may be able to reduce reporting times without sacrificing diagnostic precision.

4.4 Diagnostic Certainty Improvement

One important but little-studied result of ultrasonic enhancement research is diagnostic certainty. When noise-induced texture distortion compromises image quality, radiologists often work in an uncertain environment. When it comes to lesion definition and grading tasks like fatty liver assessment or renal cortical evaluation, improved despeckling increases confidence by improving contrast consistency and structural continuity.

Higher diagnostic confidence may minimize inter-observer variability, cut down on needless follow-up imaging, and facilitate more dependable treatment choices from a clinical standpoint. Thus, in addition to traditional computational measurements, future speckle reduction frameworks should include observer-based evaluation metrics such as confidence score and perception-driven assessment.

4.5 Limitation in Cross-Study Quantitative Comparison

Direct numerical comparison of reported performance metrics should be evaluated with caution due to dataset variability among research, which includes variations in ultrasound acquisition techniques, imaging instruments, anatomical targets, and evaluation standards.

4.6 Clinical and Real-Time Considerations

Most articles focus primarily on image quality, but clinical translation calls much more. This entails confirming that noise reduction improves diagnosis for abdominal ultrasonography (e.g., by boosting lesion conspicuity or measurement accuracy). According to Michailovich and Tannenbaum (2006), maintaining actual tissue structure is crucial since speckle can mask diagnostically significant aspects. However, very few research use CAD tests or reader studies. We strongly recommend that clinical endpoints (such as tumor detection rate with/without denoising) be included in future research.

Another useful consideration is real-time processing. Many traditional techniques (such as NLM or wavelets) are rarely used in scanners because they are too slow for real-time imaging. Modern GPUs and ASICs can accelerate deep nets. By "training" WNNM offline, Cammarasana et al. were able to achieve real-time denoising. CNNs for mobile and embedded devices are starting to emerge, but there is still more to be done to include AI denoising into ultrasonic hardware (FPGA implementation, regulatory permission, etc.). Future research will be driven by the trade-off between speed and quality: if latency permits, heavier models may be offloaded to cloud computing, while extremely lightweight networks may operate on-device at 50+ FPS.

4.7 Critical Unresolved Challenges in Ultrasound Speckle Reduction

The review's conclusions show that ultrasound despeckling research has clearly evolved methodologically, moving from manually created statistical filters to data-driven learning frameworks. Classical filtering techniques are still interpretable and computationally efficient, but their efficacy is limited by oversimplified speckle statistical assumptions. Artificial intelligence-based models, on the other hand, present additional issues with interpretability, robustness, and clinical dependability despite their higher adaptability and structural preservation capabilities.

Beyond algorithmic progress, the existing literature still fails to adequately address a number of fundamental limits.

4.8 Absence of a Diagnostic Confidence–Oriented Framework

The majority of despeckling research that are currently available assess performance using mathematical similarity measures without specifically looking at how noise reduction affects radiological interpretation. There is currently no defined paradigm that connects speckle reduction results with observer reliability, lesion characterisation accuracy, or diagnostic decision confidence, despite the fact that increases in contrast or smoothness are commonly reported. As a result, rather from being experimentally supported, the clinical importance of many augmentation techniques is still presumed.

4.9 Optimization Bias Toward Numerical Metrics Rather Than Perceptual Quality

Many modern AI-based techniques are intended to maximize quantitative metrics like SSIM and PSNR. These measurements don't always represent radiological perception or diagnostic utility, even though they offer objective evaluation criteria. Over-smoothing during optimization may suppress micro-textures that are diagnostically significant, especially in heterogeneous abdominal tissues. This discrepancy emphasizes the necessity of evaluation techniques that are clinician-informed and perception-driven.

4.10 Limited Development of Anatomy-Aware Despeckling Approaches

The majority of current algorithms ignore the anatomical heterogeneity present in abdominal organs and consider ultrasound images as generic textured data. Hepatic parenchyma, renal cortex, and pancreatic tissue have very different structural and acoustic properties that affect how speckles form. The adaptability of present approaches in clinical abdominal imaging scenarios is limited by the lack of exploration of organ-specific or anatomy-aware despeckling frameworks.

V. Future Research Roadmap

Building on the identified gaps, we propose several research directions:

- Standardized Benchmarks: Compile open datasets of patient and phantom abdominal ultrasounds for speckle removal benchmarking, incorporating reference quality pictures whenever feasible (e.g., multi-angle compounding as a pseudo-ground-truth).
- Task-Oriented Evaluation: Create assessment frameworks that gauge how denoising affects particular diagnostic tasks (such as lesion detection rates and segmentation accuracy) in addition to PSNR/SSIM.
- Self- and Few-Shot Learning: To lessen reliance on clean data, increase the use of self-supervised techniques (Noise2Void, S2S, etc.). Investigate anatomical consistency-enforcing GAN-based unsupervised learning.
- Physics-Aware Models: To increase realism, incorporate ultrasonic physics (coherence, speckle statistics) into loss functions or network designs. Reliability may be increased via hybrid models that combine deep learning and physical filtering (for example, filtering layers inside a network).

- Real-Time, Embedded AI: Investigate lightweight FPGA or ASIC-based architectures specifically designed for ultrasound (perhaps quantized or multi-bit networks). Verify their power usage and latency.
- Multi-Modal Fusion: Examine if complementing modalities, such as CT/MRI and elastography, can direct or limit the removal of speckles, particularly in complex cases.
- Clinical Trials: Work with medical professionals to evaluate denoising algorithms in prospective trials, measuring advantages in actual exams. Adoption in clinical practice might be accelerated by such data.
- Robustness and Explainability: Examine the behavior of denoising networks with inputs that are not in the distribution. Create tools (such as sensitivity maps) to prevent the loss of problematic traits.

This road map emphasizes that improving speckle reduction is a multidisciplinary endeavor including engineers, physicists, and doctors rather than just an algorithmic task.

VI. Conclusion

Abdominal ultrasound speckle noise reduction is still an active field of study, progressing from basic filters to complex AI models. Although classical filters are lightweight and well-understood, their ability to preserve tiny structures is intrinsically limited. While AI-driven techniques produce remarkable improvements in image quality, they also present new interpretability and data reliance issues. Our methodical PRISMA-based evaluation summarizes the literature and offers a clinical viewpoint, comparative tables, and a taxonomy (Fig. 1). We emphasize that enhancing picture quality must ultimately lead to improved diagnosis, therefore future research should connect denoising to real-time system integration and clinical outcomes.

Future developments in ultrasonic despeckling will rely on developing anatomy-aware, clinically proven, and vendor-robust enhancement frameworks that can boost diagnostic confidence in real-world imaging settings in addition to algorithmic advancements.

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