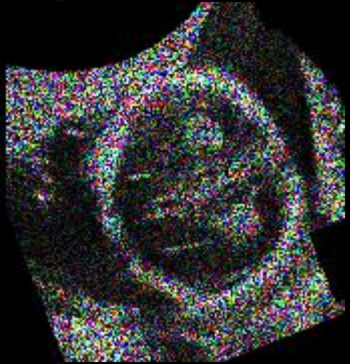
Fetal Head Ultrasound Image Denoising



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BMME 575 - Practical Machine Learning - Final Presentation - Medical Image Denoising

Background

Medical imaging (MRI, PET Scan, CT, Ultrasound, X-ray, etc) plays a big role in the diagnosis and treatment of various diseases. Medical images can be challenging to interpret if they are blurry or have noise/artifacts.

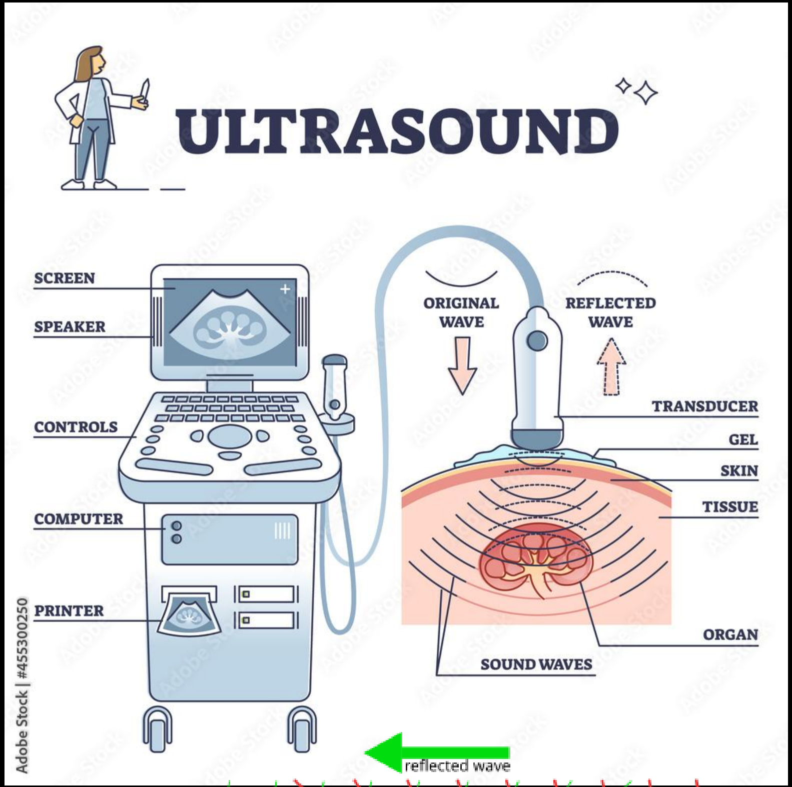
Ultrasound imaging: Uses high-frequency sound waves to generate images of internal body structures.

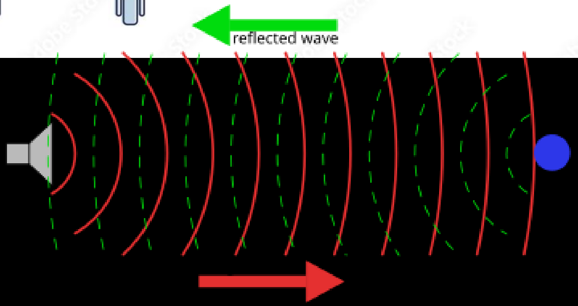
* Coherence -> Interference -> Scattering -> Speckle Noise
* Fetal movement, amniotic fluid, tissue differences, multiple complex tissues, echos, -> Scattered sound waves

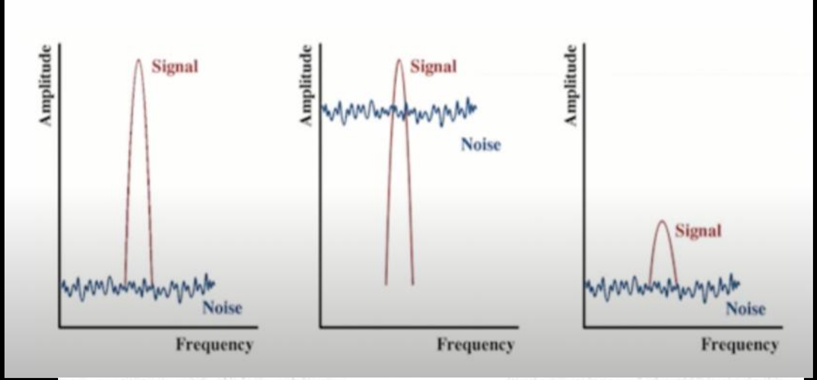
Traditional denoising methods compromise fine details

Frequency domain filtering -> Fourier, wavelet, signal goes to frequency domain

Spatial domain filtering -> direct manipulation of pixels


ULTRASOUND
SCREEN
SPEAKER
CONTROLS
COMPUTER
PRINTER
ORIGINAL WAVE
REFLECTED WAVE
TRANSDUCER
GEL
SKIN
TISSUE
ORGAN
SOUND WAVES
Adobe Stock | #455300250


reflected wave


Amplitude
Signal
Noise
Frequency
Amplitude
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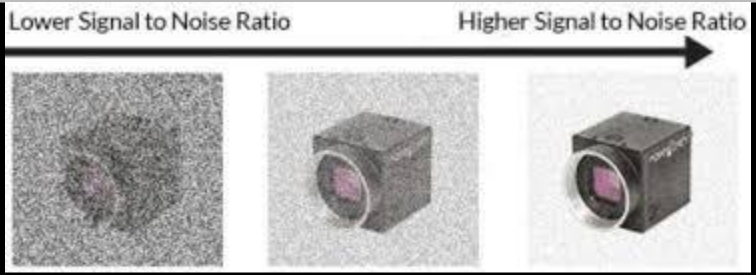
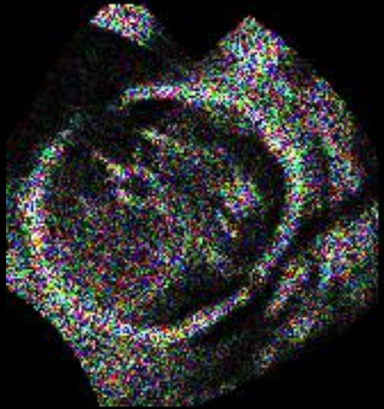
Noise
Frequency

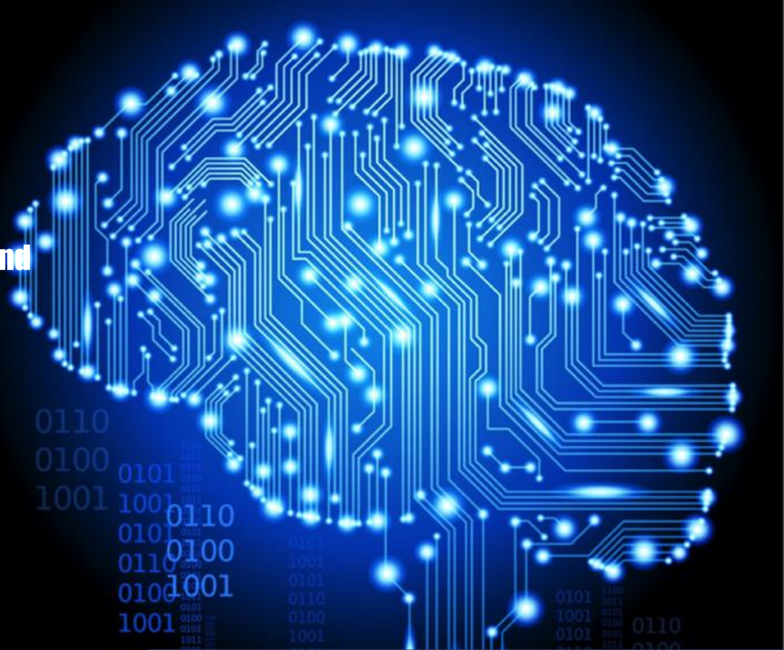

Lower Signal to Noise Ratio
Higher Signal to Noise Ratio



Methods

Input Data:

Ultrasound images - public dataset, fetal head circumference ultrasound



State of the art Method:

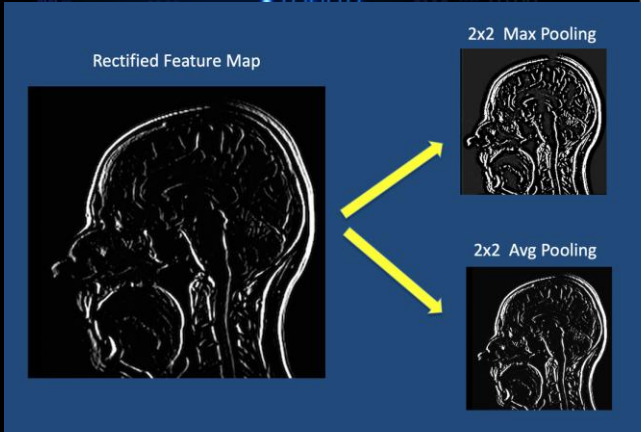
BM3D

Architecture:

Autoencoder network, LAD-CNN

LCA = fine spatial features and enhances attention mechanisms within local regions
LLA = large kernel convolutions & attention mechanisms on global contextual features.

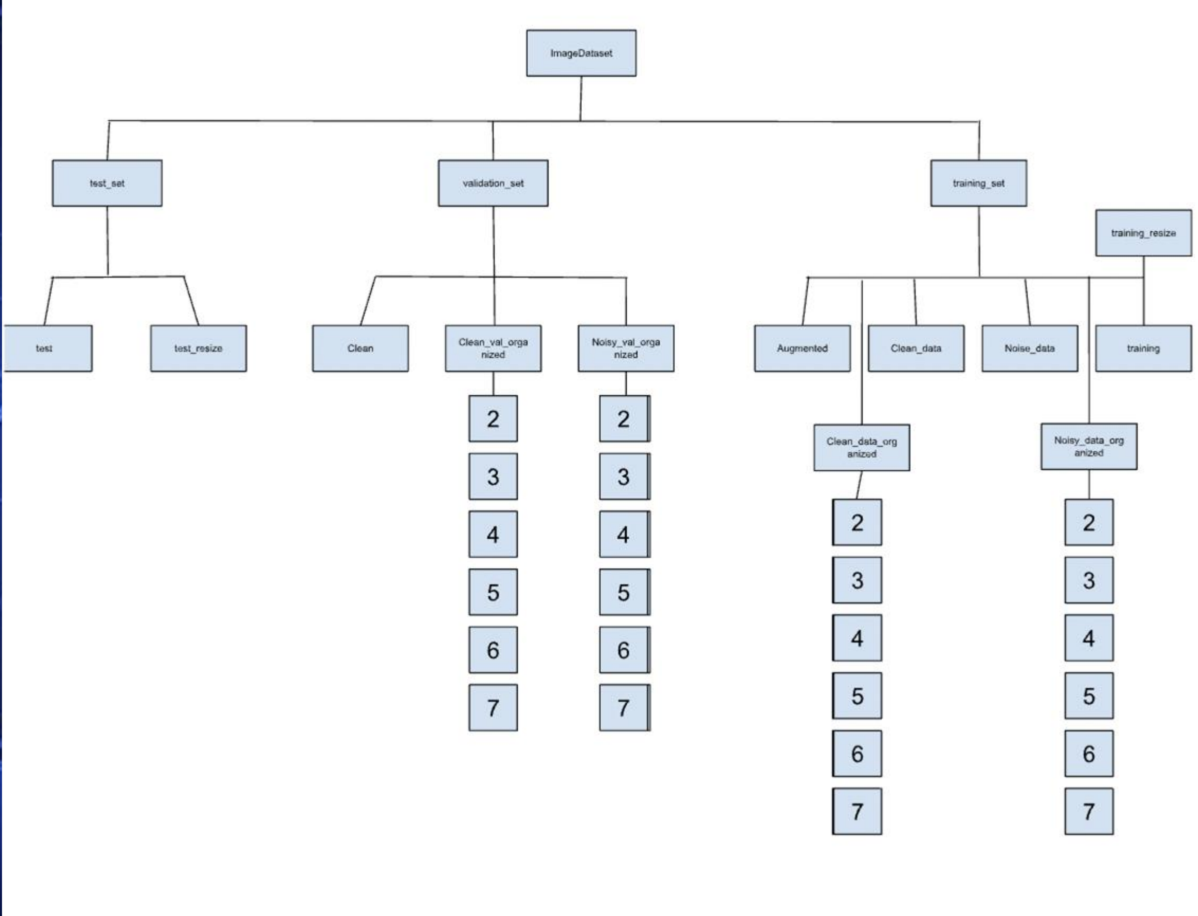
NVIDIA GeForce 4060 Laptop GPU and Intel(R) Iris(R) Xe Graphics

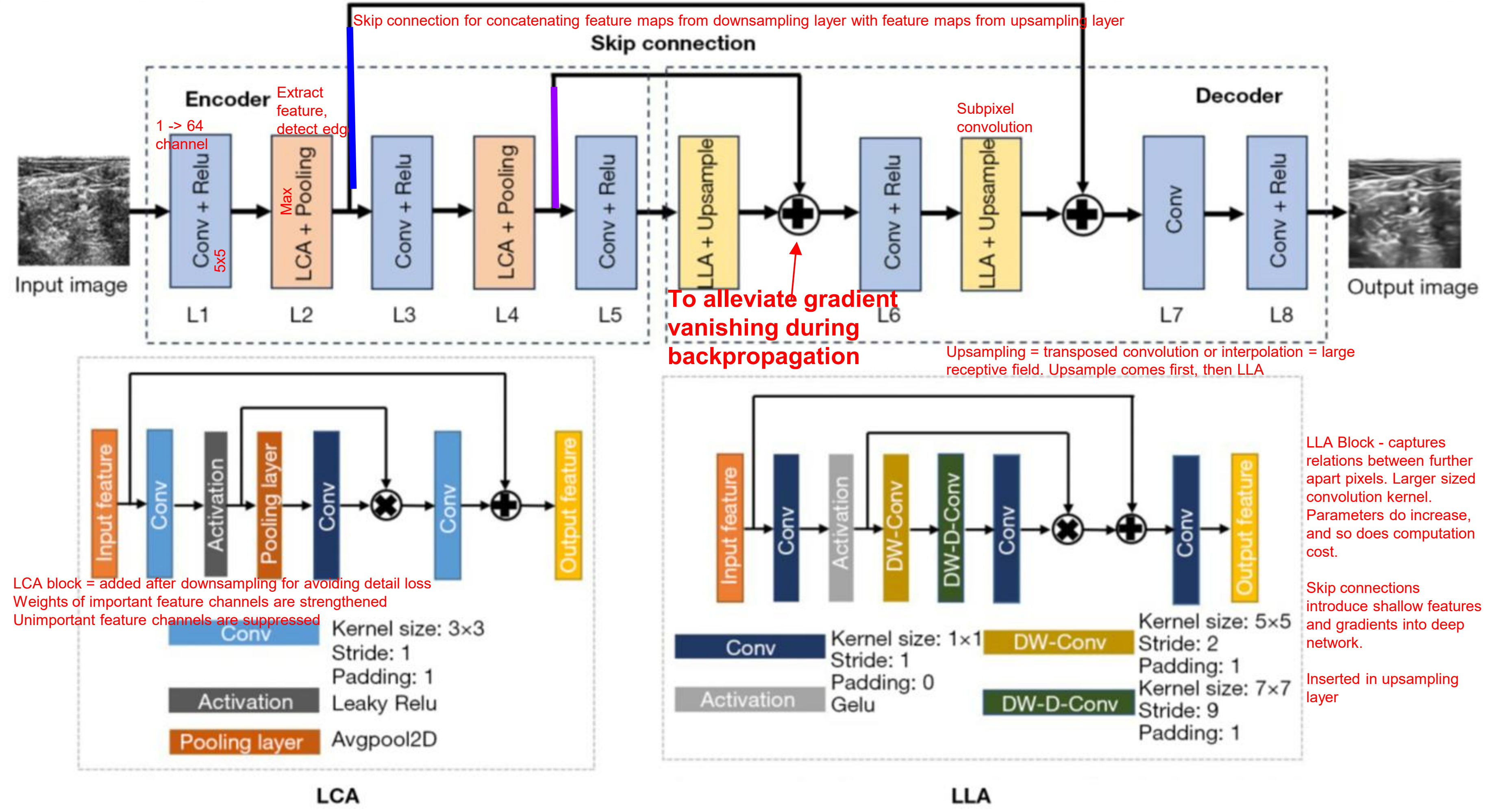


Preprocessing - About Our Dataset

Fetal Head Ultrasound dataset
Public
840 x 560 resized in training and test to 180 x 180
Image Augmentation x5 in training set = 4995 images
- Rotation
- Translation
- Flip

Creation of labels = matching ground truth and noisy images separated by noise level (speckle noise)
25% -> Validation, sorted, 1248
1334 total, 999 training, 335 testing.





Skip connection for concatenating feature maps from downsampling layer with feature maps from upsampling layer

1 -> 64 channel

5x5

Extract feature, detect edg

Max

To alleviate gradient vanishing during backpropagation

Subpixel convolution

Upsampling = transposed convolution or interpolation = large receptive field. Upsample comes first, then LLA

LCA block = added after downsampling for avoiding detail loss
Weights of important feature channels are strengthened
Unimportant feature channels are suppressed

LLA Block - captures relations between further apart pixels. Larger sized convolution kernel. Parameters do increase, and so does computation cost.

Skip connections introduce shallow features and gradients into deep network.

Inserted in upsampling layer

Table 1

LAD-CNN parameters

Layer number	Layer type	Encoder
L1	Conv + Relu	Kernel size: 5×5; padding: 2; stride: 1; Relu
L2	Pooling	Maxpool 2D; Kernel size: 2×2
L3	Conv + Relu	Kernel size: 3×3; padding: 1; stride: 1; Relu
L4	Pooling	Maxpool 2D; Kernel size: 2×2
L5	Conv + Relu	Kernel size: 3×3; padding: 1; stride: 1; Relu
L6	Conv + Relu	Kernel size: 3×3; padding: 1; stride: 1; Relu
L7	Conv	Kernel size: 5×5; padding: 2; stride: 1
L8	Conv + Relu	Kernel size: 1×1; padding: 0; stride: 1; sigmoid

DATASET DESCRIPTION +OBJECTIVE METRICS

Objective Metrics	Explanation
PSNR (Peak Signal-to-Noise Ratio)	Measures the pixel-by-pixel difference between the denoised image and the original clean image.
SSIM (Structural Similarity Index)	Evaluates image similarity based on luminance, contrast, and structural information. Ideal value closer to 1 as ranges between 0-1.
ENL (Equivalent Number of Looks)	Evaluates the smoothness of homogeneous regions in real ultrasound images.
P-Value	Statistical measure to evaluate model performance.A P-value < 0.05 indicates a significant difference between the proposed and existing models, validating the model's effectiveness.

Denoised vs. Clean= Loss Function

Loss function	Explanation
MSE(Mean Squared Errors)	• Captures the average squared difference between the original and denoised images. • Emphasizes pixel-level accuracy.
TV (Total Variation Regularization)	• Reduces artifacts in denoised images. • Smoothens images while preserving important edges and textures.
γTV-Weighing Factor	• Balances the importance of TV and MSE • A small value of 0.08 is chosen so that the TV doesn’t dominate MSE. • Ensures primary focus on pixel accuracy (MSE)
Combined Loss function	Loss = MSE + γTV * TV, where γTV = 0.08.

OBJECTIVE & SUBJECTIVE ASSESSMENT RESULTS

OBJECTIVE ASSESSMENT RESULTS - BM3D vs LAD-CNN

BM3D

	SIGMA_PSD	PSNR	SSIM	ENL
σ = 2	0.167	24.50	0.80	1.04
σ = 3	0.187	22.35	0.75	1.25
σ = 4	0.194	20.73	0.70	1.39
σ = 5	0.200	19.43	0.65	1.53
σ = 6	0.240	18.60	0.61	1.64
σ = 7	0.500	17.86	0.58	1.73

Time to Denoise a single image (σ = 3) = 1.45 s

Work In Progress

LAD-CNN

	PSNR	SSIM	ENL
σ = 2	15.63	0.27	
σ = 3	15.77	0.26	
σ = 4			
σ = 5			
σ = 6			
σ = 7			

Time to Denoise a single image (σ = 3) = s

OBJECTIVE ASSESSMENT RESULTS - ARTICLE

Table 4

Comparison of the metrics of the various models using the fetal head data set

Model	Noise level											
	σ =2		σ =3		σ =4		σ =5		σ =6		σ =7	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
NOISE	24.58	0.68	22.93	0.59	18.81	0.47	17.10	0.40	15.82	0.35	14.80	0.32
BM3D	28.55	0.81	28.45	0.72	26.10	0.69	25.34	0.65	23.37	0.60	22.01	0.57
Gauss filter	29.45	0.82	28.15	0.73	25.44	0.69	23.95	0.63	22.68	0.58	21.68	0.55
CNN-DAE	30.00	0.90	28.65	0.88	27.77	0.87	27.00	0.86	26.36	0.84	25.86	0.83
DnCNN	30.86	0.92	26.25	0.76	27.78	0.88	26.94	0.86	26.19	0.84	25.94	0.84
RED-SENet	26.45	0.85	28.77	0.91	27.07	0.88	25.52	0.86	26.26	0.86	25.66	0.84
Our model	30.88	0.92	29.13	0.91	28.09	0.88	27.25	0.86	26.49	0.86	26.01	0.85

σ, noise level; PSNR, peak signal-to-noise ratio; SSIM, structural similarity; NOISE, speckle-noised images; BM3D, block-matching and three-dimensional filtering; CNN-DAE, convolutional neural network-denoising autoencoder; DnCNN, denoising convolutional neural network; RED-SENet, residual encoder-decoder with squeeze-and-excitation network.

Table 7

Comparison of denoising time

Model	BM3D	Gauss filter	CNN-DAE	DnCNN	RED-SENet	Our model
Time(s)	7.150	0.08	0.008	0.009	0.008	0.008

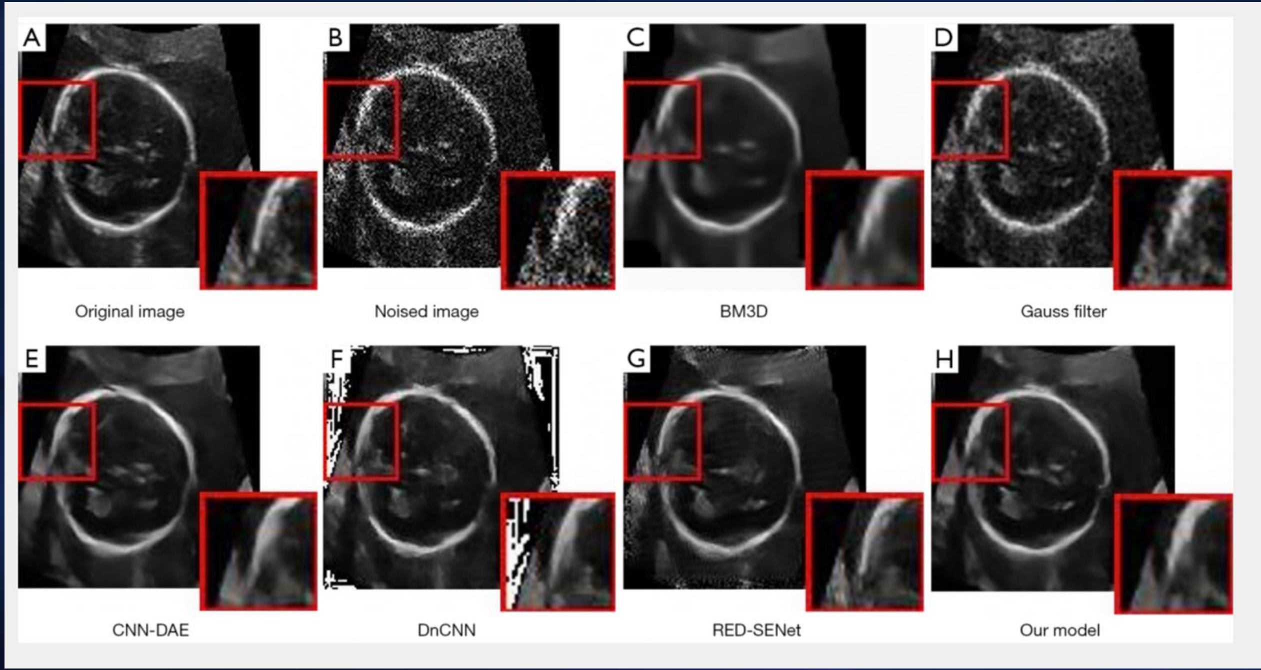
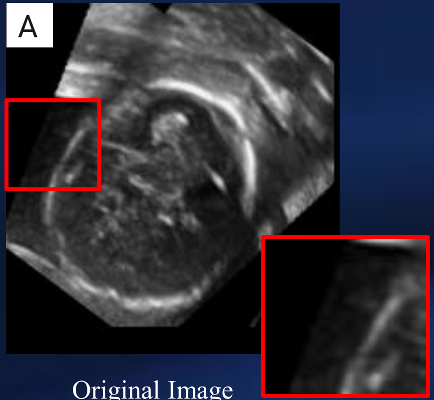
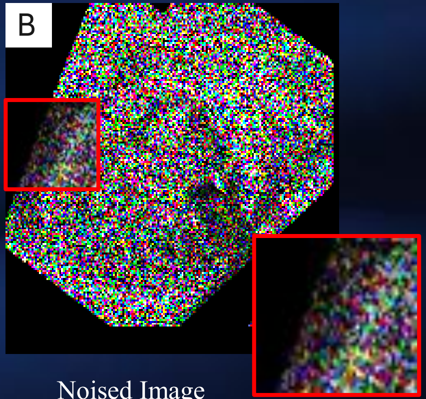


Figure 5 Subjective visual comparison of the denoised fetal head images at σ =5.0. (A) Original image, (B) noised image, (C) BM3D, (D) Gauss filter, (E) CNN-DAE, (F) DnCNN, (G) RED-SENet, (H) our model. BM3D, block-matching and three-dimensional filtering; CNN-DAE, convolutional neural network-denoising autoencoder; DnCNN, denoising convolutional neural network; RED-SENet, residual encoder-decoder with squeeze-and-excitation network; σ, noise level.

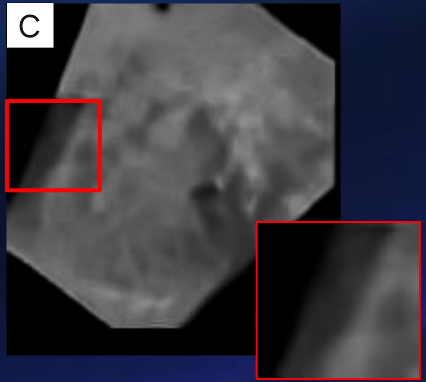
SUBJECTIVE RESULTS - JOURNAL PAPER



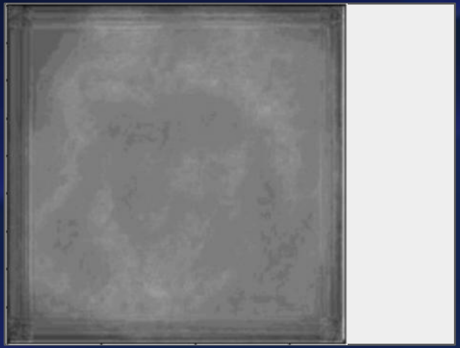
Original Image



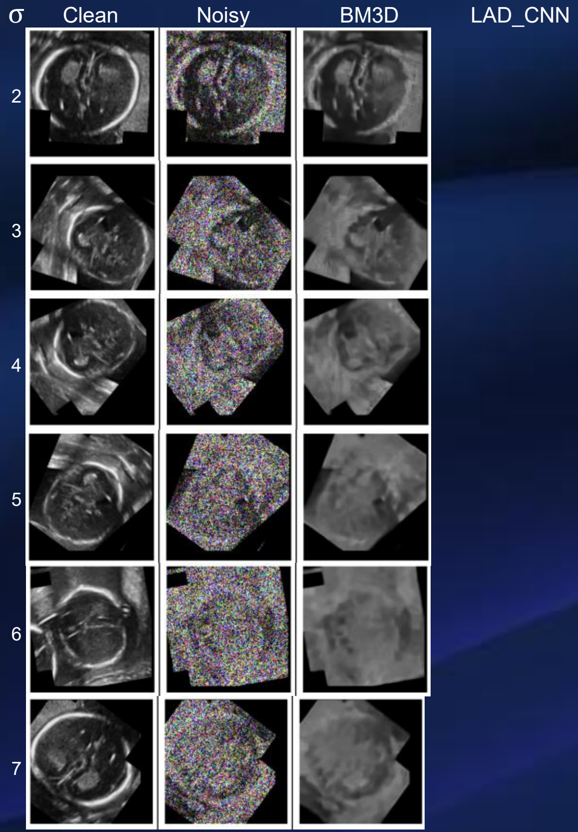
Noised Image



BM3D



SUBJECTIVE RESULTS - OUR IMPLEMENTATION - BM3D vs LAD-CNN



SUBJECTIVE RESULTS - ALL NOISE LEVELS - BM3D vs LAD-CNN

Shortcomings of the Study

- Mismatch between model architecture for LAD-CNN components in tables, and diagram in the paper:
    - Skip connection after downsampling, Activation function, pooling, channel attention mechanism (LCA and LLA Blocks)
- Limited Explanation of Model Design choices for LAD-CNN
- Lacking GPU Memory usage and energy consumption parameters required to train models used in study
- Deployment of model on different hardware configurations
- Further expansion of model to test on higher resolution images
- Lack of Comprehensive Statistical Testing

Advantages of the Study

- **High performance in Matrics:**
  - LAD_CNN model consistently outperforms other alternatives in PSNR and SSIM across different noise levels
- **Effective use of Attention Mechanisms:**
  - Interpretation of LCA and LLA enhances both texture preservation and noise reduction
- **Efficiency:**
  - Relative low parameter count (533,155) compared to alternatives for faster processing speed
- **Real-World applicability:**
  - Demonstrates significant improvement in clinical image clarity, aiding diagnostic accuracy
- **Dataset Diversity**
  - Tested on cardiac ultrasounds, brachial plexus ultrasounds, Berkeley Segmentation, fetal ultrasounds

Improvements in the study / our replication

- Data collection and testing:
  - Broader dataset inclusion: extend testing to cover a wider range of ultrasound types to ensure consistency across varied clinical applications
  - Real-world application testing: collaborate with healthcare facilities for real-world deployment and feedback from clinicians - making it more accessible & less complex
- Deployment and Usability:
  - User-friendly interface: develop interfaces in integrate denoising models into existing medical imaging workflows
  - Device Optimization: Optimize the model for low-power medical devices, facilitating use in resource-constrained environments

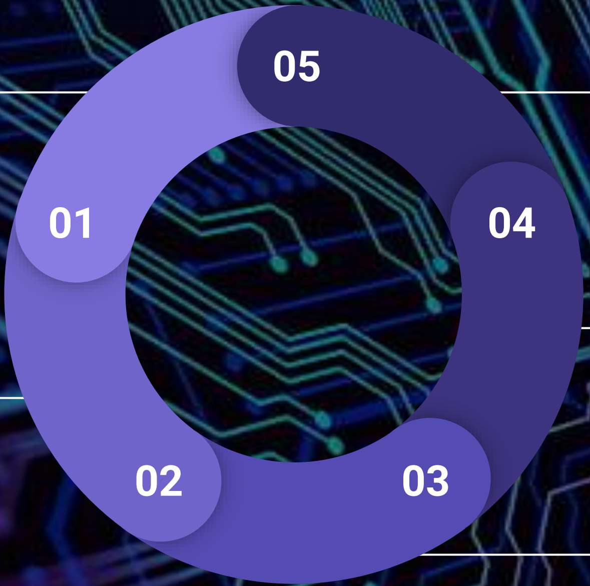
Conclusion

Denoising Problem and Solution

Speckle noise in medical imaging
Problem with traditional denoising methods
Solution → LAD-CNN

LAD-CNN vs. BM3D

BM3D →Traditional denoising methods
LAD-CNN → Modern deep-learning approach
LAD-CNN outperforms BM3D
Further optimization and testing



Future Direction

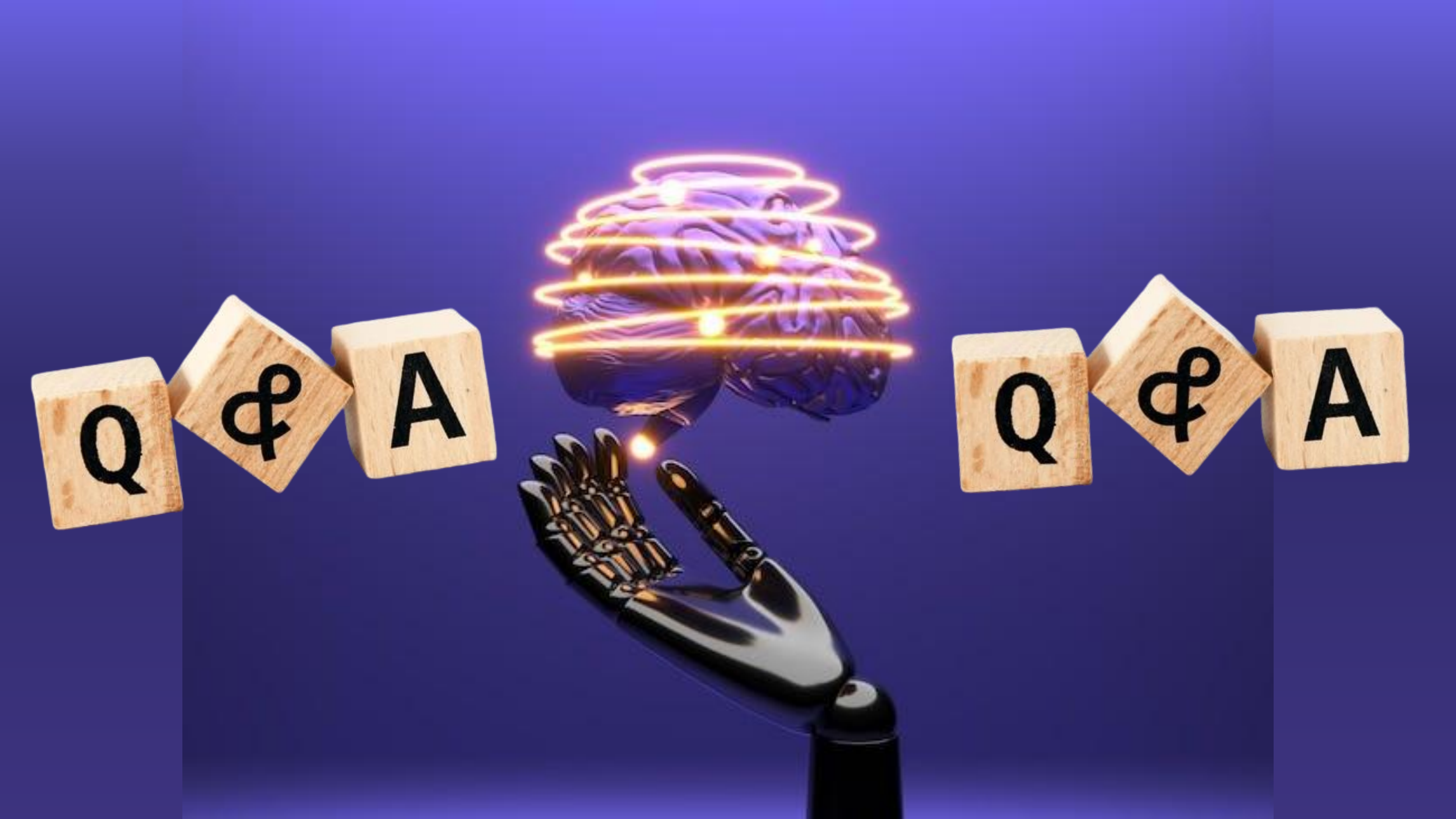
Real-world applications
User-friendly
Optimization

Advantages

High PSNR and SSIM performance
Effective attention mechanisms
Faster processing with fewer parameters
Diverse Dataset
Enhances image clarity

Shortcomings

Architecture inconsistencies
Trade-off: complexity vs. real time use
Limited applicability
Hardware & resolution gaps


Q&A
Q&A