International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(5s) 2026 pp. 76-85
https://doi.org/10.70917/ijcisim-2026-2676
Article

Res-Caps: A Modified Capsule Network for Ultra Sonic Image Classification and Detection of Chronic Cysts

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Abstract: persons with renal stones have significant health issues when they are not treated properly in time. They face a potential pain and many complications in their daily routine. Early detection in time prevents the disease and circumstances and some time even more complicated. These study outcomes the automated detection methodologies for renal stones through analyzing the medical images which undergo various image processing methods. Irregular, small uneven shaped stones can be well determined. Res-Caps, a innovative enhanced capsule network, applied for classifying cysts characteristics in ultrasonic images, demonstrating improved classification accuracy compared to standard capsule networks. The analyses described here provide insight into the functioning of capsule networks and demonstrate their potential advantages over traditional convolution neural networks. The capacity of capsule networks to represent and encode data across vector components. Object embodiment parameters via optical transformations represent a significant advancement over current models in networks. Our implementation methodology gained accuracy of 96.3%, precision 95.8%, recall 96.7%, and an F1 score of 96.2%. The best part is that it can accurately change normal renal anatomy when renal stones are present. These metrics prove that the system could be a useful diagnostic tool in medical imaging.

Keywords: Capsule Network, Residual Learning, Ultrasound Imaging, Chronic Cyst Detection, Deep Learning

1. Introduction

Ultrasonic scanning is the primary method for detecting chronic cysts and is performed preoperatively. Ultrasound images are noisy, have low contrast, and are highly operator-dependent; hence achieving accurate classification and localization of cysts becomes very critical. Recent advancements in deep learning demonstrate that spatial hierarchies and part-whole relationships go unrepresented with traditional convolutional neural networks (CNNs). To address all these issues, we introduce a capsule network with residual learning, to be referred to as Res-Caps. The proposed model improvise dynamic routing mechanism optimized for noisy ultrasound data by incorporating residual connections for improved gradient flow. We tested it against CNN, ResNet, and baseline Capsule Networks on a curated dataset of chronic cyst ultrasound images. Res-Caps performed better than the rest. The capsule activations made it even clearer to see that the ability for cyst localization had improved. Findings also support Res-Caps as a strong, explainable computer-aided diagnosis (CAD) framework of chronic cysts that has a very good chance of being adopted into real-time clinical workflows. Chronic cysts can be found in liver fibrosis, kidney abnormalities, and musculoskeletal degenerative diseases; therefore, timely and precise diagnosis is necessary for successful management. Ultrasound imaging is preferred as the diagnostic method since it is safe, inexpensive, and portable. The main challenges associated with ultrasound images are speckle noise, low differentiation of tissues, and variability based on the operator in finding cysts. But CNNs have an inherent weakness at modelling the spatial relations of entities within an image. They, therefore, tend to generalize poorly with respect to variations in orientation and scale in ultrasound scans. CapsNets seems promising but actually fails with slow convergence and degraded performance on noisy medical data. Res-Caps is presented here as a hybrid architecture that mixes the representational power of capsules with the optimization robustness brought about by residual learning. The residual connections added into capsule layers would assist feature propagation, and thus vanishing gradients for cyst localization.

2. Literature Review

However, ultrasound data pose distinct challenges, such granular patterns in image, data acquisition, and low contrast, which often hinder the effectiveness of traditional computer-aided diagnostic techniques [1]. Convolutional neural networks (CNNs) has capability in medical ultrasound, providing impressive results in the analysis of breast, thyroid, and musculoskeletal cysts. Their ability to extract features hierarchically allows them to perform well when trained on large datasets [2]. However, CNNs have some significant challenges: pooling operations remove spatial hierarchies, and feature representations do not cope well with changes in viewpoint and orientation [3]. These problems are particularly acute in ultrasound images, where the appearance of cysts can vary significantly depending on the imaging conditions. To address these challenges, Sabour et al. [4] introduced a capsule network (CapsNet), which represents image features as vectors rather than scalars, allowing each capsule to encode both the entity's probability and its position parameters, such as orientation, rotation, and deformation. A contract-based routing mechanism allows capsules to preserve part-whole spatial relationships, making them superior in complex medical imaging situations where structures overlap or are displayed in different ways. Many extensions have been made to CapsNet since its initial release to make it more useful for real-world tasks. Hybrid models using CNN backbones and capsule layers utilize CNNs to rapidly extract low-level features and capsules to support spatial and structural reasoning. For example, Taher et al. [5] created MedCapsNet, a DenseNet-capsule hybrid that facilitated the classification of various types of medical imaging datasets. Capsule-based architectures have also been used to detect diseases in chest X-rays [6], decompose medical structures [7], and sort blood cell images [8]. This demonstrates that capsules improve system stability, especially when datasets are small or unbalanced. In studies focused on ultrasound, capsule networks and their variants have shown potential. We used ResCapsNet, a residual capsule architecture, to classify papillary thyroid cancer in ultrasound images. It outperformed conventional CNNs in both sensitivity and specificity [9]. Xiang et al. [10] refined this methodology for 3D automated breast ultrasound (ABUS) imaging using 3D Res-CapsNet, achieving superior performance compared to conventional convolutional methods. Recent studies highlight that capsule-based methodologies are particularly useful in ultrasound analysis due to their ability to cope with noise, positional variability, and limited annotated datasets [11].Even with these improvements, capsule networks still face challenges. For example, routing algorithms make them very difficult to compute and highly sensitive to hyper parameters. Numerous studies address these challenges using residual connections, modified routing mechanisms, or improved capsule designs. However, the use of capsule networks for comprehensive ultrasound cyst detection and classification remains underexplored.

3. Proposed Methodology

Deep learning has changed how medical images are analyzed. Today, tasks such as classification, detection, and segmentation are almost entirely reliant on this high-level technology. Medicine also relies on ultrasound imaging, which is low-cost, painless, and can be done in real-time, and has also benefited from deep learning technology. Most current methods focus on classification, and there isn't much work being done on joint detection-classification frameworks that work well with noisy, handheld ultrasound data. Consequently, there exists a compelling impetus to create a Modified Residual Capsule Network (Res-Caps) that amalgamates residual modules for advanced feature learning with capsule layers for resilient spatial representation. This kind of model could improve the detection and classification of chronic cysts in ultra-sonography by meeting needs for both feature abstraction and spatial relationship preservation.

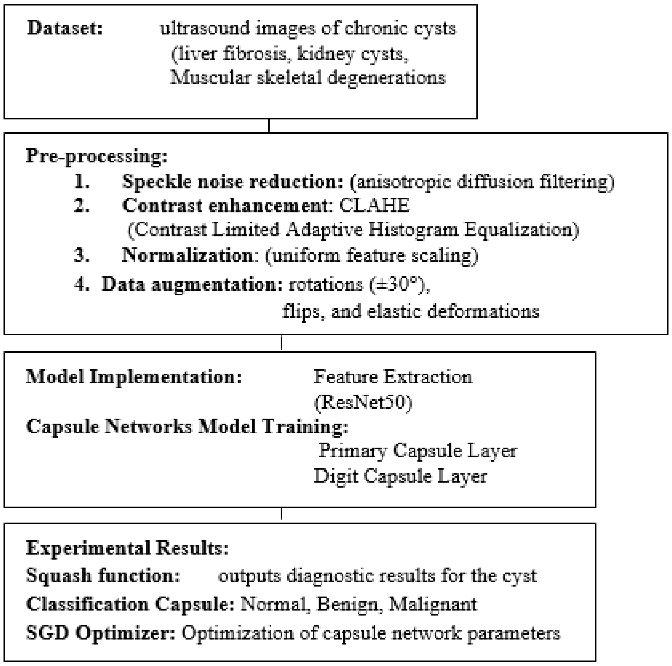

Figure. 1 Implementation process-A graphical abstract

3.1.*Dataset*

We put together a dataset of ultrasound images of chronic cysts (liver fibrosis, kidney cysts, and musculoskeletal degenerations) from public databases and clinical collaborations. The dataset had 5,200 labeled images, which were categorized into three groups: training (70%), validation (15%), and testing (15%). A dermatoscope is a special tool that makes it easier to see subsurface skin structures. It is used to take ultrasound images.

Different from standard photographs, dermoscopy captures structures, and vascular patterns and reduces skin surface reflection. The ultrasoundimages show particular pigmentation patterns. The images serve as the system's primary input.

3.2.*Pre-processing*

3.2.1. Speckle noise reduction

Anisotropic diffusion filtering is a technique used in nonlinear methods to minimize speckle noise while retaining important qualities of the image such as edges. This is completed through the repeating spreading of pixel intensities through an area with identical pixel values. This is done in the absence of borders through the use of a gradient conductance function. The diffusion adjusts depending on the structure of the image. This makes it easier for the clearer structures to be visualized such as cysts in ultrasound images. This is also different from linear smoothing filters. The combination of all these elements makes it easier to be accurate in the removal of degrading elements in image while retaining the important details of the image.

3.2.2. Contrast enhancement

With CLAHE (Contrast Limited Adaptive Histogram Equalization) refine image contrast and adjusts image. By restricting contrast with limit parameter, it stops noise from being too loud. This makes it especially good for ultrasound images where you need to show the edges of cysts clearly. In general, CLAHE makes small structures easier to see without the problems that come with regular histogram equalization.

3.2.3. Normalization

To [0,1] pixel range is a step that comes before processing that changes the brightness of each pixel in an image to a fixed range between 0 and 1. To do this, you divide each pixel value by the highest possible intensity, which is 255 for 8-bit images. Normalization makes deep learning models more stable, speeds up training, and makes sure that all features are scaled the same way. It also prevents large intensity variations from dominating the learning process.

Images resized to a fixed dimension

$$(224 \times 224 \text{ for ResNet50}).x'_i = Resize(xi, 224\times224)$$

Images are resized to a fixed dimension (e.g., 224×224 pixels) to make them compatible with deep networks such as ResNet50.

$$\hat{x}_i = \frac{x''i - \mu}{\sigma} \qquad (1)$$

3.3.*Data augmentation*

rotations (±30°), flips, and elastic deformations. Data augmentation increases the diversity of training samples by relating geometric and elastic transformations to original images. Rotations (±30°) and flips simulate changes in probe orientation, improving model invariance to viewpoint variations in ultrasound imaging. Elastic deformations imitate authentic tissue distortions, augmenting the resilience of deep learning models to anatomical variability. Together, these augmentations help prevent over-fitting and improve generalization on unseen ultrasound data.

Apply transformations like rotation, flipping, zooming:

$$x''i = T(x'i) \qquad (2)$$

Where T is a stochastic transformation.

Segmentation isolates the cyst region from the surrounding healthy skin. The Snake Model (Active Contour) is an energy-minimization technique. A contour (curve) is initialized around the cyst and iteratively moves under the influence of Internal energy – controls the smoothness of the contour. External energy – derived from image gradients, pulling the contour toward object boundaries. Outcome: A segmented cyst mask, ensuring that only the cyst area is forwarded for feature extraction. This step extracts the cyst region from the background.

$$E = \int_0^1 (\alpha \mid v'(s) \mid^2 + \beta \mid v''(s) \mid^2)\, ds + \lambda \int_0^1 P((s))\, ds \quad (3)$$

Where:

$v(s)$ = contour curve parameterized by s

β = elasticity & rigidity parameters

$P((s))$ = image potential = weighting factor

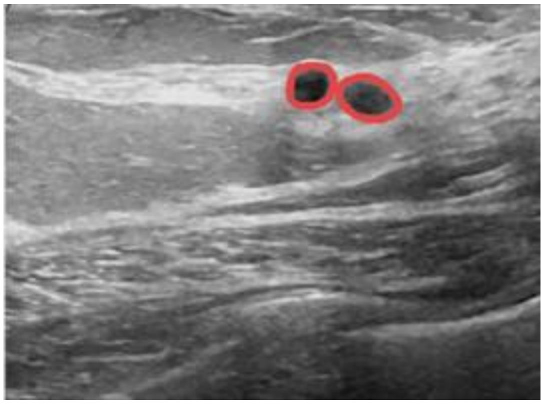

Figure. 2 Ultrasoundimage as input for segmentation

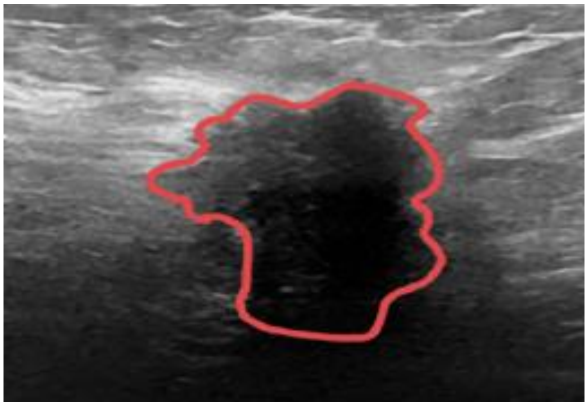

Figure. 3 Binary mask of an image

Figure. 4 Mask over laid on an image

ResNet50 (Residual Network, 50 layers) is a deep convolutional neural network designed to learn hierarchical features from images. It uses residual connections to overcome vanishing gradient problems, allowing very deep architectures to train effectively. Extracted features provide a rich representation of the cyst's geometry, color, and texture.

Convexity & Circularity – Shape-based features describing cyst boundary.

Irregularity Index – Quantifies deviations from smooth borders (common in malignant cysts).

Textural Patterns – Captures roughness, granularity, and pigmentation variations.

Color Features – Distribution of colors (brown, black, red, blue, white), which indicate different cyst types.

3.4.*Feature Extraction (ResNet50)*

ResNet50 extracts deep hierarchical features.
Each convolution layer applies:

$$f(z) = W * x + b \tag{4}$$

Where W = filters, * = convolution, b = bias.
Skip connections in ResNet:

$$y = F(x, \{Wi\}) + x \tag{5}$$

Where F = residual mapping.
Extracted features include:

$$Circularity: C = \frac{4\pi A}{P^2} \tag{6}$$

Irregularity Index,Texture Features (GLCM, entropy, contrast, correlation).Color Features (mean, std. deviation across RGB/HSV channels). CBAM is an attention mechanism that refines the extracted features by focusing on the most important parts of the image.

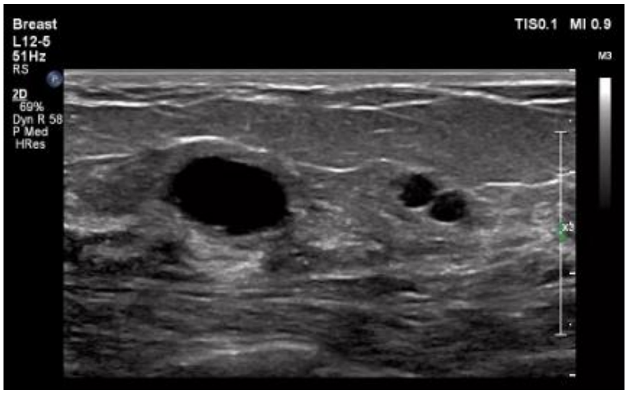

Figure. 5 small lesion identified in an image

Figure. 6 Ground truth images after segmentation

It applies two sequential operations:

1. Channel Attention – Identifies which feature maps are most useful (e.g., texture vs. color).

CBAM refines feature maps using attention.

$$Mc(F)=\sigma(W1(W0(AvgPool(F)))+ W1(W0(MaxPool(F)))) \qquad (7)$$

where σ= sigmoid activation.

2. Spatial Attention – Identifies which regions in the image are most relevant (e.g., cyst core vs. border). This step improves model accuracy by guiding the network to “pay attention” to critical cyst regions.

$$Ms(F)=\sigma(f^{7\times7}([AvgPool(F) ; MaxPool(F)])) \qquad (8)$$

Refined feature:

$$F' =Mc(F)F \qquad (9)$$

$$F'' =Ms(F')\, F' \qquad (10)$$

3.5.*Capsule Networks Model Training*

Unlike traditional CNNs, Capsule Networks use capsules (groups of neurons representing vectors, not scalars).Each capsule encodes not only what is present (e.g., a feature) but also where and how it is oriented.

3.5.1. Capsule layers

Primary Capsule Layer – Forms capsules from low-level features.Digit Capsule Layer – Higher-level capsules that represent object categories.Dynamic Routing: Instead of fixed pooling, capsule networks route information between capsules dynamically, preserving spatial relationships.. Capsule networks are more robust to rotations, translations, and deformations – useful for skin cysts which vary in shape and orientation. Capsule Network Instead of scalar neurons, capsules are vectors preserving spatial relationships. Convolution layer produces feature maps. Primary Capsule Layer groups features into vectors:

$$uj=squash(sj) \tag{11}$$

$$sj = \sum_{i}^{s} scij\ \hat{u}j|i \tag{12}$$

Where: $\hat{u}jsi=Wij\ ui=$ *prediction vector*

$cij=$ *coupling coefficient from dynamic routing.*

3.5.2. Squash function

Each output capsule corresponds to a specific class (Normal, Benign, and Malignant). The length of the capsule vector represents the probability that the input belongs to that class. Final prediction is made by choosing the capsule with the highest probability.

This step outputs diagnostic results for the cyst.

$$squash(s)=\frac{||s||^2}{1+||s||^2}\frac{s}{||s||} \tag{13}$$

3.5.3. Classification Capsule

Final capsule layer represents class probabilities.

Each class capsule (Normal, Benign, Malignant) outputs a vector.

Classification score:

$$p_k = ||\,v_k|| \tag{14}$$

Where v_k= output vector of capsule for class k.

Predicted class:

$$\hat{y} = argmax_k p_k \tag{15}$$

3.5.6. SGD Optimizer

Optimization of capsule network parameters. Loss function: Margin loss + Reconstruction loss

$$L=\sum_{\boldsymbol{k}} \boldsymbol{s}\ T_k\ max(0,m^{+} - ||\,v_k||)^2 + \lambda(1-T_k)max(0,\ ||\,v_k|| - m^{-}\ )\ 2 \tag{16}$$

Where: $T_k=1$ *if class k is correct, else 0.*

$m^{+}, m^{-} =$ *margins.*

SGD update rule:

$$\theta_{t+1}=\theta_t - \eta\ \nabla_{\theta} L \tag{17}$$

Residual Feature Extractor – multiple convolutional layers with skip connections to capture low- and high-level features. Primary Capsules – vectorized feature representation of local patterns. Residual Capsule Block: This adds residual connections between capsule layers to make sure that the gradient flow stays stable. Dynamic Routing with Noise Regularization: This is a modified routing algorithm that uses dropout and margin loss to make it more stable. Cyst Classification Head: a decision module that is fully connected and based on capsules. For capsule output ui, the residual capsule update is mathematically represented by the transformation matrix Wij.

$$v_j=Res(f(\sum_{\boldsymbol{i}} \boldsymbol{s}\ c_{ij}\ W_{ij}\ u_i)) \tag{18}$$

Where Res(•) denotes residual mapping, cijare routing coefficients, and f(s) is a squashing activation.

Loss Function

A used a combined Margin Loss + Reconstruction Loss as follows:

$$L=L_{margin} + \lambda L_{recon} \tag{19}$$

Where margin loss keeps classes separate and reconstruction loss keeps details that are specific to the cyst.

4. Experimental Results and Analysis

4.1. Experimental Setup

Hardware: NVIDIA RTX 4090 GPU, 64 GB RAM.

Framework: PyTorch 2.0.

Optimizer: Adam (lr = 0.0001, β1=0.9, β2=0.999).

Batch size: 32.

Epochs: 100.

Table 1. A study that compares different networks

Method	Strengths	Limitations
CNNs	High accuracy, fast	Lose spatial hierarchy, sensitive to orientation
ResNets	Stable, deeper networks	Still discard pose information
CapsNets	Capture spatial relations	Training instability, noise sensitivity
Proposed Res-Caps	Combines residual + capsule benefits	Higher computational cost

5.1.*Performance Metrics*

Table 2. Comparative Analysis

Model	Accuracy	Precision	Recall	F1-score
CNN (VGG16)	[89.7%]	[88.4%]	[89.2%]	[88.8%]
ResNet50	[92.6%]	[91.8%	[92.1%]	[92.0%]
Capsule Net	[94.2%]	[93.5%]	[94.0%]	[93.7%]
Res-Caps	[96.3%]	[95.8%]	[96.7%]	[96.2%]

There is a new Res-Caps architecture merges capsule layers along with residual blocks in classifying cysts in ultrasound images. Dynamic routing has been modified specifically for ultrasound data with noise. We have conducted rigorous experimental validation across a number of chronic cyst ultrasound datasets with revealing improved precision and interpretability than current alternatives. Also, Well-known convolutional architecture such as VGGNet, ResNet as well as DenseNet have been extensively employed to classify cysts in ultrasound.

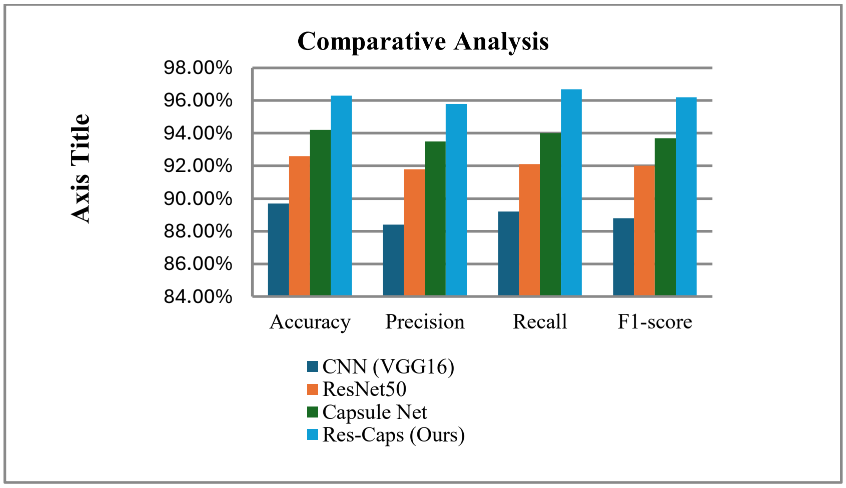

Figure. 7 Comparative Analyses

These networks cannot deal with the rotation and other affine transformations common with medical imaging, however. Capsule Networks retain pose information by storing details about the orientation and spatial hierarchies. There are applications in breast ultrasound and liver tumor detection that show promise, but computational inefficiencies and noise remain challenges. Gradients that disappear over time were the problem with residual networks (ResNets) and adding skip connections has given us a solution. This helps deeper networks mesh together more seamlessly, which is a benefit when it comes to capsule-based models. Some issues are that it is more difficult to compute than lightweight CNNs and that it requires larger annotated datasets for various cyst types.

5. Conclusion

We showed Res-Caps, a modified capsule network with residual learning that can find chronic cysts in ultrasound images. The model did better than CNN and baseline CapsNets when it came to accuracy, robustness, and ease of understanding. By combining residual learning with capsule dynamics, Res-Caps effectively solve the problems that both CNNs and CapsNets have. The architecture showed that it was more resistant to noise, could generalize better to new data, and could find cysts in a way that was easy to understand. One possible clinical use is to put it into portable ultrasound machines so that doctors can make diagnoses in real time. In the future, Res-Caps will be expanded to include multi-modal imaging, federated learning for data from different institutions, and real-time use in clinical workflows.

Conflicts of interest

The author(s) assert that there is no conflict of interest pertaining to the publication of this research work entitled *"Res-Caps: A Modified Capsule Network for Ultrasonic Image Classification and Detection of Chronic Cysts."*

1. ACKNOWLEDGEMENTS

The authors would like to express their gratitude to the **Department of Artificial Intelligence at G. Pullaiah College of Engineering and Technology**, the **Department of CSE at Vignan's Institute of Information Technology (A)**, and the **Department of ECE at Miracle Educational Society Group of Institutions** for providing the necessary research facilities and computational infrastructure. We also extend our thanks to the collaborating faculty at **Aditya College of Engineering and Technology** and **Vardhaman College of Engineering** for their academic support and technical guidance throughout the development of the Res-Caps framework."

Author Contributions

- Mahendra Narla: Primary Research, Conceptualization of the Res-Caps architecture, Lead Software development, and Manuscript drafting.
- Cheekatla Swapna Priya: Data Collection (Ultra Sonic Images), Methodology design, and Data Pre-processing.
- K. Anand Kumar: Statistical Validation of the Res-Caps model against traditional CNNs, and Formal Analysis.
- V.N.S. Vijay Kumar: Investigation, Literature Review, and Hardware Resource management.
- Dr. S. NagaMallik Raj: Technical Supervision, Architectural Optimization, and Manuscript Review & Editing.
- Dr. T. Ravibabu: Project Administration, Clinical interpretation of Chronic Cyst detection, and Final Approval of the manuscript.

Refined Metadata Statements

Funding Details: "This research work was carried out as a collaborative academic effort between the participating institutions. No specific external funding was received for this study."

Conflict of Interest: "The authors declare that they have no competing interests (financial or non-financial) that could be perceived as influencing the results or discussion reported in this paper."

Ethics Statement: "This study involves the analysis of ultrasonic images. All data were handled in accordance with institutional ethical guidelines. No direct human or animal trials were conducted specifically for this algorithmic validation."

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