Ultrasound-Based Uterine Fibroid Detection: A Literature Review

Background and Importance of CAD for Uterine Fibroids

Uterine fibroids (leiomyomas) are among the most common benign tumors in women of reproductive age, with incidence estimates of 20–40% (and up to 80% in lifetime risk). They can cause heavy menstrual bleeding, pelvic pain, infertility, and other symptoms that significantly impact quality of life. Ultrasound imaging is the first-line, non-invasive modality for fibroid diagnosis and monitoring due to its wide availability, safety, and relatively low cost. In fact, ultrasound typically has high sensitivity and specificity for fibroid detection and is the **primary imaging tool** in clinical practice. However, several challenges persist in ultrasound-based diagnosis of fibroids:

- **Operator Dependence & Variability:** The accuracy of ultrasound detection depends heavily on the sonographer's experience. Less experienced operators may miss small or atypically located fibroids. There is also a lack of standardized acquisition views, and differences in ultrasound equipment can affect image quality. These factors lead to inter-observer variability and potential misdiagnoses.
- **Overlap with Other Pathologies:** Ultrasound can sometimes confuse large subserosal fibroids with ovarian or adnexal masses. Fibroids with unusual presentations may be mistaken for other pelvic tumors, leading to diagnostic uncertainty.
- **Image Quality Issues:** Ultrasound images suffer from speckle noise, acoustic shadowing, and attenuation artifacts that obscure tissue boundaries. Fibroids often have low contrast with the surrounding myometrium, making **small or deep lesions** difficult to delineate. Blurry edges and uterine motion (e.g. due to breathing) further complicate manual assessment.

Early and accurate detection of fibroids is crucial to prevent complications (e.g. infertility) and to guide timely treatment such as medical therapy or minimally invasive procedures. Given the limitations of manual ultrasound interpretation, there is strong motivation to develop **computer-aided diagnosis (CAD)** systems and automated algorithms to assist clinicians. Automated detection could reduce observer bias, improve consistency, and save radiologists' time by flagging fibroids for closer review. Moreover, as fibroids are a major cause of hysterectomy worldwide, better diagnostic tools may enable earlier intervention and more conservative treatments.

Research Trend: In the last decade, substantial research has focused on applying image processing, machine learning (ML), and more recently deep learning (DL), to ultrasound images for **automated fibroid detection**. The literature covers the entire pipeline from image preprocessing and segmentation of the fibroid region to feature extraction and classification of fibroid vs. normal tissue. Below, we review approximately 30 key studies, encompassing both classical approaches and modern AI techniques, that have contributed to advancements in this domain. The review also notes the challenges identified and the innovations proposed, as well as the contrast between global research efforts and any available studies from Sri Lanka.

Traditional Image Processing and Segmentation Techniques

Early approaches to automated fibroid detection relied on classical image processing techniques to enhance and segment ultrasound images, followed by conventional classifiers. Preprocessing is a critical first step: because **speckle noise** is inherent in ultrasound, many studies emphasized noise reduction and contrast enhancement to make fibroids more discernible. Common speckle filters (median, Lee, Frost) and anisotropic diffusion methods have been used to suppress noise while preserving edges. However, overly aggressive noise filtering can erase subtle boundary details, so methods must balance noise removal with feature preservation.

After preprocessing, **segmentation** aims to isolate the fibroid region from the surrounding uterus. Traditional segmentation methods applied to uterine ultrasound images include:

- **Thresholding and Region Growing:** Simple intensity thresholding can roughly segment a fibroid if it has distinguishable echogenicity. More robust is *region growing*, where seeds are placed (manually or automatically) and neighboring pixels are added if they meet similarity criteria. For example, Rundo *et al.* (2016) combined multi-seed region growing with a split-and-merge strategy to segment fibroids in MRI-guided focused ultrasound treatments. This achieved good results in MRI, though ultrasound introduces more noise.
- **Active Contour Models:** *Snake* algorithms and their variants were popular for medical image segmentation. An early ultrasound study by Shivakumar *et al.* (2015) used a **gradient vector flow (GVF) active contour** to segment fibroid boundaries in 2D ultrasound. Active contours iteratively evolve an initial curve toward object edges by minimizing an energy function; however, they require careful initialization near the fibroid and can get stuck on spurious edges from noise.
- **Statistical Shape Models (SSM):** To incorporate prior knowledge of fibroid shape, Ni *et al.* (2015) introduced a *dynamic statistical shape model* for segmenting fibroids in ultrasound during HIFU therapy. They built a shape prior of the lesion boundary variations and integrated it with an active contour. This *SF-SSM* approach (stochastic shape model + observation model) improved robustness against blurry

or incomplete edges in HIFU ultrasound images. The method outperformed several standard ultrasound segmentation algorithms in accuracy and robustness, even on low-quality images.

- **Morphological Operations and Clustering:** Jeyalakshmi and Kadarkarai (2010) presented a knowledge-based approach using **mathematical morphology** to segment *fluid-filled fibroids* (which appear as cystic areas). Similarly, Fallahi *et al.* (2014) applied a two-step process on MRI: fuzzy C-means (FCM) clustering to segment fibroid regions, followed by morphological operations to refine the result. While that study was on MRI, it demonstrated the utility of combining clustering with morphology – a strategy also feasible for ultrasound with appropriate modifications (e.g., using textural cues for clustering).
- **Multi-scale Texture Analysis:** Some researchers encoded texture and edge information to guide segmentation. Zhang *et al.* (2015) developed a method for HIFU ultrasound that encoded lesion texture patterns and boundary gradient features to assist segmentation. By integrating texture analysis, their approach could better distinguish fibroid tissue from normal myometrium, which often have subtly different speckle textures.

Overall, these classical segmentation approaches had **mixed success**. They demonstrated that incorporating prior knowledge (shape models, expected texture) and advanced contour models could achieve reasonably accurate fibroid outlines. For instance, Ni *et al.* reported high Dice similarity and robust performance with their shape-model-based method. However, challenges remained: fibroid borders can be extremely indistinct on ultrasound, and many methods struggled if the fibroid was very small, had similar echogenicity to normal tissue, or if multiple fibroids were present touching each other. Moreover, many traditional methods required manual tuning or initialization (e.g., selecting a threshold or placing initial contour points), limiting full automation.

Segmentation for Therapy Planning: It is worth noting that a significant motivation for accurate fibroid segmentation has been **HIFU treatment planning**. High-Intensity Focused Ultrasound ablation uses either ultrasound or MRI guidance. In ultrasound-guided HIFU, real-time segmentation of the fibroid is needed to target the therapy and avoid harming surrounding tissue. The literature reflects this: numerous studies in 2014–2016 (Liao et al., Zhang et al., Ni et al., etc.) tackled fibroid ultrasound segmentation specifically in the context of HIFU, proposing solutions to cope with issues like respiratory motion and lesion deformation. These works laid a foundation, but their complexity and need for careful parameter tuning opened the door for more data-driven approaches like machine learning, discussed next.

Feature Extraction and Classical Machine Learning Classification

Classical machine learning approaches for fibroid detection typically followed a *two-stage pipeline*: first extract a set of discriminatory features from the ultrasound image (or from a segmented region of interest), then apply a machine learning classifier to decide if a fibroid is present.

Hand-Crafted Feature Extraction: A variety of features have been explored, aiming to capture the textural, morphological, and intensity characteristics of fibroid tissue on ultrasound:

- **Texture Features:** Given the importance of visual texture in ultrasound, statistical descriptors like Gray-Level Co-occurrence Matrices (GLCM) features (contrast, homogeneity, etc.), histogram features, and wavelet coefficients were widely used. *Wavelet transform features* in particular proved useful for capturing multi-scale texture. N. Sriraam et al. (2010) pioneered a computer-aided diagnostic tool using **wavelet packet features** derived from ultrasound images. In their method, sub-band energies from a wavelet decomposition of the image were fed into a neural network to distinguish fibroid-containing images from normal. This early study, presented at an IEEE biomedical conference, demonstrated the feasibility of automated fibroid recognition, though performance was modest by today's standards.
- **Gabor and Frequency Features:** Gabor filters (which capture oriented edge patterns) and other frequency-domain features have also been applied. One study combined **Gabor filter responses** with wavelet features and used a Support Vector Machine (SVM) for classification. They reported a *100% accuracy on a dataset of 86 images*, although such perfect performance likely reflects an overly small or homogeneous dataset. Nonetheless, it indicates that fibroids do have distinct texture patterns that, when effectively encoded, can be learned by classifiers.
- **Shape and Morphology:** When segmentation is available, shape features (contour irregularity, size, etc.) can be informative. Fibroids are often roughly spherical or ovoid. Prabakar *et al.* (2014) implemented a LabVIEW-based tool to segment fibroids and measure their size using morphological features. The goal was not only detection but also providing the volume/diameter of the fibroid for clinical decision-making. Shape features are less useful for initial detection (since one must detect to get the shape), but they play a role in confirmation and assessment once a region is proposed.

Classical Classifiers: After feature extraction, classical ML algorithms like *Support Vector Machines (SVM)*, *Artificial Neural Networks (shallow NNs)*, *Random Forests*, and *Bayesian classifiers* have been tried:

- Sriraam's 2010 study employed a simple **backpropagation neural network (BPNN)** classifier on wavelet features, which was an early form of machine learning CAD for fibroids. In a follow-up, the same group explored SVMs with wavelet and Gabor features (as noted above), finding SVMs effective in separating classes in their feature space.
- Padghamod & Gawande (2014) reported on classifying ultrasonic uterine images (fibroid vs normal) using statistical features and achieved accuracy in the mid-90% range. Although the details of their method are sparse, it likely involved training an SVM or ANN on a small dataset, which was common in early studies.
- A more recent effort by Sumathy *et al.* (2022) presented a **decision support tool** for fibroid treatment using machine learning algorithms. They compared multiple classifiers on clinical and imaging data to predict whether a patient would require surgery or medical management. While not purely an image classification task, it highlights the use of ML in broader fibroid-related decision-making.

Despite some encouraging results, classical ML approaches were constrained by the quality of the features. Hand-crafted features may not capture all the variability in fibroid appearances. Ultrasound images can differ due to machine settings, patient body habitus, fibroid composition (fibroids can undergo degeneration or calcification, altering their echo texture), etc. Features that work well on one dataset might not generalize to another. Many early studies used very limited data (often <100 images), sometimes reporting unrealistically high accuracies (even 100% in one case) that likely would not hold on larger test sets. The need for extensive feature engineering and the lack of large annotated datasets were significant hurdles.

Transition to Learning-Based Features: These limitations set the stage for applying deep learning to this problem. Deep learning methods (particularly convolutional neural networks) can automatically learn optimal features directly from the data, given enough training examples. By around 2015, the first attempts to apply deep CNNs for medical images began to appear, and by the late 2010s, researchers turned to deep learning for ultrasound fibroid detection, as discussed below.

Deep Learning Approaches for Fibroid Detection and Segmentation

With the success of deep learning in general image recognition, many recent studies have leveraged **Convolutional Neural Networks (CNNs)** and their variants for ultrasound-based fibroid detection. Deep learning offers end-to-end learning of features and classification, potentially overcoming the limitations of manual feature design. Key developments in this area include:

CNNs for Image-Level Classification

Early applications of deep learning treated fibroid detection as an *image classification* problem – i.e., determining if a given ultrasound image contains a fibroid or not. This is essentially a binary classification (fibroid vs normal uterus). Several architectures and strategies have been explored:

- **Transfer Learning with Pre-trained CNNs:** Given limited medical image data, many studies fine-tune CNNs pre-trained on large datasets like ImageNet. Shahzad *et al.* (2023) evaluated popular pre-trained architectures (VGG16, ResNet50, and InceptionV3) on a Kaggle ultrasound fibroid dataset. After preprocessing (scaling, normalization) and data augmentation, they fine-tuned these models for fibroid classification. The results showed InceptionV3 reached ~90% accuracy and ResNet50 ~89%, whereas VGG16 was lower (~85%). Their most interesting finding was that a **custom dual-path CNN (DPCNN)** they proposed achieved 99.8% accuracy, outperforming the fine-tuned standard models. This suggests that a tailored architecture can capture ultrasound-specific features better than generic ImageNet features. They also noted that applying fine-tuning techniques significantly boosts performance of pre-trained models in this domain.
- **Attention-Enhanced CNNs:** Xi *et al.* (2024) introduced an **EfficientNet-B0 CNN with attention mechanisms** for fibroid classification. EfficientNet is a family of models known for balancing accuracy and efficiency. By adding an attention module, the network could focus on the most informative regions of the image – presumably the fibroid if present – and ignore irrelevant background. Using a dataset of 1,990 ultrasound images (half with fibroids, half without), their attention-augmented EfficientNet achieved an impressive 99% classification accuracy. This high performance underscores the power of modern CNNs; however, the authors caution that further validation is needed on more diverse populations and that future work should aim for high sensitivity and specificity across varied settings. (An extremely high accuracy on a balanced dataset implies both sensitivity and specificity were near 99% in their study.)
- **Custom Deep Models:** Beyond standard CNNs, researchers have experimented with bespoke network architectures. Dilna *et al.* (2022) proposed an approach named **MBF-CDNN** – essentially a *Monarch Butterfly Optimization (MBO) tuned*

deep neural network with fuzzy clustering. The details combine an optimization algorithm (MBO) for hyperparameter tuning and a fuzzy logic-based bounding to refine predictions. They reported about **94.7% accuracy, 94.4% sensitivity, and 95% specificity** on their dataset. This performance is comparable to the deep transfer learning models above. It demonstrates that even with relatively small networks, careful integration of optimization and fuzzy techniques can yield high accuracy.

- **3D Ultrasound and Specialized Tasks:** While most studies use 2D ultrasound images, some have looked at 3D ultrasound volumes. One referenced study achieved **91.3% accuracy detecting fibroids from 3D ultrasound data** using a CNN. Three-dimensional ultrasound can improve visualization of fibroids and may provide more information for a CNN to learn, though 3D data are rarer. Another study cited in literature achieved **98.8% accuracy on 2D ultrasound** fibroid detection, highlighting that with clean data and possibly limited scope, CNNs can be extremely effective. These high metrics, however, should be viewed in context – they may come from controlled datasets or specific experimental conditions.

Encouragingly, deep learning models often **outperform human experts or at least narrow the gap**. Huo *et al.* (2022) developed a DCNN model for fibroid detection and conducted a rigorous evaluation against clinicians. In a test on 488 images, the DCNN achieved ~94.3% accuracy, significantly higher than the average 86.6% accuracy of junior sonographers on the same set. The model's performance was statistically **on par with senior radiologists** (who scored ~95.2% accuracy). Moreover, when junior examiners used the AI model as an assistive tool, their diagnostic accuracy jumped to 94.7% and became **indistinguishable from the experts**. Specifically, AI assistance improved junior doctors' sensitivity from 83.2% to 92.8% in detecting fibroids, and specificity from 90.8% to 97.1%. This study underscores a key trend: AI is not just about automation, but also augmentation – a properly validated model can **elevate the performance of less experienced practitioners to expert level**. It also addressed generalization by using an external validation set and multiple sonographers, adding credibility to the results.

Object Detection and Real-Time Systems

Rather than simply classifying an image, some works have tackled **object detection** – i.e., localizing fibroids within the ultrasound image with bounding boxes or similar. This is important for clinical usability because a sonographer typically needs to know *where* the fibroid is, not just that it exists. One notable study by Yang *et al.* (2023) developed a **real-time automatic detection system** using a deep learning detector. They integrated their model into an ultrasound imaging workflow to highlight fibroid regions as the scan is being performed. Although details of the model architecture were not fully given in the abstract, the term "detector" and real-time operation suggest use of an object detection CNN (e.g. YOLO or Faster R-CNN) that can draw boxes around fibroids on the fly. The system was able to assist and speed up fibroid identification during scanning. Real-time performance is crucial if AI is to be used during live ultrasound exams; achieving this requires efficient models and possibly specialized hardware (GPUs).

Yang et al. reported that their detector could process images quickly enough for live use and improved the workflow of the sonographer, but the accuracy in terms of detection rates was not explicitly stated in the snippet. Nonetheless, the mere fact that such a system was developed and tested by 2023 indicates the maturity of deep learning solutions. We can infer that techniques like one-stage detectors (which are fast) were likely employed. This complements the classification approaches by moving toward **Computer-Aided Detection (CADe)** tools that not only say “fibroid present” but pinpoint it on the image.

Deep Learning for Segmentation and Volume Measurement

Deep learning has also been applied to the **segmentation task** for fibroids, often with the aim of measuring fibroid size or integrating with treatment planning. U-Nets and other segmentation CNNs are natural choices here:

- A 2021 study by Behboodi and Rivaz trained **U-Net based networks** for ultrasound image segmentation, achieving about **86.2% accuracy** in delineating structures on ultrasound. (The accuracy metric likely refers to pixel-wise classification accuracy or a related measure for segmentation.) This approach demonstrates that CNNs can learn to segment fibroid regions, though performance can vary with dataset and definitions.
- In a very recent work, Shen *et al.* (2025) developed a **superpixel-based self-attention network** for uterine fibroid segmentation in ultrasound guidance images. Instead of classifying every pixel, their method first over-segmented the image into superpixels (small regions) and extracted features from each superpixel. A self-attention CNN then classified each superpixel as tumor or not, and merged them to form the final segmented fibroid region. This two-step region-based approach is computationally efficient and leverages the structured nature of ultrasound image regions. On a dataset of 140 HIFU-guidance ultrasound images, the method achieved a **mean Intersection-over-Union (IoU) of 75.95%** for the fibroid segmentation. This was an improvement of ~5.5% IoU over a standard pixel-wise segmentation transformer model, indicating the effectiveness of combining superpixel preprocessing with attention mechanisms for ultrasound. The authors

noted significant gains ($p < 0.05$) in both IoU and Hausdorff distance compared to baseline, reflecting more precise and smooth segmentations.

- While most segmentation research in ultrasound has addressed 2D images, a few have looked into **3D segmentation** using deep learning, especially when 3D ultrasound data or MRI data are available. For example, Liu *et al.* (2025) applied a 3D VNet (a 3D CNN U-Net variant) with deep supervision and attention gates to segment fibroids from MRI volumes. They achieved a Dice coefficient of ~0.88 for MRI fibroid segmentation. Although that study was MRI-based, the network architecture ideas (deep supervision, attention gates) are transferrable to ultrasound if 3D ultrasound volumes are used or multiple 2D slices are combined. It shows how *attention mechanisms* and multi-scale features can boost performance in segmenting fibroids even in challenging imaging modalities.
- **Volume measurement and outcome prediction:** Some studies have used segmentation outputs to compute fibroid volume or treatment-related metrics. Suomi *et al.* (2019) took a classical approach by assembling a comprehensive feature set (including volume, shape, and intensity features) from fibroid segmentations to predict HIFU treatment outcomes. Meanwhile, Slotman *et al.* (2024) focused on MRI, developing a deep learning pipeline to automatically segment the uterus, fibroids, and non-perfused (treated) regions in MRI after HIFU, in order to compute the non-perfused volume ratio – an indicator of treatment success. They achieved Dice scores of 0.74–0.90 for the various structures and high correlation between AI-derived volumes and manual measurements. Again, though MRI-based, this underscores the importance of accurate segmentation for quantitative assessment. For ultrasound, an equivalent would be automatically calculating fibroid diameter or volume from a 3D ultrasound scan, which would be very useful in monitoring fibroid growth/shrinkage over time or response to therapy.

Performance and Challenges in DL Segmentation: Deep segmentation models, while powerful, face challenges with ultrasound: obtaining **ground truth masks** requires expert manual delineation (a time-consuming task), and fibroid borders in ultrasound may be ambiguous even to experts. As a result, segmentation datasets for fibroids tend to be small (tens to low-hundreds of images), and models might not generalize broadly. Some approaches like Shen et al.'s superpixel method try to leverage unsupervised steps (superpixels) to maximize the value of limited training data. Data augmentation (cropping, flipping, adding noise) is also heavily used to artificially expand training samples. Despite near-human or better-than-human performance reported in controlled studies, deploying these models in diverse clinical settings will require addressing differences in ultrasound machines, scan protocols, and patient populations.

Toward Comprehensive CAD Systems and Future Directions

Bringing together the above components, researchers aim to create comprehensive **computer-aided diagnostic systems** for uterine fibroids on ultrasound. Such a system might incorporate preprocessing, real-time detection/localization, segmentation for measurement, and classification of fibroid type or treatment recommendation. We highlight some key points and emerging trends:

- **Integration of Detection and Diagnosis:** The line between detection (finding a fibroid) and diagnosis (assessing its significance) is blurring in AI systems. For example, the DCNN model by Huo et al. not only detected fibroids but also effectively acted as a second reader to improve diagnosticians' performance. In the future, an AI could plausibly flag an ultrasound image with a fibroid and even suggest the fibroid's type (submucosal, intramural, subserosal) or whether it is likely to cause symptoms, by analyzing its location and characteristics. Some recent papers have started looking into classifying fibroid *sub-types* or predicting symptom severity from images, but this is still an emerging area.

- **Speed and Real-Time Feedback:** Real-time systems (like Yang et al. 2023) are important for practical use. A radiologist performing an ultrasound could benefit from immediate AI feedback highlighting suspected fibroid regions. The challenge is ensuring **low latency** – models must be efficient. Solutions include using lighter architectures, model quantization, or leveraging the parallel processing of modern ultrasound machines. The fact that a 2023 study achieved real-time detection indicates feasibility.

- **Generalization and Robustness:** A recurring theme is the need to validate algorithms on diverse data. Many authors have called for larger, multi-center datasets to ensure AI models work on different ethnic groups, different machine models, and both transabdominal and transvaginal ultrasound views. Future research is focusing on improving the **generalization** of models – for example, using self-supervised learning on unlabeled ultrasound data, or federated learning to train on data from multiple hospitals without pooling the data, as hinted by some works in broader ultrasound AI research.

- **Higher Sensitivity and Specificity:** While many current models boast high accuracy, a true clinical-grade system must aim for extremely high sensitivity (to not miss fibroids, especially those that could be clinically significant) while maintaining high specificity (to avoid false alarms). The EfficientNet study (Xi et al. 2024) explicitly notes the need to boost sensitivity and specificity in diverse populations as a future direction. Fine-tuning on more data and incorporating domain-specific knowledge (e.g., known false-positive patterns like shadowing from bowel gas) could help achieve this.

- **Multi-Modal Approaches:** Some researchers suggest combining ultrasound with other modalities or data. For instance, an AI could use both ultrasound images and patient clinical data (age, symptoms, lab tests) to improve diagnostic accuracy. Though our focus is on ultrasound imaging, such multi-modal AI could be powerful – e.g., distinguishing fibroids from adenomyosis or other masses might be improved by incorporating Doppler blood flow information or MRI if available. We are also seeing AI applied to *MRI* of fibroids (as in segmentation for volume calculations); a comprehensive system might leverage MRI as a confirmatory tool when ultrasound results are uncertain.

In summary, deep learning has revolutionized ultrasound fibroid detection in the past 5 years, yielding systems with accuracy in the 90–99% range and the ability to assist clinicians effectively. The literature suggests that a combination of approaches – classification networks for detection, object detectors for localization, and segmentation networks for measurement – can provide a full solution. The remaining challenges are largely around making these solutions robust, generalizable, and seamlessly integrable into clinical workflow.

Global Research versus Sri Lankan Context

Globally, the research landscape on ultrasound fibroid detection is rich, with contributions from Asia (particularly China and India), Europe, and North America. China, for example, has produced high-impact studies (such as the SciRep 2022 and 2025 papers) likely due to the large volume of patients and interest in non-invasive treatment like HIFU. Indian researchers have also been active, often focusing on classification problems and novel hybrid techniques (e.g., the MBF-CDNN method). In the West, there’s significant work on MRI detection of fibroids (since MRI is considered the gold standard for mapping fibroids prior to interventions), but ultrasound-focused studies are fewer, possibly due to more routine use of MRI for pre-surgical planning in those settings.

In **Sri Lanka**, ultrasound is a primary modality for gynecological imaging, but based on available literature, there have been limited published studies on applying AI or advanced image analysis specifically for uterine fibroid detection. Most local research on fibroids appears to concentrate on clinical and epidemiological aspects (e.g., symptomatology, treatment outcomes, quality-of-life assessments) rather than imaging analytics. For instance, Karunagoda *et al.* (2019) explored Ayurvedic treatments for fibroids, and other Sri Lankan studies have dealt with translating fibroid symptom questionnaires or comparing treatment modalities. One comparative study evaluated ultrasound scan accuracy against MRI in detecting fibroids in a local population, finding that ultrasound agreed reasonably with MRI for fibroid size and location, but had limitations for very **posterior wall fibroids and small lesions** (which were sometimes missed on ultrasound). This reinforces the need for improved ultrasound detection – potentially via AI – in the local context.

Encouragingly, there are signs of emerging interest in Sri Lanka in leveraging AI for ultrasound. Amarakoon *et al.* (2021) reportedly investigated deep neural networks for identifying uterine fibroid tumors in ultrasound examinations. This work (presented at a digital health conference) indicates that Sri Lankan researchers are beginning to engage with AI in this domain. However, as of now, no extensive Sri Lankan study on ultrasound fibroid CAD appears in the mainstream literature. This represents an opportunity for research groups in Sri Lanka to contribute. With the increasing availability of expertise in machine learning and collaborations between engineers and clinicians, Sri Lanka could develop its own AI models tuned to local patient demographics and ultrasound machine settings.

Global vs Local Summary: Globally, the field is moving fast towards highly accurate, AI-driven fibroid detection systems, integrating seamlessly with ultrasound devices. In Sri Lanka, the adoption of such technology is still nascent. The lack of local published work on AI for fibroid detection highlights a gap that new research (such as the intended project behind this literature review) can aim to fill. By learning from the global studies reviewed above – their methodologies, successes, and pitfalls – Sri Lankan researchers can accelerate development of an automated fibroid detection system suitable for local healthcare needs. Such a system could be invaluable in busy gynecology clinics, improving diagnostic consistency and enabling earlier intervention for women with fibroids.

Conclusion

The literature on ultrasound-based uterine fibroid detection spans from early rule-based algorithms to state-of-the-art deep learning models. Classical methods established important techniques in image preprocessing, segmentation, and feature-based classification, but had limitations in handling ultrasound's complexities. Modern AI approaches, particularly deep CNNs, have achieved breakthrough performance, with some models matching expert radiologists in accuracy. Key contributions include the use of attention mechanisms to focus on fibroid regions, the adaptation of architectures like U-

Net for segmentation, and the demonstration of real-world efficacy where AI helps junior clinicians reach expert-level diagnoses.

Nonetheless, challenges such as generalization, data scarcity, and the need for real-time operation are active areas of research. The innovations continue, with recent papers proposing hybrid models (e.g., superpixel attention networks or optimization-guided deep networks) to further enhance accuracy and robustness.

This literature review provides a comprehensive foundation (approximately 30 studies) for understanding current methodologies, which will inform the development of a well-rounded fibroid detection system in Chapter 2 of the research project. By building on these findings, the forthcoming work can contribute novel improvements and address gaps (especially in the Sri Lankan setting) in automated uterine fibroid detection using ultrasound imaging.

Sources:

- Xi, H., & Wang, W. (2024). *Deep learning based uterine fibroid detection in ultrasound images*. BMC Med. Imaging, 24:218.
- Shen, W. et al. (2025). *A superpixel based self-attention network for uterine fibroid segmentation in HIFU guidance images*. Sci. Reports, 15:21970.
- Huo, T. et al. (2022). *Artificial intelligence-aided method to detect uterine fibroids in ultrasound images: a retrospective study*. Sci. Reports, 13:3714.
- Shahzad, A. et al. (2023). *Automated Uterine Fibroids Detection in Ultrasound Images Using Deep CNNs*. Healthcare (MDPI), 11(10):1493.
- Dilna, K.T. et al. (2022). *Classification of Uterine Fibroids in Ultrasound Images Using Deep Learning Model*. Proc. 22nd Int. Conf. Computational Science (ICCS), pp.50–56.
- Ni, B. et al. (2015). *Segmentation of uterine fibroid ultrasound images using a dynamic statistical shape model in HIFU therapy*. Comp. Med. Imaging Graph, 46(3):302–314.
- Sriraam, N. et al. (2010). *Detection of Uterine Fibroids Using Wavelet Packet Features with BPNN Classifier*. IEEE IECBES, pp.406–409.
- Jeyalakshmi, T.R. & Kadarkarai, K.R. (2010). *Segmentation and Feature Extraction of Fluid-filled Uterine Fibroid – A Knowledge-Based Approach*. Int. J. of Science and Tech., 4:405–416.

- Shivakumar, K. et al. (2015). *Segmentation and Analysis of Fibroid from Ultrasound Images*. Int. J. Computer Applications, (Feb 2015).
- Yang, T. et al. (2023). *Real-Time Automatic Assisted Detection of Uterine Fibroid in Ultrasound Images Using a Deep Learning Detector*. Ultrasound Med. Biol., 49(7):1616–1626.
- (Additional sources as cited in-line above, etc.)