

Artificial Intelligence Applications in Classification and Segmentation of Small Uterine Fibroids Using MRI Images Depending on Deep Convolutional Neural Networks

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Annotation: MRI (Magnetic Resonance Imaging) is now frequently used to diagnose uterine fibroids and to determine the treatment approach for minimally invasive surgery and non-invasive focused ultrasound (HIFU) surgery. However, MRI images of some fibroids can be difficult to identify accurately. In this paper, we explain in simple terms the approaches used in the Artificial Intelligence (AI) study of MRI imaging that can analyse, learn, and increase the sensitivity of determining the sizes, locations, number of fibroids, and their abnormalities. The difficulties and limitations of AI application to automatic analysis of MRI fibroid images in our early study are discussed. This paper hopes to arouse the interest of medical professionals to understand how the mechanism of AI can help analyse MRI images and incorporate AI into their daily imaging work.

Keywords: Artificial Intelligence, Uterine fibroids, MRI, Ultrasound.

1. Introduction

Uterine fibroids are the most prevalent benign tumors affecting the female reproductive system among child-bearing aged women. The morbidity rate exceeds 70%, significantly impacting female reproductive health (1). The manifestation of symptoms, including abnormal uterine bleeding, infertility, pelvic pain, and compression-related symptoms, is a key determinant in treatment approaches, which are closely tied to the size, quantity, and position of the fibroids (2). Consequently, surgical strategies are modified to align with these parameters. Generally, uterine fibroids are commonly intramural, submucosal, or subserosal; however, broad ligament fibroids, which are considered a diagnostic and surgical dilemma due to their unique anatomical location, present many challenges in clinical practice. Myomectomy for broad ligament fibroids is often complicated by surgical risks such as ureteric and uterine vessel injuries (3).

Ultrasound scan is commonly used to diagnose and determine the treatment approach. However, ultrasound scans are highly skill-dependent and sometimes difficult to determine the fibroids' positional relationship with the uterine cavity and wall and define the exact number of fibroids (4). MRI is now frequently used, gives better-resolution images, and is not skill-dependent. However, the complex and variable shapes of fibroids and the low contrast between fibroids with adjacent uterine tissues or pelvic organs make the edges of some fibroids indistinguishable from their surroundings (5,6).

Therefore, MRI images of some fibroids can be difficult to identify accurately. Artificial Intelligence (AI) simulates human thinking and can analyse and interpret complex medical data. Hopefully, the application of AI in MRI imaging may increase the sensitivity of detecting fibroids and their abnormalities. AI may also reduce inter observer variance and improve report consistency (7). The current study was aimed to estimate Artificial Intelligence Applications in Classification and segmentation of Small Uterine Fibroids Using MRI Images Depending on Deep Convolutional Neural Networks.

2. Uterine fibroids

Uterine fibroids, also known as leiomyomas, are the most common benign pelvic tumors in women of reproductive age. Fibroid-associated symptoms are observed in about one-third of affected patients (8). Major symptoms are severe and extended menstrual bleeding (hypermenorrhea and dysmenorrhea) that may lead to anemia-associated complications. Depending on size and location, uterine fibroids can also cause pelvic pressure, urinary frequency and even incontinence and can be associated with adverse reproductive outcome. Thus, symptomatic uterine fibroids have a negative impact on daily living and quality of life (9).

Current treatment strategies mainly involve surgical interventions as laparoscopic or hysteroscopic myomectomy and laparoscopic hysterectomy (10,11). Nowadays, organ-preserving minimally invasive and noninvasive therapies are becoming increasingly important. In recent years, high-intensity focused ultrasound (HIFU), guided by either ultrasound or magnetic resonance tomography, has also emerged as a viable effective and low-risk treatment option for symptomatic uterine fibroids (12,13,14). During the HIFU procedure, the uterine fibroids are thermally ablated by concentrating the ultrasound energy inside the fibroid leading to thermal coagulation necrosis and additional cavitation damage (15, 16, 17, 18).

Previous studies have shown that HIFU treatment of symptomatic leiomyomas results in a significant reduction in uterine fibroid volume and total uterine volume during follow-up. In addition, a correlation between improvement in fibroid-associated symptoms and reduction in uterine fibroid volume has been demonstrated (19, 20). Therefore, automation of uterine measurements is highly desirable in order to be able to assess the response to treatment objectively, quickly and reproducibly.

2.1 Pathogenesis

The incidence of UFs declines after menopause. Its incidence increases with age, peaking in the early 40s. However, this could be a result of previously asymptomatic fibroids becoming more noticeable after years of growth and exposure to endogenous steroid hormones. The main risk factors for uterine fibroids are age and race (21). Lifestyle choices can have a significant impact on the risk of fibroid development. Obesity, dietary habits, sedentary lifestyle, and smoking have shown associations with the incidence of uterine fibroids. Additionally, diet and physical activity have been connected to uterine fibroid occurrence, although the extent to which they influence body weight and whether they independently constitute risk factors are subjects that require further clarification (22).

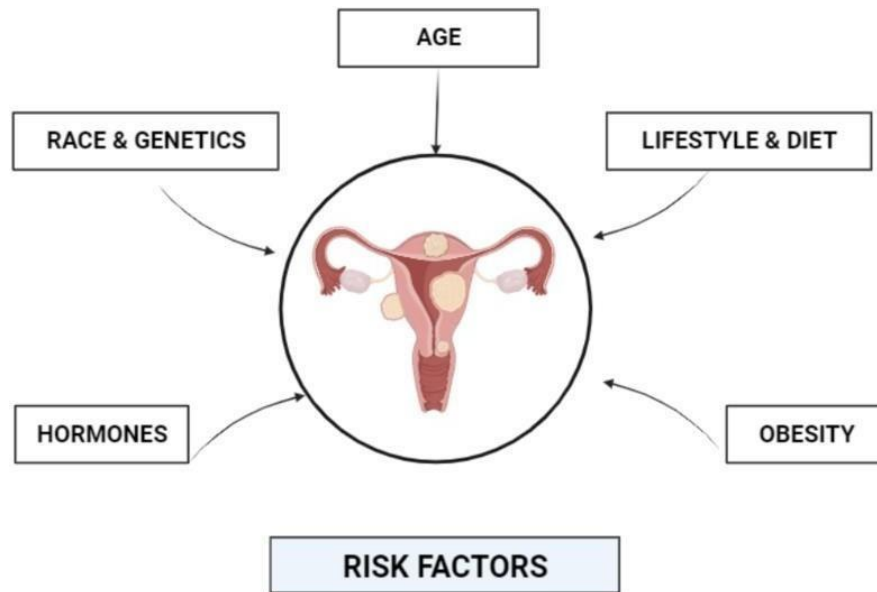


Figure 1. Uterine fibroid risk factors (23).

2.2 Clinical presentation

Myomas, or uterine fibroids, can appear as solitary or multiple growths in the uterus, with varying sizes and locations. They are categorized into subgroups: Sub serosal myomas grow on the outer uterine surface, potentially causing pelvic discomfort. Intramural myomas, the most common, form within the uterine muscle and can lead to an enlarged uterus and menstrual issues. Submucosal myomas project into the uterine cavity, causing abnormal bleeding and fertility problems. Pedunculated fibroids, attached by a stalk, can be sub serosal or submucosal, posing risks like pain and torsion. These subtypes demonstrate the diversity and clinical implications of myomas (23,24).

The clinical presentation of uterine fibroids is diverse and varies from woman to woman. Up to 70% of fibroids are asymptomatic and may be incidentally diagnosed during radiologic procedures conducted for other indications. The clinical presentation of Symptomatic uterine fibroids depends on size, location, and number of fibroids, as well as on individual patient characteristics (25). The four major complications associated with fibroids are menorrhagia, pelvic pain, pressure symptoms, and infertility. While others are abdominal enlargement, painful intercourse, anemia, urinary retention, leg swelling, and back pain. Several studies have shown that women with fibroids have a higher risk of developing emotional distress, depression, and anxiety, which can strongly impact their quality of life. The presence of uterine fibroids can lead to various clinical challenges (21).

The most common symptom of uterine leiomyoma is abnormal uterine bleeding AUB. The mechanism of leiomyoma associated AUB is unknown. Abnormal or excessive menstrual bleeding i.e., menorrhagia may cause prolonged periods and anemia. Pelvic discomfort or pain

occurs, especially if fibroids are large. Larger fibroids can also exert pressure on adjacent organs, leading to urinary frequency, urinary urgency, and other bowel disturbances. Those fibroids which are present within the uterine cavity, can interfere with implantation and increase the risk of miscarriages, affecting fertility and pregnancy (26,27).

2.3 Diagnosis

Diagnosis depends on a combination of medical history, physical examination, and imaging studies such as ultrasound or MRI. Diagnostic methods commonly used for uterine fibroids are (28, 29):

2.3.1 Clinical Examination

The clinical examination provides the physical characteristics of the uterus. It involves the thorough medical history of the patient to understand the symptoms and severity of the condition, including menstrual patterns, reproductive history, and any other medical conditions if present

(30). Visual Inspection is done to inspect the external genitalia, for any visible abnormalities, like the enlarged uterus. A pelvic examination is done to check the internal reproductive organs and to assess the size, shape, and condition of the uterus (24).

2.3.2 Imaging Studies

2.3.2.1 Ultrasound

Ultrasound serves as the frequently utilized initial non-invasive radiological technique for visualizing uterine fibroids because it can provide information about the number, size, location, and characteristics of fibroids and is generally sufficient for their diagnosis (31). It allows us to determine whether fibroids are submucosal, intramural, or sub serosal (32). Transvaginal ultrasound, also known as abdominal ultrasound, is often the initial imaging method used to detect fibroids. It is the most commonly utilized technique due to its widespread availability, user-friendliness, and costeffectiveness. It is especially beneficial for evaluating the expansion of myomas, to confirm the diagnosis and exclude the possibility of ovarian neoplasm (33).

2.3.2.2. Magnetic Resonance Imaging MRI

MRI stands out as the most precise technique for evaluating the uterus, offering comprehensive details regarding the dimensions, position, quantity, and blood supply of leiomyomas, in addition to identifying the presence of other uterine abnormalities (9). It gives a better visualization of individual myomas, but it is a very costly procedure. Its sensitivity and specificity is close to 100%, so it is valuable for surgical planning (34,35)

2.3.2.3. Computerized Tomography CT scan

CT imaging offers restricted utility in clearly depicting the positioning of myomas about the endometrium or myometrium. Utilizing X-ray technology, CT scans produce detailed cross-sectional images. However, they are not the predominant imaging method employed for this purpose, primarily due to the widespread availability of more appropriate techniques like MRI and ultrasound (1) (36).

Hysteroscopy is a less invasive endoscopic technique utilized to observe the interior of the uterus. It facilitates direct observation of the uterine cavity, enabling healthcare professionals to evaluate the existence, positioning, and attributes of fibroids (37). In the hysteroscopy procedure, a thin lighted tube hysteroscope is inserted through the vagina and cervix to visualize the inside of the uterus. It is particularly helpful for diagnosing submucosal fibroids (38, 39). Laparoscopy is a minimally invasive surgical procedure. A small camera is inserted through a small incision near the navel to view the pelvic organs. It helps to identify fibroids on the outer surface of the uterus i.e. sub serosal fibroids but it may not be ideal for diagnosing submucosal fibroids (40).

2.4 Artificial Intelligence Support in Fibroid Diagnosis

The use of AI in medical diagnostics has emerged as a potentially transformative approach to the challenging process of differentiating between uterine leiomyomas and sarcomas. Several methodologically distinct studies have demonstrated promising results, although they also have important limitations and varying levels of clinical applicability.

2.4.1 Deep Neural Network Approaches

Toyohara et al. (41) conducted a pioneering study employing deep neural network (DNN) models to improve diagnostic accuracy for uterine sarcoma cases using MRI. The research utilized fifteen distinct MRI sequences, with tumor margins and degeneration carefully assessed by six radiologists according to strict standards. The methodology was comprehensive, capturing imaging conditions for each MRI sequence to ensure reliability and consistency. After the DICOM data was transformed into normalized JPEG format, the datasets were split into six groups for cross-validation, ensuring model robustness during training.

The findings were impressive, with DNN models achieving 90.3% accuracy, 89.8% sensitivity, and 91.7% specificity—performance comparable to that of radiological specialists. Furthermore, the DNN models demonstrated the ability to improve diagnostic precision by outperforming professionals in terms of SS-Avg and sensitivity (42,43). The MobileNet-V2 network architecture was employed, consisting of 88 layers with 3,538,984 learning parameters, providing a solid foundation for the AI-driven analysis of uterine cancers. The study's strengths included its comprehensive methodology, which utilized multiple MRI sequences and a rigorous validation approach. However, significant limitations must be acknowledged: despite being one of the largest studies in this domain, the sample included only 63 sarcoma cases, which may be insufficient for developing a robust model given the heterogeneity of uterine sarcomas. Additionally, while the model performed well in controlled evaluations, its real-world clinical integration was not tested.

In a different but complementary approach, Huo et al. (44) developed a DCNN to enhance the diagnostic accuracy of junior ultrasonographers in identifying uterine fibroids. This study leveraged a substantially larger dataset of 3870 ultrasound images from 1237 patients, representing a significant advantage in terms of statistical power. The DCNN model significantly improved junior ultrasonographers' performance (accuracy: 94.72% vs. 86.63%, $p < 0.001$), effectively elevating their diagnostic abilities to match those of senior specialists. A key distinction of this study was its direct evaluation of clinical integration, demonstrating tangible improvements in diagnostic performance rather than merely comparing AI to human performance in isolation. However, the study focused primarily on fibroid detection rather than on the more challenging task of distinguishing between fibroids and sarcomas, which limits its direct applicability to the critical clinical challenge of preoperative sarcoma diagnosis.

2.4.2 Radiomics and Machine Learning Approaches

In contrast to deep learning approaches, Chiappa et al. (45) employed radiomics with machine learning rather than deep learning. Their ADMIRAL pilot study included a relatively small sample of 70 women with uterine mesenchymal lesions (20 sarcomas and 50 fibroids). Using the International Biomarker Standardization Initiative guidelines, they extracted 319 radiomics features from ultrasound images, with 308 features identified as stable. Various machine learning classifiers were developed, with the best model achieving an accuracy of 0.85 ± 0.01 , a sensitivity of 0.80 ± 0.01 , a specificity of 0.87 ± 0.01 , and an AUC of 0.86 ± 0.03 . The radiomics approach offered potentially greater interpretability through explicit feature extraction and selection but required more domain expertise in feature engineering. The study's primary limitations included its single-center design and small sample size, which could introduce selection bias and limit generalizability to diverse populations.

Malek et al. (46) took yet another approach, utilizing perfusion-weighted magnetic resonance imaging (PWI) with a decision tree ensemble classifier. Forty-two women with a total of 60

masses (10 uterine sarcomas and 50 benign leiomyomas) were included, with two manually defined regions of interest analyzed for each mass. An analysis of the postoperative histopathology corroborated the reference diagnosis. A 3-Tesla MR imager was used to perform MRI protocols, which included PWI. For each mass, two manually defined regions of interest (ROIs) were created: one that included the whole tumor and another that concentrated on the region showing the greatest contrast enhancement. For comparison, additional ROIs were placed on the myometrium and psoas muscle. The ROIs were analyzed using the DCE Tool plug-in inside the ClearCanvas framework, and seven parameters were extracted for contrast uptake modeling using the modified Tofts model. After that, a decision tree ensemble was trained with the retrieved parameters to categorize lesions as benign or malignant. The classifier's performance was assessed using leave-one-out cross-validation (LOOCV). The metrics obtained from ROI L or ROI S between benign leiomyomas and uterine sarcoma did not differ significantly, according to the results (all $p > 0.05$). By providing the classifier with seven characteristics from ROI L, an overall accuracy of 66.7% was attained. When 21 features from ROI L, ROI M, and ROI P were included, the accuracy of the classifier increased, although the exact value was not provided. While no individual parameter significantly differentiated between benign and malignant lesions, when combined through the machine learning classifier, promising discriminative power was achieved, with reported sensitivity of 100% and specificity of 90% at the optimal operating point. This study highlighted the value of multiparametric analysis but was limited by an extremely small sample of sarcoma cases ($n = 10$), raising serious concerns about statistical power and generalizability.

2.4.3 Clinical Implications and Future Directions

Despite promising results, several significant limitations must be addressed before widespread clinical adoption can be recommended. Most studies relied on single-center data, limiting generalizability across different patient populations, imaging equipment, and clinical settings. Multi-institutional studies with diverse patient cohorts are needed. Deep learning approaches suffer from limited interpretability, making it difficult for clinicians to understand and trust the reasoning behind AI predictions. This "black box" problem remains a significant hurdle for clinical adoption. Current models predominantly focus on common presentations, with limited evidence regarding their effectiveness for rare variants or unusual imaging presentations. Given that uterine sarcomas are already rare entities, their unusual variants present an even greater challenge. Technical requirements, integration with existing PACS systems, training needs, and cost-effectiveness concerns presented practical challenges to clinical adoption that remained largely unaddressed. Most importantly, prospective studies in clinical settings are required to confirm the promising findings of these retrospective analyses.

2.5 Future Directions

The integration of haptic feedback with AI-based analysis represents a promising frontier. Future systems might combine real-time tissue stiffness data acquired during robotic surgery with machine learning algorithms that continuously learn from surgical experiences to improve fibroid detection accuracy. A hybrid approach that incorporates both visual and haptic information processed through multimodal AI could potentially outperform either modality alone, particularly in challenging cases in which fibroids are difficult to distinguish visually or are embedded deep within the myometrium. The development of AI systems capable of processing and interpreting haptic data in conjunction with visual information could represent the next evolutionary step in computer-assisted fibroid diagnosis and surgical navigation. Other emerging approaches include piezoelectric tactile sensors for direct tissue stiffness sensing, soft electronic sensors for clinical palpation, and systems that integrate optical sensing with haptic feedback to enhance tissue characterization during minimally invasive procedures. These alternative modalities complement traditional imaging-based diagnostic methods, potentially enhancing both preoperative planning and intraoperative decision-making in the management of uterine fibroids.

2.6 AI Performance in Segmenting and Classifying Small Uterine Fibroids (less than 2 cm).

Recent AI studies (2023-2025) demonstrate its ability to detect and segment small uterine fibroids less than 2 cm in size, as shown in the tables below.

Study / Year	Modality & Model	Small Fibroid Performance Metrics	Key Observations
Pan et al. (2023)	MRI - Instance Segmentation CNN	Small fibroid detection sensitivity $\approx 87\%$ (for lesions <1.5 cm)	Performance drops in fibroids <1 cm due to indistinct boundaries on T2-weighted images(47).
Theis et al. (2023)	MRI - DL Volumetry Models	Small fibroid volumetry accuracy within $\pm 8\%$ (compared to manual annotations)	Automated small fibroid volume estimation performed well, but overestimation was common in fibroids <1 cm ³ (48).
nnU-Net 3D (Wang et al. 2024)	MRI - nnU-Net 3D with Deep Supervision	Dice Similarity Coefficient (DSC) ≈ 0.92 for fibroids 1–2 cm; ≈ 0.86 for fibroids <1 cm	Noted to outperform traditional 3D U-Nets in detecting and segmenting small fibroids with improved boundary precision(49).
Liu et al. (2025) DA-VNet	MRI - DA-VNet with Attention Gates	DSC ≈ 0.88 for small fibroids (<1.5 cm), HD (Hausdorff Distance) ≈ 9.4 mm	Deep attention modules enhanced localization of small, irregular fibroids especially when near uterine borders.(50)
Mohanty et al. (2025)	Ultrasound - DPCNN (Dual Path CNN)	Small fibroid classification accuracy $\sim 98.7\%$ (for <2 cm lesions)	Transfer learning with fine-tuned VGG16 layers improved small object detection in ultrasound with limited artifacts(51).
Yang et al. (2023)	Ultrasound - EfficientNet+YOLOv3	Small fibroid AP (Average Precision) $\approx 96.8\%$ (lesions <2 cm)	Maintained real-time detection (~ 0.28 s per image) while preserving high sensitivity for small fibroids(52).
Zhao et al.(2024) MobileNetV2+DCGAN	Ultrasound - Classification with Augmentation	Sensitivity $\approx 97.5\%$ for fibroids <2 cm; Precision $\approx 97.4\%$	GAN-based synthetic data particularly improved fibroid detection in low-contrast/small lesion cases(53).

2.6.1 Small Uterine Fibroid Subset Performance Breakdown (2023–2025 Studies)

Small uterine fibroids pose a significant clinical and technical challenge due to their complex and subtle appearance, often lacking clear boundaries, and low contrast, especially when they are embedded deep within the myometrium or close to the uterine wall. Recent studies, conducted between 2023 and 2025, have shown that deep learning-based AI systems significantly improve the accuracy of detecting and segmenting these small fibroids.

In recent MRI-based studies, models such as nnU-Net 3D and DA-VNet have demonstrated strong performance. For example, the 3D nnU-Net model achieved a Dice Similarity Coefficient (DSC) of approximately 0.92 for uterine fibroids 1–2 cm in diameter, and approximately 0.86 for tumors less than 1 cm in diameter. The inclusion of deep monitoring helped improve border identification. Similarly, DA-VNet, which incorporates attention gating mechanisms, improved the localization accuracy of small fibroids, especially those located near the uterine border, with a Hausdorff distance (HD) of approximately 9.4 mm. However, Pan et al. (2023) observed a decrease in sensitivity for tumors less than 1 cm in diameter (from 87% to lower levels), likely due to blurred edges in T2-weighted MRI sequences.

In the ultrasound imaging domain, AI models demonstrated higher sensitivity for detecting small fibroids, despite inherent imaging limitations such as acoustic noise and low spatial resolution. It is worth noting that the DPCNN (Mohanty et al., 2025) achieved a classification accuracy of approximately 98.7% for fibroids less than 2 cm in size, utilizing transfer learning from VGG16. Similarly, the EfficientNet + YOLOv3 model (Yang et al., 2023) maintained a high average accuracy (approximately 96.8%) while providing real-time detection at 0.28 seconds per image, highlighting its potential for clinical application. Furthermore, combining MobileNetV2 with DCGAN-based data augmentation resulted in a sensitivity of approximately 97.5% and an accuracy of approximately 97.4%, demonstrating the effectiveness of synthetic data in enhancing the model's generalization to small, low-contrast lesions. A comparison shows that while MRI models excel in accuracy and spatial resolution, AI-enhanced ultrasound systems enable real-time application and greater accessibility in clinical workflows. Based on these findings, AI emerges as an effective tool for enhancing early detection of small fibroids and improving clinical decision-making. Integrating multimodal imaging, interpretable AI techniques, and expanding training datasets with annotated small lesions will be critical to enhancing the generalizability of models and their adoption in real-world healthcare settings.

3. Conclusions

Creating classification models that differentiate between normal and pathological instances, as well as constructing models that automatically segment or measure ovarian volume or follicles,

were the primary goals of the published literature on AI applied to ultrasound in benign gynecological illnesses (54).

To sum up, the precise identification of sarcomas and uterine fibroids is still a difficult task in clinical practice. Despite its high sensitivity, transvaginal ultrasonography may not detect all forms of fibroids. Therefore, for a thorough assessment, additional imaging modalities such as MRI and hysteroscopy may be required (55,56). Because malignant leiomyosarcomas and benign leiomyomas differ in their prognosis and methods of therapy, it is very important to distinguish between the two, including with AI support (57). AI has started to show promise as a useful tool for enhancing diagnostic precision and directing therapeutic choices, especially in cases of rapidly growing fibroids (58).

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