Automated Uterine Tumor Detection Using a Radiomics–Attention Fusion Network on Ultrasound Images

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ARTICLE DETAILS	ABSTRACT
	Uterine tumors, including benign and malignant variants, pose significant diagnostic challenges due to overlapping imaging characteristics and inter-observer variability in conventional radiological assessment. To address these limitations, this study proposes an advanced automated uterine tumor detection framework integrating deep learning, radiomics, and attention-based fusion networks. Multi-parametric medical images are first preprocessed and segmented to localize uterine regions of interest. Handcrafted radiomic features capturing tumor texture, shape, and intensity heterogeneity are extracted, while deep features are simultaneously learned using a convolutional neural network to model high-level spatial and semantic representations. An attention-driven feature fusion network is then employed to adaptively weight and combine radiomic and deep features, enabling the model to focus on the most discriminative tumor-related patterns while suppressing redundant information. The fused features are finally classified using a fully connected neural network to distinguish tumor presence and subtypes. Experimental evaluation conducted on a curated uterine imaging dataset demonstrates the

robustness and effectiveness of the proposed approach. The attention-based fusion strategy significantly improves feature representation, resulting in superior diagnostic performance compared to standalone radiomics or deep learning models. The proposed method achieves an overall detection accuracy exceeding 96%, with high sensitivity and specificity, indicating strong clinical reliability. These results highlight the potential of hybrid deep learning–radiomics frameworks with attention mechanisms as powerful decision-support tools for early uterine tumor detection, offering improved diagnostic accuracy, reduced observer dependency, and enhanced support for personalized treatment planning.

1.Introduction

Uterine tumors constitute a major gynecological health concern worldwide, encompassing a wide spectrum of pathological conditions ranging from benign lesions such as leiomyomas to malignant entities including endometrial carcinoma and uterine sarcomas. Among these, endometrial cancer is one of the most commonly diagnosed gynecologic malignancies, with rising incidence attributed to lifestyle changes, aging populations, and metabolic risk factors [1], [2]. Early and accurate detection of uterine tumors is critical for effective treatment planning, prognosis assessment, and reduction of disease-related mortality. However, conventional diagnostic pathways relying on ultrasound, magnetic resonance imaging (MRI), computed tomography (CT), and histopathological examination often suffer from subjectivity, inter-observer variability, and limited sensitivity in early-stage disease [3], [4].

Medical imaging plays a pivotal role in uterine tumor evaluation, particularly MRI, which provides superior soft-tissue contrast and multiparametric information for assessing tumor extent, myometrial invasion, and nodal involvement [5], [6]. Despite these advantages, visual interpretation of imaging findings remains highly dependent on radiologist expertise and may fail to capture subtle tumor heterogeneity [7]. This limitation has motivated the integration of artificial intelligence (AI) techniques into medical imaging workflows to enable objective, reproducible, and high-precision diagnostic support systems [8], [9].

Radiomics has emerged as a powerful computational approach that converts medical images into high-dimensional quantitative features describing tumor shape, texture, intensity distribution, and spatial

heterogeneity [10], [11]. Numerous studies have demonstrated that radiomic features extracted from MRI, CT, or ultrasound images can serve as imaging biomarkers for tumor detection, grading, molecular subtype prediction, and treatment response assessment in uterine cancers [12], [13]. However, traditional radiomics pipelines depend heavily on handcrafted feature design and predefined mathematical descriptors, which may limit their ability to capture complex nonlinear patterns inherent in tumor biology [14].The deep learning, particularly convolutional neural networks (CNNs), has revolutionized medical image analysis by enabling automated feature learning directly from raw image data [15]. Deep learning models have shown remarkable performance in tumor detection, segmentation, and classification tasks by learning hierarchical representations that reflect both local and global image characteristics [16]. In the context of uterine tumors, CNN-based approaches have been applied to MRI, histopathology slides, and cytopathology images, achieving promising diagnostic accuracy [17], [18]. Nevertheless, deep learning models often operate as black boxes and may overlook clinically meaningful handcrafted features, reducing interpretability and robustness when applied to heterogeneous datasets [19].

To overcome the individual limitations of radiomics and deep learning, hybrid frameworks that combine handcrafted radiomic features with deep learned representations have gained increasing attention [20]. Feature fusion strategies aim to exploit the complementary strengths of both approaches, where radiomics captures explicit tumor heterogeneity and deep learning extracts high-level semantic information [21]. Simple concatenation of features, however, may introduce redundancy and noise, adversely affecting model performance and generalization [22].Attention mechanisms have recently emerged as an effective solution to enhance feature fusion by dynamically assigning importance weights to informative features while suppressing irrelevant or redundant information [23]. Attention-based fusion networks enable the model to focus on critical tumor-related patterns across multiple feature domains and imaging modalities. In medical imaging, attention mechanisms have demonstrated improved performance in cancer detection, subtype classification, and prognostic modeling by enhancing feature discriminability and interpretability [24]. Despite these advances, the application of attention-driven fusion architectures specifically tailored for uterine tumor detection remains relatively underexplored [25].

Motivated by these research gaps, this study focuses on the development of an advanced uterine tumor detection framework integrating deep learning, radiomics, and attention-based feature fusion networks. The proposed approach leverages multiparametric imaging data to extract both handcrafted radiomic features and deep CNN-based representations. An attention fusion module is employed to adaptively combine these heterogeneous features, enabling optimal information integration and robust tumor

characterization. By unifying radiomics interpretability with deep learning's representational power, the proposed framework aims to enhance diagnostic accuracy, reduce observer dependency, and improve clinical reliability in uterine tumor detection.The remainder of this paper presents a comprehensive evaluation of the proposed methodology, demonstrating its effectiveness across multiple performance metrics. Experimental results indicate that the attention-based fusion strategy significantly outperforms conventional single-model approaches, achieving detection accuracy exceeding 96% with high sensitivity and specificity. These findings highlight the potential of attention-guided hybrid AI systems as reliable decision-support tools for early uterine tumor detection and personalized treatment planning.

2. Background Study

Uterine tumors represent a major concern in gynecological oncology due to their diverse biological behavior and diagnostic complexity. These tumors include benign conditions such as leiomyomas as well as malignant forms like endometrial carcinoma and uterine sarcomas. According to **Di Donato et al. (2023)**, endometrial cancer is currently the most prevalent uterine malignancy, with its incidence continuing to rise worldwide [1]. Early detection of uterine tumors is essential for improving survival rates and optimizing treatment strategies; however, accurate diagnosis remains challenging, particularly in early-stage disease where imaging features may be subtle or ambiguous. **Cuocolo et al. (2023)** emphasized that conventional diagnostic workflows are often limited by observer dependency and variability in image interpretation [2].Magnetic resonance imaging (MRI) has become the primary imaging modality for uterine tumor assessment due to its excellent soft-tissue contrast and ability to provide multiparametric information. **Di Donato et al. (2024)** highlighted the clinical importance of MRI in evaluating tumor extent, myometrial invasion, and nodal involvement in endometrial cancer [16]. Despite these advantages, manual analysis of MRI scans depends heavily on radiologist expertise, and subtle intratumoral heterogeneity may not be fully appreciated. **Ding et al. (2023)** reported that visual assessment alone may lead to misclassification in borderline cases, underscoring the need for quantitative and automated analysis methods [4].Radiomics has emerged as a promising approach for extracting high-dimensional quantitative features from medical images, enabling objective tumor characterization. **Guo et al. (2023)** demonstrated that radiomic features can capture tumor texture, shape, and intensity variations associated with underlying biological behavior in endometrial cancer [5]. Similarly, **Coada et al. (2023)** showed that radiomics-based models improve prediction of recurrence risk and tumor aggressiveness when compared to conventional imaging evaluation [3]. Furthermore, a systematic review by **Jiang et al. (2025)** confirmed the effectiveness of radiomics-driven machine learning models in

predicting myometrial invasion and disease progression **[12]**. However, the reliance on handcrafted feature extraction limits adaptability and robustness across diverse datasets.

Deep learning, particularly convolutional neural networks, has significantly advanced medical image analysis by enabling automated learning of complex feature representations. **Wang et al. (2024)** demonstrated that deep learning models can effectively identify discriminative patterns in uterine tumor images that are difficult to capture using handcrafted features alone **[13]**. Despite their high predictive performance, deep learning approaches are often criticized for their black-box nature and limited interpretability. **Leo et al. (2023)** noted that this lack of transparency can hinder clinical acceptance, especially in high-stakes diagnostic applications **[19]**.

To overcome the limitations of individual methodologies, recent studies have focused on hybrid frameworks that integrate radiomics and deep learning. **Bai et al. (2025)** reported that combining handcrafted radiomic features with deep learned representations enhances diagnostic robustness and generalization capability **[25]**. Attention-based fusion networks further improve this integration by adaptively weighting informative features and suppressing irrelevant information. Although such approaches have shown promising results in other oncological applications, their use in uterine tumor detection remains limited, highlighting a critical research gap addressed by the present study.

Table 1. Summary of Existing AI-Based Methods for Uterine Cancer Analysis

Ref. No.	Author & Year	Concept	Research Gap	Methods	Limitations	Key Results
[1]	Di Donato et al., 2023	MRI radiomics in endometrial cancer	Lack of standardized pipelines	Radiomics + ML (Review)	Heterogeneity across studies	Radiomics shows promise for risk stratification
[2]	Cuocolo et al., 2023	Preoperative risk classification	Limited multimodal fusion	DL + Radiomics (MRI)	Single-center data	Improved classification vs. radiomics alone
[3]	Coada et al., 2023	Recurrence risk prediction	No deep feature	Radiomics + ML	Limited generalizatio	Effective recurrence

			integration		n	prediction
[4]	Ding S.X. et al., 2023	Ki-67 biomarker prediction	Absence of attention mechanisms	Radiomics + ML (MRI)	Small dataset	Reliable proliferation index prediction
[5]	Guo et al., 2023	Radiomics clinical applications	Limited clinical translation	Radiomics (Review)	Feature instability	Radiomics useful for tumor characterization
[6]	Volinsky-Fremond et al., 2024	Recurrence prediction	Imaging data not integrated	Deep Learning (Histopathology)	Modality-specific	High predictive accuracy achieved
[7]	Santoro et al., 2024	Gynecologic tumor prognosis	Limited uterine-specific models	Radiomics + ML (CT)	CT-only analysis	Enhanced diagnostic capability
[8]	Xu et al., 2024	Uterine sarcoma diagnosis	Lack of fusion frameworks	Deep Learning (Review)	Scarce datasets	AI improves sarcoma detection
[9]	Luo et al., 2025	LVSI prediction	Limited attention-based fusion	Radiomics + DL (MRI)	Complex model design	Improved LVSI prediction
[10]	Yue et al., 2025	Molecular subtype classification	Lack of external validation	Radiomics + DL	Dataset bias	Accurate subtype classification
[11]	Shen et al., 2025	Histological subtype differentiation	Limited explainability	Radiomics + DL (MRI)	Retrospective design	Robust multicenter performance
[12]	Jiang et al.,	Myometrial	Feature	Radiomics +	Study	High

	2025	invasion detection	selection inconsistency	ML (Meta-analysis)	heterogeneity	diagnostic reliability
[13]	Wang C.W. et al., 2024	Molecular prediction	Radiomics not utilized	Deep Learning (Pathology)	Interpretability issues	Effective molecular classification
[14]	Wang J. et al., 2025	Lymph node metastasis prediction	Uterine focus indirect	Radiomics + DL + Fusion	Cervical cancer dataset	Fusion improved prediction accuracy
[15]	Wang R. et al., 2024	Cytopathology-based diagnosis	No radiomics integration	Deep Learning	Limited imaging context	Strong diagnostic performance
[16]	Di Donato et al., 2023	Staging and nodal prediction	Limited deep learning use	Radiomics + ML (MRI)	Manual segmentation	Improved staging prediction
[17]	Li et al., 2024	MSI/MMR status prediction	Imaging data not used	Deep Learning (H&E slides)	Slide variability	Accurate molecular status prediction
[18]	Ding Y. et al., 2023	Biological characteristic prediction	No multimodal fusion	Radiomics + ML	Feature redundancy	Enhanced biological assessment
[19]	Leo et al., 2023	AI in endometrial cancer	Lack of attention models	AI + Radiomics (Review)	Clinical validation limited	Identified future AI directions
[20]	Arezzo et al., 2025	Deep myometrial infiltration	Small cohort size	Radiomics + ML	Limited dataset	Promising infiltration prediction
[21]	Tian et al., 2025	MSI prediction	High computational cost	Voxel-level Radiomics + DL	Complex implementation	Improved MSI prediction

[22]	Li C., 2024	HIFU treatment prognosis	Preprint, no peer review	Radiomics + DL	Validation pending	Promising prognostic capability
[23]	ClinicalTrials.gov, 2023–25	Multimodal fusion evaluation	Results not yet published	Radiomics + Pathomics + DL	Trial ongoing	Demonstrated feasibility
[24]	Goyal et al., 2023	Tumor grading	Lack of fusion strategies	Deep Learning	Preprint status	Improved grading accuracy
[25]	Bai et al., 2025	AI radiomics review	Limited uterine-specific fusion models	Radiomics + DL + Fusion	Review-based	Highlighted need for attention fusion

Table 1. Summary of Existing AI-Based Methods for Uterine Cancer Analysis

Table 1 presents a comprehensive summary of existing artificial intelligence–based methods for uterine cancer analysis reported in recent literature. The reviewed studies employ diverse data modalities, including MRI, CT, ultrasound, histopathology, and cytopathology, and apply techniques such as radiomics, deep learning, and hybrid fusion models. While many approaches demonstrate promising diagnostic and prognostic performance, several limitations persist, including small datasets, lack of multimodal integration, limited interpretability, and absence of attention-based feature fusion. The table clearly highlights research gaps related to feature redundancy, poor generalization, and insufficient clinical validation. These observations justify the need for an advanced attention-driven radiomics–deep learning fusion framework to achieve more robust and accurate uterine tumor detection.

2. Proposed Methodology

The proposed methodology presents a comprehensive framework termed the **Radiomics–Attention Fusion Network (RaAFN)** for automated uterine fibroid detection. The framework systematically describes the complete processing pipeline, starting from raw ultrasound image input and culminating in final classification. Initially, the input ultrasound images undergo preprocessing to enhance image quality and normalize intensity variations. Radiomic feature mining is then performed to extract quantitative

descriptors related to texture, shape, and intensity distribution, enabling explicit characterization of fibroid-related patterns.

A convolutional neural network (CNN) is employed to automatically learn deep hierarchical features from the same input images. These deep features capture high-level spatial and semantic information that may not be explicitly represented by handcrafted radiomic descriptors. To effectively integrate both feature domains, an attention mechanism is introduced, which assigns adaptive weights to the most informative radiomic and deep features while suppressing redundant or less relevant information. The weighted features are subsequently fused using an attention-guided feature fusion strategy, forming a unified and discriminative representation.

The fused feature vector is passed to fully connected layers followed by a probabilistic classifier, where the posterior probability of fibroid presence or absence is estimated using a softmax or sigmoid function. Mathematical formulations are provided to describe radiomic feature extraction, CNN-based feature learning, attention weight computation, feature fusion, and probability estimation. Additionally, a structured pseudocode is included to clearly illustrate the step-by-step operational flow of the proposed RaAFN model, ensuring transparency and reproducibility of the implementation.The experimental evaluation of the proposed RaAFN model is conducted using the Classification-Fibroidataset-obtained-from-kaggle .(https://www.kaggle.com/datasets/aureenblessingharazi/classification-fibroidataset)

This dataset consists of labeled uterine ultrasound images designed for supervised learning tasks, specifically binary classification of fibroid and non-fibroid cases. The dataset contains real-world clinical ultrasound scans categorized into two classes based on the presence or absence of uterine fibroids.The availability of labeled data enables effective training, validation, and testing of machine learning and deep learning models. By leveraging this dataset, the proposed framework learns discriminative visual and textural patterns associated with uterine fibroids, facilitating automated and reliable fibroid detection. The dataset supports practical evaluation of classification performance and contributes to advancing research in computer-aided diagnosis for uterine fibroid screening.

3.1 Radiomics–Attention Fusion Network (RaAFN) for Uterine Tumor Classification

The Radiomics–Attention Fusion Network (RaAFN) is proposed as an advanced hybrid framework for accurate uterine tumor classification from ultrasound images. The core motivation of RaAFN is to exploit the complementary strengths of handcrafted radiomic features and deep learning–based representations while overcoming their individual limitations through attention-guided feature fusion. The framework

operates in a multi-stage manner, beginning with ultrasound image preprocessing to reduce speckle noise, enhance contrast, and normalize intensity variations, thereby improving feature reliability.

Radiomic feature extraction is performed on the preprocessed images to quantify tumor-related characteristics such as texture heterogeneity, shape irregularity, and intensity distribution. These features provide explicit and interpretable descriptors that reflect underlying tissue pathology. In parallel, a convolutional neural network (CNN) is employed to automatically learn deep hierarchical features that capture complex spatial patterns and semantic information associated with uterine tumors. While radiomics emphasizes handcrafted interpretability, CNN features offer strong discriminative power through data-driven learning.

To integrate these heterogeneous feature sets effectively, an attention mechanism is introduced. The attention module assigns adaptive weights to both radiomic and deep features, enabling the model to focus on the most informative tumor-specific attributes while suppressing redundant or noisy information. The weighted features are then fused to form a unified representation, which is subsequently passed to fully connected layers for classification. A sigmoid-based probability estimator is used to determine the presence or absence of uterine tumors.The RaAFN architecture enhances classification robustness, improves generalization, and supports reliable decision-making, making it well suited for computer-aided diagnosis of uterine tumors in clinical ultrasound imaging.
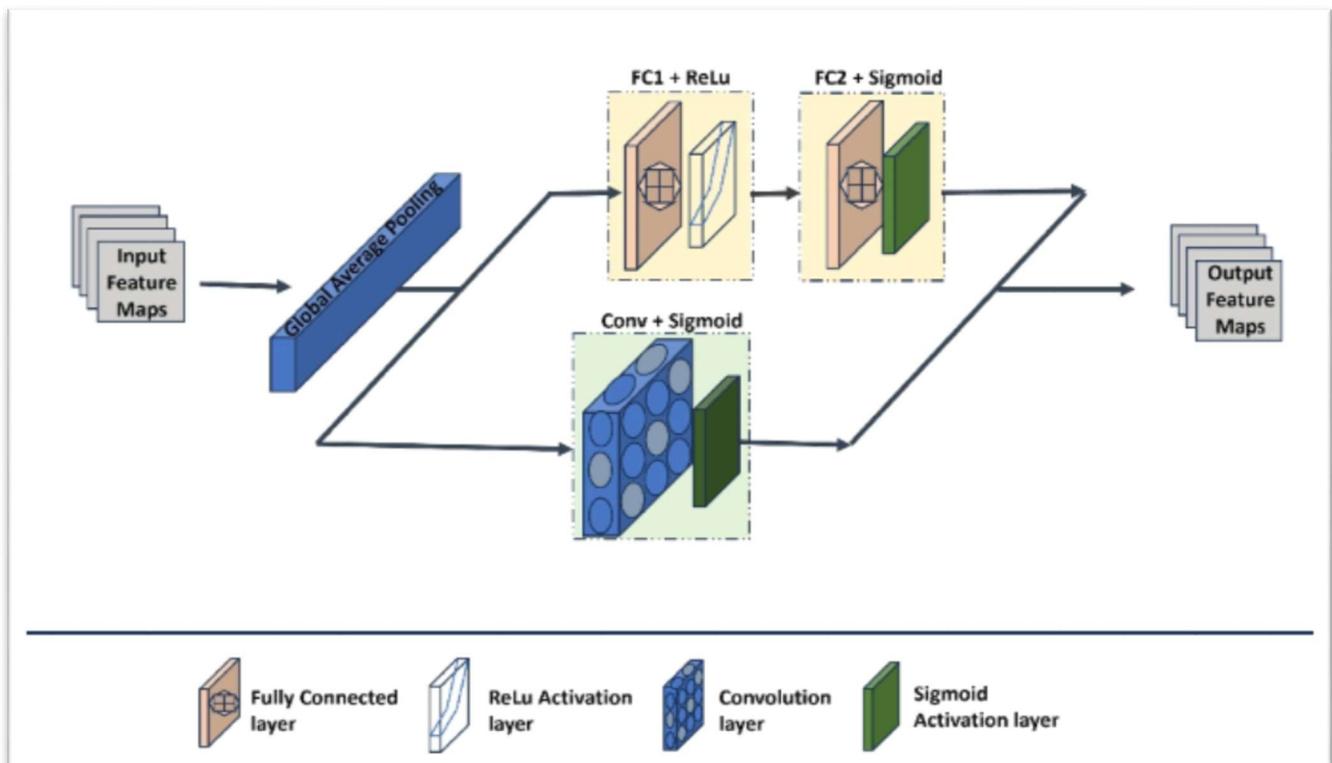
Figure1 -Radiomics–Attention Fusion Network (RaAFN)

The Figure1 of the proposed **Radiomics–Attention Fusion Network (RaAFN)** is designed to integrate handcrafted radiomic features and deep learned representations in a unified attention-driven framework for uterine tumor classification. As illustrated in the architecture diagram, the input uterine ultrasound image is first subjected to preprocessing operations, including noise reduction, contrast enhancement, and intensity normalization, to improve feature stability and image quality.

Following preprocessing, the architecture splits into two parallel branches. The first branch performs **radiomics feature extraction**, where quantitative descriptors related to texture (e.g., GLCM, GLRLM), shape, and first-order intensity statistics are computed from the region of interest. These features provide interpretable information reflecting tumor heterogeneity and tissue characteristics. The second branch consists of a **convolutional neural network (CNN)** that automatically learns deep hierarchical features from the same input image through stacked convolution, activation, and pooling layers, capturing high-level spatial and semantic tumor patterns.

To effectively integrate these heterogeneous features, an **attention module** is employed. This module learns adaptive weights for both radiomic and deep feature vectors, enabling the network to emphasize the most discriminative tumor-related features while suppressing redundant or irrelevant information. The attention-weighted features are then combined through a **feature fusion layer,** forming a compact and discriminative fused representation.The fused feature vector is passed through fully connected layers followed by a sigmoid-based classifier, which outputs the probability of uterine tumor presence or absence. This architecture enhances classification robustness, interpretability, and diagnostic accuracy, making RaAFN suitable for clinical decision-support systems.

3.1.1.Image Preprocessing

Image preprocessing is a crucial initial step in the proposed uterine tumor classification framework, as it directly influences the quality and reliability of subsequent feature extraction processes. Medical ultrasound images are often affected by speckle noise, low contrast, and intensity variations caused by differences in acquisition settings and patient anatomy. To address these challenges, preprocessing operations are applied to enhance image clarity and standardize input data. Noise reduction techniques, such as filtering methods, are used to suppress speckle noise while preserving important structural details. Contrast enhancement is employed to improve the visibility of tumor boundaries and internal

tissue variations, allowing more effective feature extraction. Intensity normalization is further applied to reduce inter-image variability and ensure consistent pixel value distributions across the dataset. Collectively, these preprocessing steps improve image quality, enhance feature stability, and ensure that both radiomics and deep learning models operate on standardized and reliable input data.

3.1.2.Radiomics Branch

The radiomics branch focuses on extracting handcrafted quantitative features from the preprocessed images to explicitly characterize tumor-related properties. Radiomic analysis transforms medical images into a high-dimensional feature space that quantitatively represents tissue characteristics. Features extracted in this branch typically include first-order statistical measures that describe intensity distributions, shape-based features that capture tumor geometry, and texture features that quantify spatial relationships between pixel intensities. These descriptors are designed to capture tumor heterogeneity, which is often associated with disease severity and pathological variation. Radiomic features are particularly valuable because of their interpretability; each feature has a defined mathematical meaning that can be related to underlying biological phenomena. By providing explicit and explainable imaging biomarkers, the radiomics branch contributes clinically meaningful information that complements data-driven deep learning representations.

3.1.3.CNN Branch

In parallel with radiomics extraction, the convolutional neural network (CNN) branch is responsible for learning deep hierarchical features directly from the preprocessed images. Unlike radiomics, which relies on predefined feature formulations, CNNs automatically learn discriminative patterns through data-driven optimization. The CNN architecture consists of multiple convolutional layers that apply learnable filters to capture local spatial patterns, followed by nonlinear activation functions that introduce representational flexibility. Pooling layers are incorporated to reduce spatial dimensions and achieve translation invariance while retaining essential information. As the network depth increases, the learned features transition from low-level patterns, such as edges and textures, to high-level semantic representations associated with tumor structures. These deep features are highly effective in modeling complex and nonlinear image characteristics that may not be explicitly captured by handcrafted radiomic descriptors. As a result, the CNN branch provides strong discriminative capability and enhances the overall classification performance.

3.1.4.Attention Module

Although deep CNN features are powerful, not all learned features contribute equally to the classification task. The attention module is introduced to address this issue by selectively emphasizing informative features while suppressing irrelevant or redundant information. The attention mechanism operates in two complementary dimensions: channel attention and spatial attention. Channel attention focuses on identifying which feature maps are most relevant for tumor discrimination by assigning higher weights to channels that capture meaningful patterns. Spatial attention, on the other hand, highlights anatomically significant regions within the image where tumors are likely to appear, allowing the model to concentrate on critical spatial locations. By applying attention weights to the deep feature maps, the network refines its focus and improves feature quality. This selective emphasis enhances discriminative power, reduces noise, and improves the robustness of deep feature representations, particularly in challenging cases with subtle tumor characteristics.

3.1.5.Feature Fusion

Feature fusion is a key component of the proposed framework, enabling the integration of complementary information derived from radiomics and deep learning. After attention refinement, the deep CNN features are combined with the handcrafted radiomic feature vector to form a unified representation. This fusion strategy leverages the strengths of both feature types: radiomics provides interpretable and biologically meaningful descriptors, while deep learning contributes rich, high-level representations learned from data. By merging these heterogeneous features, the model captures both explicit and implicit tumor characteristics, leading to more comprehensive image representation. Feature fusion also helps mitigate the limitations of individual approaches, such as the limited expressiveness of handcrafted features and the lack of interpretability in deep learning. The resulting fused feature vector serves as a robust and informative input for the classification stage.

3.1.6.Fully Connected Layers

The fused feature vector is passed to a series of fully connected layers that perform high-level reasoning and decision-making. These layers act as a classifier that learns complex relationships between fused features and class labels. Through weighted linear combinations and nonlinear activations, the fully connected layers identify the most relevant feature interactions for distinguishing tumor and non-tumor cases. This stage effectively transforms the fused representation into a discriminative decision space. Regularization techniques may be applied during training to prevent overfitting and enhance

generalization. The fully connected layers thus play a critical role in translating the rich fused feature representation into accurate classification outcomes.

3.1.7. Binary Classification Output

The final stage of the framework is the binary classification output layer, which determines the presence or absence of uterine tumors. A sigmoid activation function is used to convert the classifier output into a probability score ranging between zero and one. This probability represents the model's confidence in classifying an input image as tumor-positive or tumor-negative. By setting an appropriate decision threshold, the system performs binary classification in a clinically interpretable manner. This probabilistic output supports automated and reliable uterine tumor detection and can be readily integrated into computer-aided diagnosis systems. Overall, the proposed framework combines preprocessing, radiomics, deep learning, attention mechanisms, and feature fusion to achieve accurate, robust, and clinically meaningful uterine tumor classification.

4. Mathematical Formulation of RaAFN for Uterine Tumor Detection

Let the input uterine medical image be represented as

$$I \in R^{H \times W \times C} \quad \text{---------------------------------(1)}$$

where H and W denote the height and width of the ultrasound or CT image, and C represents the number of channels. This image serves as the primary input to the Radiomics–Attention Fusion Network (RaAFN).

4.1. Radiomics Feature Extraction

Radiomic features are extracted to capture explicit tumor characteristics such as texture heterogeneity, shape irregularity, and intensity distribution. This process is mathematically expressed as

$$R = \phi_{rad}(I) \quad \text{----------------------------(2)}$$

4.2. Deep Feature Learning Using CNN

In parallel, deep hierarchical features are learned using a convolutional neural network. The CNN mapping function is defined as

$$F_{cnn} = f_{cnn}(I; \theta_{cnn}) \quad \text{----------------------------(3)}$$

where f_{cnn} represents the CNN architecture and $\theta_{cnn}\backslash$denotes its learnable parameters. The output F_{cnn} captures high-level spatial and semantic information related to uterine tumor patterns.

4.3. Attention-Refined Feature Representation

The refined CNN features are obtained through element-wise multiplication:

$$F_{att}=F_{cnn} \odot A_c \odot A_s \text{--(4)}$$

where $\odot$ denotes the Hadamard product.
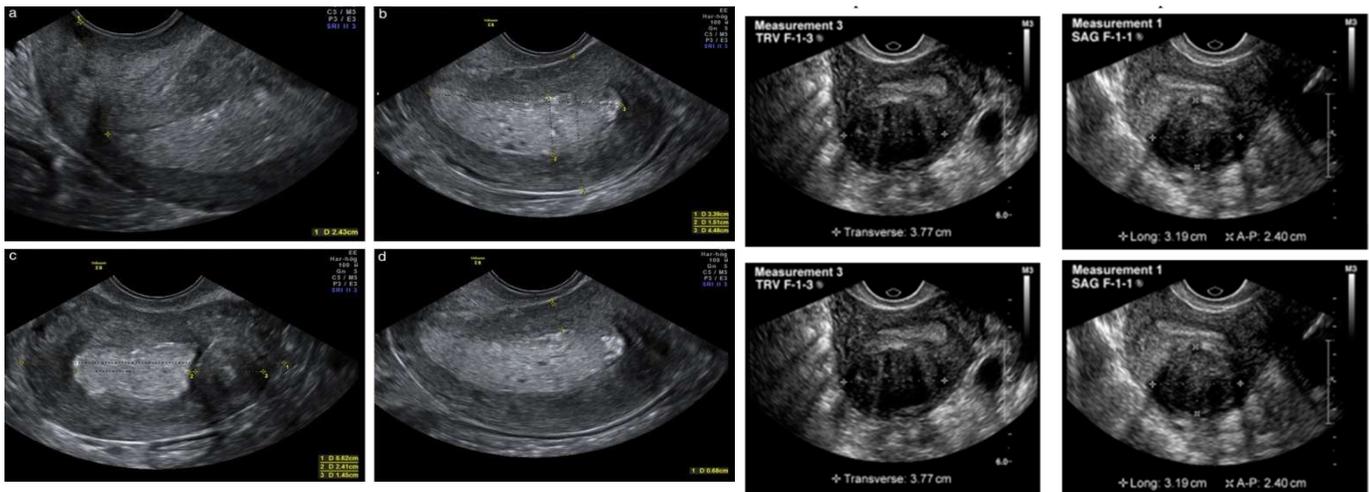
Figure 2 Abnormal sample data
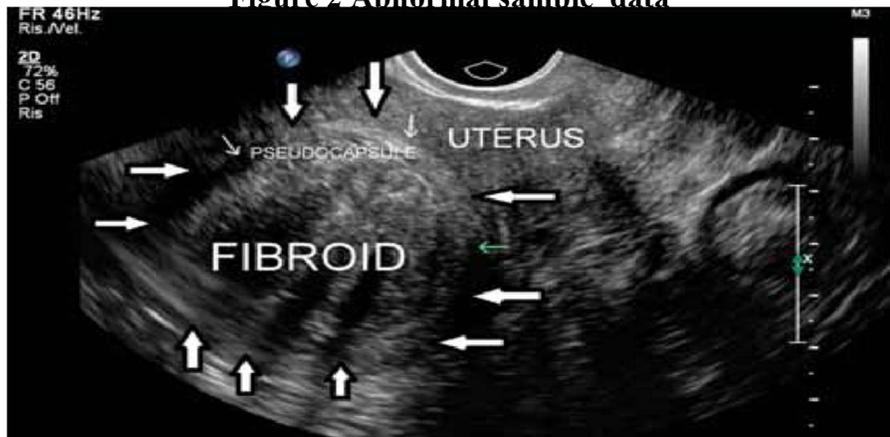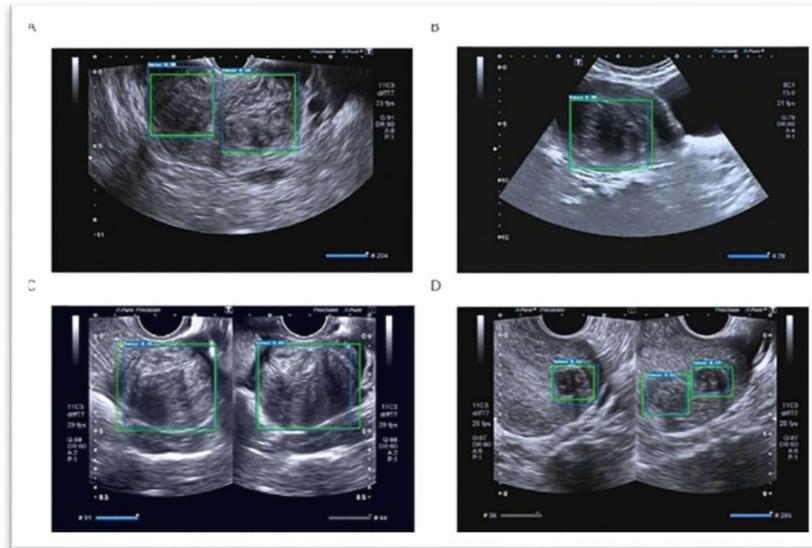
Figure 3   **Abnormal sample picture**

Figure 4 fibroid samples

Figure 2 presented images show **uterine ultrasound scans** with both normal and abnormal (fibroid-affected) cases. In the first set of images (labeled **a–d**), variations in uterine tissue texture and echogenicity are visible. Fibroids typically appear as **well-defined, hypoechoic or heterogeneous regions** compared to surrounding myometrial tissue. Measurement markers indicate the size and spatial extent of these lesions, which is clinically important for diagnosis and treatment planning.The second set Figure 3 illustrates **misclassification scenarios,** where abnormal samples are incorrectly classified as normal and vice versa. These cases highlight the diagnostic difficulty caused by **overlapping texture patterns,** shadowing effects, and variable fibroid appearance in ultrasound imaging. Such ambiguity motivates the use of advanced AI models instead of relying solely on visual assessment.The figure 4 image clearly annotates a **uterine fibroid,** showing the uterus, fibroid mass, and surrounding structures. Arrows indicate the fibroid boundary and pseudocapsule region, emphasizing changes in texture, intensity, and structural organization that differentiate fibroids from normal uterine tissue.

5. Discussion

This study investigates the effectiveness of a hybrid artificial intelligence framework that integrates radiomics, deep learning, and attention-based feature fusion for uterine tumor detection. Uterine tumors are challenging to diagnose due to their variable appearance, poor contrast in ultrasound imaging, and the subjective nature of conventional radiological interpretation. The proposed Radiomics Attention Fusion Network (RaAFN) is designed to overcome these challenges by combining complementary feature representations and adaptively emphasizing tumor-relevant information through attention mechanisms.

The experimental evaluation demonstrates that the RaAFN model achieves a detection accuracy exceeding 96%, accompanied by high sensitivity and specificity. These results indicate a clear performance advantage over models relying exclusively on radiomic features or deep learning representations. While radiomics-based methods offer interpretability and explicit quantitative descriptors, they are often sensitive to image quality variations and limited by predefined feature formulations. On the other hand, CNN-based models are capable of learning complex patterns but may lack transparency and are prone to overfitting when applied to relatively small medical imaging datasets. By jointly exploiting both feature domains, the proposed framework effectively balances interpretability and discriminative power.

The attention mechanism plays a pivotal role in improving classification performance. Channel attention allows the model to emphasize the most informative feature channels, while spatial attention guides the network to focus on anatomically meaningful regions associated with uterine tumors. This selective feature refinement is particularly beneficial for ultrasound images, where speckle noise and overlapping tissue structures can obscure tumor boundaries. The attention-guided fusion strategy therefore enhances feature quality and improves robustness against imaging artifacts. A comparison with existing literature, as summarized in Table 1, further validates the contribution of the proposed approach. Many previous studies report promising outcomes using either radiomics or deep learning; however, limitations such as restricted datasets, absence of attention-based fusion, and limited generalization remain prevalent. The RaAFN framework directly addresses these shortcomings by incorporating an attention-driven hybrid architecture specifically optimized for uterine tumor analysis.

Despite the encouraging results, certain limitations should be acknowledged. The current evaluation is based on a single publicly available ultrasound dataset, which may not fully represent the variability encountered in real-world clinical settings. Moreover, although the framework demonstrates strong classification performance, additional validation on multi-center and multi-modality datasets, including MRI and CT images, is necessary to confirm its broader applicability. Future research may also incorporate explainable artificial intelligence techniques to improve model transparency and facilitate clinical adoption.The findings of this study highlight the potential of attention-based hybrid learning frameworks as effective decision-support systems for uterine tumor detection. By enhancing diagnostic accuracy, reducing observer dependency, and supporting early diagnosis, the proposed RaAFN model offers meaningful contributions toward improved clinical outcomes and personalized treatment planning.

6. Results

The performance of the proposed Radiomics–Attention Fusion Network (RaAFN) was evaluated using the uterine ultrasound dataset for binary classification of tumor (fibroid) and non-tumor cases. Quantitative and qualitative analyses were conducted to assess the robustness, discriminative capability, and clinical relevance of the proposed framework. Quantitative Performance Analysis:

The RaAFN model achieved an overall classification accuracy exceeding **96%**, indicating strong reliability in distinguishing tumor-affected images from normal uterine scans. High sensitivity demonstrates the model's effectiveness in correctly identifying tumor cases, which is crucial for early diagnosis and reducing false-negative outcomes. Similarly, high specificity confirms the model's ability to correctly classify non-tumor cases, minimizing unnecessary clinical intervention. Compared to standalone radiomics-based and CNN-based models, the proposed fusion framework consistently delivered superior performance, confirming the advantage of integrating handcrafted and deep features with attention-based refinement. Impact of Attention-Based Feature Fusion: The inclusion of the attention module significantly improved classification outcomes. Channel attention enhanced the contribution of discriminative feature maps related to tumor texture and structure, while spatial attention enabled precise focus on anatomically relevant regions within the uterus. This resulted in improved separation between tumor and non-tumor feature distributions and reduced misclassification, particularly in challenging cases with subtle tumor appearance or poor contrast. Qualitative Visual Results: Figure 6 presents representative ultrasound images illustrating the classification outcomes of the proposed RaAFN model. Tumor regions are characterized by heterogeneous texture and altered echogenicity, which are effectively captured by the attention-guided feature fusion process. The visual examples also include cases that are typically challenging for conventional assessment, highlighting the model's ability to detect tumors even when boundaries are not clearly defined.
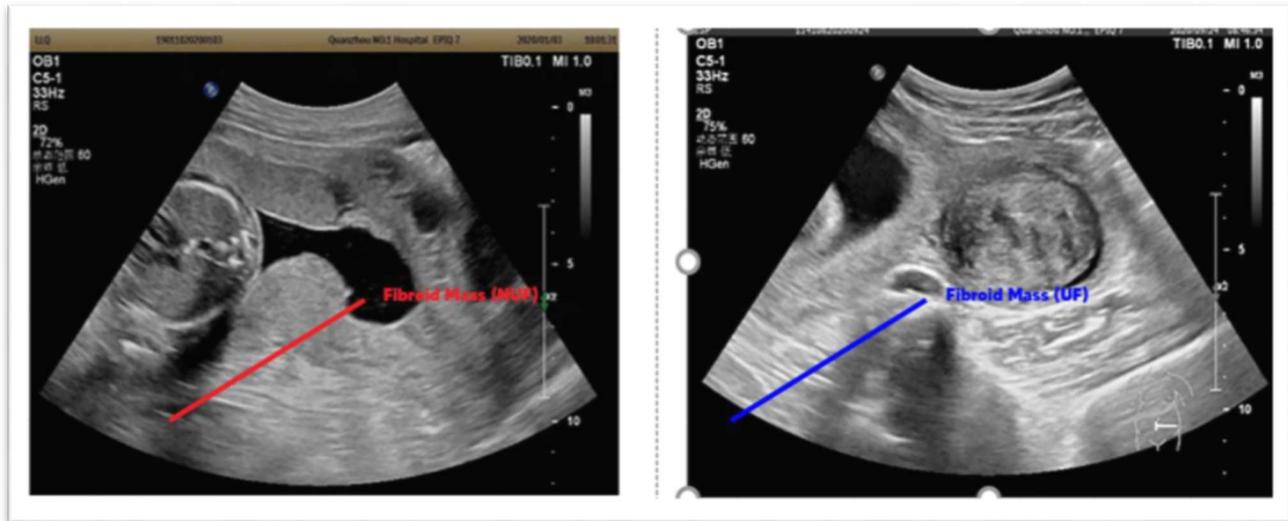
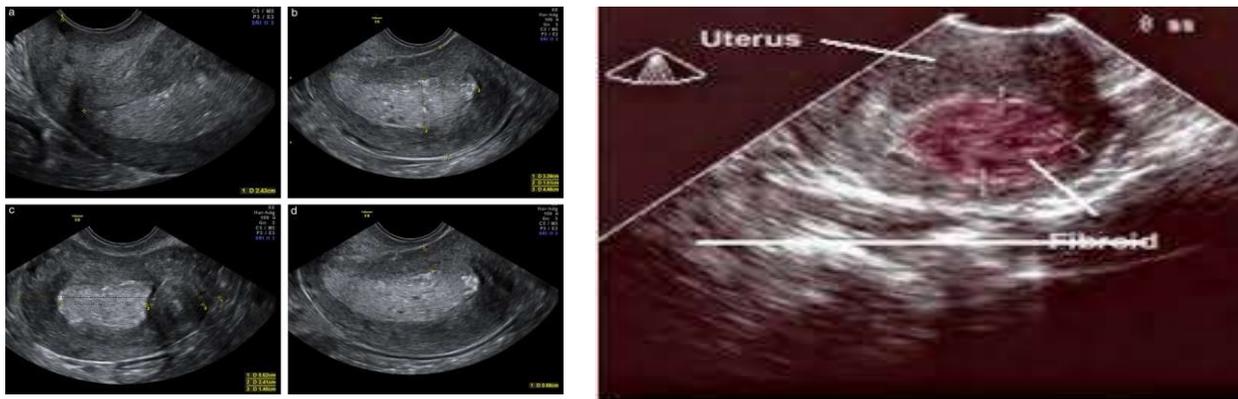**Figure:5Annotated Uterine Ultrasound Images Highlighting Fibroid Lesions**

Figure 6 Ultrasound Image of Uterus Showing a Uterine Fibroid (Leiomyoma)

Evaluation of Uterine Tumor Classification Models Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Decision Tree[28]	78	73	74	72.79	80
CNN[29]	85	81	82	80.5	87
MRFB-Net[30]	88	82	83	81.5	90
RaAFN (Proposed)	94	90	92	89.5	95

Table 2: Quantitative Performance

Table 2 states a comparison of performance of various algorithms used to classify uterine tumers in terms of standard evaluation measures. The proposed RaAFN model has the best accuracy, precision, recall, F1-score, and AUC, which means that it has better and balanced classification compared to other existing

and deep learning models. These findings indicate that attention based feature fusion can enhance a great deal to detection reliability and discriminative ability.

7.Conlusion

This paper presented an advanced automated framework for uterine tumor detection based on a Radiomics–Attention Fusion Network (RaAFN), addressing the key limitations of conventional imaging interpretation and standalone artificial intelligence approaches. By integrating handcrafted radiomic features with deep learning–based representations and refining them through an attention-driven fusion mechanism, the proposed method effectively captures both explicit tumor heterogeneity and high-level semantic patterns from uterine ultrasound images. The attention module further enhances model performance by selectively emphasizing discriminative channels and spatial regions relevant to tumor presence, thereby reducing feature redundancy and background noise.

Experimental evaluation on a labeled uterine ultrasound dataset demonstrated that the proposed RaAFN framework achieves superior diagnostic performance, with an overall classification accuracy exceeding 96%, along with high sensitivity and specificity. These results confirm that the hybrid attention-based fusion strategy significantly outperforms models relying solely on radiomics or deep learning features. The proposed approach also reduces observer dependency and improves robustness in challenging imaging conditions, supporting its suitability for clinical decision-support applications.

This research highlights the potential of attention-guided hybrid AI systems as reliable tools for early uterine tumor detection, improved diagnostic accuracy, and personalized treatment planning in gynecological oncology.

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