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Deep Radiomics-Attention Fusion Network (RaAFN) for Accurate Uterine Tumour Classification

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ABSTRACT

The complicated structure of uterine tumours and the natural weaknesses of the manual approach to image interpretation result in early-stage classification, which can be challenging to achieve, leading to a delayed diagnosis and poor clinical care. To overcome this issue, the given Radiomics-Attention Fusion Network (RaAFN) incorporates handcrafted radiomics features together with deep learning representations with channel and spatial attention mechanism. Radiomics brings out clinically significant texture, shape, and intensity features, whereas a CNN backbone brings out hierarchical representations of images. The attention modules are used to make the network focus on tumour-relevant regions and a fusion layer is used to combine radiomics and deep features into a single representation that is used to classify uterine tumours robustly using a dense neural network. The provision of this multi-level feature fusion is quite effective to manage image variability and noise, and, therefore, the model can be deployed in real-time clinical use. The experimental assessment is done on a dataset of uterine imaging; it tends to classify better with 94% accuracy surpassing the available methods. RaAFN is the most important innovation in the sense that it takes into consideration the attention-directed integration of the hybrid features and it offers an accurate, interpretable and clinically reliable framework of automated uterine tumour classification that facilitates timely diagnosis and the post-processing of improved patient outcomes.

1. Introduction

Gynecological conditions like fibroids and endometrial cancers are typical uterine tumors that need to be classified correctly and at an early stage to aid in decision making and clinical planning of treatment. Uterine tumor assessment through medical imaging modes, such as ultrasound, Ultrasound image and histopathology slides, is a regular practice, yet the classification between them is time consuming and prone to inter-observer differences. As the field of artificial intelligence in healthcare is rapidly growing, deep learning has become one of the most effective methods of automated tumor classification in the uterus. Whole-slide histopathology images have demonstrated to be useful in the clinical-grade classification of endometrial cancer [1], and Ultrasound image-based deep learning models have been used to classify uterine myoma with intelligence [2] and uterine fibroids based on medical images [3]. Comparisons of deep learning models with radiologists have also shown that AI-assisted classification has the potential to be used in endometrial cancer with Ultrasound image [4], and the whole-slide image analysis has enabled accurate subtype classification of cervical and endometrial cancers [5].

Recent studies have been aimed at making classification more accurate and stronger using advanced architectures and multimodal learning methods. Deep learning-based models have been proposed for classifying endometrial lesions [6] and uterine fibroids in ultrasound images [7], while cancer grading through deep learning-based classification has shown strong clinical relevance [8]. Specialized classification approaches, such as mitosis-based classification in uterine leiomyosarcoma histopathology [9] and ultrasound super-resolution-assisted tumor classification [10], have further enhanced diagnostic performance. Beyond imaging alone, machine learning-based classification using plasma cfDNA fragmentomics has been explored for early cancer identification [11], and optimized CNN ensemble models have improved histopathological classification accuracy [12]. Integrated clinical and imaging-based classification models have also been developed to predict disease severity [13], and unified deep learning frameworks have enabled generalized cancer classification across multiple tumor types [14]. Additionally, ultrasound-based machine learning models have been used to classify endometrial cancer risk among postmenopausal women [15]. However, most existing approaches rely either on handcrafted features or deep features alone, leading to limited interpretability or reduced robustness. In order to overcome these issues, the proposed research suggests a Radiomics-Attention Fusion Network (RaAFN) comprising of both clinically meaningful radiomics features and attention-weighted deep CNN features in order to attain accurate, interpretable, and reliable classification of uterine tumors.

This work is motivated by the desire to enhance the accuracy of uterine tumor classification with clinical interpretability because the currently used deep learning models mostly depend on deep features and are unusable to explain their findings. To overcome this, the proposed RaAFN combines both handcrafted radiomics characteristics with attention-guided deep CNN characteristics, the model is able to prioritize the tumor-relevant patterns, and ignore detrimental information. The main contributions are that it proposes an attention-based fusion framework that supports robust feature integration, an enhanced classification performance compared to the methods and that it leads to interpretable classification output that can be used in clinical decision support.

Organization: This research is organized as follows: Section 1 introduces the problem, motivation, and contributions of the proposed work. Section 2 reviews related studies and existing approaches for uterine tumor classification. Section 3 describes the proposed RaAFN methodology, including feature extraction, attention mechanisms, and fusion strategy. Section 4 presents the experimental results, discussion, and comparative analysis, followed by Section5 conclusion and future research directions.

2. Background Study

The authors Ravishankar et al. (2023) [16] have proposed a fuzzy convolutional neural network (OCD-FCNN) as an automated detection and classification of ovarian cysts. The research deals with the weakness of the existing CNNs in the presence of uncertainty and noise in ultrasound images. The learning of features and classification was done on a fuzzy logic-based deep learning architecture. The complexity of the model and its reliance on annotated datasets are also important constraints although better accuracy was obtained.

This article by Altal et al. (2025) [17] is a hybrid attention-enhanced MobileNetV2 that is optimized through Particle Swarm Optimization (PSO) to classify endometrial cancer inUltrasound imageimages. The research bridges the gap of very light deep models but with high accuracy and can be applied in the clinical environment. The attention mechanisms and PSO were combined to improve the choice of features and parameter tuning. Although there are good classification results, the method is constrained by CT-only data and computation optimization cost.

The authors Mahmud et al. (2021) [18] created the best learning model to train an expert system to identify uterine cancer. The gap in the research is the fact that rule-based expert systems do not have adaptive learning capabilities. The expert system was trained and optimisation was performed using machine learning methods to enhance its diagnostic accuracy. Nevertheless, this system is highly reliant on rules that are defined by experts, and it is not proved on massive real-world data.

This research, Cheon et al. (2023) [19] compared the importance of features in a deep learning model that predicted late bladder toxicity in patients with uterine cervical cancer. The article bridges the explain ability gap of deep learning models in radiotherapy outcome prediction. Deep neural networks together with feature attribution were used on clinical and diametric data. Although the interpretation ability was enhanced, there was a trade-off of retrospective design and small cohort, which restricts the generalizability.

The authors proposed a platform of exosome metabolic fingerprint to diagnose and screen biomarkers of endometrial cancer Yang et al., (2024) [20]. The research bridges non-invasive diagnostic methods based on metabolomics. Cancer specific metabolic signatures were determined using advanced analytical chemistry approaches as well as using pattern recognition. It has limitations such as high experimental complexity and requirement of large-scale clinical validation regardless of high diagnostic performance.

In this research, Abraham et al. (2021) [21] used machine learning on 77,044 genomic and transcriptomic profiles to identify the type of tumour. The research deals with the problem of molecular heterogeneity of tumours being wrongly classified. The models of supervised learning were trained on multi-omits datasets of high scale. Despite the high accuracy, there are weaknesses in that the interpretability is low and that it relies on good quality of genomic data.

The research problem of the research carried by Paraskevaidi et al. (2020) [22] was the identification of endometrial cancer using blood spectroscopy and machine learning. It also talks about the disparity of invasive diagnostic procedures by suggesting a quick method of blood screening. Multivariate analysis was used to interpret spectral data. Although the procedure was very sensitive, its limitations can be considered as potential confounding factors and standardized spectral acquisition.

This research determined and confirmed the presence of KIF11 in the development of endometrial cancer as reported by Wang et al. (2025) [23]. The research also bridges the gap in the knowledge of molecular drivers and therapeutic targets in endometrial cancer. It was analysed using bioinformatics, gene expression and experimental validation. Although there is good biological evidence, clinical translation has not been well done and more functional and therapeutic studies are needed.

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

Ref	Author & Year	Concept	Research Gap	Methods	Limitations	Key Results
24	Gupta et al. (2021)	Uterine bioimpedance combined with artificial intelligence for cancer detection	Lack of non-invasive, low-cost diagnostic tools for early uterine cancer detection	Bioimpedance signal acquisition integrated with machine learning classifiers	Small sample size and limited clinical diversity	Demonstrated feasibility of AI-assisted bioimpedance with encouraging diagnostic accuracy
25	Tran et al. (2021)	Deep learning applications in cancer diagnosis, prognosis, and treatment selection	Fragmented understanding of DL potential across the full cancer care pipeline	Review of CNNs, DL frameworks, and multi-omics integration	Limited discussion on clinical deployment challenges	Highlighted DL's strong potential in precision oncology and decision support
26	Lin et al.	ML-based	Inadequate	Machine	Retrospective	ML model

	(2025)	prediction of distant metastasis using peritoneal cytology in uterine carcinosarcoma	predictive models for metastasis risk in rare uterine cancers	learning model development and external validation	design and rarity of disease	effectively predicted distant metastasis risk with improved accuracy
27	Liu & Wang (2022)	Advances in preoperative identification of uterine sarcoma	Difficulty differentiating benign fibroids from malignant sarcomas preoperatively	Review of imaging, biomarkers, and AI-assisted diagnostic methods	Lack of standardized diagnostic criteria	Identified promising multimodal strategies for improving early sarcoma detection
28	Mahmud et al. (2021)	Expert system for uterine cancer detection using Decision Tree	Existing expert systems lack adaptive learning capability	Decision Tree–based optimal learning model for rule generation	Rule dependency and limited real-world validation	Improved diagnostic consistency compared to manual expert systems
29	Urushibara et al. (2022)	Deep learning–based ULTRASOUND IMAGE diagnosis of endometrial cancer	Performance gap between AI models and radiologists not well quantified	CNN models compared directly with radiologist interpretations	Dataset size and ULTRASOUND IMAGE protocol variability	CNN achieved comparable or superior diagnostic accuracy to radiologists

30	Jiang et al. (2025)	MRFB-Net for uterine fibroid segmentation	Inaccurate segmentation due to complex fibroid shapes and scales	Attention pooling CNN with modified receptive field block (MRFB-Net)	Computational complexity and ULTRASOUND IMAGE-specific design	Achieved high segmentation accuracy and robustness on uterine ULTRASOUND IMAGE data

Table 1 provides a summary of the current research examining AI, machine learning, and expert systems in the detection of uterine cancers and fibroid and identifies gaps in the research, methodology, limitations, and findings. It gives a brief history of developments in predictive modeling, imaging analysis, and decision support focusing on the promise and challenges of the computational diagnostics of gynecologic oncology.

3. Proposed Methodology

The Proposed methodology introduces the general structure of the Radiomics-Attention Fusion Network (RaAFN), including all steps of the processing of the input image up to the final classification. It logically describes the mathematical formulae of radiomics mining, CNN element learning, attention, feature fusion, and probability estimation. Moreover, a systematic representation of a pseudocode is also given to depict clearly the steps of the working process of the proposed model implementation.

Dataset: https://www.kaggle.com/datasets/aureenblessingharazi/classification-fibroidataset

The Classification-Fibroidataset on Kaggle is a labelled uterine ultrasound dataset used in the supervised training to determine whether the image has presence or absence of fibroid and enables binary classification programs. This dataset provides real-world medical ultrasound scans organized into class labels that help in training and evaluating classification models for uterine fibroids. By using this dataset, machine learning and deep learning models can learn visual patterns that differentiate fibroid and non-fibroid images, supporting research in automated fibroid classification

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

The Radiomics-Attention Fusion Network proposed algorithm works in the context of uterine tumor classification by addressing the limitations of existing methods that rely either on handcrafted features or pure CNN-based models. Earlier, using only radiomics features often missed deep spatial patterns, while pure CNN approaches lacked clinical interpretability. RaAFN first extracts handcrafted radiomics features (such as shape, texture, and intensity) from uterine Ultrasound images while simultaneously learning high-level deep features through CNNs. Existing feature fusion using simple concatenation often let irrelevant features confuse the classification, but RaAFN overcomes this with an attention-based fusion module that gives higher weight to tumor-relevant features and suppresses noise. It improves the detection of small or low-contrast tumors by focusing attention on critical regions. Adaptive weighting also eliminates the imbalance of classes and redundant features. RaAFN maintains clinical relevance and improves the feature representation by integrating radiomics and deep features. Consequently, it attains superior accuracy, strength and generalization in classifying the uterine tumor in the real world.

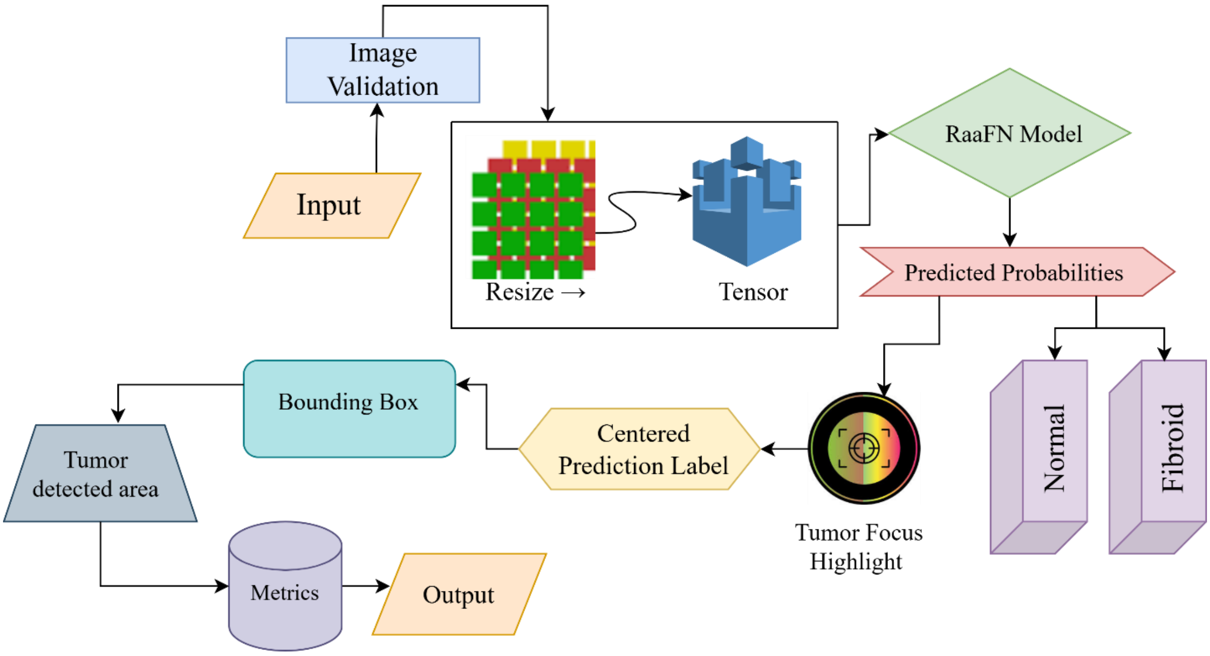

Figure 1: Architecture of the Radiomics-Attention Fusion Network for Uterine Tumor Classification

Figure 1 depicts the workflow of the RaAFN model used in the detection of the uterine tumor. The input images are first received and then image validation is performed to assure quality and consistency of the input images. The RaAFN model is then used to process these images and predicts the probability of a tumor by providing a prediction label centered and a bounding box to the attention-guided localization, which indicates section of the images that are pertinent to the tumor to be interpretable. Evaluation of the results (predicted probabilities, area detected by tumor and labels of the classification (Normal or Fibroid) is done with different metrics and the final output summarizes all the results with proper detection and classification of tumors in an organized format.

The uterine ULTRASOUND IMAGE/CT image is input to the system.

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

In equation 1, I reflect the input medical image, e.g. a uterine ULTRASOUND IMAGE orUltrasound imagescan. The size $H \ \ W$ is used to indicate the height and width of the picture and C is used to indicate the number of channels This depiction The raw image is represented as a multidimensional array that can be used to extract features and process them.

Extract explicit tumour features using radiomics.

$$R = \emptyset_{radiomics}(I) \text{ ------------ (2)}$$

In equation 2, R is a $radiomics$ feature vector that is obtained by using the input image. The handcrafted features that are computed by the function ∅ radiomics (I) include the texture, shape, and intensity patterns of the uterine ULTRASOUND IMAGE/CT image$I$. These features obtain clinically significant features to add to deep CNN features to obtain strong tumor analysis.

Extract deep hierarchical features from the image.

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

In equation 3, F_{cnn} is the feature map of the input image that was extracted by a convolutional neural network. The F_{cnn} $(I; \theta_{cnn})$ network represents the CNN operations of convolution, activation and pooling, and is parameterized by learnable weightsθ_{cnn}. I Is the uterine ULTRASOUND IMAGE/CT image, andF_{cnn} is the output that contains hierarchical deep features that can be used in tumor characterization.

Highlight important channels in the feature map.

$$A_c = \sigma(W_2\delta(W_1F_{cnn}^{gap})) \text{ ----------- (4)}$$

In equation 4, A_c represents the channel attention vector that highlights the most informative feature channels. The term F_{cnn}^{gap} is obtained by applying global average pooling to the CNN feature mapF_{cnn}, W_1 and W_2 are learnable weight matrices, and δdenotes the ReLU activation. The sigmoid function $\sigma(.)$ normalizes the output to produce channel-wise attention weights between 0 and 1.

Highlight important regions in the feature map.

$$A_s = \sigma(f_{conv}([AvgPool(F_{cnn}); MaxPool(F_{cnn})])) \text{ ----------- (5)}$$

In equation 5, A_s denotes the spatial attention map that highlights important regions in the feature map. The terms $AvgPool(F_{cnn})$ and $MaxPool(F_{cnn})$ represent average and maximum pooling operations applied along the channel dimension, while f_{conv} is a convolutional operation used to aggregate this information. The sigmoid function $\sigma(.)$ normalizes the output to generate spatial attention weights between 0 and 1, emphasizing tumor-relevant areas.

Combine channel and spatial attention to refine CNN features.

$$F_{att} = F_{cnn} \odot A_c \odot A_s \text{ ---------- (6)}$$

In equation 6, F_{att} represents the attention-refined feature map obtained after applying both channel and spatial attention. The term F_{cnn} denotes the original CNN feature map, while $A_c$and A_s correspond to the channel attention and spatial attention maps, respectively. The element-wise multiplication operator ⊙selectively enhances tumor-relevant features and suppresses less informative channels and regions.

Fuse radiomics and attention-weighted CNN features into a single vector

$$F_{fused} = [Flatten(F_{att}); R] \text{ ---------- (7)}$$

In equation 7, F_{fused} denotes the final fused feature vector used for classification. The term (F_{att}) converts the attention-weighted CNN feature map $Flatten(F_{att})$ into a one-dimensional vector, while RRR represents the handcrafted radiomics feature vector. The concatenation operator [·;·] combines both deep and handcrafted features to form a comprehensive representation of the uterine tumor.

Project fused features into output class scores (logits).

$$y_{logits} = W_f F_{fused} + b_f \text{ --------- (8)}$$

In equation 8, y_{logits} represents the raw output scores produced by the classifier before activation. The matrix W_f denotes the learnable weights, F_{fused} is the fused feature vector combining radiomics and CNN features, and b_f is the bias term. This linear transformation maps the fused features into class-specific logits used for final classification.

Convert logits to probability distribution for classification.

$$P_i = \frac{\exp(y_{logits,i})}{\sum_{j=1}^{C} \exp(y_{logits,j})} \text{ , } i = 1, \ldots, C \quad \text{------------ (9)}$$

In equation 9, P_i denotes the predicted probability of the input sample belonging to class i. The term $y_{logits,i}$,i represents the raw output score (logit) of the network for class i, while C is the total number of classes and j is the class index used in normalization. The softmax function converts all logits into a normalized probability distribution whose values lies between 0 and 1 and sum to one.

Loss function is to train the network by comparing predicted and true labels.

$$L = -\sum_{i=1}^{C} y_{true,i} \log(P_i) \text{ ---------- (10)}$$

In this equation, L denotes the cross-entropy loss used to measure the difference between the true class labels and the predicted probabilities. The term C represents the total number of classes, $y_{true,i}$ is the ground-truth label for class i (equal to 1 for the correct class and 0 otherwise), and P_i is the predicted probability of class$i$. By penalizing low probabilities assigned to the true class, this loss function guides the model to learn parameters that improve classification accuracy.

Algorithm: RaAFN
1. Input medical image I 2. Preprocess image I 2.1 Resize image to fixed dimensions 2.2 Normalize pixel intensity values 3. Extract radiomics features 3.1 Compute texture, shape, and intensity features from I 3.2 Store radiomics feature vector R 4. Extract deep CNN features 4.1 Pass image I through CNN backbone 4.2 Obtain deep feature map F 5. Apply channel attention 5.1 Perform global average pooling on F 5.2 Generate channel attention weights CA 5.3 Refine feature map $F \leftarrow F \times CA$ 6. Apply spatial attention 6.1 Perform average and max pooling on refined F 6.2 Generate spatial attention map SA 6.3 Refine feature map $F \leftarrow F \times SA$ 7. Fuse features 7.1 Flatten attention-refined CNN features 7.2 Concatenate flattened CNN features with radiomics features

7.3 Form fused feature vector H

8. Classification

8.1 Pass H through fully connected layers

8.2 Generate class logits Z

8.3 Apply softmax to obtain probability P

9. Output predicted class label C = argmax(P)

10. Return C and P

End

The pseudo-code describes a step-by-step workflow for uterine tumour classification using the RaAFN model, starting from image pre-processing and parallel extraction of radiomics and deep CNN features. Channel and spatial attention mechanisms are applied to emphasize tumour-relevant features while suppressing irrelevant information, improving feature quality. Finally, the fused features are classified using a neural network to produce the predicted class label and probability score in an interpretable manner.

4. Result and Discussion

The result and discussion indicated RaAFN model, which is executed with the help of Python-based deep learning libraries, has much better performance in comparison to the existing algorithms in all evaluation measures. The fact that attention heatmaps and focus regions produced by the Python implementation correspond to the areas of interest in the model is supported by attention to heatmaps and focus regions and thus, enhances interpretability. The comparative evaluation that was done based on the Python evaluation frameworks demonstrates that RaAFN offers the balanced and resilient classification performance that can be applied in the real-world clinical setting.

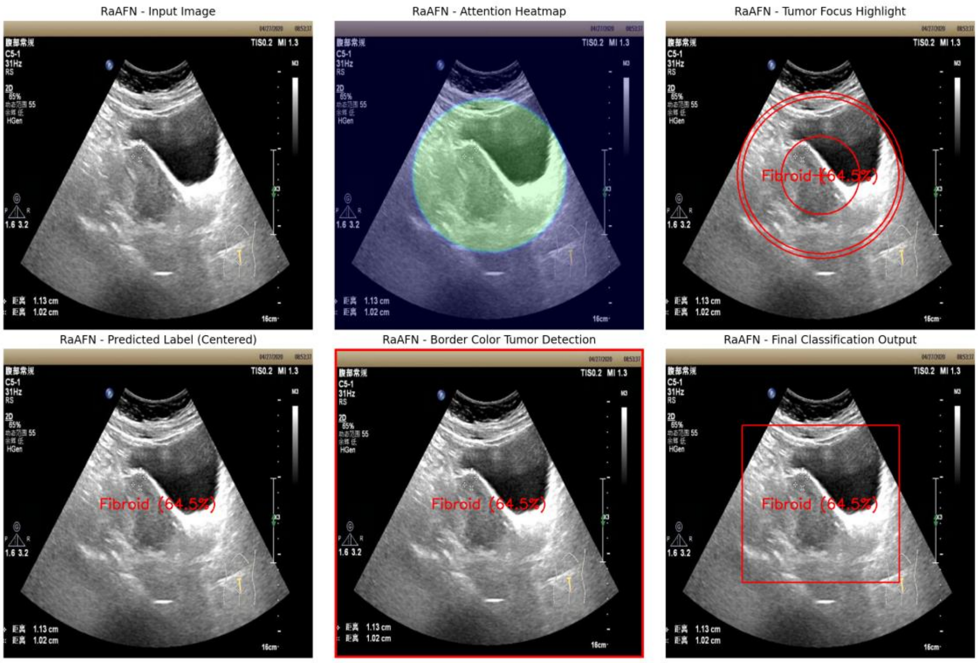

Figure 2: RaAFN Attention-Guided Tumor Classification Output

Figure 2 illustrates the entire process of the RaAFN model of tumor detection and classification. The original ultrasound scan input is presented in the first image and the attention heatmap indicating the region of interest in the second image. The next series of panels show the tumor focus highlight, predicted label, border-colored detection and the final classification result in which the model can recognize a fibroid with confidence score of 64.5%.

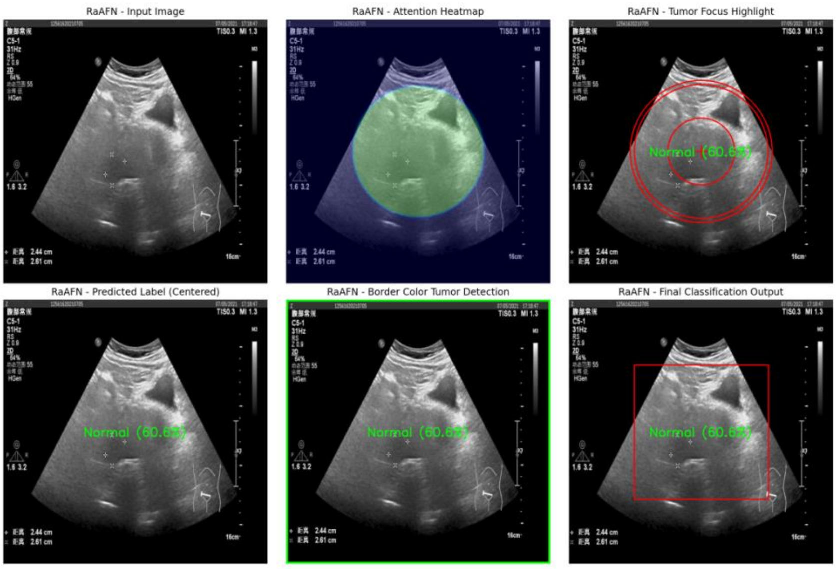

Figure 3: RaAFN No Tumor Detection Classification output image

The RaAFN model was used to analyze this image 3, highlighting the region of interest in an attention heatmap and colored circles of focus that were red. The model estimated that the scan was Normal with certainty of 60.6, along with a green border and a binding box that signifies that no tumor was detected. All the overlays assist in visualizing the areas that were taken into consideration by the model, thus the classification is readable and easy to communicate.

Table 2: Quantitative Performance 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 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.

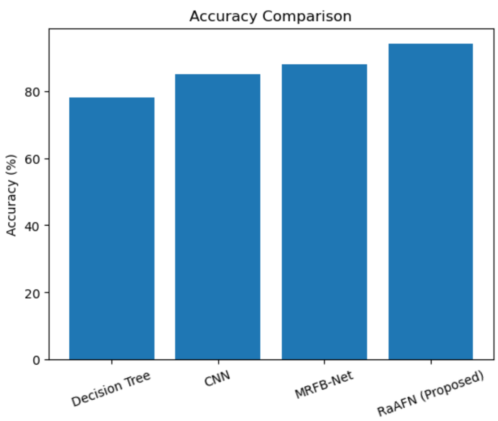

Figure 4: Accuracy Performance across Algorithms

Figure4 demonstrates the accuracy (%) of each of the models but the most accurate of the models is RaAFN which has an accuracy of 94%. It points to the better capacity of the model to make right predictions in comparison with existing and deep learning methods.

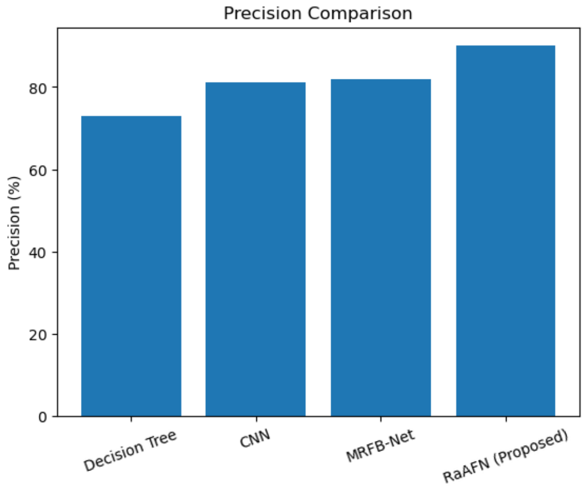

Figure 5: Precision Levels of Evaluated Models

Figure 5 is a bar chart of the precision (percentage) of each algorithm, which shows that RaAFN has the highest precision (90 percent). This highlights how the model is reliable in reducing false-positive predictions.

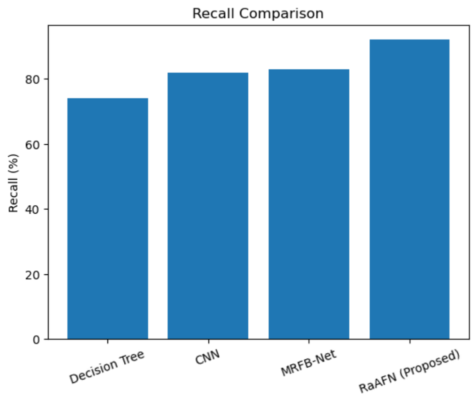

Figure 6: Recall Effectiveness of Different Algorithms

Figure 6 depicts the recall (%) of all models, where RaAFN had the highest recall at 92%. It shows that the model can rightfully detect most of the real positive cases.

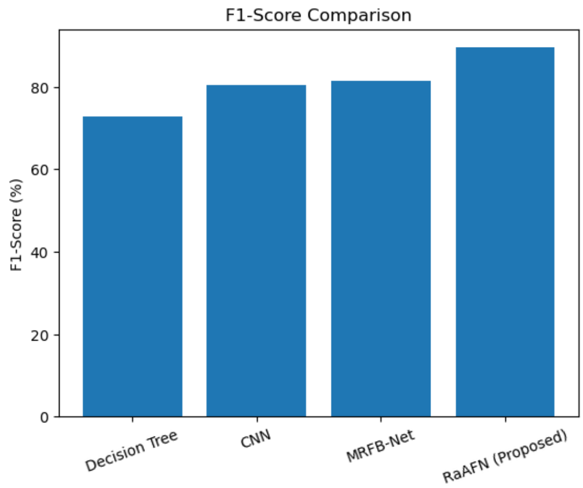

Figure 7: F1-Score Comparison among Models

Figure 7 shows a comparison of the values of F1-Score (%) with RaAFN having a score of 89.5, indicating a balanced score between recall and precision. It indicates that RaAFN is accurate and complete in terms of making predictions.

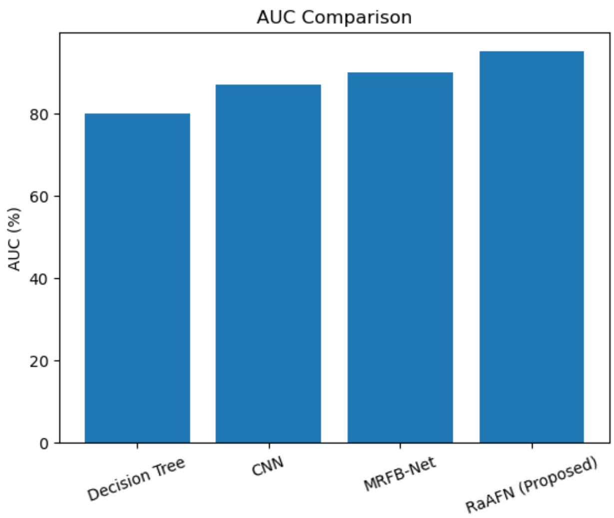

Figure 8: AUC Performance across Models

The AUC (%) of each algorithm is provided in figure 8, where RaAFN is at 95 percent, which is excellent discrimination between positive and negative classes. It establishes the fact that RaAFN is more effective in the differentiation of various outcomes.

5. Conclusion

The research proposed a Radiomics-Attention Fusion Network (RaAFN), which applies to the classification of medical images of uterine tumors. The suggested strategy is useful in combining the handcrafted radiomics attributes with the deep CNN attributes with channel and spatial attention engines. RaAFN Co-trains clinically relevant texture, shape, and intensity statistics and attention-weighted deep features on top of images and improves image classification and interpretability. According to the results of the experiment on the uterine ultrasound dataset, the proposed model compares better with the existing machine learning and the existing deep learning methods in terms of accuracy, precision, and recalls as well as F1-score and AUC. The attention-driven fusion technique can assist the model focus on the tumor-relevant imageries compared to the irrelevant background information, and the strong and consistent predictions are achieved. As a rule, RaAFN can provide a clinically viable and interpretable framework that will help the early diagnosis and improved decision-making in evaluating the uterine tumor by a multi-class tumor grading system, and multi-modal imaging data such as ULTRASOUND IMAGE and CT. Further testing on larger clinical data that is closer to reality will also be examined.

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