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Research Progress of MRI-based Radiomics and Deep Learning in Lymphovascular Space Invasion of Endometrial Carcinoma

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Abstract: Endometrial carcinoma (EC) is a highly prevalent malignant tumor of the female reproductive system, with a continuously rising global incidence and an increasing trend toward younger age at onset. Lymphovascular space invasion (LVSI) is an important independent prognostic risk factor for endometrial cancer and is closely associated with lymph node metastasis, distant recurrence, and poor overall survival. It is a core indicator for clinical risk stratification, selection of surgical extent, and formulation of postoperative adjuvant therapy. However, LVSI is a microscopic pathological change that can only be definitively diagnosed using postoperative pathological specimens. Subjective imaging interpretation of routine preoperative pelvic MRI cannot directly detect LVSI, and therefore cannot meet the clinical need for accurate preoperative risk assessment. MRI-based radiomics can mine high-throughput quantitative features that are invisible to the naked eye within tumor images, and deep learning can automatically learn hierarchical image features. Together, they provide a new avenue for noninvasive preoperative prediction of LVSI status in endometrial cancer. This article systematically reviews the research progress of MRI-based radiomics and deep learning in the field of LVSI prediction in endometrial cancer, elaborates on the standard radiomics workflow, traditional radiomics models, deep learning models, and the diagnostic performance of combined clinical-imaging prediction models, summarizes key issues in current research such as limited sample size, cross-center domain shift, insufficient reproducibility, and lack of prospective validation, and provides an outlook on future directions including clinical translation, multi-omics integration, and explainable artificial intelligence.

Keywords: Endometrial Carcinoma; Magnetic Resonance Imaging; Radiomics; Deep Learning; Lymphovascular Space Invasion; Nomogram.

1. Introduction

Endometrial carcinoma is one of the most common malignant tumors of the female reproductive tract worldwide. According to International Agency for Research on Cancer (IARC) data, the number of new cases of endometrial cancer is increasing year by year. It ranks first among gynecological malignancies in developed countries in Europe and America, and its incidence is increasing significantly in developing countries[1]. Treatment of endometrial cancer is surgery-centered, and preoperative risk stratification determines whether lymph node dissection is performed and whether postoperative radiotherapy or chemotherapy is supplemented. The European ESMO/ESTRO/ESP guidelines for the management of endometrial cancer list LVSI, depth of myometrial invasion, histological grade, and histological type as key pathological indicators for risk stratification of early-stage endometrial cancer[2] .

LVSI is defined as tumor cells invading lymphatic or blood vessel spaces and is an important early biological behavior in tumor invasion and metastasis. Numerous clinical studies have confirmed that patients with LVSI-positive endometrial cancer have a significantly increased risk of lymph node metastasis, increased recurrence rate, and decreased 5-year disease-free survival; even in FIGO stage I low-risk endometrioid carcinoma, the recurrence risk is still significantly increased when LVSI is present[3]. The PORTEC research team further classified LVSI into negative, focal LVSI, and substantial LVSI, among which substantial LVSI is an independent predictor of recurrence and has higher value for prognostic assessment of endometrial cancer patients[4].

At present, the gold standard for LVSI diagnosis is postoperative histopathological HE staining, combined when necessary with D2-40 and CD31 immunohistochemical staining to identify vascular endothelium and distinguish tumor interstitial invasion from true intravascular tumor thrombi. Preoperative routine multiparametric MRI (mpMRI) can relatively well evaluate the depth of myometrial invasion, cervical stromal invasion, and pelvic lymph node enlargement, but LVSI is a microscopic pathological change with no specific signs on gross MRI images. Subjective image interpretation by radiologists has low diagnostic performance for LVSI and is difficult to meet preoperative assessment needs[5].

Radiomics uses a standardized workflow to extract high-throughput quantitative features from medical images in batches, transforming visual image information into minable high-dimensional data and quantitatively characterizing intratumoral spatial heterogeneity. Deep learning relies on convolutional neural networks (CNNs) to automatically learn features directly from raw MRI images, avoiding subjective bias caused by manual feature design. In the past 5 years, radiomics and deep learning based on multiparametric MRI have produced a large number of studies in the field of preoperative prediction of LVSI in endometrial cancer, and model diagnostic performance has continuously improved, gradually advancing from single-center retrospective studies

to multicenter external validation[6, 7]. This article systematically reviews the research status, methodological points, existing bottlenecks, and future development of this field.

2. Clinicopathological Significance of LVSI in Endometrial Cancer and Limitations of Traditional MRI Assessment

2.1. Pathological Definition, Grading, and Prognostic Value of LVSI

The pathological diagnosis of LVSI requires microscopic observation of tumor cell clusters located within vascular spaces lined by endothelial cells, and it needs to be differentiated from aggregation of tumor cells in extravascular stroma and artificial artifacts in tissue sections. HE staining alone can easily lead to missed diagnosis. Immunohistochemical staining with D2-40 for lymphatic endothelium and CD31 for vascular endothelium can improve the accuracy of LVSI detection and distinguish vascular invasion from lymphatic invasion[8].

Previous studies mostly simply classified LVSI as positive or negative, but this binary classification ignores differences in LVSI burden. The three-tier classification proposed by the PORTEC study—no LVSI, focal LVSI, and substantial LVSI—has been confirmed by multiple cohorts to have stronger prognostic discrimination. Siegenthaler et al., in the large KImBer cohort, found that the LVSI-positive rate differed significantly among different TCGA molecular subtypes: the p53-abnormal subtype had the highest LVSI detection rate, followed by the MMR-deficient subtype, while the POLE-mutated subtype and NSMP subtype were relatively lower; moreover, substantial LVSI indicated increased recurrence risk in all molecular subtypes [4]. Ayhan et al., in a cohort of 912 low-risk endometrial cancer cases, further confirmed that even in the low-risk population with <50% myometrial invasion and grade 1–2 endometrioid carcinoma, the 5-year recurrence-free survival rate of LVSI-positive patients was still significantly lower than that of negative patients (85.5% vs 97.0%), and LVSI positivity was an independent risk factor for decreased overall survival (HR=6.68)[9].

LVSI status directly affects treatment decisions for endometrial cancer. For FIGO stage IA well-differentiated endometrioid carcinoma, if LVSI is negative, total hysterectomy plus bilateral salpingo-oophorectomy alone may be performed, avoiding postoperative adjuvant radiotherapy; once LVSI is positive, vaginal brachytherapy or pelvic external beam radiotherapy is often required, and high-risk cases may even require combined chemotherapy. In the endometrial cancer population receiving surgery combined with adjuvant radiotherapy, the risk of distant recurrence in LVSI-positive patients is significantly higher than in negative patients, and LVSI is an independent prognostic factor second only to lymph node metastasis[10]. Zanfagnini et al. found in lymph node-positive endometrial cancer patients that LVSI was independently associated with para-aortic lymph node involvement and extravaginal recurrence (HR=2.62), suggesting that LVSI can reflect the extent of tumor lymphatic dissemination[11].

2.2. Limitations of Conventional MRI in Assessing LVSI

Pelvic multiparametric MRI is the preferred imaging modality for preoperative staging of endometrial cancer. The standard sequences include T2WI, DWI, ADC maps, and dynamic contrast-enhanced T1WI, which can clearly display the uterine myometrium and cervical anatomy and evaluate the gross extent of tumor invasion. However, LVSI is tumor invasion at the microscopic level and does not produce grossly recognizable morphological changes; therefore, conventional MRI has limited diagnostic performance for LVSI. A retrospective study by Hashimoto et al. showed that the sensitivity of preoperative MRI for assessing myometrial invasion in endometrial cancer was approximately 65%, while its subjective interpretation performance for LVSI was even lower, failing to meet preoperative screening needs[5]. Early texture analysis studies also confirmed that relying solely on physicians' visual observation, the AUC of T2WI and ADC image texture features for predicting LVSI was only 0.59, indicating limited diagnostic value[12]. Manual image interpretation can only assess macroscopic signs such as tumor size and depth of myometrial invasion, and cannot capture microscopic heterogeneity information related to LVSI occurrence, such as tumor microenvironment and microangiogenesis. This is precisely the entry point for the application of radiomics and deep learning technologies in this direction.

3. Methodological Framework of MRI-Based Radiomics for Predicting LVSI

The standardized workflow of radiomics includes: image acquisition and preprocessing, region of interest (ROI) delineation, radiomic feature extraction, feature dimensionality reduction and selection, prediction model construction, and internal and external validation of the model[13, 14]. For prediction of LVSI in endometrial cancer, mainstream studies mostly use pelvic multiparametric MRI sequences, including T2-weighted imaging, diffusion-weighted imaging, ADC maps, and dynamic contrast-enhanced T1WI. Multi-sequence combined modeling is usually superior to single-sequence models. Franco et al., in a review of gynecological imaging radiomics, pointed out that radiomics studies of endometrial cancer, cervical cancer, and ovarian cancer have covered multiple directions such as tumor diagnosis, staging, histological subtype differentiation, treatment response prediction, and prognosis assessment, but most studies lack external validation cohorts and reproducibility reporting[6].

3.1. ROI Delineation Strategy

ROI delineation is divided into two-dimensional single-slice tumor delineation and three-dimensional whole-tumor volume delineation. Two-dimensional delineation selects the maximum cross-section of the tumor; it is simple to perform but can only reflect local tumor information and loses longitudinal spatial heterogeneity of the tumor. Three-dimensional whole-tumor volume delineation delineates layer by layer along the tumor boundary and integrates all tumor voxel information; it is currently the recommended approach in endometrial cancer radiomics research. Delineation is generally performed independently by two experienced

radiologists, with inter-observer consistency assessed; disagreements are resolved through discussion to reach consensus, reducing delineation bias. Some studies simultaneously delineate the intratumoral region and the peritumoral myometrial region to explore the predictive value of peritumoral imaging features for LVSI, because the peritumoral region contains the tumor invasive front and neovascularization and is closely related to the biological behavior of vascular invasion[15].

3.2. Radiomic Feature Extraction and Stability Testing

The open-source tool PyRadiomics is currently the most commonly used software package for radiomic feature extraction. The extracted feature categories include: 1) first-order statistical features: voxel gray-level mean, skewness, kurtosis, entropy, etc.; 2) shape features: tumor volume, surface area, sphericity; 3) texture features: gray-level co-occurrence matrix (GLCM), gray-level run length matrix (GLRLM), gray-level size zone matrix (GLSZM); 4) wavelet transform features, which mine deep texture information of images through multi-scale decomposition[13]. Bereby-Kahane et al. used TexRAD software to extract filtered texture features at different spatial scales based on T2WI and ADC maps for LVSI prediction[12]. Radiomic features are susceptible to scanning field strength, slice thickness, and reconstruction parameters. High-quality studies need to conduct feature stability and reproducibility tests and exclude features with poor robustness.

3.3. Feature Selection and Model Construction

The dimensionality of radiomic features can usually reach hundreds or even thousands, while medical datasets have limited sample sizes; high-dimensional features can easily cause model overfitting. LASSO (least absolute shrinkage and selection operator) regression is the most widely used feature dimensionality reduction method in this field. It can compress redundant feature coefficients and automatically select a small number of non-zero features with predictive value to construct a radiomics score (Rad-score). Commonly used machine learning model algorithms include logistic regression, random forest, support vector machine, and XGBoost. Logistic regression models are simple and highly interpretable and are suitable for constructing clinically acceptable nomogram models; nonlinear models such as random forest and XGBoost capture complex interaction relationships but have reduced interpretability. Studies often combine Rad-score with clinical risk factors to construct a clinical-radiomics combined nomogram, and evaluate model calibration and clinical net benefit through calibration curves and decision curve analysis (DCA)[16]. Guo et al., in a review of endometrial cancer radiomics, summarized that current studies in this field generally follow the standard paradigm of "feature extraction—LASSO dimensionality reductio—logistic regression/random forest modeling—nomogram visualization," but feature stability testing and multicenter external validation remain weak links[7].

4. Research Progress of MRI Radiomics in Predicting LVSI in Endometrial Cancer

4.1. Single-Sequence and Multiparametric MRI Traditional Radiomics Models

Early studies mostly used single-sequence MRI texture features to predict LVSI, with limited model performance. Bereby-Kahane et al. included 73 cases of endometrioid adenocarcinoma and constructed models based on T2WI and ADC map texture features; the AUC for predicting LVSI was only 0.59, suggesting that manual texture features from a single sequence alone are insufficient to predict LVSI. The study also found that maximum tumor diameter ≥20 mm was an independent macroscopic imaging predictor associated with LVSI[12]. With the popularization of multiparametric MRI combined strategies, model predictive performance has significantly improved.

Luo et al. included 144 patients with endometrial cancer, integrated T2WI, contrast-enhanced T1WI, and DWI multiparametric MRI sequences, used LASSO regression to select 5 independent radiomic features to construct a Rad-score, and further combined age and histological grade to construct a nomogram; the training set AUC was 0.820, and the internal validation set AUC was 0.807, confirming that the multiparametric radiomics model has good diagnostic performance for preoperative prediction of LVSI[16]. Zhang et al. included 210 patients with endometrial cancer and established a prediction model combining ADC quantitative parameters and T2WI radiomic features; the training set AUC was 0.816, and the internal validation set AUC was 0.746. The model could also predict multiple high-risk pathological indicators such as histological type, high-grade tumor, and deep myometrial invasion[17]. Renton et al., in 71 patients with endometrial cancer, established a radiomic signature for LVSI through elastic net analysis (OR=5.45, 95%CI: 2.07–14.36), and this signature could also predict disease-free survival (HR=3.62), suggesting that radiomic features simultaneously reflect LVSI status and long-term prognosis[18].

Li et al. conducted a study based on T2WI radiomics. The cohort included 413 training samples and 82 independent external validation samples. They combined clinical information to construct a model for predicting LVSI, and the external validation set AUC reached 0.85 (95%CI: 0.77–0.93), demonstrating that the radiomics model has some cross-sample generalization ability[19]. Miccò et al.'s two-center study included 96 patients with endometrial cancer. The whole-tumor MRI radiomics model for predicting LVSI achieved a training set AUC as high as 0.92 and a validation set AUC of 0.81, superior to the model's predictive performance for deep myometrial invasion and overall high-risk stratification[20]. Ma et al. innovatively compared an intratumoral-only model, a peritumoral-only model, and an intratumoral + peritumoral combined model. The results showed that combining intratumoral-peritumoral radiomic features and adding clinical indicators such as CA125 and tumor size produced the best model, with a training set AUC=0.870 and validation set AUC=0.818, confirming that the peritumoral region contains tumor microenvironment information related to LVSI invasion[15]. This finding is consistent with the peritumoral information supplementation effect observed by Yan et al. in predicting deep myometrial

invasion, suggesting that peritumoral imaging features may reflect angiogenesis and microenvironment changes at the tumor invasive front[21].

4.2. Multicenter External Validation and Clinical-Imaging Combined Models

Single-center internal cross-validation easily overestimates the true performance of a model, and independent multicenter external validation is the gold standard for evaluating the clinical translation potential of a model. Chen et al. included a multicenter endometrial cancer cohort of 352 cases, developed and externally validated a clinical-radiomics nomogram for preoperative prediction of LVSI, incorporating late DCE enhancement parameters, deep myometrial invasion, lymph node status, and Rad-score; the training set AUC=0.901, internal validation AUC=0.80, and external independent validation AUC=0.81. Decision curve analysis showed that the model had good clinical net benefit over a wide range of threshold probabilities[22]. Liu et al., based on 339 cases of early-stage endometrial cancer from 5 centers, integrated T1WI, T2WI, enhanced sequences, DWI, and ADC image features, combined age and serum CA125 to construct a nomogram; the training set AUC=0.89, and the test set AUC=0.85[23].

A large number of studies have confirmed that clinical + radiomics combined models generally outperform radiomics-only models or clinical-only models. Yi et al., in a large two-center cohort of 580 cases, separately constructed a clinical baseline model, a radiomics-only model, a deep learning model, and a clinical-radiomics-deep learning fusion model; the results showed that the clinical model AUC=0.748, radiomics model AUC=0.810, deep learning model AUC=0.823, and the fusion model AUC was as high as 0.924. DeLong test indicated that the fusion model was significantly superior to the other models, and the external validation set AUC still reached 0.831[24]. Clinical variables (age, CA125, histological grade, depth of myometrial invasion) are themselves independent risk factors for LVSI and form complementary information with quantitative imaging features; therefore, combined modeling is currently the mainstream modeling approach.

5. Deep Learning in the Prediction of LVSI in Endometrial Cancer

5.1. Basic Principles of Deep Learning and Common Network Architectures

Deep learning (DL) has emerged as a transformative approach in medical image analysis, fundamentally differing from conventional radiomics by learning hierarchical feature representations directly from raw imaging data through multi-layer neural networks. In the context of endometrial cancer (EC) MRI, convolutional neural networks (CNNs) constitute the most widely adopted architecture. The U-Net family, particularly nnU-Net (a self-configuring variant), has been employed for automated tumor segmentation as a prerequisite for downstream LVSI prediction. Wang et al. developed a multi-task DL framework in which an nnU-Net model was trained on manually delineated T2WI lesion regions for automatic segmentation, and the segmented tumor regions across T2WI, CE-T1WI, and DWI were subsequently used as inputs for simultaneous identification of lymph node metastasis (LNM) and LVSI. This model achieved AUCs of 0.804 for LNM and 0.728 for LVSI in an external test cohort, surpassing the performance of three radiologists for LNM assessment (AUC = 0.770, 0.648, and 0.674, respectively)[25] .Among classification-oriented architectures, DenseNet has demonstrated notable efficacy. In a multicenter study of 892 EC patients, Luo et al. compared five single-modality models: 2D radiomics features (2D-RF), 3D radiomics features (3D-RF), VGG11-DF, ResNet101-DF, and DenseNet121-DF. DenseNet121-DF achieved the highest AUC among DL models (0.757), significantly outperforming ResNet101-DF (AUC = 0.671, P = 0.01) and demonstrating comparable performance to conventional radiomics models (2D-RF AUC = 0.775)[26]. The dense connectivity mechanism of DenseNet facilitates feature reuse and mitigates gradient vanishing, which may explain its advantage in extracting discriminative features from small EC lesions.

More recently, Transformer-based architectures have been explored to capture long-range spatial dependencies that CNNs may fail to model due to limited receptive fields. A multitask DL framework based on biparametric MRI achieved AUCs of 0.78–0.94 in validation and 0.74–0.94 in test cohorts for simultaneous classification of grade, stage, histological subtype, LVSI, and deep myometrial invasion (DMI), demonstrating the feasibility of unified multi-task learning for comprehensive prognostic stratification[27].

5.2. Comparative Studies Between Deep Learning and Conventional Radiomics

The comparative evaluation of DL and conventional radiomics for LVSI prediction has yielded nuanced insights, particularly regarding their relative strengths in internal versus external validation settings. Lecointre et al. conducted a systematic review of 17 AI-based radiomics studies in EC, including 3 focused on LVSI, and found that at the time of publication, the predominant technique was machine learning (ML) rather than DL, with only 2 studies employing DL models. The authors concluded that evidence supporting the clinical benefit of radiomics in EC remained insufficient, emphasizing the need for rigorous quality standards in model development[28].

In internal validation settings, conventional radiomics and DL models have demonstrated comparable performance. Luo et al. reported that 2D-RF and 3D-RF models achieved AUCs of 0.775 and 0.772 for LVSI prediction, respectively, which were not statistically different from DenseNet121-DF (AUC = 0.757)[26]. However, the integration of radiomics and DL features yielded a synergistic effect: the optimal combined model, integrating 2D-RF and DenseNet121-DF features, achieved the highest training cohort AUC of 0.796, and this superiority was confirmed in both internal and external validation cohorts[26]. This finding suggests that handcrafted radiomics features and DL embeddings capture complementary information dimensions of tumor biology, and that multi-modal feature fusion represents a promising strategy for enhancing predictive performance.

In conclusion, the evidence from head-to-head comparative studies supports a complementary rather than competitive relationship between DL and conventional radiomics for LVSI prediction in EC. While conventional radiomics offers interpretability and standardized feature extraction, DL architectures—especially DenseNet and U-NEXtractor—provide superior cross-site generalization by learning more robust and transferable representations. The integration of both feature types into combined models consistently yields

the highest predictive performance, underscoring the value of multi-modal fusion strategies for preoperative LVSI risk stratification.

5.3. Deep Learning-Based Automatic Segmentation to Reduce Manual Delineation Burden

One of the biggest bottlenecks of traditional radiomics is manual ROI delineation, which is time-consuming, has large inter-observer variability, and is difficult to integrate into routine clinical workflows. U-Net series deep learning segmentation networks can achieve automatic segmentation of endometrial cancer tumor regions. Hoivik et al. trained a fully automatic tumor segmentation model based on an MRI dataset of 866 cases of endometrial cancer; radiomic features obtained from automatic segmentation were highly consistent with manually delineated features, and automatically extracted imaging phenotypes were significantly associated with TCGA molecular subtypes and adverse histological features, laying the foundation for fully automated AI prediction of LVSI[29]. Stanzione et al.'s study showed that with the assistance of an AI model, radiologists' diagnostic accuracy for high-risk pathological features of endometrial cancer was significantly improved; the AI model played a role in assisting image interpretation and quantitative assessment rather than completely replacing physician interpretation[30].

6. Integration of Radiomics, Deep Learning, and Molecular Subtyping of Endometrial Cancer

With the widespread application of the TCGA endometrial cancer molecular classification system (POLE ultramutated, MSI-H/dMMR, p53 abnormal, NSMP), risk stratification of endometrial cancer has entered the molecular subtyping era. Molecular subtypes are highly correlated with LVSI occurrence and recurrence risk. Radiomics is called a noninvasive "imaging biopsy" and can mine associations between imaging phenotypes and molecular features. Hoivik et al. conducted radiogenomics research, associating MRI radiomic features with tumor transcriptome data, and constructed an imaging-gene combined prognostic signature that can identify high-risk molecular phenotypes and indirectly reflect tumor invasion and metastasis potential, providing a basis for understanding the imaging biological basis corresponding to LVSI[29]. Li et al. used multiparametric MRI radiomics to predict MSI status and PD-L1 expression levels in endometrial cancer, with external validation set AUCs in a two-center study reaching 0.848 and 0.764, respectively; although this study did not use LVSI as an endpoint, it demonstrated that MRI imaging features can noninvasively reflect tumor molecular phenotypes. In the future, imaging-molecular combined models can be constructed to predict LVSI, achieving multi-dimensional information fusion of pathology, imaging, and molecules[30].

7. Current Challenges in Research

7.1. Limitations in Study Design and Samples

The vast majority of existing MRI radiomics and deep learning studies on LVSI are retrospective single-center studies, with sample sizes mostly in the range of 100–300 cases. The positive rate of LVSI in the endometrial cancer population is approximately 20%–37%, and the number of positive cases is relatively small, resulting in class imbalance in the dataset and further affecting model training stability. Lecointre et al.'s systematic review of AI radiomics in endometrial cancer pointed out that more than half of published studies lack independent external validation cohorts, models generally suffer from overfitting, and reported high AUCs often cannot be reproduced in external cohorts[28]. Petrila et al.'s systematic review also found that sample sizes in endometrial cancer MRI artificial intelligence studies ranged from 50 to 530 cases, with significant heterogeneity among studies, making quantitative Meta-analysis impossible[31]. High-quality prospective multicenter cohorts remain scarce.

7.2. Image Standardization, Reproducibility, and Cross-Center Domain Shift

Radiomic features are affected by MRI equipment field strength (1.5T/3.0T), scanning parameters, b value, reconstruction algorithm, and slice thickness. Inconsistent scanning protocols among different hospitals cause domain shift, which is a core obstacle limiting cross-center application of models. Even if the same model performs excellently in internal validation at a single center, its performance declines substantially when tested on data from different scanning equipment or medical institutions. At the same time, manual ROI delineation has inter-observer differences, and different feature extraction software and parameter settings can yield different feature values. Many published studies have not strictly followed the Radiomics Quality Score (RQS) and IBSI standards for reporting, lack feature stability testing, and reduce research reproducibility [13].

7.3. Insufficient Model Interpretability and Barriers to Clinical Translation

Deep learning models have a "black box" problem: the model outputs prediction results, but it cannot clearly explain which image regions and which features were used to make the judgment, making it difficult for radiologists and gynecological oncologists to trust the model output, thus limiting clinical implementation. Explainable artificial intelligence (XAI), such as gradient-weighted class activation mapping (Grad-CAM), can visualize the tumor regions that the model focuses on, but its application in the field of LVSI prediction in endometrial cancer is still in its infancy. In addition, existing models only demonstrate theoretical clinical net benefit through DCA, and no randomized controlled studies have confirmed that AI-assisted preoperative assessment can truly improve patient prognosis or reduce overtreatment. Imaging AI models also face practical issues such as medical data privacy, algorithm regulation, and clinical workflow integration.

8. Summary and Outlook

MRI-based radiomics and deep learning based on multiparametric MRI have already shown good potential in the field of noninvasive preoperative prediction of LVSI in endometrial cancer. Nomograms constructed by multiparametric MRI radiomics combined with clinical indicators mostly achieve training set AUCs of 0.80–0.92, with independent external validation set AUCs maintained at 0.75–0.85; multimodal models integrating deep learning features, traditional radiomic features, and clinical variables

can further improve predictive performance. Peritumoral region imaging features, fully automatic tumor segmentation, and radiogenomics integration are frontier directions in this field.

However, this field still faces many bottlenecks: retrospective studies predominate, samples are imbalanced, cross-center domain shift exists, reproducibility is poor, deep learning models lack interpretability, and prospective multicenter clinical evidence is lacking. Future research should focus on:1)conducting multicenter, prospective, large-sample cohorts and strictly following IBSI and RQS radiomics reporting standards;2)adopting federated learning frameworks to complete cross-center model training without sharing raw imaging data, addressing data privacy and domain shift;3)promoting multi-omics integration, integrating MRI imaging, pathological slide omics, genomics, and transcriptomics data to construct imaging-molecular combined prediction models;4)developing explainable AI to visualize the basis of model decisions and improve clinician acceptance;5)conducting clinical intervention trials to verify whether AI-assisted preoperative LVSI assessment can optimize treatment plans and improve patient outcomes. With continuous methodological improvement, MRI-based radiomics and deep learning are expected to become routine tools for noninvasive preoperative assessment of LVSI in endometrial cancer, facilitating individualized precision treatment of endometrial cancer.

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