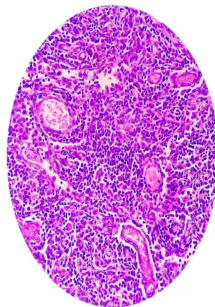

Enhancing Endometrial Cancer Subtyping with MRI



Accurate molecular classification of endometrial cancer (EC) is pivotal for risk stratification, treatment decisions and outcome prediction. The 2023 FIGO staging guidelines underscore the importance of integrating molecular subtypes—POLEmut, MMRd, NSMP and p53abn—into routine diagnosis. However, economic constraints, technical limitations and the need for invasive tissue sampling have hindered universal adoption. Magnetic resonance imaging (MRI), while valuable in EC assessment, lacks the specificity to distinguish these molecular variants. Radiomics and deep learning (DL) offer promising alternatives by extracting nuanced imaging features to infer underlying tumour biology. A recent review in *Insights into Imaging* proposes a clinical-radiomics DL model based on MRI to non-invasively classify EC subtypes, validated across multiple centres.

Radiomics and Deep Learning Integration

The study incorporated a retrospective multicentre design, reviewing EC cases from three hospitals between January 2020 and March 2024. Eligible patients had undergone pelvic MRI, histopathological confirmation and molecular typing. Radiomics analysis extracted 386 handcrafted features per MRI sequence, while DL employed MoCo-v2 for contrastive self-supervised learning, producing 2048 features per case. To improve feature robustness and reduce correlation, features were filtered using statistical and machine learning techniques, culminating in the selection of the most predictive variables. These were then embedded into 12 machine learning algorithms, and a radiomics DL model was established using logistic regression as the optimal classifier.

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The DL model alone demonstrated moderate classification ability, particularly for POLEmut and p53abn subtypes. However, when combined with handcrafted radiomics features, the integrated radiomics DL model showed enhanced accuracy. The highest performance gains were observed for POLEmut and p53abn, where DL features added complementary information to the radiomics input, especially in internal validation. However, performance dipped slightly for MMRd, likely due to less distinctive imaging patterns.

Combining Clinical Parameters for a Robust Model

To improve diagnostic reliability, clinical variables such as age, menopausal status, tumour grade, CA125, LVSI and lymph node status were incorporated into the model. These variables were chosen through multivariate logistic regression based on their predictive power for specific molecular subtypes. When integrated with radiomics DL outputs, the resulting clinical-radiomics DL model achieved the highest macro-average AUCs: 0.79 in internal and 0.74 in external validation sets.

Subgroup analysis showed that this model offered superior classification for all four molecular subtypes. POLEmut and p53abn subtypes, associated with favourable and poor prognoses respectively, were particularly well-predicted. Notably, the addition of clinical information improved the identification of NSMP and MMRd subtypes, where imaging features alone had been less effective. SHAP analysis revealed that DL and radiomics features had the highest influence on model decisions for POLEmut, while clinical-pathological indicators had greater weight for p53abn. These findings underscore the importance of a multi-dimensional model to address the heterogeneity of EC.

Clinical Relevance and Model Implications

The results validate the utility of a clinical-radiomics DL model for non-invasive EC subtype classification. This innovation addresses the limitations of molecular testing, particularly in settings where resources or biopsy tissue are scarce. The integration of clinical parameters ensures that the model leverages real-world diagnostic context, while advanced image-derived features contribute granular tumour characterisation.

This approach aligns with the shift towards personalised medicine in oncology. Identifying subtypes preoperatively allows clinicians to tailor surgical and adjuvant treatments more precisely, potentially reducing over- or under-treatment. Moreover, the model demonstrated consistent

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performance across centres, suggesting its generalisability and potential for broader clinical deployment. However, technical challenges remain. Manual tumour segmentation, scanner variability and uneven subtype distribution limit the model's scalability and robustness. The exclusion of ADC maps due to data availability further constrained feature extraction. Addressing these gaps in future work could enhance model accuracy and interpretability.

The clinical-radiomics DL model provides a powerful, non-invasive tool for stratifying EC patients by molecular subtype using multiparametric MRI. Its strong performance across training, internal and external cohorts supports its clinical relevance and generalisability. While limitations persist, particularly in the standardisation of imaging inputs and subtype balance, the model represents a significant step toward integrating artificial intelligence into routine EC diagnostics. Future work should aim for prospective validation, automated lesion segmentation and inclusion of broader datasets to support its integration into precision oncology workflows.

Source: [Insights into Imaging](#)

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