

Editorial for “Detecting Adverse Pathology of Prostate Cancer With a Deep Learning Approach Based on a 3D Swin-Transformer Model and Biparametric MRI: A Multicenter Retrospective Study”

Prostate cancer (PCa) is the second most prevalent cancer among men worldwide.¹ Timely and accurate diagnosis is important to avoid overtreatment of men with indolent, clinically insignificant PCa and to offer radical curative treatment with life-threatening, clinically significant PCa.²

Radical prostatectomy (RP) has become the standard care for eligible patients because of its cancer control and improved survival. Although most patients remained disease-free after RP, 20%–30% of patients develop recurrence of the disease at follow-up.³ Therefore, the assessment of reliable prognostic predictors of recurrence after RP is clinically important for guiding clinical decision-making and patient counseling. To date, several factors are considered adverse pathology (AP) features such as preoperative prostate-specific antigen (PSA) levels, Gleason score, tumor stage, surgical margin status, lymph node invasion, extracapsular extension (ECE), and seminal vesicle invasion (SVI). All of them have been identified as prognostic factors for recurrence after RP.^{3,4}

MRI has an established role in diagnosis of PCa.⁵ Due to the complex nature of the PCa diagnosis pathway by MRI, diagnostic performance has varied widely.^{6,7} The use of biparametric MRI, excluding dynamic contrast-enhanced (DCE), despite its enormous potential, is still controversial, particularly when there is suboptimal diagnostic quality for T2WI and DWI sequences.⁸

Developing artificial intelligence models using machine learning, particularly deep learning, has an expanding role in radiology with great potential in prostate MRI.⁹


In this JMRI paper,¹⁰ the authors use a deep learning approach of 3D Swin-Transformer (TransNet) based on biparametric MRI to predicting AP of PCa. An integrated model combining TransNet signature and clinical characteristics (TransCL) has also been developed. These models can provide personalized surgical treatment planning and are very important for clinical decisions.

The results of this multicenter study, which include 616 men who underwent RP, showed that TransNet and TransCL can aid in prediction of the presence of AP, and single adverse pathologic feature, such as ECE, SVI, and positive surgical margin. The AUC of TransCL (0.813) and TransNet (0.791) were superior to the clinical model (0.749) and radiologist's interpretation (0.664).

The TransCL model that combined biopsy Gleason group grade, PI-RADS scores, PSA level, apparent diffusion coefficient values, and lesion maximum cross-sectional diameter showed a performance superior to those of the TransNet and the clinical model, which was only based on the clinical characteristics.

In the paper, the authors choose to use biparametric MRI images, excluding DCE. This could affect the results since the PIRADS v2.1 indicates that, despite a rather minor role, DCE should be used in prostate MRI analysis.⁵ Regions of interest (ROIs) were extracted for each patient considering two types of 3D ROIs, containing the lesion level and the prostate level. The pre-processed ROIs were used as input images for the deep learning model of this study. Since the ROIs were manually defined, this could limit the clinical applicability of the model. The study needs to be validated with a higher level of evidence, such as multiple external validation data or prospective data in the future.

Despite these limitations, this study demonstrates the potential of these models to aid a precise diagnosis of AP presence, affecting the therapeutic approach.

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References

1. Rawla P. Epidemiology of prostate cancer. *World J Oncol* 2019;10(2):63-89.
2. Mottet N, Bellmunt J, Bolla M, et al. EAU-ESTRO-SIOG guidelines on prostate cancer. Part 1: Screening, diagnosis, and local treatment with curative intent. *Eur Urol* 2017;71(4):618-629.
3. Brooks MA, Thomas L, Magi-Galluzzi C, et al. Validating the association of adverse pathology with distant metastasis and prostate cancer mortality 20-years after radical prostatectomy. *Urol Oncol Semin Orig Investig* 2022;40(3):104.e1-104.e7.
4. Cooperberg MR, Hilton JF, Carroll PR. The CAPRA-S score: A straightforward tool for improved prediction of outcomes after radical prostatectomy. *Cancer* 2011;117(22):5039-5046.
5. Turkbey B, Rosenkrantz AB, Haider MA, et al. Prostate imaging reporting and data system version 2.1: 2019 update of prostate imaging reporting and data system version 2. *Eur Urol* 2019;76(3):340-351.
6. Stabile A, Giganti F, Rosenkrantz AB, et al. Multiparametric MRI for prostate cancer diagnosis: Current status and future directions. *Nat Rev Urol* 2020;17(1):41-61.
7. Panebianco V, Barchetti F, Barentsz J, et al. Pitfalls in interpreting mp-MRI of the prostate: A pictorial review with pathologic correlation. *Insights Imaging* 2015;6(6):611-630.
8. Belue MJ, Yilmaz EC, Daryanani A, Turkbey B. Current status of Biparametric MRI in prostate cancer diagnosis: Literature analysis. *Life* 2022;12(6):1-21.
9. Article R. Deep learning-based artificial intelligence applications in prostate MRI: Brief summary. *Br J Radiol* 2022;95:20210563.
10. Zhao L, Bao J, Wang X, et al. Detecting adverse pathology of prostate cancer with a deep learning approach based on a 3D Swin-Transformer model and biparametric MRI: a multicenter retrospective study. *J Magn Reson Imaging* 2024;59:2101-2112.

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