Artificial intelligence for prostate cancer detection and classification on magnetic resonance imaging: abridged secondary publication

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KEY MESSAGES

1. We used CapsuleNet for prostate lesion detection and classification via the Prostate Imaging Reporting and Data System, incorporating relative spatial information and the clinical context of lesions in relation to various anatomical structures.
2. Deep learning methods for CapsuleNet classification have only achieved satisfactory outcomes. To improve outcomes, we used MiniSegCaps, an end-to-end network that integrates classification and segmentation, specifically designed for a small dataset.
3. MiniSegCaps demonstrated impressive performance. We also developed a graphical user interface to illustrate its integration with the clinical workflow.

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Introduction

Magnetic resonance imaging (MRI) is the primary imaging modality for diagnosing prostate cancer. The Prostate Imaging Reporting and Data System (PI-RADS) for multiparametric MRI provides essential MRI interpretation guidelines but is subject to inter-reader variability.[1,2] MRI-guided biopsy is increasingly favoured for risk assessment, replacing the conventional transrectal ultrasound-guided biopsy.[3] The growing demand for prostate MRI has led to an increase in referrals, increasing radiologists' workload.[4] The PI-RADS facilitates the classification of lesions based on risk and demonstrates high sensitivity in the detection of high-grade prostate lesions.[5] However, it displays poor inter-reader and intra-reader consistency; thus, substantial expertise is necessary. Less experienced radiologists exhibit greater inter-reader variability in PI-RADS scoring.

Deep learning networks facilitate automatic lesion segmentation and classification, reducing radiologists' workload and mitigating inter-reader variability. Deep learning–based lesion detection and PI-RADS classification algorithms are essential for integrating prostate MRI findings into clinical practice. Some networks can differentiate prostate cancer from normal tissues and calculate the probability of malignancy. Current methods for PI-RADS classification remain semi-automated; lesion masks must be manually entered into the model. These convolutional neural networks require substantial annotated data and data augmentation to address class imbalance. Few networks integrate lesion detection and classification tasks within a single framework and achieve reliable performance at a PI-RADS cutoff value of ≥4.

In PI-RADS, classification depends not only on lesion dimensions, edge morphology, and signal intensity but also on positional relationships (such as extraprostatic extension/invasion) and zonal location relative to the transition and peripheral zones.[5] Each lesion is assigned a score of 1 to 5 based on diffusion-weighted and T2-weighted MRI, along with the presence or absence of dynamic contrast enhancement. The contribution of these scores to the overall PI-RADS assessment varies depending on the lesion's zonal location. For lesions in the transition zone, the PI-RADS score is primarily determined by the T2-weighted score, and the diffusion-weighted imaging score serves as a modifier. For lesions in the peripheral zone, the diffusion-weighted imaging score is predominant, and the presence of dynamic contrast enhancement serves as a modifier.[5] These spatial relationships and lesion features (location, scale, and dimension) can be encoded and represented by CapsNet in a single capsule vector, enabling prostate cancer detection and classification. We aimed to compare our MiniSegCaps model with baseline segmentation methods for prostate cancer segmentation and classification.

Methods

Of 569 patients who underwent multiparametric

MRI (including T2-weighted, diffusion-weighted, and dynamic contrast-enhanced sequences) at our institution, 494 had one or more detectable prostate cancer lesions classified by radiologists based on their PI-RADS score.[5] Of these patients, 32 were excluded owing to a history of prostate cancer treatment (including antihormonal therapy, radiation therapy, focal therapy, and prostatectomy) or the presence of an incomplete MRI sequence. Thus, 462 patients with a PI-RADS score of ≥1 were included in the analysis.

We used a multitask network—MiniSegCaps—which is an end-to-end multiclass VNet designed to jointly segment prostate lesions and predict their PI-RADS categories. Selected for its robust performance on small datasets, MiniSegCaps is based on MiniSeg and follows a U-Net-like encoder-decoder architecture.

The encoder and decoder of MiniSeg extract high-dimensional features from input images and generate segmentation outputs, respectively. The model uses three-channel input comprising T2-weighted images, apparent diffusion coefficient maps, and zonal masks (Figs 1 and 2). The encoder processes image data into high-dimensional features through a series of convolutional blocks, which are further processed by capsules in subsequent layers. The capsule predictive branch includes two convolutional capsule layers that encode spatial information about objects into capsule vectors. The number of capsule types in the final convolutional capsule layer corresponds to the number of segmentation categories, which are supervised by a margin loss. This branch is specifically designed to predict binary high-grade or low-grade PI-RADS categories.

To support radiologists in the clinical diagnosis of prostate cancer, we developed a graphical user interface integrated into the overall workflow to automatically generate prostate cancer diagnostic reports. These reports include the predicted lesion mask, lesion visualisation on T2-weighted images and apparent diffusion coefficient maps, predicted probabilities for each PI-RADS category, and the position and dimensions of each lesion. The main steps of the workflow within the graphical user interface include image data importation, zonal segmentation, lesion overlay on multiparametric MRI, image preprocessing (cropping and normalisation), lesion segmentation, PI-RADS classification, and diagnostic report generation.

Results

We compared our MiniSegCaps model with baseline segmentation methods for prostate cancer segmentation using the Dice coefficient metric. Additionally, we implemented a combined version of MiniSeg and CapsuleNet, supervised with ordinal encoding ground truths, to demonstrate the effectiveness of incorporating capsule layers into MiniSegCaps.

Among baseline methods, two-dimensional U-Net, attention U-Net, and U-Net++ achieved an average Dice coefficient of 51%, which was lower than the 65% achieved by MiniSeg in image-level evaluations. Performance in patient-level evaluations followed a similar trend, indicating that the lightweight MiniSeg model performs better when handling small datasets.

Both MiniSegCaps and MiniSegCaps without CapsGRU substantially outperformed MiniSeg, SegNet, and FocalNet. This result indicates that the integration of capsule layers into MiniSegCaps enables better differentiation of prostate cancer from normal tissues by capturing the relative spatial relationships between prostate cancer and various anatomical structures.

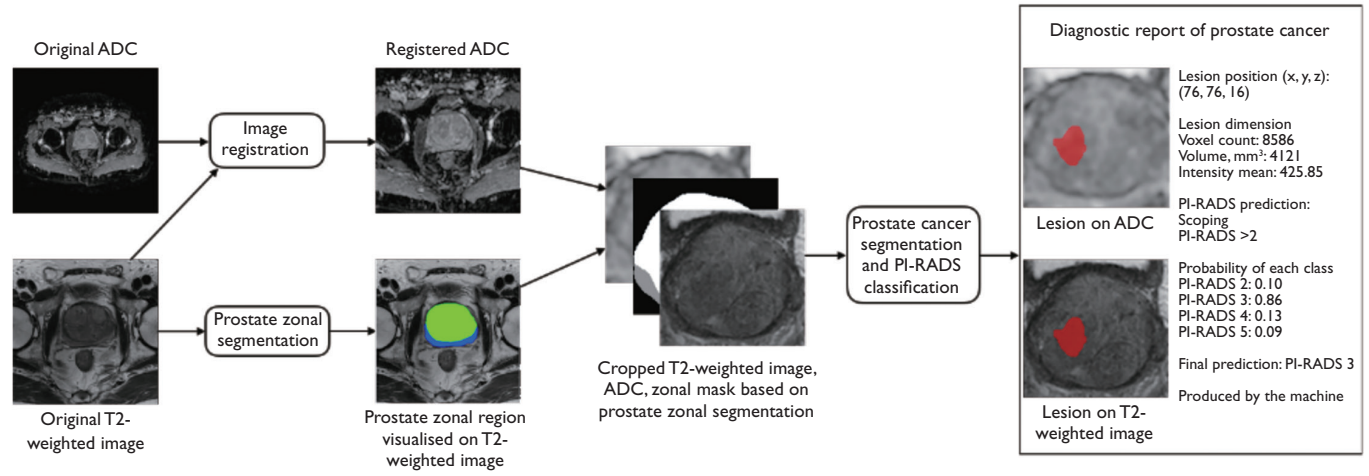

FIG 1. Step 1: image preprocessing (registration and normalisation); step 2: zonal segmentation and cropping; step 3: prostate cancer segmentation and classification; and step 4: diagnostic report generation

Abbreviations: ADC=apparent diffusion coefficient, PI-RADS=Prostate Imaging Reporting and Data System

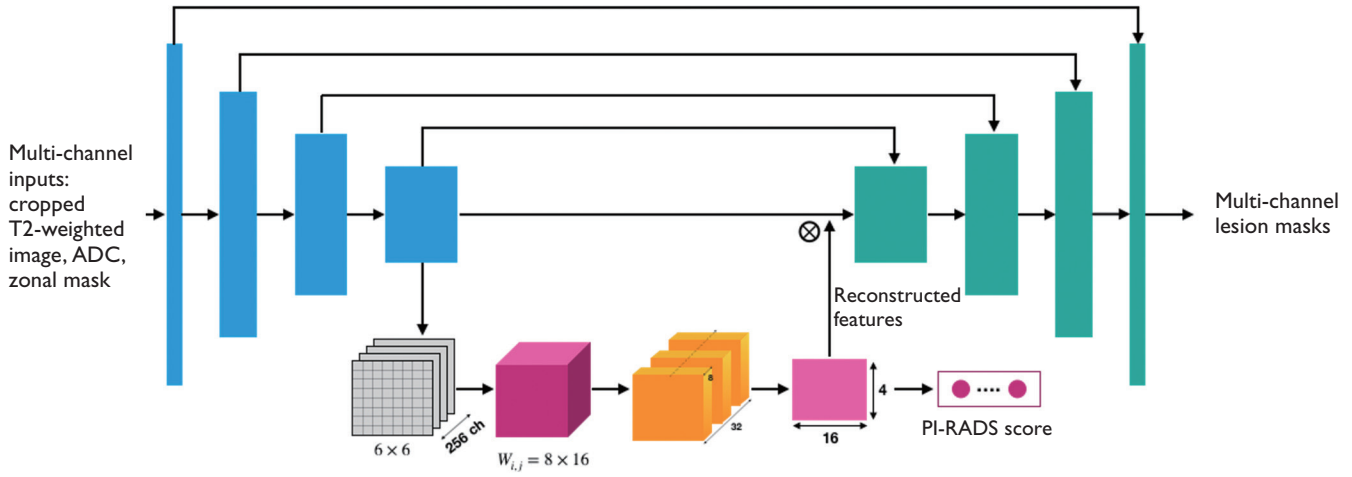

FIG 2. The architecture of the proposed MiniSegCaps model includes MiniSeg (a lightweight segmentation network serving as the backbone for lesion mask prediction), a capsule predictive branch for PI-RADS scoring, and a CapsGRU module for utilising spatial information across adjacent slices. The MiniSeg module extracts convolutional feature maps from input multiparametric MRI and generates multi-channel masks for prostate cancer segmentation. Features learned by the final downsampling block of MiniSeg (6×6×256) are used as inputs for the capsule predictive branch to perform PI-RADS classification. Capsule feature stacks (8×32) generated by PrimaryCaps are processed by the CapsGRU module to incorporate inter-slice spatial information during the learning process. Reconstructed features (6×6×256) produced by three fully connected layers in the capsule branch are also integrated into the MiniSeg module to enhance lesion identification

Abbreviations: ADC=apparent diffusion coefficient, MRI=magnetic resonance imaging, PI-RADS=Prostate Imaging Reporting and Data System

For PI-RADS classification, the average accuracies of three categories produced by baseline methods were 57% (PI-RADS ≥3), 63% (PI-RADS ≥4), and 65% (PI-RADS ≥5) in patient-level evaluation, slightly exceeding the corresponding results in image-level evaluation. MiniSegCaps (comprising a convolutional encoder, a deconvolutional decoder with fused feature inputs, and a Capsule predictive branch with CapsGRU) outperformed MiniSegCaps without CapsGRU and the combined MiniSeg and CapsuleNet model. The inclusion of CapsGRU in MiniSegCaps improved consistency across adjacent slices, enhancing PI-RADS classification performance. Consequently, MiniSegCaps achieved the highest accuracy in all PI-RADS categories. It also increased the accuracy of PI-RADS classification by an average of 15% in patient-level evaluation, compared with MiniSeg (or VNet).

For binary high-grade/low-grade PI-RADS classification, MiniSegCaps achieved a patient-level accuracy of 71.56% and a sensitivity of 76.32% for high-grade lesions (PI-RADS ≥4). CapsGRU further enhanced the overall performance of binary high-grade/low-grade lesion differentiation, compared with MiniSegCaps without CapsGRU.

Conclusion

Our MiniSegCaps model jointly predicted lesion segmentation and PI-RADS classification, achieving superior performance in prostate cancer segmentation and PI-RADS classification compared with other methods. Its performance for PI-RADS ≥3, a critical threshold in clinical decision-making, was particularly robust.

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Disclosure

The results of this research have been previously published in:

1. Jiang W, Lin Y, Vardhanabhuti V, Ming Y, Cao P. Joint Cancer Segmentation and PI-RADS Classification on Multiparametric MRI Using MiniSegCaps Network. Diagnostics (Basel) 2023;13:615.

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