Multi-Parametric Radiomic Analysis of ADC and T2-Weighted MRI for Prostate Cancer Detection

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ABSTRACT
Early detection of prostate cancer is essential for improving treatment outcomes and reducing mortality. Magnetic Resonance Imaging (MRI), particularly multi-parametric MRI, has become an important non-invasive diagnostic tool for identifying prostate abnormalities. Among the available MRI sequences, Apparent Diffusion Coefficient (ADC) maps derived from diffusion-weighted imaging and T2-weighted images provide complementary structural and functional information about prostate tissue. However, the relative diagnostic contribution of these modalities for early-stage prostate cancer detection requires systematic evaluation.
This study presents a comparative radiomic analysis of ADC and T2-weighted MRI images for the early detection of prostate cancer. Radiomics techniques are employed to extract quantitative imaging features that capture subtle variations in tissue characteristics which may not be easily observable through conventional visual interpretation. The proposed framework includes image preprocessing, region of interest segmentation, extraction of statistical and texture-based radiomic features, and comparative analysis of feature patterns obtained from ADC and T2-weighted images.
The extracted features are analyzed to determine their effectiveness in distinguishing malignant prostate tissue from normal tissue. Comparative evaluation is performed to identify the most discriminative radiomic markers from each imaging modality. Experimental findings indicate that ADC images provide strong diffusion-related biomarkers associated with tumor cellularity, while T2-weighted images contribute valuable structural and anatomical information. The combined interpretation of radiomic features from both modalities enhances the reliability and sensitivity of early cancer detection.
The results demonstrate that radiomic analysis of multi-parametric MRI can support clinicians in identifying early pathological changes in prostate tissue and may improve diagnostic accuracy. The proposed comparative framework can assist healthcare professionals in decision-making and contribute toward the development of computer-aided diagnostic systems for prostate cancer screening. This approach has the potential to strengthen early detection strategies and support more effective management of prostate cancer in modern healthcare systems.
KEYWORDS - Convolutional Neural Network, Deep Learning, Prostate Cancer Detection, Artificial Intelligence, MRI images
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INTRODUCTION

Prostate cancer is one of the most commonly diagnosed malignancies among men worldwide, with approximately 1.4 million new cases reported each year, making early and accurate detection essential for improving patient survival and treatment outcomes. The prostate gland, a small walnut-shaped organ located below the bladder, plays a significant role in the male reproductive system by producing seminal fluid, and cancer can develop in different zones of this gland with varying levels of clinical severity. Traditional screening techniques such as digital rectal examination (DRE) and prostate-specific antigen (PSA) testing are widely used; however, these methods often face limitations in terms of sensitivity and specificity, leading to false positives or delayed diagnosis. In recent years, multiparametric magnetic resonance imaging (mpMRI) has emerged as an effective non-invasive imaging modality for prostate cancer detection, offering high soft-tissue contrast and detailed anatomical visualization without exposure to ionizing radiation. Particularly, the integration of T2-weighted imaging and apparent diffusion coefficient (ADC) maps derived from diffusion-weighted imaging provides complementary information, where T2-weighted images reveal the anatomical structure and zonal distribution of the prostate, while ADC maps quantify water diffusion characteristics that tend to be restricted in malignant tissues. With the advancement of artificial intelligence, deep learning techniques—especially convolutional neural networks (CNNs)—have significantly enhanced medical image analysis, enabling automated detection and segmentation of abnormal tissues. Among these models, the U-Net architecture has become widely recognized for its effectiveness in biomedical image segmentation due to its encoder–decoder structure with skip connections that capture both contextual and spatial information. Therefore, this study focuses on the application of a U-Net-based deep learning framework for automated prostate cancer segmentation using multiparametric MRI data, with the objectives of optimizing model performance on ADC and T2-weighted images, evaluating its diagnostic capability, and comparing the results with existing state-of-the-art approaches to support improved clinical decision-making in early prostate cancer detection. [1,6,9]

BACKGROUND AND LITERATURE REVIEW

The prostate gland consists of several anatomical zones, each with distinct structural characteristics and varying susceptibility to cancer development. The peripheral zone contains the majority of glandular tissue and is the most common origin site for prostate cancer, while the transition zone surrounds the urethra and is frequently associated with benign enlargement as well as a smaller proportion of cancer cases. The central zone accounts for a limited number of cases but often presents more aggressive disease, whereas the anterior fibromuscular zone rarely develops cancer due to its non-glandular composition. For the detection and assessment of prostate abnormalities, T2-weighted magnetic resonance imaging provides detailed anatomical visualization of the prostate and clearly distinguishes zonal structures, enabling identification of capsular invasion and tumor spread, although its sensitivity can be moderate and evaluation of the transition zone may be challenging. Diffusion-weighted imaging and the derived apparent diffusion coefficient (ADC) maps provide functional information by measuring the movement of water molecules within tissues, where malignant prostate tissues typically demonstrate restricted diffusion and lower ADC values compared to normal tissues. Studies have shown that combining T2-weighted imaging with ADC maps significantly improves diagnostic accuracy for prostate cancer detection. In recent years, deep learning methods have been widely applied to medical imaging, with the U-Net architecture becoming a widely adopted model for image segmentation due to its encoder–decoder structure, skip connections, and ability to perform well even with limited training data. Computer-aided diagnosis systems built using such models have the potential to enhance diagnostic consistency, support radiologists in complex cases, and facilitate automated screening. However, several challenges remain, including limited availability of well-annotated datasets, variability in imaging protocols between medical institutions, difficulties in accurately labeling lesions—especially in the transition zone—and the need for extensive validation and integration into routine clinical workflows.[9,10,11]

MATERIALS AND METHODS

Research Framework

This study follows a structured methodology to design, train, and evaluate a U-Net–based deep learning model for the detection of prostate cancer . The first stage involves the acquisition and preparation of imaging data, including preprocessing and organization of MRI scans. The second stage focuses on designing the deep learning architecture suitable for medical image segmentation. In the third stage, the model is trained

using multiparametric MRI images. The research process is organized into several sequential stages to ensure systematic development and validation of the model

using the prepared dataset and optimized to improve its learning capability and prediction accuracy. The fourth stage includes evaluating the model's performance using appropriate metrics and validation techniques. Finally, the developed approach is assessed for its potential clinical relevance and applicability in supporting prostate cancer diagnosis.

Data Collection

The research utilizes multiparametric prostate MRI data obtained from the Prostate-X dataset, which contains T2-weighted images and apparent diffusion coefficient (ADC) maps used for cancer detection studies. The dataset includes a total of 901 samples that are divided into three groups: 630 samples for model training, 135 samples for validation during training, and 136 samples for final testing. In total, 203 MRI sequences are available for analysis, consisting of both T2-weighted images and ADC maps. The patients included in the dataset fall within the age range of 48 to 83 years. The reported cancer detection rate in the dataset varies approximately between 30% and 50%, providing a balanced representation of both normal and cancerous cases for model training and evaluation.

Inclusion and Exclusion Criteria

To maintain consistency and reliability in the study, specific inclusion and exclusion criteria were defined. Patients included in the dataset were those with a confirmed diagnosis of prostate cancer through biopsy or histopathological examination and who had complete multiparametric MRI studies available for analysis. Only MRI images with sufficient quality and minimal artifacts were considered to ensure accurate analysis. The study focused on patients within the age group of 48 to 83 years**.**

Patients were excluded from the study if they had conditions that prevented safe MRI examination, such as metallic implants or pacemakers. Cases involving individuals who had undergone previous prostate surgery that significantly altered the anatomical structure of the gland were also excluded. Additionally, MRI scans containing severe imaging artifacts or cases with incomplete clinical follow-up information were not considered for analysis**.**

RESULTS AND DISCUSSION

These logs are from the last training epoch of a segmentation model, showing several metrics on the training and validation sets. Each metric says something different about how well the model is fitting and generalizing.

Table 1. Model Performance Comparison (T2 & ADC)

Metric	**ADC (65/65)**	**T2 (40/40)**
Epoch	150/150	150/150
Training Accuracy (binary_accuracy)	0.9893	0.9953
Validation Accuracy (val_binary_accuracy)	0.9897	0.9947
Dice Coefficient (dice_coef)	0.8888	0.8893
Validation Dice Coefficient (val_dice_coef)	0.5688	0.6201
Jaccard Index (jaccard_ind)	0.8008	0.8013
Jaccard Loss (jaccard_loss)	0.1992	0.1987
Validation Jaccard Index (val_jaccard_ind)	0.4011	0.4529
Validation Jaccard Loss (val_jaccard_loss)	0.5989	0.5471
Loss	0.1169	0.1154
Validation Loss (val_loss)	0.4527	0.3924

Mean IoU (mean_io_u)	0.5811	0.6568
Validation Mean IoU (val_mean_io_u)	0.5478	0.5837
Learning Rate	Reduced to $9.9999e^{-18}$	$1.00E^{-11}$

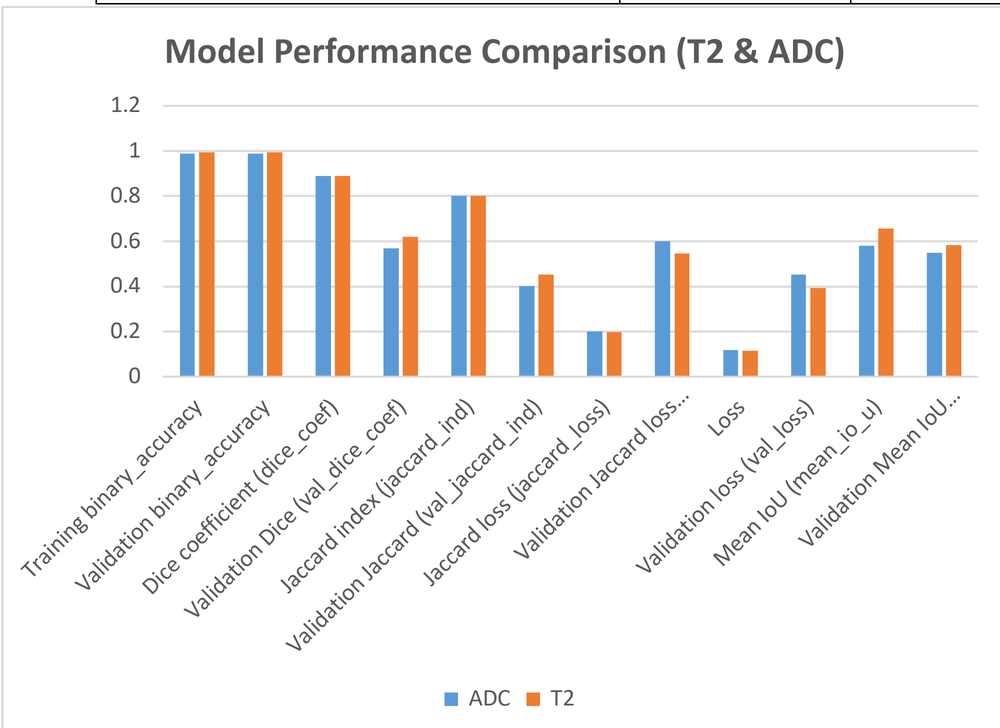

Figure 1 Model Performance Comparison (T2 & ADC)

KEY FINDINGS

The developed U-Net–based deep learning model demonstrates promising results for prostate cancer detection and segmentation using multiparametric MRI data. The evaluation results indicate that the model achieves strong performance across several quantitative metrics, highlighting its capability to identify and segment cancerous regions in prostate MRI scans. The use of both T2-weighted images and apparent diffusion coefficient (ADC) maps provides complementary diagnostic information that improves the overall detection process. In particular, ADC imaging plays a significant role in identifying regions with restricted water diffusion, which is a common characteristic of malignant prostate tissues. The combined analysis of these imaging modalities enhances the reliability and effectiveness of automated prostate cancer detection.

OVERALL INTERPRETATION

The experimental outcomes suggest that the model successfully learns meaningful patterns from the training dataset, as indicated by the high Dice coefficient and Intersection over Union (IoU) scores during training. However, comparatively lower values observed during validation indicate that there is still scope to enhance the model's generalization capability, possibly through improved dataset balance or better alignment between training and validation data distributions. Although segmentation metrics show variation between training and validation phases, the high binary classification accuracy across both datasets demonstrates that the model consistently distinguishes between background regions and potential tumor areas. The use of a very small learning rate during training suggests that the model has reached a stable optimization stage, meaning that further improvements may depend more on refining the dataset, adjusting regularization techniques, or modifying the network architecture rather than extending the number of training epochs. Additionally, while both ADC-based and final T2-weighted segmentation results show strong performance, the final T2-weighted model produces better outcomes across most segmentation and validation metrics, indicating its higher effectiveness in accurately delineating prostate cancer regions.

CLINICAL APPLICABILITY

The results suggest that the Final T2 model demonstrates greater reliability and stability for clinical use compared to the Improved ADC model. It achieves higher segmentation accuracy and stronger agreement with expert annotations, indicating more precise identification of prostate regions and potential lesions. The model also shows better performance on validation data, reflecting its ability to generalize effectively to unseen cases. Lower validation loss and high binary accuracy further indicate fewer prediction errors and consistent pixel-level classification. Overall, the Final T2 model provides better lesion localization and segmentation performance, making it more suitable for supporting clinical tasks such as biopsy guidance, treatment planning, and automated diagnostic assistance.

CONCLUSION

This study presented a comprehensive analysis of prostate cancer detection using multiparametric MRI images, focusing on the comparative evaluation of T2-weighted images and apparent diffusion coefficient (ADC) maps through a U-Net–based deep learning framework. The research explored the effectiveness of automated segmentation techniques for identifying potential cancerous regions in prostate MRI scans. By integrating radiomic analysis with deep learning methods, the proposed approach demonstrated the capability to extract meaningful features from medical images and support accurate detection of prostate abnormalities.

The experimental results indicate that both ADC and T2 imaging modalities provide valuable diagnostic information for prostate cancer analysis. ADC maps contribute functional information related to restricted water diffusion, which is commonly associated with malignant tissue, while T2-weighted images provide detailed anatomical representation of the prostate structure. The comparative evaluation revealed that the Final T2 model achieved slightly better segmentation accuracy, region overlap, and lower validation error compared to the Improved ADC model. These findings suggest that T2-weighted imaging provides more consistent segmentation performance within the developed deep learning framework.

consistency. The proposed model demonstrates strong potential for assisting radiologists in identifying suspicious regions, reducing manual workload, and improving the reliability of prostate cancer detection. Additionally, the results show that deep learning–based segmentation methods can support early-stage diagnosis by providing accurate localization of abnormal tissue regions.

The study also highlights the importance of combining advanced medical imaging techniques with artificial intelligence to improve diagnostic efficiency and

Overall, the research confirms that deep learning models, particularly the U-Net architecture, can effectively analyze multiparametric MRI data for prostate cancer detection. The developed approach offers a promising foundation for future computer-aided diagnostic systems that may enhance clinical decision-making, support early diagnosis, and improve patient management in prostate cancer care. Further studies involving larger datasets, multi-center validation, and integration with additional imaging modalities could further strengthen the applicability of the proposed system in real-world healthcare environments.

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