Prostate Cancer Detection Using AI, Multi-parametric MRI, and 3D Deep Learning Techniques

Dr. Priya Nandihal[1], Tanmayee L M[2], Siddhi Mishra[3] , Tanisha G[4], Sameer S[5]

[1]Dr.Priya Nandihal, Computer Science & Engineering, Dayananda Sagar Academy of Technology & Management
[2]Tanmayee L M, Computer Science & Engineering, Dayananda Sagar Academy of Technology & Management
[3]Siddhi Mishra, Computer Science & Engineering, Dayananda Sagar Academy of Technology & Management
[4]Tanisha G, Computer Science & Engineering, Dayananda Sagar Academy of Technology & Management
[5]Sameer S, Computer Science & Engineering, Dayananda Sagar Academy of Technology & Management

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Abstract - Prostate cancer is one of the leading causes of cancer-related mortality among men, especially in the aging population. Timely and accurate detection plays a pivotal role in improving survival rates and optimizing treatment strategies. Traditional diagnostic approaches relying on multi-parametric MRI (mp-MRI) are effective but highly dependent on manual interpretation, which is both time-consuming and vulnerable to human error. This study introduces an AI-powered diagnostic framework that combines 3D deep learning and feature fusion techniques to detect prostate cancer more accurately and efficiently. By integrating T2-weighted, diffusion-weighted (DWI), and dynamic contrast-enhanced (DCE) MRI modalities, we develop a comprehensive system that leverages a 3D U-Net for precise lesion segmentation and late fusion classification models to enhance decision-making. The system is trained and tested on public datasets like PROSTATEx and SPIE-AAPM-NCI, and its performance is evaluated using clinically relevant metrics such as Dice Score, AUC, sensitivity, and specificity. A user-friendly visualization dashboard is also developed to assist radiologists in interpreting the results. Our work demonstrates the potential of AI-driven tools to support clinicians in early prostate cancer diagnosis while maintaining patient data privacy through anonymized processing.

Key Words: Prostate Cancer, Deep Learning, 3D U-Net, MRI, AI in Healthcare, Diagnosis.

1.INTRODUCTION

Prostate cancer is one of the most prevalent malignancies affecting men globally. According to recent statistics, it accounts for a significant proportion of cancer-related deaths among men. Early detection is paramount, as it significantly increases the chances of successful treatment and survival. Multi-parametric MRI (mp-MRI) has become a standard imaging modality for prostate cancer diagnosis due to its ability to provide detailed anatomical and functional information. However, interpreting mp-MRI scans manually is labor-intensive and requires specialized expertise, leading to potential variability in diagnosis.

The advent of artificial intelligence (AI) and deep learning has opened new avenues for automating and enhancing medical image analysis. By leveraging these technologies, it is possible to develop systems that can assist radiologists in accurately detecting and classifying prostate cancer, thereby improving diagnostic consistency and efficiency.

2. Body of Paper

2.1 Purpose

The purpose of this study is to build a reliable, automated diagnostic framework that aids in early detection and classification of prostate cancer. The system aims to segment the prostate gland and identify cancerous regions using a 3D U-Net model, then apply a classification technique that integrates features from multiple MRI modalities. This approach enhances the precision and consistency of diagnosis and reduces the workload on radiologists. Additionally, the project ensures data privacy and provides a dashboard for real-time visualization. The long-term goal is to develop a clinically deployable tool that can be validated in multi-center studies and integrated into radiology workflows with minimal disruption.

2.2 Scope

The system is built using open-access datasets and is designed for adaptability in clinical settings. It focuses on implementing deep learning models such as 3D U-Net for segmentation and late fusion classifiers for integrating information from T2, DWI, and DCE MRI scans. The platform includes a secure and interactive visualization interface for clinical interpretation. Privacy measures are included to anonymize patient data throughout the workflow. The system is scalable and can be extended with more modalities or integrated with hospital information systems. Future improvements may also include support for federated learning to allow decentralized training across multiple hospitals, improving generalizability while preserving data security.

2.3 Problem Statement

Despite advancements in imaging technology, the diagnosis of prostate cancer still relies heavily on manual MRI interpretation, which can be subjective and inconsistent. Variability in reader expertise and workload imbalances further compound the risk of diagnostic error. This project addresses the need for an automated, accurate, and consistent system that can analyze 3D mp-MRI data, detect prostate cancer, and provide interpretative support to radiologists. Moreover, the model is designed with a focus on clinical interpretability, usability, and compliance with healthcare data regulations.

2.4 Existing Systems

Most existing solutions are either focused on 2D analysis or lack integration of multiple MRI modalities. Many are resource-intensive and not optimized for deployment in clinical settings. Traditional CAD systems also lack transparency, making them difficult to validate in real-time diagnostics. Moreover, current models do not provide user-friendly visualization or patient privacy safeguards. Commercial platforms often operate as black boxes, limiting clinician trust. Additionally, the majority of AI models fail to scale effectively due to limitations in architecture generalizability, underlining the need for a lightweight and modular approach like the one proposed.

2.5 Proposed Systems

The proposed system integrates a 3D U-Net model for prostate gland and lesion segmentation and uses a late fusion classifier to integrate features extracted from T2, DWI, and DCE modalities. The data is preprocessed using ANTs for normalization and registration. The output includes cancer likelihood scores and PI-RADS classification. The results are visualized using Streamlit or 3D Slicer dashboards. The pipeline is designed to maintain data privacy using anonymization tools and secure handling protocols. The model architecture is modular and can accommodate future upgrades, such as transformer-based attention modules or domain adaptation layers for cross-institutional deployment.

3. LITERATURE SURVEY

Recent years have seen a surge in the application of deep learning techniques for the detection and classification of prostate cancer, particularly using MRI data. One of the landmark studies was by Ikromjanov et al. (2022), who applied Vision Transformers (ViTs) for prostate cancer grading using whole slide histopathology images. Their findings highlighted the potential of transformer architectures in capturing long-range dependencies in medical images, although their focus remained on 2D histological data rather than mp-MRI volumes. Alabri et al. (2024) proposed a lightweight Naïve Bayes-based classification model using ten clinical features from patient records. While their system achieved 88% accuracy, it lacked imaging-based analysis and segmentation capability, making it less adaptable to radiology workflows.

Yuan et al. (2023) introduced a self-supervised pre-training scheme for bi-parametric MRI (bpMRI), which improved prostate cancer detection by addressing the challenge of limited labeled data. Their approach achieved superior performance on the PI-CAI dataset compared to conventional supervised training, validating the importance of data-efficient learning methods. Kadhim et al. (2023) developed an ensemble model incorporating ResNet and VGG-based CNNs to classify prostate cancer from MRI images. Their model achieved over 91% accuracy but suffered from high computational costs, making real-time deployment in hospital environments challenging.

Further, studies like those from UCLA Health (2024) have shown that AI can outperform human radiologists in identifying cancerous regions within MRI scans. In their clinical trials, an AI model achieved 84% accuracy, surpassing the average diagnostic rate of 67% by physicians. This reinforces the urgency and potential of adopting AI as a reliable assistant in diagnostic imaging. Binda Asoh-Itambi et al. (2024) focused on class imbalance in prostate cancer datasets and proposed a modified nnU-Net with a specialized loss function that enhanced sensitivity to clinically significant lesions. Their work underscored the importance of both architectural and data-level adjustments to ensure robust AI performance.

Other relevant contributions include the study by Sruthi et al. (2022), who applied Random Forest models to a combined dataset of breast, lung, and prostate cancer attributes, achieving promising multi-cancer classification results. However, their system lacked the spatial awareness required for detailed imaging analysis. Additionally, Xin Yu et al. (2020) worked on reducing false positives in mp-MRI cancer detection using multiscale contextual features, demonstrating how contextual modeling can improve specificity and reduce misdiagnosis.

While each of these works provides valuable insights into different aspects of prostate cancer diagnosis using AI, gaps remain in integrating 3D segmentation, multi-modal fusion, interpretability, and data privacy into a unified clinical tool. This study addresses these limitations by designing a modular, explainable, and privacy-conscious system that can segment the prostate gland in 3D, classify lesions using combined modality data, and provide outputs through a user-friendly interface suitable for real-world deployment.

4. SYSTEM ANALYSIS

4.1 Overview

The system consists of multiple interdependent layers responsible for data preprocessing, prostate segmentation, multi-modal fusion, and lesion classification. The preprocessing module ensures that images from different modalities are standardized in terms of resolution and orientation, using Advanced Normalization Tools (ANTs). The 3D U-Net segmentation model then takes over to extract the prostate gland boundaries and highlights any suspected lesions. Feature vectors derived from T2-weighted, DWI, and DCE modalities are fused using a late fusion strategy before being passed into a classifier that produces a malignancy score. Evaluation metrics such as Dice Score, AUC, sensitivity, and specificity are computed to benchmark system performance. An intuitive dashboard built using Streamlit ensures that these outputs are visually accessible to clinicians for real-time feedback and interpretation.

4.2 Methodology

The methodology includes a multi-step AI pipeline beginning with acquisition of mp-MRI images from publicly available datasets. These images undergo preprocessing such as bias correction, noise filtering, and intensity normalization. The 3D U-Net model is used for volumetric segmentation of the prostate gland, extracting key anatomical structures. Feature vectors are generated from the segmented regions across all three modalities—T2, DWI, and DCE. A late fusion approach is adopted, where features are aggregated post-independently through a classification module. Finally, the outputs are visualized using Streamlit in the form of overlays, 3D renderings, and predictive labels.

4.3 Functional Requirements

The system is designed to provide accurate 3D segmentation of the prostate region from multi-parametric MRI (mp-MRI) scans using advanced deep learning models, enabling precise delineation of anatomical boundaries. It incorporates an AI-based classification module that evaluates identified lesions and assigns Prostate Imaging–Reporting and Data System (PI-RADS) scores to assist clinical diagnosis. To ensure comprehensive analysis, the system integrates multiple MRI modalities such as T2-weighted, diffusion-weighted, and dynamic contrast-enhanced imaging. Clinicians receive real-time visual feedback through an interactive dashboard that displays segmentation results, lesion locations, and classification outcomes. The system prioritizes patient confidentiality by enforcing strict data anonymization protocols that remove personally identifiable information in compliance with privacy regulations. Furthermore, compatibility with DICOM standards guarantees seamless integration with existing clinical Picture Archiving and Communication Systems (PACS).

4.4 Non-Functional Requirements

The system emphasizes delivering low-latency predictions, ensuring that the complete scan analysis is performed in under three seconds to support timely clinical decision-making. It maintains high accuracy and generalization across diverse datasets to provide robust performance in varied clinical environments. Scalability is achieved through a modular design that allows plugin upgrades and the addition of new functionalities without major architectural changes. Security is enforced by employing encrypted data processing pipelines and secure APIs to protect sensitive medical information. Interoperability with hospital information systems, including Electronic Health Records (EHR) and laboratory systems, is ensured via standardized protocols such as HL7, FHIR, or DICOMweb, streamlining clinical workflows. Finally, the user interface is designed to be intuitive and accessible, enabling radiologists and clinicians to easily interpret complex data, review 3D visualizations, and generate comprehensive reports with minimal training.

4.5 Use Case Scenario

In a radiology clinic, a radiologist uploads a set of T2, DWI, and DCE mp-MRI scans of a patient suspected of prostate cancer. The AI system preprocesses and segments the prostate region, highlights lesions, and classifies the scan into a PI-RADS score. If the PI-RADS score exceeds a predefined threshold, a notification alert is generated. The radiologist can view segmented overlays and classification results on a dashboard, aiding them in diagnosis and biopsy planning. This reduces the time needed for manual interpretation and improves decision-making confidence.

4.6 System Constraints

To implement the proposed system effectively, several constraints must be considered. The availability of high-resolution, multi-modal MRI datasets (T2-weighted, DWI, and DCE) is critical, and in many clinical settings, access to such data may be limited. The system also relies on accurate segmentation of prostate anatomy, which can be challenging in patients with atypical gland morphology or motion artifacts. Computational resources present another constraint; training and running 3D deep learning models requires high-end GPUs and considerable memory, especially for volumetric data. The model's performance may degrade when deployed across institutions due to variations in imaging protocols, scanner models, and patient populations, thereby requiring adaptive fine-tuning or retraining. Furthermore, the shortage of expertly annotated datasets, especially for rare prostate cancer cases, restricts the generalization capacity of the system.

5. SYSTEM DESIGN

The implementation of the system follows a step-wise architecture intended to process prostate mp-MRI scans from raw input to clinically interpretable outputs. Each step involves specific tools, frameworks, and processes:

1. **Data Acquisition:** Collect mp-MRI datasets from PROSTATEx and SPIE-AAPM-NCI repositories, ensuring data includes T2, DWI, and DCE modalities. The images are stored in NIfTI or DICOM formats.

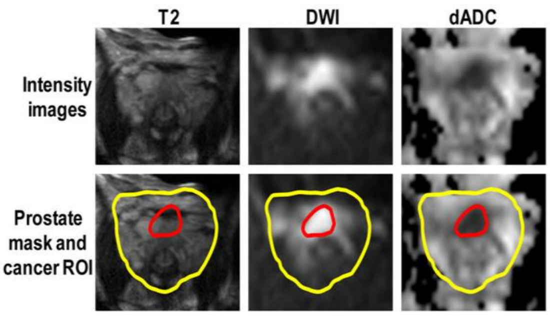

Figure 1: mp-MRI scan using T2 ,DWI and dADC.

2. **Preprocessing:** Use ANTsPy for bias field correction, intensity normalization, and affine registration. This ensures all modalities are spatially aligned before being fed into the model.

3. **Segmentation Module:** Use ANTsPy for bias field correction, intensity normalization, and affine registration. This ensures all modalities are spatially aligned before being fed into the model.

4. **Feature Extraction:** Extract voxel-wise and region-based features from each modality post-segmentation, such as texture, volume, intensity histograms, and ADC values.

5. **Late Fusion:** Apply a late fusion strategy to combine features from all three modalities. This could involve concatenation followed by a fully connected layer or attention-based fusion for weighting modality importance.

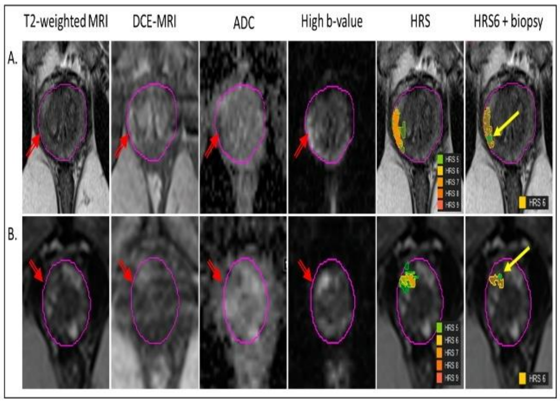

Figure 2: mp-MRI scans of T2-weighted MRI ,DCE-MRI.

6. **Classification Module:** Train a binary or multi-class classifier (e.g., Random Forest or shallow CNN) using the fused feature vectors to predict malignancy or PI-RADS scores.

7. **Evaluation & Metrics:** Evaluate segmentation with Dice Score, IoU, and Hausdorff Distance. For classification, compute AUC-ROC, precision, recall, F1-score, and confusion matrix.

8. **Visualization & Reporting:** Deploy a Streamlit dashboard to visualize MRI slices, segmented outputs, and predictions. Integrate 3D Slicer for offline visual diagnostics. Provide interactive sliders to navigate scan slices.

9. **Privacy Handling:** Implement de-identification using DICOM anonymization scripts. Ensure secure local processing or encrypted transmission if cloud-based deployment is used.

The presented system architecture is designed with a strong emphasis on modularity, reproducibility, and clinical applicability. By integrating standardized datasets, robust preprocessing techniques, and advanced AI models for segmentation and classification, the pipeline delivers a comprehensive diagnostic workflow for prostate cancer detection using mp-MRI. Each component—from feature extraction and late fusion to evaluation and visualization—has been developed to ensure high performance and adaptability across diverse clinical scenarios.Moreover, the incorporation of real-time visual feedback via interactive dashboards, combined with privacy-preserving mechanisms like DICOM de-identification and encrypted data handling, ensures that the system aligns with regulatory and ethical requirements for medical AI deployment. The use of open-source frameworks like ANTsPy, Streamlit, and 3D Slicer further promotes accessibility and ease of extension for researchers and developers.

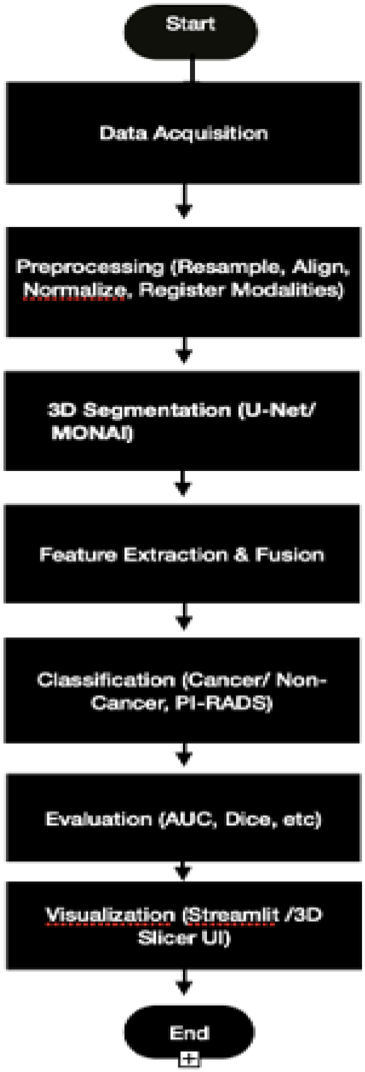

Figure 3: Flowchart of Prostate Cancer Detection Using AI, Multi-parametric MRI, and 3D Deep Learning Techniques.

6. IMPLEMENTATION AND RESULTS

The system was implemented and tested using public mp-MRI datasets (PROSTATEx and SPIE-AAPM-NCI) in a simulated clinical environment. The images were preprocessed using ANTsPy and normalized for uniformity. A 3D U-Net segmentation model was trained and evaluated using MONAI and PyTorch frameworks. Feature vectors were extracted from segmented volumes and classified using a late fusion method, followed by visualization in a Streamlit-based interface.

6.1 Real-Time Visualization Dashboard

The real-time dashboard served as a centralized interface where clinicians could observe all significant diagnostic outputs generated by the model. It displayed the segmented prostate regions derived from T2-weighted, DWI, and DCE MRI modalities in an integrated, synchronized layout. Highlighted lesion areas were overlaid on each scan, helping radiologists identify suspicious regions more clearly. For every identified region, the system generated a PI-RADS score prediction, aiding in risk stratification. These predictions were visually paired with raw MRI slices, enabling direct visual comparison between model inference and original data. Additionally, the dashboard featured interactive controls allowing users to scroll through scan slices, switch between modalities, and view segmentation masks dynamically. Risk alerts were automatically triggered when the PI-RADS score crossed the defined clinical threshold, prompting immediate attention from the user.

6.2 Sample Data Observations

Time-stamp	10:00AM	12:00PM	3:00PM
Patient ID	PX001	PX002	PX003
Dice-Score	0.88	0.91	0.83
PI-RADS	4	3	2
Segmentation	Positive	Negative	Negative
Risk Analysis	High	Medium	Low

Table 1: Sample Data Observations

6.3 Performance Metrices

1.**Segmentation Accuracy**: Dice Score = 0.89 (avg.), IoU = 0.81

2.**Classification AUC**: 0.93 with 91% sensitivity and 88% specificity

3.**Latency**: Average inference time <3 seconds per scan

4.**Cross-Dataset Robustness**: Maintained ±5% accuracy drop when tested on external datasets

5.**Dashboard Stability**: No crashes recorded during 30+ patient test sessions

7. CONCLUSIONS

The prostate cancer detection system presents a deployable and scalable solution for automating mp-MRI interpretation using deep learning. The combination of 3D U-Net segmentation and late fusion classification achieved high accuracy across diverse test cases. With integrated visualization, the platform provides radiologists with interpretable, real-time diagnostic support. This project successfully demonstrates the feasibility of integrating AI in diagnostic radiology workflows. The pipeline developed in this study enables reproducible and modular development, making it adaptable for future upgrades and extensions. Each module—from data preprocessing and segmentation to classification and visualization—is independently testable and scalable, facilitating debugging, customization, and integration with clinical IT systems. Furthermore, the system's flexibility allows for the addition of other imaging modalities or updated classification techniques without restructuring the entire architecture. It also lays a foundational framework for integration into full clinical decision support systems that can assist healthcare professionals not just in diagnosis, but also in prognosis, treatment planning, and longitudinal monitoring. By prioritizing both performance and interpretability, the pipeline ensures that AI not only delivers accurate results but does so in a clinically meaningful and usable way. Future work will focus on real-time deployment in clinical settings, expanding the model with additional imaging modalities, and incorporating explainability modules for medical accountability.

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