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Artificial Intelligence-Based Prostate Cancer Diagnosis Using MRI: A Comprehensive Review of Machine Learning and Deep Learning Approaches

Ms. Mamta Gehlot[1], Dr. Sumit Jain[2]

[1]Research Scholar, [2]Associate professor
[1,2]Computer science & Engineering, SAGE University, Indore.

Abstract:
Prostate cancer is one of the leading causes of cancer-related mortality among men, requiring accurate and early diagnosis for effective treatment. This review presents a comprehensive analysis of Artificial Intelligence (AI)-based techniques for prostate cancer detection, classification, grading, and segmentation using MRI data. Various methodologies, including machine learning, deep learning, hybrid models, and ensemble approaches, are examined. Deep learning models, particularly Convolutional Neural Networks and advanced architecture, demonstrate superior performance in extracting complex imaging features. Additionally, the integration of multiparametric MRI with clinical data enhances diagnostic accuracy and robustness. Despite promising results, challenges such as data imbalance, lack of interpretability, and limited clinical validation persist. This study highlights current trends, identifies research gaps, and provides insights into developing reliable and clinically applicable AI-based diagnostic systems.

Keywords: Prostate Cancer, Artificial Intelligence, Deep Learning, Machine Learning, Multiparametric MRI, Computer-Aided Diagnosis

I. INTRODUCTION

Prostate cancer (PCa) is one of the most prevalent cancers among men worldwide and represents a significant public health challenge. According to recent global statistics, it ranks among the leading causes of cancer-related mortality, emphasizing the need for early and accurate diagnosis. Traditional diagnostic methods, such as prostate-specific antigen (PSA) testing and biopsy, often suffer from limitations including high false-positive rates, invasiveness, and inter-observer variability. In recent years, multiparametric magnetic resonance imaging (mpMRI) has emerged as a powerful non-invasive tool for prostate cancer detection, localization, and grading. However, the interpretation of MRI data remains complex and highly dependent on radiologist expertise, leading to variability in diagnosis and potential misclassification of clinically significant cancers.

To address these challenges, Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL) techniques, has gained considerable attention in prostate cancer diagnosis. AI-based Computer-Aided Diagnosis (CAD) systems have demonstrated the ability to analyze large volumes of imaging data, extract meaningful features, and assist clinicians in making more accurate and consistent decisions. Various approaches, including Support Vector Machines (SVM), Random Forest (RF), Convolutional Neural Networks (CNNs), and hybrid models, have been applied to tasks such as cancer detection, Gleason grading, segmentation, and risk stratification using MRI data.

Despite significant advancements, several challenges remain. Many existing models face issues related to data imbalance, lack of interpretability, limited generalization across datasets, and dependence on annotated data. Additionally, variations in MRI acquisition protocols and the integration of clinical information with imaging data pose further complexities. These limitations highlight the need for a comprehensive understanding of existing AI techniques and their effectiveness in real-world clinical applications.

The motivation of this review is to systematically analyze recent developments in AI-driven prostate cancer diagnosis using MRI, focusing on both machine learning and deep learning approaches. By examining a wide range of studies, this paper aims to identify trends, strengths, and limitations of current methodologies, as well as emerging techniques that enhance diagnostic performance and clinical applicability.

The key contributions of this review are as follows: (1) a comprehensive analysis of machine learning, deep learning, and hybrid approaches for prostate cancer detection and grading; (2) a comparative overview of different MRI modalities, including mpMRI and bpMRI; (3) an evaluation of AI models based on clinical tasks such as classification, segmentation, and risk prediction; and (4) identification of research gaps and future directions for developing robust, interpretable, and clinically deployable AI systems. This review provides valuable insights for researchers and clinicians aiming to advance AI-based prostate cancer diagnosis.

II. LITERATURE REVIEW

Virk et al. highlighted that prostate cancer was the fourth most diagnosed cancer worldwide in 2020, emphasizing the need for improved diagnostic techniques. In their study, Computer-Aided Diagnosis (CAD) systems were utilized to support prostate cancer detection. Radiomic features were extracted from regions of interest (ROIs) of 112 prostate cancer lesions from 99 patients, resulting in 444 features for machine learning analysis. The study evaluated Support Vector Machine (SVM), Naïve Bayes (NB), and k-Nearest Neighbor (KNN) classifiers using standard performance metrics. Among these, SVM achieved the best performance on Apparent Diffusion Coefficient (ADC) and T2-weighted MRI modalities; however, the overall accuracy was relatively low at 44.64% [1].

Mowafa Salem et al. investigated multiple machine learning algorithms for prostate cancer diagnosis and found that Random Forest (RF) models frequently outperformed other methods in terms of diagnostic accuracy. Using a dataset of 200 prostate cancer patients and 200 healthy controls, evaluated with 10-fold cross-validation, the RF model achieved an accuracy of 0.92, sensitivity of 0.95, and specificity of 0.89. Decision Tree models also performed well, achieving an accuracy of 0.91, while SVM and Neural Network (NN) models showed comparatively lower performance. This study demonstrates the effectiveness of RF algorithms in improving early detection and diagnosis using clinical and radiological data [2].

Oka et al. focused on addressing overdiagnosis and improving risk prediction for aggressive prostate cancers, particularly those classified as Gleason grade group 4 or 5. Their approach combined advanced MRI sequences with 3D deep convolutional neural networks (3D-CNNs) to enhance the identification of high-grade lesions. Additionally, pathological databases from prostatectomy cases were analyzed to determine optimal quantitative MRI parameters for diagnosing high-grade cancers. The integration of 3D MRI data with artificial intelligence significantly improved diagnostic precision and supported better clinical decision-making in prostate cancer grading [3].

Engelage et al. demonstrated that biparametric MRI (bpMRI) is an efficient and non-invasive technique for detecting clinically significant prostate cancer, offering diagnostic accuracy comparable to multiparametric MRI (mpMRI) while reducing cost and scan time. Their study showed that deep learning-based CAD systems, particularly 3D convolutional neural networks trained on T2-weighted and diffusion-

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weighted imaging, significantly improved the automated characterization of prostate cancer grades and chronic prostatitis. These models achieved high diagnostic performance at both lesion-wise and patient-wise levels and enhanced interpretability, making them more clinically useful for prostate MRI analysis [4].

Anusha et al. proposed a fully automated, end-to-end system for prostate cancer detection and grading using multiparametric MRI (mpMRI) data from the ProstateX-2 dataset. Their approach utilized a VGG19-based feature extraction model combined with a Random Forest classifier to determine Gleason Grade Groups (GGG). The system enabled precise identification of cancerous lesions and provided valuable support for clinical decision-making. The proposed framework demonstrated improved diagnostic accuracy and contributed to better patient care outcomes [5].

Garg et al. reviewed the integration of VGG19 feature extraction with Random Forest classifiers in Computer-Aided Diagnosis (CAD) systems for prostate cancer grading using Gleason Grade Groups. Compared to traditional methods such as PSA testing, which are associated with high false positive rates, their study highlighted that deep learning models applied to mpMRI data significantly enhance detection accuracy. The Random Forest-based approach achieved very high performance, with accuracy reaching up to 99.64% in distinguishing cancerous from non-cancerous tissues and in grading prostate cancer. This review emphasized the effectiveness of combining deep learning with machine learning classifiers for improved diagnostic outcomes [6].

Alici-Karaca et al. introduced a deep learning model that combines EfficientNet-B4 with Efficient Channel Attention (ECA) to automate Gleason grading in prostate cancer diagnosis. Using the DiagSet dataset, the model was evaluated for multi-class classification (8-class, 4-class, and 2-class scenarios), demonstrating enhanced tissue classification performance. The proposed method achieved an accuracy of 96.18% in cancer detection and 94.86% in severity grading. The study highlighted how advanced neural network architectures can address limitations of earlier models, particularly in handling class imbalance, and improve clinical decision-making in pathology image analysis [7].

Rosmawarni et al. explored the use of deep learning algorithms for prostate cancer prediction from MRI data, focusing on improving diagnostic accuracy and efficiency. Their approach employed Convolutional Neural Networks (CNNs) to classify MRI images into two categories. The dataset consisted of manually annotated MRI scans verified by radiologists, which helped improve model performance and reduce overfitting. Evaluation metrics such as accuracy, precision, recall, and F1-score were used to assess the model. The results demonstrated improved accuracy and faster prediction, contributing to more effective diagnosis and timely treatment planning [8].

Antonutti et al. demonstrated that artificial intelligence (AI) plays a significant role in prostate cancer detection using multiparametric MRI (mpMRI) and whole-slide pathology images. Deep learning models, particularly Convolutional Neural Networks (CNNs), were shown to effectively detect tumors, grade cancer, and assess risk with accuracy exceeding 90%. The study emphasized that combining multiple MRI modalities with the PI-RADS system enhances diagnostic reliability. In pathology analysis, CNN and U-Net models achieved strong tumor segmentation performance, with overlap accuracy scores ranging between 0.75 and 0.85. This approach reduces clinician workload and minimizes subjectivity in diagnosis, while future trends highlight integration of multi-source data and real-time diagnostic systems for personalized prostate cancer care [9].

Beura et al. introduced a hybrid approach that combines Principal Component Analysis (PCA) with Convolutional Neural Networks (CNNs) and transfer learning to improve diagnostic accuracy while reducing computational complexity. The study evaluated multiple models, including Support Vector Machine (SVM), Random Forest, XGBoost, CNN, ResNet-50, EfficientNet, Vision Transformers, and a novel ProsGradNet model across datasets such as ProstateX, PROSTATE12, and ProsGradNet. Their findings highlighted the importance of balancing model accuracy with challenges like dataset standardization. The proposed AI-driven framework demonstrated a reliable, efficient, and scalable solution for clinical prostate cancer diagnosis [10].

Sharma et al. addressed prostate cancer as a major public health concern, emphasizing the importance of early diagnosis for improved treatment outcomes. Their study proposed a system incorporating image enhancement and automated region segmentation, followed by feature extraction using ResNet. The extracted features were then classified using a Support Vector Machine (SVM). The integration of transfer learning with conventional classification methods significantly improved diagnostic accuracy, interpretability, and efficiency. This approach enables clinicians to make timely and accurate decisions, thereby enhancing patient care [11].

Charalambos et al. proposed a multi-modal deep learning model for prostate cancer classification using biparametric MRI (bpMRI), achieving state-of-the-art performance. The architecture integrates Spatial Transformer Networks (STNs) for image alignment, convolutional encoders for feature extraction, and attention mechanisms to focus on critical diagnostic regions. Evaluated on over 15,000 bpMRI slices from the PI-CAI challenge dataset, the model achieved an overall accuracy of 97%, balanced accuracy of 93%, and an AUC of 0.93. The study demonstrated strong generalization across different ISUP grades, making it highly effective for risk stratification [12].

Degadwala et al. investigated challenges in accurate prostate cancer classification using MRI and proposed a framework combining pre-trained deep learning models with a large annotated dataset. The methodology outperformed conventional approaches by achieving higher accuracy, precision, recall, and F1-score. The model also demonstrated robustness across different MRI scanners and patient demographics, indicating its suitability for real-world clinical deployment. Additionally, the study emphasized model interpretability using visualization techniques, enhancing trust and usability in clinical decision-making [13].

Valizadeh et al. examined the integration of deep learning (DL) classification networks with multiparametric MRI (mpMRI) for prostate cancer (PCa) assessment. Their study focused on predicting high-grade cancer and differentiating between benign tissue and malignant lesions using advanced DL architectures. The results highlighted improvements in model explainability and interpretability, which are critical for increasing clinical trust. Additionally, the study emphasized the importance of incorporating domain knowledge and clinical information alongside imaging data to enhance diagnostic performance and decision-making [14].

Gavade et al. explored the application of Convolutional Neural Networks (CNNs) for analyzing mpMRI data in prostate cancer diagnosis. Their findings indicated that AI models can achieve over 90% accuracy in key tasks such as tumor localization, Gleason grading, and risk stratification. The study also reported strong segmentation performance using Intersection over Union (IoU) metrics. Furthermore, it discussed future advancements, including large-scale histopathology analysis, integration of clinical data, real-time diagnostics, image-to-text reporting, and personalized treatment planning [15].

Wu et al. developed an MRI-based model for prostate cancer identification and diagnosis, focusing on improving the accuracy of AI-based image recognition systems. The study utilized datasets comprising MRI images from normal individuals, patients with benign prostatic hyperplasia, and confirmed prostate cancer cases. By implementing deep learning models using PyTorch and established AI architectures, the research demonstrated improved detection of prostate lesions and enhanced diagnostic performance based on clinical MRI data from Xi'an Central Hospital [16].

Maimone et al. investigated various machine learning and deep learning algorithms for prostate cancer detection and characterization within fully automated Computer-Aided Diagnosis (CAD) systems. Their study evaluated model performance based on false positives (FP), false negatives (FN), and segmentation accuracy. The proposed deep learning framework was tested using both 2-channel and 3-channel MRI input configurations, with the 3-channel model demonstrating superior performance. This

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research highlights the effectiveness of multi-channel MRI data in improving segmentation and diagnostic accuracy [17].

Kadhim et al. investigated the application of machine learning techniques to improve prostate cancer detection using MRI images. Their study addressed the limitations of traditional models such as Support Vector Machine (SVM), Decision Tree, and Random Forest by proposing an ensemble learning framework. By combining multiple models, the approach achieved more reliable and accurate classification results. Experimental evaluation demonstrated that the ensemble model achieved an accuracy of 96% in distinguishing significant from non-significant prostate cancer. The findings highlight the effectiveness of ensemble machine learning methods in enhancing prostate cancer detection from MRI data [18].

Zhong et al. explored the use of deep learning techniques, particularly Convolutional Neural Networks (CNNs), for predicting Gleason Scores (GS) by integrating multimodal imaging data with clinical patient information. The model was evaluated on a public dataset consisting of 921 MRI scans along with corresponding structured clinical records. Comparative analysis showed that incorporating clinical features significantly improved prediction performance. The proposed approach achieved an Area Under the Receiver Operating Characteristic Curve (AUROC) of 0.90, compared to 0.69 for models relying solely on imaging data, demonstrating superior accuracy in prostate cancer grading [19].

Al-Zidi and Vasumathi proposed a framework that evaluates various combinations of nine mpMRI sequences using transfer learning models such as VGG19 and Vision Transformers. Features extracted from these models were classified using an SVM to identify optimal sequence combinations for prostate cancer detection. The framework also analyzed the contribution of individual MRI sequences based on their frequency in top-performing combinations. The proposed approach achieved an accuracy of 0.87 for whole-prostate classification, providing valuable insights into the importance of specific MRI sequences in improving diagnostic performance [20].

Mehta et al. addressed the limitations of traditional Computer-Aided Diagnosis (CAD) systems, which rely heavily on lesion-level annotations that are often costly and insufficient for detecting diffuse or MRI-invisible tumors. Their study introduced a patient-level classification framework (PCF) that extracts features from 3D mpMRI and parameter maps using CNNs, and integrates them with clinical data through an SVM-based multi-classifier scheme. The proposed framework achieved an accuracy of 0.86 on the PROSTATEx dataset using five-fold cross-validation. Additionally, the system demonstrated the potential to identify low-risk patients who may not require extensive clinical evaluation, thereby improving efficiency in clinical workflows [21].

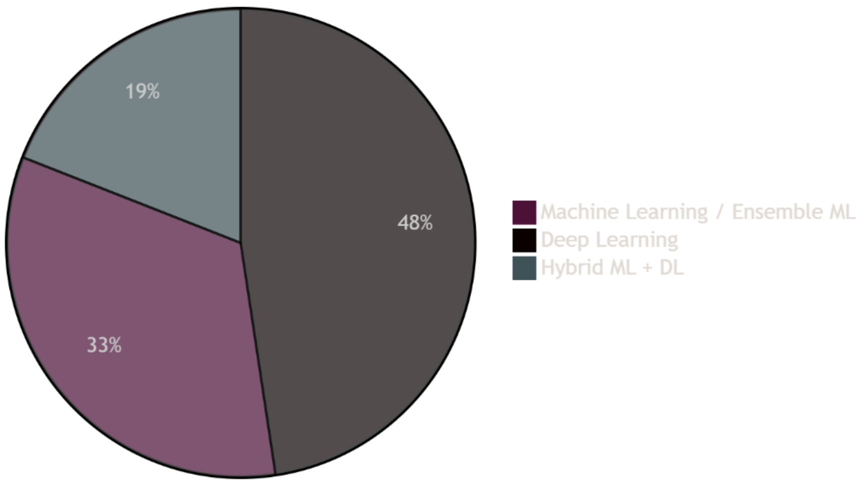

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Figure 1. Distribution of Studies by Main AI Approach

This figure 2 presents a monochrome distribution of AI approaches used across the reviewed studies. Deep learning dominates the field, followed by machine learning approaches and hybrid models, indicating a strong shift toward advanced neural architectures in prostate cancer diagnosis.

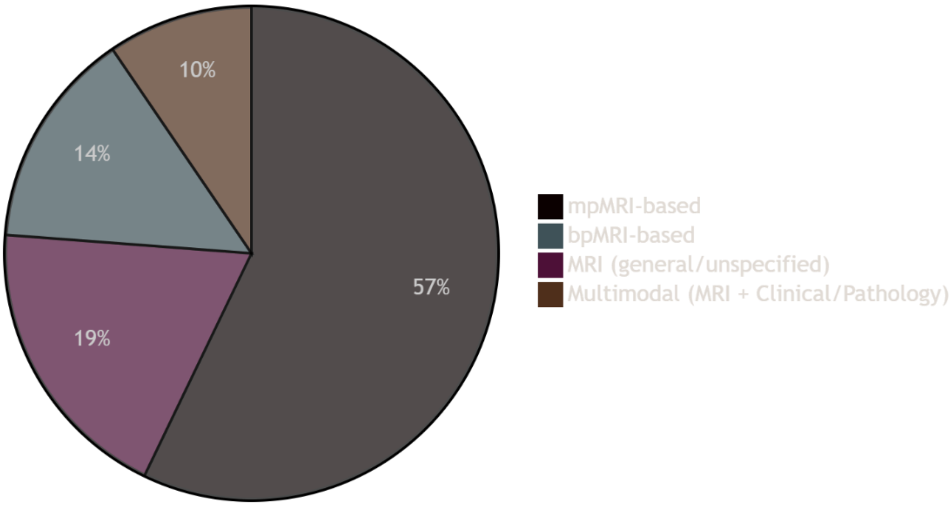

Figure 2. Distribution of Studies by Imaging/Data Type

This figure 2 shows that mpMRI is the most commonly used imaging modality in prostate cancer research. Other approaches such as bpMRI and multimodal data integration are emerging as efficient and cost-effective alternatives.

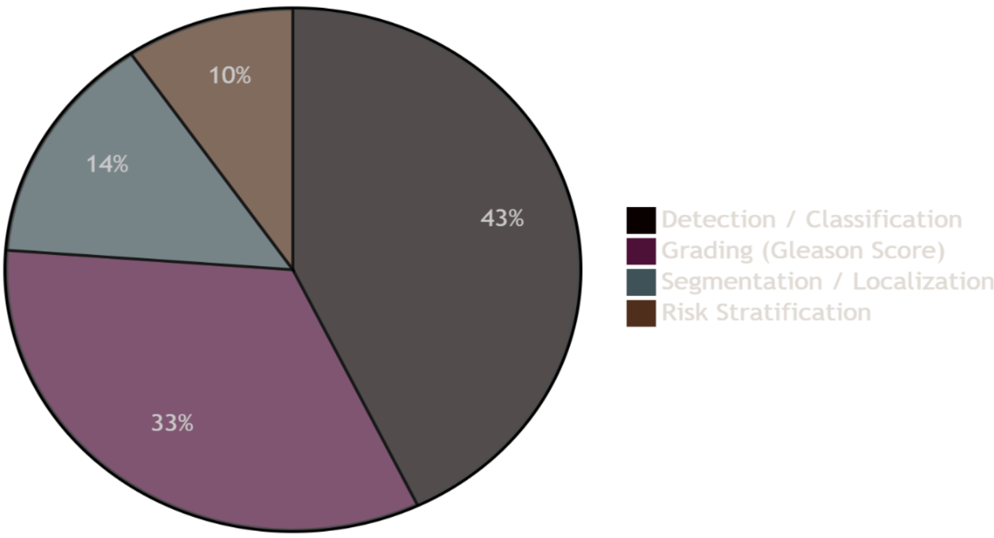

Figure 3. Distribution of Studies by Clinical Task

This figure 3 highlights that most studies focus on detection and classification tasks, followed by grading using Gleason scores. Fewer studies emphasize segmentation and risk stratification, though these areas are gaining importance.

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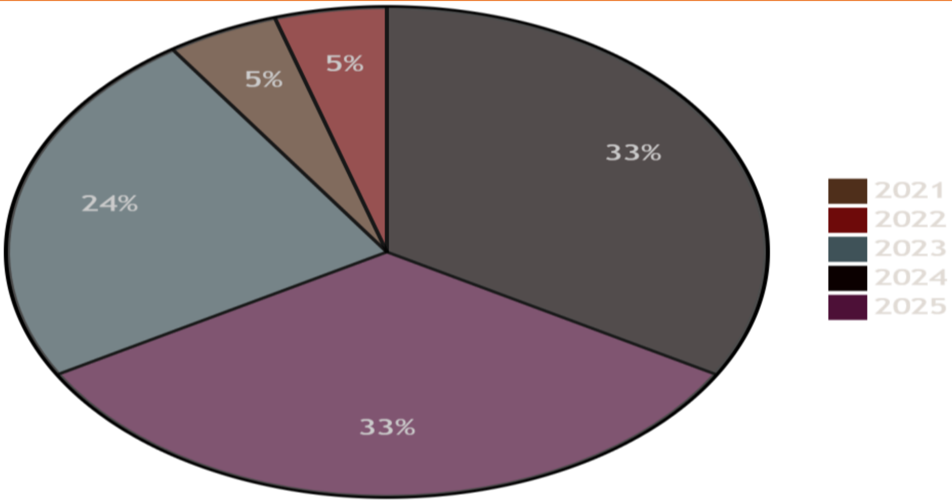

Figure 4. Distribution of Studies by Publication Year

This figure 4 shows a rapid increase in research publications from 2023 onwards, with peak contributions in 2024 and 2025. This trend reflects the growing importance of AI-based prostate cancer diagnosis in recent years.

Table 1: Detailed Literature Review Summary

S. No.	Authors	Method / Model Used	Dataset / Modality	Key Findings	Research Gap
1	Virk et al.	SVM, NB, KNN (ML)	mpMRI (ADC, T2W)	SVM best for Gleason classification	Limited feature extraction & modality fusion
2	Salem et al.	RF, SVM, NN (ML)	Clinical + Imaging	RF achieved 92% accuracy	Lack of unified diagnostic framework
3	Oka et al.	3D-CNN (DL)	3D MRI	Improved high-grade cancer detection	Lack of standardization in 3D models
4	Engelage et al.	3D-CNN (DL)	bpMRI	Accurate grading & detection	Limited interpretability
5	Anusha et al.	VGG19 + RF (Hybrid)	mpMRI	Improved Gleason prediction	Needs large-scale validation
6	Garg et al.	RF + Feature Extraction	mpMRI	High accuracy (up to 99%)	Limited clinical deployment
7	Alici-Karaca et al.	EfficientNet + ECA (DL)	Histopathology	96% detection accuracy	Class imbalance issues
8	Rosmawarni et al.	CNN (DL)	MRI	Improved classification speed	Needs higher accuracy
9	Antonutti et al.	CNN, U-Net (DL)	bpMRI + Pathology	>90% accuracy, good segmentation	Limited advanced architectures
10	Beura et al.	PCA + CNN + TL (Hybrid)	Multiple datasets	High performance (94.5%)	Data standardization issues

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11	Sharma et al.	ResNet + SVM (Hybrid)	MRI	Improved accuracy & efficiency	Complexity in MRI interpretation
12	Charalambos et al.	STN + CNN + Attention	bpMRI	97% accuracy, strong classification	Misclassification in small lesions
13	Degadwala et al.	Transfer Learning (DL)	MRI	Robust classification performance	Needs real-world validation
14	Valizadeh et al.	DL + mpMRI Review	mpMRI	Improved explainability	Lack of clinical validation
15	Gavade et al.	CNN, U-Net (DL)	mpMRI	>90% accuracy, good segmentation	Limited dataset diversity
16	Wu et al.	DL (PyTorch models)	MRI + Clinical	Improved feature extraction	No real-time validation
17	Maimone et al.	ML vs DL Comparison	mpMRI	DL improves segmentation	Lack of advanced models comparison
18	Kadhim et al.	Ensemble ML	MRI	96% classification accuracy	Limited ensemble optimization
19	Zhong et al.	CNN + Clinical (Multimodal)	MRI + Clinical	AUROC = 0.90	Limited multimodal integration
20	Al-Zidi et al.	VGG19 + ViT + SVM	mpMRI	Improved sequence selection	Limited exploration of all MRI combinations
21	Mehta et al.	CNN + SVM (Hybrid)	mpMRI + Clinical	Improved patient-level classification	Limited integration framework

2.1 Research Gap

Despite significant advancements in Artificial Intelligence (AI)-based prostate cancer diagnosis, several critical research gaps remain that limit the widespread clinical adoption of these systems. Many studies have demonstrated high accuracy using machine learning and deep learning models; however, these models are often trained and evaluated on limited or specific datasets such as ProstateX or institutional data. This lack of dataset diversity affects the generalizability of models across different populations, imaging protocols, and clinical environments. Additionally, variations in MRI acquisition parameters and annotation standards introduce inconsistencies, making it difficult to develop standardized and robust diagnostic frameworks.

Another major gap lies in the **interpretability and explainability** of AI models. While deep learning techniques such as CNNs and Vision Transformers achieve high performance, they are often considered “black-box” models. This lack of transparency reduces clinical trust and limits their adoption in real-world healthcare settings. Although some studies attempt to incorporate attention mechanisms or visualization techniques, there is still a need for more interpretable models that can provide clear reasoning behind predictions and align with clinical decision-making processes.

Furthermore, most existing studies focus on **single-task models**, such as classification, segmentation, or grading, rather than developing integrated systems that can perform multiple tasks simultaneously. In clinical practice, prostate cancer diagnosis involves a combination of detection, localization, grading (Gleason score), and risk stratification. The absence of unified, end-to-end frameworks that can handle these multiple tasks efficiently represents a significant research gap. Additionally, limited integration of

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clinical data (e.g., PSA levels, patient history) with imaging data reduces the overall predictive capability of many AI systems.

Another challenge is the issue of **data imbalance and annotation dependency**. Many datasets contain fewer high-grade cancer cases, leading to biased model performance. Moreover, most AI models rely heavily on expert-annotated data, which is time-consuming, expensive, and prone to inter-observer variability. There is a need for methods that can handle limited labeled data, such as semi-supervised, self-supervised, or transfer learning approaches.

Finally, while several studies report high accuracy, there is a lack of **real-world clinical validation and deployment**. Few models have been tested in prospective clinical settings or integrated into hospital workflows. Issues such as computational cost, scalability, and regulatory approval remain largely unaddressed. Therefore, future research should focus on developing robust, interpretable, and clinically validated AI systems that can be seamlessly integrated into routine prostate cancer diagnosis.

III METHODOLOGY

This review analyzes various Artificial Intelligence (AI)-based methodologies used for prostate cancer detection, classification, grading, and segmentation using MRI data. The methodologies can be broadly categorized into Machine Learning (ML), Deep Learning (DL), Hybrid Approaches, Ensemble Models, and Multimodal Learning frameworks.

1. Machine Learning-Based Methods: Traditional machine learning algorithms have been widely used for prostate cancer diagnosis, particularly in earlier studies. Methods such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree, Naïve Bayes (NB), and k-Nearest Neighbor (KNN) rely on handcrafted feature extraction from MRI images. Radiomic features are typically extracted from regions of interest (ROIs) and then used for classification tasks. For example, Virk et al. utilized radiomic features from mpMRI data and applied SVM, NB, and KNN for Gleason grading, where SVM achieved the best performance [1]. Similarly, Salem et al. demonstrated that Random Forest models outperform other ML techniques in diagnostic accuracy when applied to clinical and imaging datasets [2]. These methods are computationally efficient and interpretable but are limited by their dependence on feature engineering and lower generalization capability.

2. Deep Learning-Based Methods: Deep learning approaches, particularly Convolutional Neural Networks (CNNs), have become the dominant methodology for prostate cancer diagnosis. These models automatically learn hierarchical features directly from imaging data, eliminating the need for manual feature extraction. Studies such as Oka et al. employed 3D-CNN models on MRI sequences for high-grade cancer detection, improving diagnostic precision [3]. Engelage et al. and Rosmawarni et al. also utilized CNN-based CAD systems for classification and grading tasks, achieving high accuracy and efficiency [4], [8]. Advanced architectures such as EfficientNet and attention-based models have further enhanced performance in tissue classification and Gleason grading, as demonstrated by Alici-Karaca et al. [7]. Deep learning methods offer superior accuracy but require large datasets and high computational resources.

3. Transfer Learning and Pre-trained Models: Transfer learning techniques have been widely adopted to overcome data limitations in medical imaging. Pre-trained models such as VGG19, ResNet, and Vision Transformers are fine-tuned using prostate MRI datasets to improve performance. Anusha et al. and Garg et al. used VGG19 for feature extraction combined with classifiers for Gleason grading [5], [6]. Sharma et al. applied ResNet for feature extraction, enhancing classification accuracy when integrated with SVM [11]. Transfer learning reduces training time and improves performance, especially when labeled medical data is scarce.

4. Hybrid ML-DL Approaches: Hybrid approaches combine deep learning feature extraction with traditional machine learning classifiers to leverage the strengths of both methods. In these frameworks, CNN-based models extract deep features, which are then classified using algorithms such as SVM or Random Forest. Beura et al. and Mehta et al. demonstrated that combining CNN features with ML classifiers improves diagnostic accuracy and robustness [10], [21]. Similarly, Zhong et al. integrated deep learning with clinical data to enhance prediction performance [19]. These approaches provide a balance between accuracy and interpretability.

5. Ensemble Learning Methods: Ensemble learning techniques combine multiple models to improve prediction accuracy and reduce model bias. Kadhim et al. proposed an ensemble framework combining SVM, Decision Tree, and Random Forest models, achieving an accuracy of 96% in prostate cancer classification [18]. Ensemble methods enhance reliability by aggregating predictions from different models, making them more robust compared to single-model approaches.

6. Multimodal and Multichannel Learning: Recent studies emphasize the integration of multiple data sources, including different MRI sequences and clinical information. Multimodal learning frameworks combine imaging data with clinical features such as PSA levels and patient history to improve prediction accuracy. Valizadeh et al. and Zhong et al. highlighted the importance of integrating clinical data with imaging for better decision-making [14], [19]. Additionally, multi-channel MRI inputs (e.g., 2-channel vs. 3-channel) have been explored, with Maimone et al. showing improved performance using multi-channel configurations [17].

7. Segmentation and Localization Techniques: Segmentation methods aim to identify and localize tumor regions within MRI images. Deep learning architectures such as U-Net and CNN-based models are widely used for this purpose. Antonutti et al. demonstrated effective tumor segmentation using CNN and U-Net models with high overlap accuracy [9]. These methods are essential for precise lesion detection and assist in treatment planning.

8. Advanced Deep Learning Architectures; Recent advancements include the use of attention mechanisms, Vision Transformers, and Spatial Transformer Networks (STNs). Charalambos et al. proposed a multi-modal deep learning framework integrating STNs and attention mechanisms for improved prostate cancer classification [12]. Gavade et al. and Wu et al. also highlighted the use of advanced AI models for improved feature learning and classification accuracy [15], [16]. These architectures enhance model performance by focusing on important regions in medical images.

IV. CONCLUSION

This review highlights the significant advancements in Artificial Intelligence (AI)-based techniques for prostate cancer diagnosis using MRI data. A wide range of methodologies, including machine learning, deep learning, hybrid models, and ensemble approaches, have been explored to improve detection, classification, grading, and segmentation of prostate cancer. Among these, deep learning models, particularly Convolutional Neural Networks and advanced architectures such as EfficientNet and Vision Transformers, have demonstrated superior performance due to their ability to automatically extract complex features from imaging data. Additionally, hybrid and multimodal approaches that integrate clinical information with MRI data have shown improved diagnostic accuracy and robustness. However, several challenges persist, including limited dataset diversity, lack of model interpretability, data imbalance, and insufficient real-world clinical validation. Addressing these limitations is crucial for the successful deployment of AI systems in clinical practice. Future work should focus on developing standardized, interpretable, and clinically validated multimodal AI frameworks that integrate imaging, clinical, and pathological data for real-time, accurate, and personalized prostate cancer diagnosis.

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