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REVIEW ARTICLE

# A survey of artificial intelligence/machine learning-based trends for prostate cancer analysis

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## Abstract
Different types of cancer are more commonly encountered recently. This may be attributed to a variety of reasons, including heredity, changes in the living conditions (food, drinks, pollution, etc.), advancement in technology which allowed for better diagnosis of diseases, among others. Prostate one of the main types of cancers witnessed in males; it has indeed been identified as the second type cancer leading to death in males. Accordingly, it has received considerable attention from the research community where computer scientists and data analysts are closely collaborating with pathologists to develop automated techniques and tools capable of classifying and identifying cancerous cases with high accuracy. These efforts are described in the literature in a large number of research articles which makes it hard and time consuming for researchers to grasp the current state of the art. Instead, review articles form a valuable source for researchers who are interesting in coping with the developments in the field. Generally, the literature includes several survey papers on prostate cancer; each of them tackles some aspect of the domain up to the time when the survey was prepared. Hence the need for the survey described in this paper which highlights the scope of each of the previous survey papers encountered in the literature and adds upon the latest developments in the field as described in more recent papers published mainly in 2023 and 2024. The survey focuses on the main artificial intelligence and machine learning techniques for diagnosing prostate cancer based on various types of data, including MRI. The most recent techniques employed in analyzing prostate cancer data, the various types of data, the available datasets, the reported results, etc. are all covered. This will help researchers in their efforts to keep track of the recent developments in the field and to realize the challenges which need more attention along the path towards developing robust and effect decision support systems for pathologists to have higher self confidence in handling their patients.

**Keywords** Prostate cancer · Machine learning · Deep learning · Data analysis · Image analysis

## 1 Introduction

Prostate is part of the male reproductive system including prostate, seminal vesicles, penis, and testicles, and the uncontrolled cell growth starting at the prostate region can generate tumors (CDC 2024). Figure 1a shows the anatomy of prostate and Fig. 1b shows sample anatomy of malignant tumors in prostate forming Prostate Cancer (PCa) (VectorStock 2024; CUCBC 2024). Tumors can be benign or malignant where a benign tumor can grow but does not spread and a malignant or cancerous tumor can grow and spread into other organs. The malignant tumors can be cancerous, and if not detected and treated in time, it can lead to death. A list of abbreviations used in this paper is given in Table 1.

PCa is the second leading cause of death in men due to the malignant tumor originated in the prostate. PCa is the most common cancer in males and approximately 1,414,259

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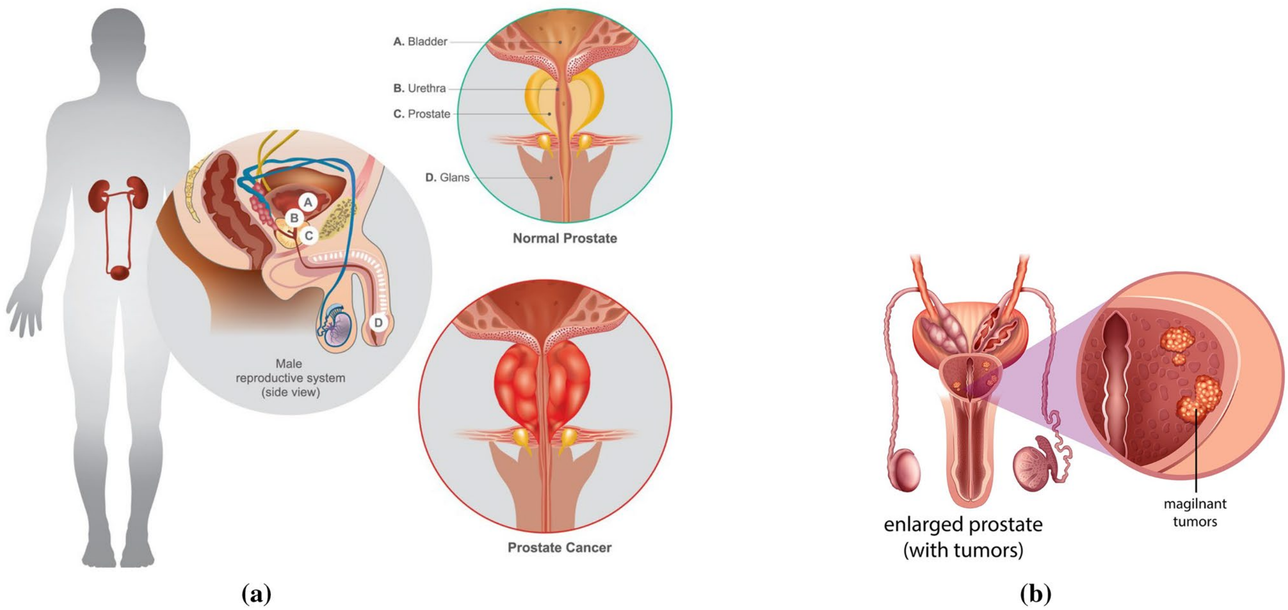


**Fig. 1** Left: Male anatomy of prostate (VectorStock 2024). Right: Anatomy of prostate cancer (CUCBC 2024)

**Table 1** A list of abbreviations used in the paper

| | |
|---|---|
| Prostate cancer | PCa |
| Digital rectal exam | DRE |
| Prostate-specific antigen | PSA |
| Computed tomography | CTs |
| Magnetic resonance imaging | MRIs |
| Machine learning | ML |
| Deep learning | DL |
| Transfer learning | TL |
| Computer aided-diagnosis | CAD |
| T1 weighted MRI | T1W MRI |
| T2 weighted MRI | T2W MRI |
| Diffusion weighted MRI | DW MRI |
| Multi-parameter transfer learning | MPTL |
| Region proposal network | RPN |
| Deep multi-scale attention 3D-V-net | DMSA-V-Net |
| Convolutional neural network | CNN |

males were diagnosed with PCa in 2020 (Cancer.Net 2021). Males aging 65 or older are generally diagnosed with PCa, and the risk is higher in older males. Although males from any age or ethnicity can be affected by PCa, statistics show African-American males and males with family history of PCa are at comparatively higher risk (Berenguer et al. 2023).

Various types of tests are done to diagnose PCa. Digital rectal exam (DRE), prostate-specific antigen (PSA) tests, Gleason score test, medical imaging like X-rays, ultrasounds, Computed tomography (CTs), Magnetic resonance imaging (MRIs), pathological images, etc. are gaining popularity for PCa detection and diagnosis. The results of these tests help to identify tumors and the severity of PCa (i.e., stage and grade). There are four stages of PCa according to the location, spread, and severity of the disease. Stage I PCa involves slowly growing tumor located in one-half of one side of the prostate with low PSA levels, whereas stage II PCa patients have larger tumor with higher risk of growing and the PSA levels are low to medium. Growing tumors with high PSA levels belong to stage III, and tumors which spread to other organs are in stage IV. Gleason scores are assigned based on the similarity between the tumor and healthy tissues and are commonly used for PCa grading and graded between 6 and 10, where 6 is the lowest Gleason score and represents low grade PCa, 7 represents medium grade PCa, and 8, 9, 10 show high grade PCa (Cancer.Net 2021).

Medical imaging is another major diagnosis method for PCa diagnosis and different types of imaging provide different perspectives on the tumors (Schlemmer et al. 2021). Medical imaging are used to detect tumors or lesions from the prostate region. Figure 2 shows some sample different modalities MRIs with tumor annotation for three PCa patients (Saha et al. 2021), and Fig. 3 shows sample pathology images of normal prostate tissue and PCa tissue (Linkon et al. 2021). PCa analysis from medical images consists of few major tasks - i) PCa detection (i.e., detecting or identifying if the patient has PCa or not), ii) PCa segmentation (i.e., tumor region extraction from medical images for PCa patients), iii) PCa classification (i.e., classifying type, severity, and other characteristics from medical images of PCa patients), iv) Patient monitoring (i.e., checking for recurrence of PCa in patients and

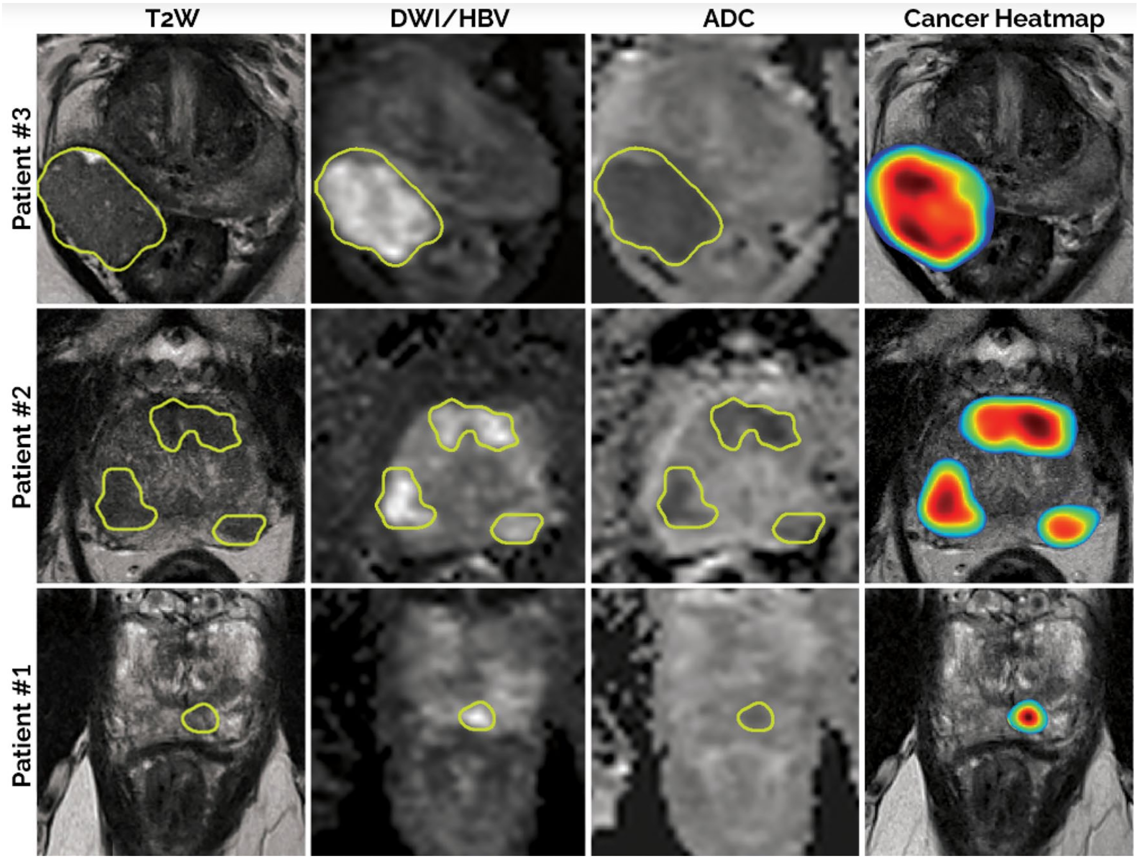


**Fig. 2** Sample MRIs of PCa (Saha et al. 2021)

their regular state), v) Treatment decision (i.e., deciding possible treatment choices for PCa patients based on their medical image analysis), and vi) Prognostics (i.e., survival predictions and analysis of PCa patients) (Padhani et al. 2023; Sekhoacha et al. 2022).

The objective of this paper is to provide a coverage of the existing research efforts on PCa analysis focusing on various studies which deals with medical images based discovery. It includes some recent reviews on PCa analysis, some novel approaches used with various machine learning (ML) and deep learning (DL) models, the popular publicly available datasets for PCa research, etc. The paper also summarizes the current challenges and possible future scopes for automated PCa analysis systems. This serves a need for researchers to keep track of the development in the literature over time under one umbrella instead of having it scattered and requires tremendous effort to thoroughly cover. We searched for publication from 2020 to 2024 in 'PubMed' (PubMed 2024) and 'Google Scholar' (GoogleScholar 2024) with keywords 'prostate cancer', 'prostate cancer analysis', 'prostate cancer medical image analysis', 'PCa detection from medical images', 'PCa segmentation from medical images', and 'PCa classification from medical images'.

The rest of this paper is outlined as follows. The main part of the work is included in Sect. 2 which consists of a number of important subsections. Section 2.1 covers existing review articles from the literaure. Section 2.2 includes the research works on PCa analysis with summaries of some existing works on PCa, including some relevant existing surveys, as well as ML, DL, and hybrid methods, respectively. Section 2.3 mentions some benchmark datasets for PCa analysis with their sources. Section 2.4 includes the performance metrics used in PCa image analysis. Section 3 discusses the scope of research, challenges of PCa analysis, and concludes the paper.

## 2 Methods

This survey was conducted to complement existing surveys as described in the literature. We selected research papers not covered by other surveys, but we felt relevant for researchers interested in utilizing AI, ML and DL techniques for analyzing prostate cancer data. We start by covering some of the completed surveys to help the reader in better understanding the state-of-the-art in the field.

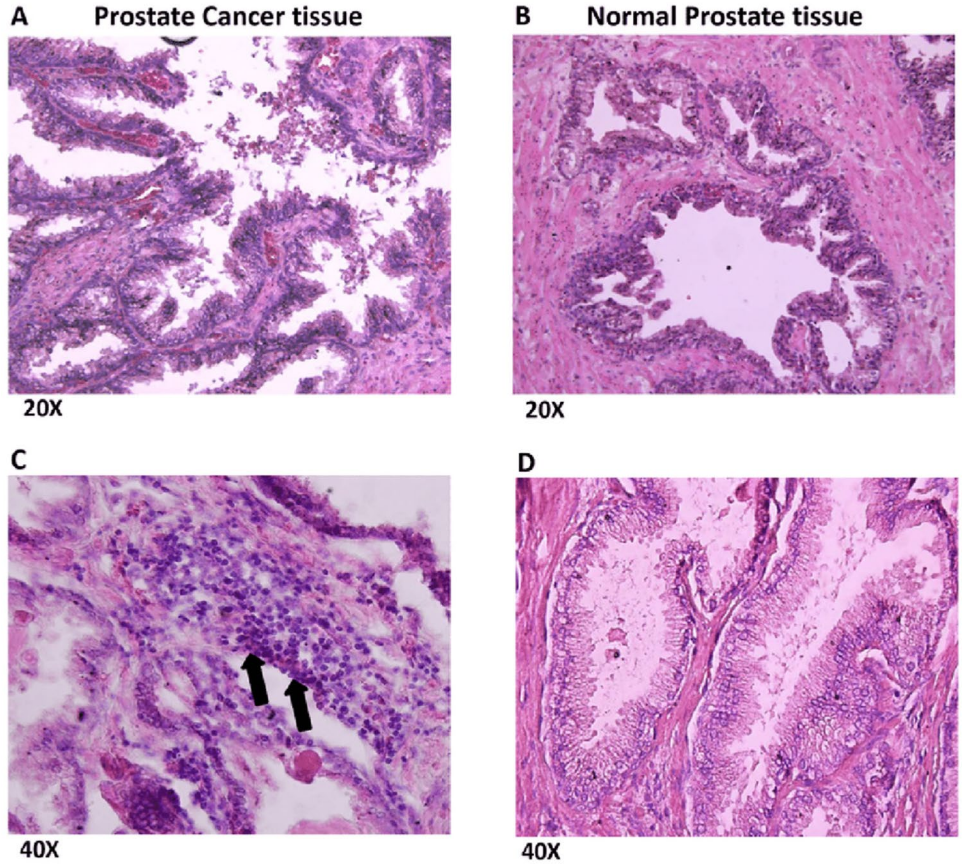


**Fig. 3** Sample pathology images of nomal prostate tissue and PCa tissue (Linkon et al. 2021)

Then, we identified and included in this survey some of the major contributions described in the literature and not covered by the existing surveys. we mainly focused on the recent works whi employed AI, ML and DL techniques for PCa diagnosis. The papers included in this survey were selected by the authors after careful review of the relevant publications retrieved from Google Scholar and PubMed. All the authors agreed on the inclusion of the covered papers.

Aligned with the advance in the imaging technology and the associated computing domain, researchers have demonstrated considerable interest in exploring medical image analysis for prostate cancer detection, segmentation, severity analysis. In this regard, a variety of artificial Intelligence models including ML and DL methods have been applied to medical image analysis for knowledge discovery as part of decision support systems to guide domain experts and increase their self confidence. Some researchers worked on summarizing the existing literature and produced valuable survey articles. In this section, we included few recent reviews or survey papers to show the current state of the research, and then we cover some of the recent novel research works with their contributions, data and results. We classify the works covered based on their similarities and comparison of their results.

## 2.1 Survey/review articles

In this section, we present a brief overview of some of the completed relevant surveys starting from the most recent ones.

Islam et al. (2024) conducted a survey which covered the usage of deep DL techniques, e.g.,, VGG16, VGG19, ResNet50, and ResNet50V2 for feature extraction and random forest for classification of MRI for PCa. They reported that ResNet50 outperformed the other models. They cited 25 references of which only 5 references are from 2023 and none of the references are from 2024 though the article was submitted in March 2024 and was published in May 2024.

Chu et al. (2023) provided a generalized review on PCa analysis using medical images like MRI, ultrasound, histopathology images, etc. The authors included in their survey research articles published until early 2023 by focusing on efforts which used AI-based analysis for different steps in the diagnosis of PCa patients; out of their list of references, only 7 articles were published in 2022 and none were published in 2023. They discussed various ML and DL models used for radiomics and gleason score analysis to detect clinically significant PCa data, and they compared the data for risk analysis. They described the differences between ultrasound data and different modality MRIs, and how pathomics uses tissue sample images in AI analysis. Surgical and radiation based treatment decision making were also discussed with AI-based prognosis analysis, including survival predication and recurrence prediction.

Another diagnosis based review was conducted by He et al. (2023). The authors focused on DL based MRI analysis for PCa patients. From 196 references cited in their paper, only 10 were published in 2023. The authors discussed two types of computer aided-diagnosis (CAD) systems - CADe for detection and CADx for diagnosis. After discussing the basics of AI, ML, DL, CNNs, they described the whole DLA step by step for MRI-based PCa detection and diagnosis, the performance metrics, etc. Then, they summarized recent DL based detection, classification and segmentation researches, and how DLA can be used in radiotherapy decisions and prognostic assessments. They concluded with few common limitations of DL models that affected the accuracy of PCa CAD systems.

A systematic review of 41 prostate cancer MRI publications analysis from January 2017 to April 2022 was completed by Belue et al. (2022); out of these only 4 were published in 2022. They discussed and compared the clinical parameters of the datasets used in those 41 papers in detail. Both clinical and technical characteristics of the datasets, their implications and results were explained with the models applied for their analysis. Finally, they concluded by summarizing the limitations of their review and highlighted future scope of PCa image analysis.

Ghezzo et al. (2022) concentrated on qualitative radiomic analysis and summarized 76 PCa analysis research articles which were published until December 2020. They chose AI-based models which were used for PCa detection, clinical significance analysis, prediction of biochemical recurrence, prediction and management of radiation therapy, treatment monitoring, detection and prediction of metastases, and prediction of enlarged prostate from medical image analysis. They compared the datasets, methods, outcomes, critical settings, analysis and performances of these research articles; and they commented on the competitiveness of the models. The risk, metastases, and radiation prediction from medical images, like MRI were discussed in detail with the scope for improvements specified.

Eleven papers upto October 2020 on various ML and DL based models for PCa detection, classification and analysis were summarized by Suarez-Ibarrola et al. (2022); out of these only 4 articles were published in 2020. Most of the added researches detected and classified PCa by lesion detection from MRIs using popular ML and DL models; some others used histology images from biopsy for PCa analysis. Their features, validation methods, performance scores, and outputs were discussed and compared to analyze different AI models. They also discussed the ground truth annotation process and the validation process of benchmark datasets, and how they effect the detection and classification. They concluded with few generic limitations of AI models when applied on medical images, and few possible future scopes.

Khan et al. (2021) provided a brief review on MRIs segmentation based prostate analysis. The authors covered in their survey only 3 articles which were published in 2013. They included some basic information on prostate anatomy, prostate carcinoma, etc. They elaborated on the MRI techniques used for PCa analysis- T1 weighted (T1W MRI), T2 weighted (T2W MRI), diffusion weighted (DW MRI), apparent diffusion coefficient map (ADC map) used for post-biopsy bleeding detection, recognition of individual zones in prostate, and differentiation between healthy and unhealthy tissues. Then, they discussed image pre-processing methods like denoising, normalization, data augmentation to prepare the dataset for prostate and/or tumor segmentation. The segmentation processes were discussed with ML models like atlas-based segmentation and deformed model based segmentation. They also described DL models by explaining feature encoder based models, upsampling based models, resolution increment of feature based models, and regional proposal based models. The papers from 2005 to 2020 were compared based on their methods, datasets, pre-processing, and performance. The class imbalance issues of medical datasets were discussed thoroughly and 6 publicly available prostate MRI datasets were mentioned.

Ninety eight research articles which were published until February 2018 on early recurrent PCa detection from various medical images like CT, PET, MRI etc. were discussed by De Visschere et al. (2019); out of these references 18 were published in 2018. The study described the data collection process, inclusion criteria and imaging techniques. They compared all of those research articles based on the imaging type, output, aim and positivity rate of recurrence of PCa in patients. Then a qualitative analysis was done on the performance scores, ML models applied, and their implications. They also analyzed the diagnosis of recurrent PCa, treatment decisions based on medical images, and the validation of those choices.

Goldenberg et al. (2019) provided an AI-based PCa review paper for pathological images by concentrating on papers published until 2019. The authors cited 88 references out of which only 2 were published in 2019. They described AI, ML (supervised, unsupervised, reinforcement, handcrafted feature based, non handcrafted feature based) and DL explaining every step. Then they discussed the segmentation process and the steps of pathological PCa image segmentations using ML and DL models. They also covered treatment processes, like intervention, surgery, automatic diagnosis, monitoring and the role of ML in them. They described the genomic classifiers used in ML models for PCa diagnosis, and how these results can be fused with other patient data.

To sum up, we included in this paper some of the relevant review articles related to PCa research and which were published between 2018 and 2024. Table 2 summarizes all these efforts. In addition to the ones summarized in this section, many other research groups also worked on similar surveys on medical image based PCa analysis using various AI models and performed different comparisons to provide guidelines and scope for future researchers.

## 2.2 AI-based research articles

PCa medical image analysis is a research field which has been explored by researchers from different domains with various AI models. Researchers have been applying ML, DL, transfer learning (TL) and hybrid methods for data management, data pre-processing, abnormality detection, abnormal region segmentation, abnormal region classification, abnormality analysis, post-processing, and report generation (Rodrigues et al. 2023; Rouvière et al. 2023). Some researchers provided new novel ideas, whereas others replicated previous contributions or combined multiple perspectives to create hybrid models. In this section, we included some of the AI-based PCa analysis research efforts with their contributions and performance analysis. Tables 3, and 4 show the summaries of the aforementioned CNN and UNet-based research efforts for PCa analysis.

### 2.2.1 Advanced DL based approaches

Singla et al. (2023) proposed a novel U-Net based model by incorporating transformers and CNNs on prostate MRI images in PROMISE-12 dataset. They discussed the U-Net based models used in medical image analysis for brain tumor, stroke lesions, prostate cancer, breast cancer, liver cancer, and nasopharyngeal cancer to provide a general overview of the efficiency of variations of U-Nets

**Table 2** Summary of related survey/review papers on prostate analysis

| Ref | Type | Timeline | Discussion | DataType |
|---|---|---|---|---|
| Chu et al. (2023) | Diagnosis | Upto 2023 | Radiomics<br>Clinical significance<br>Risk analysis<br>Treatment<br>Prognostics | Medical images |
| He et al. (2023) | Diagnosis | – | CAD systems<br>Detection<br>Classification<br>Segmentation<br>Radiotherapy<br>Prognostics | MRI |
| Belue et al. (2022) | Diagnosis | 2017–2022 | Clinical parameters<br>Technical parameters<br>ML models | MRI |
| Ghezzo et al. (2022) | PCa Management | Until 2020 | Detection<br>Prediction<br>Radiation therapy<br>Monitoring<br>Metastases detection<br>Metastases prediction | Medical images |
| Suarez-Ibarrola et al. (2022) | Diagnosis | Until 2020 | Detection<br>Classification<br>Comparisons<br>ML, DL models | MRI |
| Khan et al. (2021) | Segmentation | 2005–2020 | Anatomy<br>MRIs<br>Pre-processing<br>ML & DL models | MRI |
| De Visschere et al. (2019) | Early recurrence detection | Until 2018 | Recurrence prediction<br>Comparisons<br>Treatment decisions<br>Diagnosis | Medical images |
| Goldenberg et al. (2019) | Diagnosis | – | Detection<br>Segmentation<br>Classification<br>ML, DL models<br>Prognostics | Medical images |

**Table 3** Summary of related works on UNet-based prostate analysis

| Ref | Type | Approach | Performance | DataType |
|---|---|---|---|---|
| Mehmood et al. (2023) | Classification | CNN<br>TL<br>Efficient-Net | Acc: 88.89%<br>Prec: 91.67%<br>Rec: 88.00%<br>F1: 89.47% | MRI |
| Singh et al. (2023) | Detection<br>Segmentation | 3D CNN | Acc: 86.62%<br>Prec: 84.93%<br>Spec: 84.73%<br>Sen: 88.57%<br>F1: 86.71% | MRI |
| Li et al. (2023) | Detection<br>Segmentation | 3D MaskRCNN | Acc: 83.6%<br>Spec: 81.9%<br>Sen: 84.7%<br>AUC: 84.2%<br>DSC: 84.9% | MRI |
| Dai et al. (2023) | Detection<br>Segmentation | MaskRCNN | Acc: 94.7%<br>DSC: 60.4% | MRI |
| Singla et al. (2023) | Segmentation | Transformer-based U-Net | DSC: 80.0% | MRI |
| Li et al. (2023) | Segmentation | Attention-based multiscale learning | DSC: 84.39%<br>HD: 0.7732<br>CC: 0.9361<br>Jacc: 82.64% | MRI |
| Song et al. (2023) | Segmentation | DMSA-V-Net | DSC: 70%<br>Spec: 99%<br>Sen: 86%<br>Rec: 88.41% | MRI |
| Gavade et al. (2023) | Segmentation<br>Classification | U-Net<br>LSTM | Acc: 90.69%<br>Spec: 96.88%<br>Prec: 95.17%<br>Rec: 92.09%<br>F1: 92.09%<br>DSC: 67%<br>RoC: 0.953 | MRI |
| Pellicer-Valero et al. (2022) | Detection<br>Segmentation<br>Prediction | Retina U-Net<br>CNN | AUC: 75%<br>Spec: 88%<br>Sen: 71% | MRI |
| Adams et al. (2022) | Segmentation<br>Dataset generation | U-ResNet | DSC: 0.4 – 0.88 | MRI |
| Duran et al. (2022) | Segmentation | ProstAttention-Net<br>U-net | DSC: 87%<br>k: 0.120 | MRI |
| Chahal et al. (2022) | Segmentation | Unet<br>Xception net | DSC: 97.5% | MRI |
| Ye et al. (2022) | Segmentation<br>Classification | PSP-net<br>VGG-16 | Acc: 87.95%<br>Prec: 87.33%<br>Rec: 89.73%<br>AUC: 0.87<br>DSC: 91.3% | MRI |
| Hassan et al. (2022) | Classification | CNN<br>NN<br>GB<br>SVM<br>RF | Acc: 97% | MRI<br>Ultrasound |

in medical image analysis. Then, they proposed their transformer-based U-Net; transformer embeddings were used at the fifth level of the contracting path. The attention mechanism of the transformer was used for feature refinements while keeping the image scaling intact. The model was able to achieve around 0.80 dice score, improving the original U-Net dice score of 0.78 for PCa segmentation. Feature refinement with the transformers clearly

**Table 4** Summary of related works on CNN-based prostate analysis

| Ref | Type | Approach | Performance | DataType |
|---|---|---|---|---|
| Saha et al. (2021) | Detection | Ensemble<br>3D CNN<br>Attention | FP: 1.29 | MRI |
| Iqbal et al. (2021) | Detection | SVM<br>LSTM<br>ResNet | Acc: 100%<br>Spec: 100%<br>MCC: 100 | MRI |
| Chen et al. (2021) | Segmentation | 3D AlexNet | Acc: 92.1%<br>Spec: 89.6%<br>Sen: 90.2%<br>AUC: 96.4%<br>MAD: 0.356<br>HD: 1.024<br>DSC: 97.68 | MRI |
| Comelli et al. (2021) | Segmentation | ENet<br>UNet<br>ERFNet | DSC: 90%<br>Sen: 93%<br>PPV: 89% | MRI |
| Khosravi et al. (2021) | Classification | CNN | AUC: 0.89<br>k: 0.467 | MRI<br>Pathology |
| Aldoj et al. (2020) | Detection | 3D CNN | AUC: 91%<br>Spec: 90.5%<br>Sen: 81.2% | MRI |
| Abbasi et al. (2020) | Detection | CNN<br>DT<br>SVM<br>Bayes | AUC: 1.00<br>Spec: 100%<br>Sec: 100%<br>PPV: 100%<br>TA: 100% | MRI |
| Arif et al. (2020) | Detection<br>Segmentation | 3D CNN | AUC: 0.89<br>Spec: 76%<br>Sen: 92% | MRI |
| Khan et al. (2020) | Segmentation | FCN<br>SegNet<br>U-Net<br>DeepLabV3+ | DSC: 91% | MRI |

improved the performance of the original U-net for cancer region segmentation.

Singh et al. (2023) proposed a novel DL technique for PCa detection using a 3D convolutional neural network (CNN). They converted the 3D dicom MRIs from the PROSTATEx dataset into multiple 2D png images, and then applied data augmentation to increase the dataset size. The images were stacked and used as inputs in a 3D CNN model for lesion segmentation. They also applied Faster RCNN with Inception-Resnet-V2 transfer learning on the dataset for their experiments. Their model achieved 86.62% accuracy with around 85% or higher precision, specificity, sensitivity, and F1-score. Although the proposed model was simple and the performance was comparable to other DL models, the methodology and the contributions of the pathological data used in the proposed method were not clearly explained. A CNN based TL model was used in Mehmood et al. (2023) on PROSTATEx dataset for PCa MRI classification into low grade and high grade classes. The MRIs were pre-processed by reshaping and resizing them; they were divided into 3 modalities, namely ADC, T2w sagittal and t2w transaxial. Three EfficientNets were used for each modality, and then the features were combined to classify the MRIs. Each EfficientNet used TL to train the models, and the hyperparameter tuning method was applied to fine tune the output. The proposed Multi-Parameter Transfer Learning (MPTL) model outperformed similar VGG-16, GoogleNet, ResNet and inceptionV3 by achieving 88.89% classification accuracy, and 88–91% precision, recall and F1-score. As the proposed model was able to perform better than other state-of-the-art approaches, the transfer learning process needed more detailed explanation and step-by-step description.

A 3D maskRCNN was used in Li et al. (2023) for PCa detection and segmentation on 133 MRIs of their own collected dataset from Netherlands. They used 93 MRIs for training and 40 for testing their model. A 3D CNN model was used to extract features from the input MRIs for the region proposal network (RPN) to generate ROI anchor boxes. The features and RPN outputs were used for ROI alignment, and the 3D maskRCNN model used them to generate the detection and segmentation outputs. The performance metrics were evaluated for both detection and segmentation, and the proposed model was able to gain 83.6% classification accuracy and 84.2% AUC, whereas the segmentation achieved 84.9% dice score. Although the performance scores were high, the low amount of data used for training and testing showed the requirement for experimenting with larger datasets with proper data augmentation to generalize the outcomes of their proposed model. Another maskRCNN based PCa detection and segmentation was proposed in Dai et al. (2023). Data collected from 262 patients was divided into 3 cohorts, namely histology based delineation, MRI based delineation, and unlabeled cohort. After pre-processing the images, a non-local maskRCNN was applied to classify and segment the lesions from the images. The novel proposed model performed well compared to similar PCa detection and segmentation approaches with 94.7% detection accuracy and 60.4% segmentation dice score.

An attention-based DL model was proposed in Li et al. (2023) for PCa segmentation. They used data collected between 2013 and 2016 from 98 patients in Haikou People's Hospital of Central South University and the Affiliated Hospital of Xiangya Medical College. 2D slices were extracted from the 3D MRIs and then fed into the feature encoders. Attention blocks were used for feature learning and then decoders were used to generate the segmentation outputs. The proposed model was used for prostate segmentation and PCa segmentation separately, and the results were compared to U-Net, U-Net++, SE-Net, Dual attention, MS-Net and ConvLSTMs. The results showed comparable performances with 91.65% dice score for prostate segmentation and 84.39% dice score for prostate cancer segmentation. The visual segmentation representations also showed how precisely the proposed model was able to extract both prostate and cancerous regions.

Another attention based DL model, called Deep multi-scale attention 3D-V-net (DMSA-V-Net), was proposed in Song et al. (2023) for PCa lesion segmentation on PROSTATEx dataset. After pre-processing the data using dilation and linear interpolation, a 3D CNN encoder was used for feature extraction. Then spatial attention blocks were applied with upsampling and the decoder used the multiscale features with feature concatenations to generate the final segmentation outputs. The results showed that the spatial attention mechanism was able to improve the segmentation outputs and achieved 70% dice scores by outperforming four state-of-the-art DL models by 8% to 26%.

Gavade et al. (2023) proposed a DL model for PCa segmentation and classification of MRIs into cancerous or non-cancerous classes based on the I2CVB dataset. The dataset was divided into 90–10 ratio for training and validation. Then, they were resized, normalized and shuffled to pre-process and fed them into a U-Net for ROI segmentation. The segmented ROIs were then used as inputs to a Long Short Term Memory (LSTM) network for classifying the MRI into cancerous or non-cancerous classes. The proposed model outperformed similar U-nets, RNNs, and DNNs with 90.69% accuracy and 67% dice score. The proposed model was a good example of high performance hybrid model by combining two popular DL models using advantages of both.

A complete DL based approach to detect PCa, segment PCa lesion and predict Gleason scores from two MRI datasets IVO and PROSTATEx was proposed in Pellicer-Valero et al. (2022). A modified U-net called Retina U-Net CNN model was used to segment the lesions from the MRIs. The system was an end-to-end solution for the whole PCa analysis pipeline, but the paper did not provide the details of the methodologies in a consistent manner.

As described in Adams et al. (2022), a variation of the popular biomedical DL model U-Net, named U-ResNet was applied for prostate cancer segmentation from prostate MRI images. Although their major contribution was generating a benchmark dataset for prostate cancer called Prostate-158 containing 158 biparametric 3T prostate MRIs annotated by professionals for prostate cancer segmentation, they also applied two U-ResNet for segmentation. The contracting path used residual blocks in each level of U-net whereas the expansive path used transitional blocks in each level. The segmentation dice scores for the central gland, peripheral zone, and prostate cancer were between 0.87–0.88, 0.73–0.75, 0.4–0.6 for the Prostate-158 dataset, respectively. They also tested the models on two other datasets, namely Medical Segmentation Decathlon and PROSTATEx; they reported dice scores between 0.82–0.86 and 0.64–0.71 for the central gland and the peripheral zone.

An attention-based novel prostate and prostate lesion segmentation model was proposed in Duran et al. (2022). The PROSTATEx-2 dataset was used for the two-branch end-to-end multiclass U-Net based attention network with 5-fold cross-validation, where the first branch extracted the prostate region and the second branch used an attention based model to extract the lesions in the prostate region in MRIs. The first segmentation was a 2 class problem- prostate and background; and the second one was a 6 class problem with four additional Gleason score regions. The proposed model was compared to DeepLabv3+. E-Net, U-Net, and attention U-Net; the proposed mode outperformed the latter models with 0.418 k score and 87% dice score. The proposed model was another hybrid model example combining U-net and attention models to gain higher segmentation performance.

Chahal et al. (2022) proposed an U-net based Xception-Net for PCa segmentation from MRI data in PROMISE12 dataset. The 3D images were converted into 2D slices; and curvature flow and bias removal with three setups were used for pre-processing. Then, a modified U-net was used with a pre-trained Xception-Net as the encoder of U-Net. 12 separable convolution blocks were used in the encoder to extract semantic features from the MRI, and then fed into a bottleneck convolution block before sending them to the decoder. The proposed model had 97.5% dice score, outperforming VGG-19, FCN, CNN etc. The idea of using Xception-net as encoder to combine the spatial features improved the performance of the segmentation model compared to similar DL approaches.

Ye et al. (2022) proposed a PSP-Net+VGG-16 model for PCa detection and segmentation on their own collected PCa MRI dataset. They fed the input images into a PSP-Net after preprocessing them. The PSP-Net contained a ResNet models, a PPM structure and a FCN layer to segment the tumor region from the MRIs. Then, a modified pre-trained VGG-16 with two fully connected layers was used for the cancer vs. healthy MRI detection. The model achieved 87.95% classification accuracy. The proposed method was not completely explained step by step and the dice score computation result was not discussed or shown properly.

A fusion DL model was used in Hassan et al. (2022) for PCa classification from ultrasound and MRI data available from public datasets. They applied pre-trained MobileNetV2, ResNet50V2, ResNet101V2, ResNet152V2, Xception, VGG16, VGG19, InceptionRegNetV2, and InceptionV3 by replacing their last layer with a Dense layer. Then, the extracted features were fed into four ML models- Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB), and Nearest Neighbor (NN) to classify the image into cancer or healthy class. The classification accuracies for the fusion models varied between 60% to 99%, and the average classification accuracy achieved was 97.5%. The methodology was simple; it applied the DL and ML models with very basic structures, but including the justification for the proposed model could have clarified the process even further.

#### 2.2.2 CNN based approaches

Saha et al. (2021) proposed a PCa detection model by creating an ensemble of 3D CNN models on customized MRI datasets. The pre-processing steps normalized the images and generated patches from the 3D MRIs. Then, a dual attention U-Net used the whole volumes as inputs and a ResNet used the patches as input to localize the tumors; the features generated from both networks were combined to get the final cancer vs. healthy classification output. The models achieved 1.29% false positives. The ensemble CNN model performance scores could be more specific and consistent to similar research works. Another PCa detection model with SVM, LSTM and ResNet was proposed in Iqbal et al. (2021) on the POSTATE-MRI dataset. The models extracted both DL features with LSTM and ResNet-101 and conventional features like GLCM, morphological features and texture features from the pre-processed MRIs. Then an ensemble ML classifier with KNN, SVM, NB. RB, and DT used those features to train and test the classifiers to assign them into cancer or healthy classes. The proposed method achieved 100% accuracy, specificity and MCC scores for the combination of SVM and LSTM approaches. Although the model performed perfectly, the results needed to be verified with few other datasets and data division to ensure whether the performance score remained so high for every setup.

Aldoj et al. (2020) proposed a 3D CNN based PCa detection model on the PROSTATEx dataset. A simple 3D CNN with 12 convolution layers with skip connections, two fully connected layers and an output layer was used to predict lesions in MRIs. The proposed detection model achieved around 90% accuracy. Another PCa detection approach from MRI using CNN and ML hybrid model was proposed in Abbasi et al. (2020). A GoogleNet was used to extract features from the MRIs and classify them into prostate and Brachytherapy classes. They have also applied DT, SVM and Bayes classifiers to compare the GoogleNet outputs. Although the detection performances were 100%, the comparisons between a DL model and 3 ML models was not sufficient and the results needed more datasets implementations, discussion and justifications to be considered.

Arif et al. (2020) proposed a 3D CNN based PCa detection and segmentation model with MRI data. They implemented a study on 299 patients and divided them into 4 groups to analyze their data in time intervals. 3D CNN models were applied to detect and segment PCa from the data; the authors included an extensive statistical analysis. The work focused mostly on data collection and analysis as well as the detection and segmentation methodologies needed to be discussed with more specifications and explanations. An ensemble DL-based PCa segmentation model on MRI data was proposed in Khan et al. (2020). They applied FCN, SegNet, U-Net and DeepLabV3+ on the MRIs after they were resized, cropped and normalized. Data augmentation was done by patch extraction and all 4 DL models were applied separately on the pre-processed augmented data. Performance scores comparisons showed that the patch-wise DeepLabV3+ model performed better (dice score 91%) than the other three models, and hence was chosen for the final segmentation output.

Chen et al. (2021) proposed an improved 3D AlexNet for PCa segmentation from MRI on the collected data at the Second Affiliated Hospital of Zhejiang Chinese Medical University. AlexNet based on ResNet with PReLu activation function was used to improve the accuracy of the model. The input images were flipped and noise was added to them to increase the dataset size for data augmentation. Then 3D AlexNet was trained and tested and the results were compared with Inception-V4 and ResNet50 to validate the output. The proposed model gained 97.68% dice score, outperforming the other two models by 3% and 4%, respectively.

The model can be improved by updating the parameters to decrease the execution time of the proposed model. Another segmentation from the MRI dataset using three CNN models (ENet, U-Net, and ERFNet) was proposed in Comelli et al. (2021) on a customized dataset of their own. They preprocessed the images with resizing and data augmentation and then trained the DL models for 100 epochs with 5 fold cross-validation. The models were compared to each other; the ENet and U-Net gained high dice scores (i.e., around 90%); and ERFNet performed slightly worse with 87% dice score.

The main idea of the work described in Comelli et al. (2021) was applying different DL models for prostate segmentation and comparing their performance to choose the best model. However, applying the model on only one dataset limited the possibility of generalizing the decision on the DL model choice. Khosravi et al. (2021) worked on a CNN based classifier for PCa detection by using both MRI and pathology data from PROSTATEx, PROSTATE-MRI, PROSTATE-DIAGNOSIS, and TCGA-PRAD datasets. One CNN was used to classify the images as benign or cancer, and a second CNN was used to classify the cancerous ones as low grade or high grade cancer. They developed an automated UI and applied full statistical analysis on the data and the outputs; they discussed the various use cases or scenarios on the data and their classifications.

### 2.3 The Datasets

PCa analysis requires various types of datasets for model training, testing and validation. There are various publicly available datasets containing different types of medical data. Some datasets have clinical data, some have patient data, and some include medical images like prostate MRI, CT, PET, ultrasound, X-ray, pathology data like tissue images, etc. (Hulsen et al. 2019; Sunoqrot et al. 2022).

In this paper, we covered the PCa image datasets which are publicly available at different sources. Table 5 shows some popular publicly available datasets for image-based PCa analysis, their data types, and sources. These datasets have the images, their annotations/labels, ground truth images, and other relevant information in different formats. These datasets have been used by most researchers as described in the literature and highlighted in this paper.

### 2.4 Performance metrics used in testing

As described in the literature, PCa detection, segmentation, and classification tasks have been implemented using various ML, DL, TL and hybrid methods. Various performance metrics have been used for computing the performance scores of the implemented models to evaluate and validate the experimental processes. The most commonly used performance metrics for PCa analysis tasks are accuracy, precision, sensitivity, specificity, F1-score, and dice score (Müller et al. 2022; Mehmood et al. 2023; He et al. 2023). The metrics are defined with respect to the confusion matrix as follows.

According to the confusion matrix in Fig. 4,

*TP = Number of correctly predicted 'Positive'*

*FP = Number of incorrectly predicted 'Positive'*

*TN = Number of correctly predicted 'Negative'*

*FN = Number of incorrectly predicted 'Negative'*

Accuracy defines the ratio of correctly predicted positives and negatives with respect to the total sample set and computed with Eq. 1. Precision or positive predictive value (PPV) represents the ratio of relevant positive among all true

**Table 5** Summary of some publicly available datasets

| Ref | Dataset | DataType | Source |
|---|---|---|---|
| Adams et al. (2022) | Prostate-158 | MRI | https://prostate158.grand-challenge.org/ |
| LitjensG et al. (2014) | PROMISE12 | MRI | https://promise12.grand-challenge.org/ |
| PROSTATEx (2017) | PROSTATEx | MRI | https://www.cancerimagingarchive.net/collection/prostatex/ |
| Lemaître et al. (2015) | I2CVB | MRI | https://i2cvb.github.io/ |
| Litjens et al. (2015) | Prostate-3T | MRI | https://www.cancerimagingarchive.net/collection/prostate-3t/ |
| Bloch et al. (2015) | PROSTATE-DIAGNOSIS | MRI | https://www.cancerimagingarchive.net/collection/prostate-diagnosis/ |
| prostatemri (2021) | Prostate MR | MRI | https://prostatemrimagedatabase.com/ |
| Xie et al. (2022) | PCa_Bx_3Dpathology | Pathology | https://www.cancerimagingarchive.net/collection/pca_bx_3dpathology/ |
| Wilkinson et al. (2021) | NADT-Prostate | Pathology | https://www.cancerimagingarchive.net/collection/nadt-prostate/ |
| Bulten et al. (2022) | PANDA | Pathology | https://panda.grand-challenge.org/ |
| Choyke et al. (2016) | PROSTATE-MRI | MRI, Pathology | https://www.cancerimagingarchive.net/collection/prostate-mri/ |
| Zuley et al. (2016) | TCGA-PRAD | MRI, Pathology, CT, PT | https://www.cancerimagingarchive.net/collection/tcga-prad/ |
| Natarajan et al. (2020) | Prostate-MRI-US-Biopsy | MRI, Ultrasound | https://www.cancerimagingarchive.net/collection/prostate-mri-us-biopsy/ |

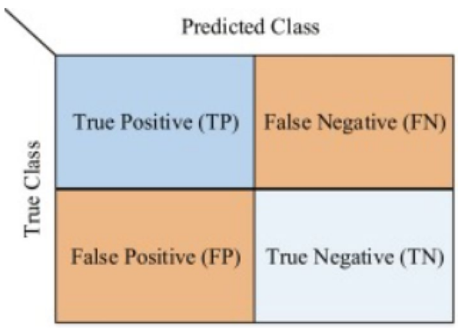


**Fig. 4** Confusion matrix (ScienceDirect 2024)

and predicted positive as shown in Eq. 2. Sensitivity or recall shows the true positive rate (TPR) whereas specificity shows the true negative rate (TNR) as mentioned in Eqs. 3 and 4 respectively. The F1-score is the harmonic mean of precision and recall shown in Eq. 5.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision = PPV = \frac{TP}{TP + FP} \tag{2}$$

$$Sensitivity/Recall = TPR = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = TNR = \frac{TN}{TN + FP} \tag{4}$$

$$F - 1\ score = \frac{2\ .\ PPV\ .\ TPR}{PPV + TPR} \tag{5}$$

The segmentation performance is measured based on the dice coefficient (DSC) representing the similarities between two images. Let, $A$ be the output image and $B$ be the ground truth. The dice score to represent the similarities between $A$ and $B$ is computed using Eq. 6. The DSC can also be represented using confusion matrix components as in Eq. 7.

$$DSC(A, B) = \frac{2|A \cap B|}{|A| + |B|} \tag{6}$$

$$DSC(A, B) = \frac{2TP}{2TP + FP + FN} \tag{7}$$

## 3 Challenges & conclusion

PCa is the second most severe cancer in male population and can lead to death if not diagnosed early. Various researchers from different fields have been trying to escalate the early detection and diagnosis of PCa patients to reduce the risks. This involves complete and accurate analysis of patient data. Current research efforts described in the literature clearly demonstrate how AI, ML TL, and DL techniques can help healthcare professionals in data analysis by an automated process which leads to decision support systems which increase self-confidence of domain experts and raise the accuracy of the diagnosis. Although some researchers worked with some ML models, most of the recent researchers have been working with DL, TL and hybrid models achieving high performance scores. Most recent novel approaches are built on some existing DL models and some modifications and/or combinations of models are applied to improve the output. Developing automated systems to assist healthcare professionals to analyze the data with AI-based models to get precise detection and diagnosis can enhance the experiences of both patients and medical professionals while creating a digital healthcare assistance system to improve the overall diagnosis of PCa.

Although the existing literature on PCa analysis covered some major research questions and researchers are still trying to minimize the research gaps, there are some major challenges to the PCa medical image analysis that require proper contributions (Turkbey et al. 2022). In other words, researchers interested in diving further in the discovery of PCa for effective diagnosis and treatment plans may consider the following suggested future research directions.

- With the development of a vast range of data capturing facilities, it will be highly attractive to employ multiple data sources in the research and development. This would not be effective without standardization of data and acquisition protocols, handling imbalanced data by employing appropriate augmentation methods, and considering different modalities.
- The amount of publicly available datasets is quite low and the existing datasets have very small number of medical images in them which makes it difficult to train complex DL models. The validation of data labels or annotations is another challenge. Due to the lack of proper annotation and ground truth, using the datasets for supervised models or computing their performance scores appropriately can be a difficult task.
- The inconsistencies between the datasets is another challenge. Different datasets have different image formats like dicom, png, nifti, etc., and they may be found

in various sizes and dimensions. These make it difficult to apply generic approaches to multiple datasets without applying extensive pre-processing to unify the data.

- Given the current heterogeneous nature of the communities due to ease of immigration and relocation, it would be visibly beneficial to consider personal, ethnical and environmental aspects and their effects on PCa patients. This may be captured by running surveys and closely watching patients at risk.
- Employing an ensemble model which integrates a variety of useful AI, ML, DL, TL, etc. techniques may lead to a more robust system with high accuracy and confidence. Developing such systems though challenging may lead to preventive a preventive approach by comprehensively analyzing multiple sources of data to investigate the causes instead of focusing on diagnosing and treating encountered cases.
- Developing complete end-to-end automated solutions for Pca detection, lesion segmentation, severity classification, and complete report generation is another major challenge. There are few research efforts on detection and segmentation separately and combined. However, there still exists the need for a complete system that can use all patient data and apply a complete analysis on every task related to PCa analysis, and finally produce a comprehensive result.

The gain from tackling these challenges will mostly lead to more robust systems with high confidence in the resulting diagnosis and prediction. However, it is essential to apply appropriate preprocessing steps to clean and prepare the data in a way that would guarantee achieving unbiased results.

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