Recent Developments in Artificial Intelligence-Based Techniques for Prostate Cancer Detection: A Scoping Review

Uzair SHAH, Md. Rafuıl BISWAS, Mahmood Saleh ALZUBAIDI, Hazrat ALP, Tanvir ALAM, Mowafa HOUSE and Zubair SHAH, 1

Abstract. Artificial intelligence (AI) techniques can contribute to the early diagnosis of prostate cancer. Recently, there has been a sharp increase in the literature on AI techniques for prostate cancer diagnosis. This review article presents a summary of the AI methods that detect and diagnose prostate cancer using different medical imaging modalities. Following the PRISMA-ScR principle, this review covers 69 studies selected from 1441 searched papers published in the last three years. The application of AI methods reported in these articles can be divided into three broad categories: diagnosis, grading, and segmentation of tissues that have prostate cancer. Most of the AI methods leveraged convolutional neural networks (CNNs) due to their ability to extract complex features. Some studies also reported traditional machine learning methods, such as support vector machines (SVM), decision trees for classification, LASSO, and Ridge regression methods for features extraction. We believe that the implementation of AI-based tools will support clinicians to provide better diagnosis plans for prostate cancer.

Keywords. Prostate cancer, medical imaging, machine learning, deep learning.

1. Introduction

After lung cancer, prostate cancer is the second most common cancer in men [1]. Reports have projected that the number of prostate cancer cases may exceed the number of lung cancer cases in men in just over a decade [1], [2]. However, early diagnosis of prostate cancer can decrease the fatality and morbidity rates. In clinical practice, the diagnosis is typically performed by a transrectal ultrasound and blood tests for prostate-specific antigens [3]. Usually, the severity of prostate cancer is measured in terms of Gleason score (ranked from 6 to 10), with a higher score representing high-grade cancer that is more likely to spread in the tissue [4], [5]. Analyzing and grading prostate cancer scores require trained professionals, who usually rank the scores through manual screening and mutual consensus of many experts relying on their skills.

The AI research community has made progress in developing AI-based methods to support pathologists and radiologists, thus improving the overall efficiency of the process of diagnosing prostate cancer [6]. Typically, AI-based methods can enable quick...
processing and accelerate the diagnosis process while ensuring consistency [7]. In prostate cancer, AI assists in systematic pathological grading to evaluate prostate cancer stratification and care [8]. While many published methods exist proposing the use of AI to diagnose prostate cancer, there are few comprehensive review that may provide a quick insight to readers exploring the recent developments in AI’s use for studying prostate cancer. This short review will serve as a quick reference for readers interested in studying and researching the role of AI methods in treating prostate cancer.

2. Methods

We performed a scoping review to highlight the advancements of AI-based tools detecting prostate cancer. We followed the guidelines from the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA-ScR) [9] to perform the review (Appendix 1). The search strategy, which included population (i.e., prostate cancer), target intervention (i.e., artificial intelligence), and target outcome (i.e., diagnosis), was applied to the most widely used databases (PubMed, Medline, Embase, and Google Scholar) in the medical domain. The search process was carried between February 10th and 14th, 2021 and extracted relevant articles published over the last three years covering the most recent publications in this domain.

3. Results and Discussion

A total of 1476 studies were retrieved by searching four databases (details in Appendix 4). Amongst these, 574 duplicate studies were excluded. Through title and abstract screening, 767 studies were excluded following the exclusion criterion of being non-English studies, non-peer-reviewed articles, or scoping review text. Through full-text screening of the remaining 135 studies, 66 studies were further removed following the exclusion criteria. A total of 69 studies were included in this review. The key characteristics of the articles surveyed are summarized in Table 1.

| Characteristics                          | Number of Studies |
|------------------------------------------|-------------------|
| Model purpose                           | Diagnosis of prostate: 43 | Grading prostate: 15 | Segmentation: 1 |
| AI Branches                              | Deep Learning: 49 | Machine Learning and Deep Learning: 2 | Segmentation: 1 |
| AI method                                | CNN: 45 | ANN: 4 | SVM: 4 | Random Forest: 3 | Logistic Regression: 2 |
| Feature Extraction Technique             | CNN: 45 | LB-FCN light: 1 | DCE: 1 | Genetic Algorithm: 1 |
| Imaging modality                         | MRI/PET/CT: 34 | Biopsy whole slide images: 13 | Tissue Microarrays: 6 | Histopathological data: 04 |

Index: ANN: Artificial Neural Network. CSLBP: completed and statistical local binary pattern. CFS: Correlation Feature Selection. DCE: Dynamic contrast-enhanced. SFIT: Scale-invariant feature transforms. EFDS: Elliptic Fourier Descriptors. CDF: Cumulative Distribution Function. ADC: Apparent Diffusion Coefficient. FCC: Frequency Cepstral Coefficients. MRI: Magnetic Resonance Imaging. PET: Positron Emission Tomography. CT: Computed Tomography
Out of these 69 studies, 94% (n=65) were peer-reviewed journal articles, while the remaining were conference papers. Of these, 20% (n=12) were published in 2018, 39% (n=26) in 2019, and 36% (n=25) in 2020. The highest number of studies were published from the United States (n=16), followed by China (n=11) and Canada (n=8) (Appendix 2).

For the majority of the studies, the data was acquired from public repositories such as the ProstateX challenge dataset, PRMISE-12 dataset, and NCBI. The most dominant imaging modalities were magnetic resonance imaging (MRI), positron emission tomography (PET) scan, and computerized tomography (CT) scan. The datasets’ descriptions are summarized in Table 2.

| Dataset | Host/Source | Type of data | Size (No. of samples) | Studies that reported the use (listed in Appendix 3) |
|---------|-------------|--------------|-----------------------|---------------------------------------------------|
| Public Dataset | clinicaltrials.gov (NIH) | PET/MRI | 122 | 42 |
| | Registry of Catastrophic Illness Patient (subpart NIH) | Electronic Health Record (EHR) | 20355 | 62 |
| | Harvard Medical School and Brigham woman's hospital | MRI | 682 | 52 |
| | GLOBOCAN 2018 | Ultrasound | 1200 | 48 |
| | ProstateX challenge data | mp-MRI | 538 | 50, 20, 38 |
| | National Centre of Biotechnology (NCBI) | Genetic dataset | 179 | 25, 67 |
| | MICCAI Prostate MR Image Segmentation 2012 | MRI | 4050 | 32, 70 |
| | ProstateGlandDB dataset | Biopsy whole slides images | 35 | 13, 64 |
| | Horosproject.org | PET Images | 7336 | 71 |
| | NCI-ISBI 2013 challenge | MRI | 771 | 5 |
| Private Datasets | Boramse Medical Center | EHR | 3791 | 40 |
| | The University of Alabama at Birmingham (UAB) | MRI Scan | 1269 | 22 |
| | Univ. of Texas Southwestern Medical Center | CT scan | 85 | 19 |

Features extraction techniques were reported in 58 studies. Most of the included studies used CNN (n=45, listed as 3, 5, 6, 7, 9, 10 – 12, 14, 15, 18, 20 – 22, 24, 25, 28, 33 – 37, 39, 42, 43, 45 – 49, 50, 53, 55, 57, 58, 60 – 64, 66 – 70 in Appendix 3) followed by radiomics (n=4, listed as 30, 31, 38, 41 in Appendix 3) and LASSO (n=2, listed as 4, 44 in Appendix 3). Other reported methods for feature extractions were gray level co-occurrence matrix (54 in Appendix 3), mean region of interest (71 in Appendix 3), genetic algorithms (13 in Appendix 3), completed and statistical local binary pattern (52 in Appendix 3), apparent diffusion coefficient and cumulative distribution function (19 in Appendix 3), frequency cepstral coefficient (26 in Appendix 3), and correlation features selection algorithm (32 in Appendix 3).

It is challenging to compare the performance of the studies as each study utilized different feature extraction techniques, imaging modality and performance metrics. However, CNN were the prominent feature extraction techniques regardless of the imaging modality [10]. This may be in part because CNN is sensitive to the training data compared to radiomics and usually requires large data for better performance.
4. Conclusion and Future Direction

This review article identifies three main themes on prostate cancer detection, i.e., diagnosis, grading, and segmentation of histopathological images where AI-based methods were leveraged. We could not find significant application of the AI-based methods for the treatment and recommended medications for prostate cancer. The studies were categorized based on the usage of the AI methods, feature extraction techniques, and types of the dataset used. The use of these AI techniques is limited to academic and research purposes only and their real-life applications into clinical practice are currently limited – though a few cases are available where the AI-based tools have been used in clinical practices. Nevertheless, with the rapid progress of AI, technology readiness levels need to be improved for utilizing these methods in real-life diagnosis of prostate cancer.

The appendix is available at https://github.com/hazratali/appendix

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