Multiparametric Magnetic Resonance Imaging in Detection Prostate Cancer

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Prostate cancer is the second leading cause of cancer-related death in men. Its early and correct diagnosis is of particular importance to controlling and preventing the disease from spreading to other tissues. Multiparametric magnetic resonance imaging (mp-MRI) is recognised as the combination of conventional anatomical MRI and at least two functional magnet resonance sequences: diffusion-weighted imaging (DWI), dynamic contrast-enhanced MRI (DCE-MRI), and, optionally, MR spectroscopy (MRS).

prostate cancer multiparametric MRI machine learning

1. Introduction

Prostate cancer (PCa) is the most common cancer in men and the second leading cause of cancer-related death in them [1][2][3]. Various methods are used for PCa screening, though these methods are invasive or have low accuracies, such as digital rectal examination, prostate-specific antigen (PSA) tests, and transrectal ultrasound (TRUS)-guided prostate biopsy [4][5][6][7]. New biomarkers, named 8-hydroxy-2-deoxyguanosine (8-OHdG) and 8-iso-prostaglandin F2α (8-IsoF2α), have been reported. Increased levels of these biomarkers indicate prostate cancer in the patient and they are measured through urine tests. Of course, validating these urinary biomarkers in relation to prostate cancer still requires significant research [8]. Meanwhile, prostate MRI plays a crucial role before a biopsy in patients with raised PSA. Multiparametric magnetic resonance imaging (mp-MRI) is a commonly used imaging procedure for diagnosing PCa. Mp-MRI is recognised as the combination of conventional anatomical MRI and at least two functional magnet resonance sequences: diffusion-weighted imaging (DWI), dynamic contrast-enhanced MRI (DCE-MRI), and, optionally, MR spectroscopy (MRS) [9][10]. Various studies have noted that mp-MRI has good accuracy for diagnosing or determining the grade of prostate cancer [11][12]. Of course, it is more challenging to determine the aggressiveness of cancer using MRI than when it is detected by a physician with good reliability. Recently, various studies have used artificial intelligence and MRI images to diagnose or assess the characterization and severity of cancers, including prostate cancer, to reduce human error, increase the speed of diagnosis and classification, and improve overall efficiency and accuracy [13][14][15]. Indeed, artificial intelligence is beneficial in acquiring important clinical information that can help physicians to provide key and critical opinions about clinical prognosis, diagnosing diseases, and treatment outcomes [16][17].

Artificial Intelligence (AI) describes the capability of a computer to model intelligent behaviour, with minimal human intervention, and to reach a certain goal based on provided data. AI has multiple branches. One of these branches is machine learning (ML). ML describes algorithms used to incorporate intelligence into machines by automatically learning from data [16][18]. There are different types of ML. In general, ML types are branched into four groups: Unsupervised learning, Semi-supervised learning, Supervised learning, and Reinforcement learning [19][20][21]. In Supervised learning, an observer provides data to the machine and labels the data types. Input and output are specified and the machine attempts to learn a pattern from the input to the expected output [22][23]. In unsupervised learning, the computer finds connections between data and discovers patterns without the help of a trainer and without the use of labels that define the type of data [24][25]. Semi-supervised learning is a learning paradigm that studies how computers learn in the attendance of labeled and unlabeled data. During semi-supervised learning, the aim is to design algorithms using combinations of labeled and unlabeled data [26]. Reinforcement learning is conducted by encouraging desirable behaviour and punishing undesirable behaviour. In this way, the computer can understand and interpret various issues by trial and error, according to the feedback it receives as a result of its actions [27][28].

The most common categories of ML algorithms are classification and regression. Examples of supervised learning algorithms include linear and logistic regression, support vector machines (SVMs; classification), K nearest neighbours (KNN; classification and regression), naive Bayes (classification), decision tree and random forests (DT and RF, respectively; both classification), and deep learning techniques (classification) [16][25].

2. mp-MRI in the Detection PCa

Mp-MRI primarily contains at least three sequences: T_2WI or T_1WI, DWI, and DCE imaging [29]. T_1WI is used to detect bleeding after a biopsy. T_2-weighted images can detect the anatomical shape of the peripheral and transitional zones, where 70% and 30% of cancers are found, respectively [9]. DWI measures the Brownian movement of free water protons inside a tissue. Malignant tissue is denser than normal tissue, triggering restricted free water movement inside the cancerous tissue, thereby decreasing the diffusion of water [30][31][32]. DCE assesses the perfusion and vascular permeability throughout the prostate and within a cancerous tissue through the rapid administration of gadolinium chelates and the use of fast T_1-weighted images. Unlike normal tissue, malignant tissue has more penetrable, heterogeneous, and disordered vessels due to neoangiogenesis [9][33].

Various studies have used mp-MRI to diagnose PCa and have noted its diagnostic performance. Di Campli et al. [34] conducted a study on mp-MRI to determine the diagnostic accuracy of PCa. A total of 85 patients underwent prostate MRI investigation at a 1.5 T MR system without an endorectal coil. In this study, the MR images were separately interpreted by three radiologists with 7 (reader 1), 3 (reader 2) and 1 year(s) (reader 3) of experience in prostate MRI, respectively (according to Prostate Imaging Reporting and Data System (PI-RADS) version 2). The sensitivity (CI 95%), specificity (CI 95%), area under the curve (AUC), and accuracy values for readers 1, 2, 3 were obtained (97.2% (90.3–99.7%), 88.9% (79.3–95.1%), 83.3% (72.7–91.1%)), (61.5% (31.6–86.1%), 23.1% (5–53.8%), 46.2% (19.2–74.9%)), (0.72, 0.70, 0.54), and 90.58, 78.82, and 77.64, respectively [34].

Kam et al. [35] assessed the accuracy of mpMRI to predict PCa pathology. In their work, 235 patients underwent mpMRI with a 1.5 T or 3 T MRI. The results of mpMRI were compared with the final radical prostatectomy specimen to analyze the performance of mpMRI for significant prostate cancer (sPCa) detection. They reported the accuracy of mpMRI for the prediction of sPCa. Overall, the sensitivity, specificity, and positive predictive value (PPV) of mpMRI for the detection of sPCa were 91%, 23%, and 95%, respectively. In 2020, Ippolito et al. [36] stated the multiparametric diagnostic accuracy of 201 patients for PCa detection. Patients underwent mp-MRI examination with a 3 T MR scanner and a body coil with sequences T_2WI, DWI, and DCE. The sensitivity, specificity, and accuracy of PI-RADS for the detection of PCa were 65.1%, 54.9%, and 64.2% (55.1–72.7%), respectively.

Consequently, in a study of systematic review and meta-analysis, Zhao et al. [37] reported the diagnostic performance of mp-MRI. The meta-analysis included 10 articles. At a per-patient level, the pooled sensitivity, specificity, and AUC values for mpMRI were 0.87 (0.83–0.91), 0.47 (0.23–0.71), and 0.84, respectively. At a per-lesion level, the pooled sensitivity, specificity, and AUC values were 0.63 (0.52–0.74), 0.88 (0.81–0.95), and 0.83, respectively.

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