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Editors

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Automated Diagnosis of Prostate Cancer Using Artificial Intelligence. A Systematic Literature Review

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Abstract. Prostate cancer is one of the most preventable causes of death. Periodic testing, seconded by precursors such as living habits, heritage, and exposure to specific materials, help healthcare providers achieve early detection, a desirable scenario that positively correlates with survival. However, the currently available diagnosing mechanisms have a great opportunity of improvement in terms of invasiveness, sensitivity and timing before patients reach advanced stages with a significant probability of metastasis. Supervised artificial intelligence enables early diagnosis and excludes patients from unpleasant biopsies. In this work, we gathered information about methodologies, techniques, metrics, and benchmarks to accomplish early prostate cancer detection, including pipelines with associated patents and knowledge transfer mechanisms, intending to find the reasons precluding the solutions from being massively adopted in the standards of care.

Keywords: Prostate cancer · diagnosis · Artificial intelligence · Automatic pathology diagnosis

1 Introduction

The work presented contains an introduction to provide knowledge and context about prostate cancer, as well as the techniques currently applied to diagnose it. It is followed by the materials and methods section where the scientific methodology that supports the work and makes it replicable is explained in detail. In the results section, the results of the collection and processing of the systematic literature search are presented and analyzed. The findings are discussed and future lines of work are proposed, the conclusion of the work and the consulted bibliography are revealed.

According to WHO [1], Cancer is a leading cause of death worldwide, accounting for nearly 10 million deceases in 2020, from which Prostate cancer (PCa) reported 1.41 million. PCa occurs when cells in the prostate gland begin to spread uncontrollably, and cell death (apoptosis) is delayed [2].

PCa is the second most common cancer in men worldwide [3]. Some regions are more affected than others, arguably due to cultural factors. In 2020, Guadeloupe presented the highest incidence rate normalized to 100,000 citizens, with 183.6 patients and 722 total casualties. The average world age-standardized rate was 30.7, with 1.4 million confirmed cases. According to the same report, Zimbabwe had the highest age-standardized rate of PCa mortality, with 41.7 casualties per 100,000 citizens and 868 total deaths. Recall that the age-standardized rate is a statistical method used to compare the incidence of events, such as disease or death, over time while considering differences in the age structure of a population.

Healthcare providers have correlated PCa primarily with habits and identified as risk factors the use of tobacco, alcohol consumption, unhealthy diet, sedentarism, and breathing highly polluted air. A secondary precursor of the affliction, with 13% of the cases in 2018, is attributed to infections, including Helicobacter pylori, human papillomavirus, hepatitis B and C viruses, and Epstein-Barr virus [4]. Contact with asbestos, contaminants such as aflatoxin, and drinking arsenic-loaded water are also possible triggers for the disease.

The Prostate Cancer Foundation (PCF) indicates that age is the biggest but not the only risk factor for PCa. Other essential precursors include heritage in that PCa patients' relatives are twice as likely to develop the disease. Race features are also crucial since African descent are about 75% more likely to suffer PCa than white men and 2.2 times more likely to die from the disease [5].

The World Cancer Research Fund International (WCRF),reported that being overweight or tall increases the risk of advanced PCa. Regarding dietary features, diets high in calcium in individuals presenting low vitamin E and low selenium concentration in blood plasma increase the risk of PCa [3].

PCa is considered a silent disease, not showing symptoms in the early stages. When present, symptoms often involve urination blockages due to an enlarged prostate or benign prostatic hyperplasia (BPH) [6].

The American Urological Association (AUA) recommends the screening test for PCa if the male falls into any of these groups: subjects between 55–69 years old, African American, family history of PCa, or symptoms like dull pain in the lower pelvic zone, a frequent need to pass urine, trouble passing urine, pain, burning or weak urine flow, blood in the urine, painful ejaculation, pain in the lower back, loss of hunger and weight, or bone pain [7].

The screening gold standard mechanisms include the prostate-specific antigen blood test (PSA) and the digital rectal exam (DRE). The PSA is the primary biomarker to detect early PCa exuberant expression in blood [8]. PSA derivates, their isoforms (free PSA, -2proPSA, prostate health index, hk2, PSA velocity or PSA doubling time), and novel urinary markers and biomarkers (PCA3) for screening to reduce PCa mortality provide limited evidence to conclude [7]. The DRE is a physical exam that characterizes the gland's shape, consistency, nodu-

larity, or thickness by touching the anterior part of the rectum. DRE is safe and easy, and although the literature supports the efficacy of DRE, it cannot spot early Cancer by itself.

When both DRE and PSA tests are abnormal, healthcare professionals may suggest imaging the prostate gland with magnetic resonance imaging (MRI) or transrectal ultrasound (TRUS) [9]. Finally, prostate biopsy provides a cell-scale analysis through histology where cancer cells are visible under the microscope. However, state-of-the-art prostate biopsy requires an intra-rectal device and a needle passing through the anterior intestine wall to collect pieces of the gland. The histology allows the identification of prostatic carcinoma, at different degrees of colonization, including extraprostatic, perineural invasion, collagenous micronodules, and glomeruloid intraglandular projections [10].

Imaging with MRI creates volumetric representations of soft tissue that give doctors a clear picture of the prostate and nearby areas. Among the several MRI sequences, the multiparametric MRI (mp-MRI) is often used to image the prostate in patients with PCa symptoms. The volumetric images help physicians identify positive PCa areas and cancer spreading trends. The mp-MRI requires an anatomical MRI (T1 or T2) and diffusion-weighted imaging (DWI), dynamic contrast-enhanced (DCE), or MR spectroscopy, to look at other parameters of prostate tissue. The recurrent use of MRI is justified as it provides information to detect target areas for biopsy. Moreover, MRI combined with TRUS, as in MRI/ultrasound fusion biopsy with an endorectal coil, improves the detection accuracy [11].

Healthcare providers report MRI findings following the Prostate Imaging Reporting and Data System (PIRADS), which provides guidelines and standards to expedite the verdicts and assure traceability among laboratories. The PIRADS is also intended to avoid the use of biopsies and treatment for benign and subclinical disease [12].

Other complementary tests in PCa diagnosis include bone density scanning, also called dual-energy x-ray absorptiometry (DXA) that produces 2D images of bone using radiotracers such as Technetium-99m (Tc99m) complexed to a diphosphonate, either methylene diphosphonate (MDP) forming Tc99m-MDP or hydroxy-diphosphonate (HDP) forming Tc99m-HDP. DXA creates contrast in regions where irrigation is prolific, thus pointing to damaged bone. The DXA helps to determine if cancer has spread to the bones by injecting a small amount of low-level radioactive material and using a special camera to detect the levels of radioactivity, creating pictures of the skeleton with shadows depicting the affected regions.

The positron emission tomography scan (PET) uses radioactive isotopes (fluciclovine F18, sodium fluoride F18 or choline C11, Manganese-52, Copper-64, Rubidium-82) synthetically created in a laboratory with a limited radiating life. The isotope specific for the prostate reaches the gland through the bloodstream. Before the radioactive isotope returns to normal, it releases a positive charge that will hit a negative one inside the prostate. The collision between opposite charges creates gamma rays that travel in opposite directions. A gamma camera detects the rays and uses the delay between them to locate the emission point. When the radioactive molecules are created out of sugar, they rapidly travel to

regions where the cells are avid of energy due to their accelerated metabolism, thus labeling the cancer cells [13].

The CT scan uses X-rays to make detailed, cross-sectional body images. In CT technology, electrons are created by thermogenesis and accelerated towards a plaque of tungsten or silver by an electrical field. When electrons strike the plaque, the reaction creates photons that are guided to the gate by the geometry of the plaque. The energy absorption of the internal structures of an object presented between the X-ray canyon and a matrix of detectors creates the contrast known as the X-ray image. The CT repeats this exercise in a circular trajectory to develop projections of the object under study and generate three-dimensional images of it through the Radon-transform [14].

Genetic tests are available for specific inherited gene changes, often used in men with a family history of cancer (BRCA or Lynch syndrome) and those with confirmed PCa and metastasis [15].

Gleason Score (GS) is a metric that evaluates the prognosis of men with PCa using samples from a prostate biopsy. Experts calculate the GS by adding the scores of the most significant areas in the sample tissue. The score ranges between 2 and 10; the lower the grade, the lower the size and cancer aggressiveness. GS helps physicians to plan treatment and determine prognosis [16].

According to Yu et al. [17], the relationship between PSA and PCa varies significantly between different studies, although positive biopsy results correlate with elevated serum levels of PSA. The use of the PSA level as a diagnostic decision-making tool for biopsies has a high rate of false-negative and false-positive results, leading to delayed diagnoses, unnecessary biopsies, and faulty treatment. Mp-MRI before TRUS-guided biopsy has a higher sensitivity for PCa but is less specific than a biopsy and PSA. The TRUS-guided biopsies for PCa diagnosis increase the risk of adverse events, including sepsis. Moreover, the result can yield a low risk with minimal risk of progression, resulting in overtreatment.

The biopsy samples undergo wax fixation, wax embedding, microscale sectioning, and staining before the tissues are ready for interpretation by a pathologist. The tissue preparation process has strict timing schemes that depend on the chemical used. Since sample preparation is not always automatic and a good verdict depends on the pathologist's expertise, histology may require more than one round of revision, which delays the emission of final reports [18].

In this work, we propose to explore the state of the art of the PCa, in terms of the type of methodologies, artifacts, benchmarks, key performance indicators, and problems or parts of the problem of PCa diagnosis and how researchers and physicians have approached these issues. The ulterior goal of this study is to provide insights and proposal to build a reliable pipeline for full diagnosis automation taking advantage of the benefits provided by AI-based methods.

2   Materials and Methods

This work employed the systematic literature review (SLR) methodology proposed by Barbara Kitchenham [19]. Regarding document classification, we adhere to Wieringa's strategy [20].

2.1   Research Questions

This study is based on the following research questions:

- RQ1. What developments have authors presented to diagnose and detect PCa using Artificial Intelligence (AI)?
- RQ2. What are the most accepted AI techniques currently diagnosing PCa?
- RQ3. Which metrics, measurements, or indexes derived from AI are applied to diagnose and detect PCa?
- RQ4. What is the form and nature of the data features used in Artificial Intelligence implementations to diagnose and detect PCa?

Documents Gathering Strategy: Kitchenham [19] suggests identifying key aspects towards bias reduction, predefined parameters, consistency, robustness, and replicability.

Search String Definition: The population comprises males at least 40 years old, and we are interested in prostate cancer diagnosis software, leading to keywords "prostate cancer" AND "software". The implementation implies technology and methodology applied to solve the problem. Then, we enforced the search string with: "segmentation" OR "classification" OR "regression" AND "automatic" OR "machine learning" OR "Artificial Intelligence". A set of methods for PCa diagnosis accompanied by measurements, metrics, and indexes are crucial for accomplishing our goal; therefore, the strings "diagnosis" AND "metric" OR "measurement" complements the search pattern.

Experimental Design: We fed the defined search string to specialized search engines – e.g., Google Scholar, IEEE Xplore, MDPI, Elsevier, Springer, and Wiley – and added "January 2020 to June 2022" as a dating constraint. We organized the results following an in-house mnemotechnic structure that, in addition to traditional bibliographic fields, records whether the techniques have been translated to commercial implementations or protected by patents. The gathered data are operationalized in lists of concepts and categories to build the response matrix where each row identifies an analyzed item. The operationalization transforms text or paragraphs into meaningful and representative tokens summarizing the article's content that answer the research question.

2.2   Study Selection Criteria

The Table 1, depicts the selection concepts used in this work.

2.3   Study Assesment

The search string yielded 719 articles. Then, after applying the inclusion and exclusion criteria, we labeled 132 articles indirectly related, 417 unrelated, 30 duplicates, and 47 discarded. The details can be observed in Fig. 1:

Table 1. Selection criteria

Inclusion criteria	Exclusion criteria
I1. Articles in English	E1. Systematic Literature Mappings (SMS) and Systematic Literature Reviews (SLR)
I2. For articles by the same author and focused on the same research, the most recent and complete one is taken	E2. Not accessible
I3. Articles published between January 2020 and June 2022	E3. Gray literature
I4. Articles that contain candidate strings in the title, keywords and/or in the abstract	E4. Articles whose content does not focus on the diagnosis or detection of prostate cancer
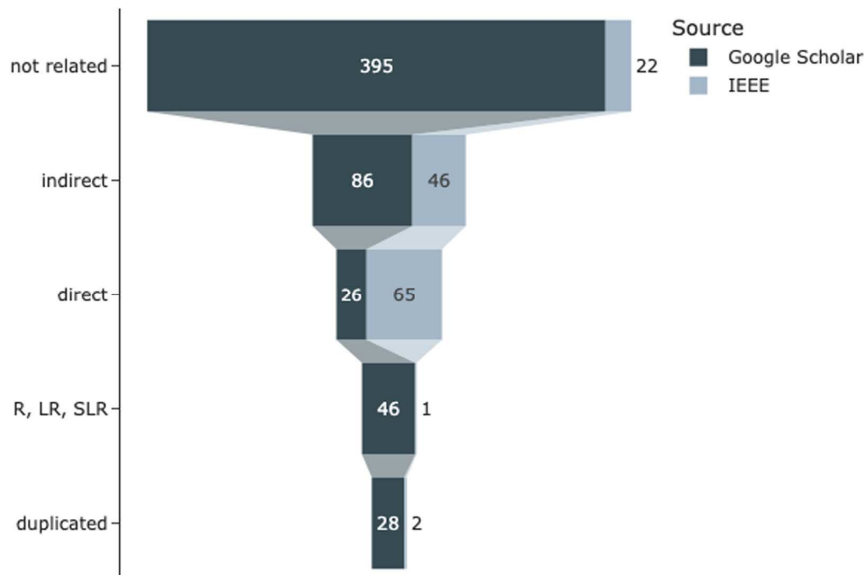
Fig. 1. Summary of article selection funnel

2.4 Data Extraction

In addition to standard bibliographic fields, we extracted the following data from each article: search engine and publisher, topic area, problem trying to solve, objectives, methods (used to provide a solution), and results. The extraction form is available in: [21].

2.5 Data Synthesis and Quality Verification

After thoroughly reviewing their content, we summarized the articles and answered the research questions. This content analysis yielded the material to categorize the documents, thus facilitating their further analysis and processing. Within the article classification, we also considered aspects such as pertinence,

used software, framework, methodology to propose a solution, level of completion, and reproducibility.

3   Results

The answers to the proposed research questions were operationalized and statistically processed. The summary form is available in: [21].

In Fig. 2 the reader can see a tree map of patents' distribution status, classification of the type of AI in terms of information transfer, and the kind of technique used.
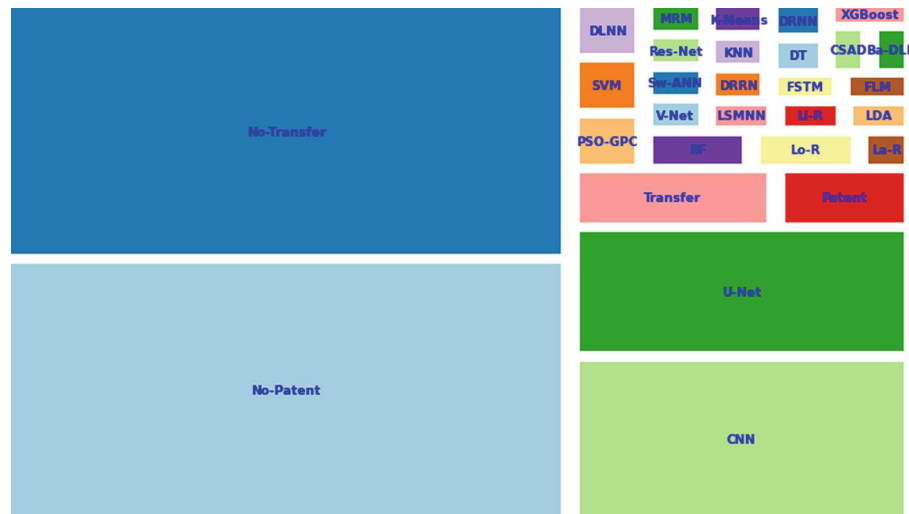
Fig. 2. Distribution of patent status, transfer learning, and techniques used in the diagnosis and treatment of PCa

The 81.31% of the selected articles did not have or use any patented component or device to date. The 79.12% of the papers did not use any knowledge transfer component or lacked reproducibility. Authors preferred the Convolutional neural network (CNN) in three of ten manuscripts. The second most used technique was the U-shape neural network (U-Net), with a frequency of nearly one over four works. The third most preferred group of techniques were the Logistic Regression (Lo-R), Random Forest (RF), Particle Swarm Optimized Gaussian Process Classifier (PSO-GPC), Deep Learning Neural Network (DLNN), and Support Vector Machine (SVM). The fourth group with frequency one was the group of Bayesian Deep Learning Networks (Ba-DLN), Cross-Modal Self-Attention Distillation (CSAD), Deep Residual Neural Networks (DRNN), Deep Residual Regression Networks (DRRN), Decision Tree (DT), Fuzzy Logic Model (FLM), Feature Space Transfer Model (FSTM), K-Means, K Nearest Neighbors (KNN), Lasso Regression (La-R), Linear Discriminant Analysis (LDA), Linear Regression (Li-R), Long Shot Term Memory Neural Network (LSMNN), Multi-Risk Model (MRM), Residual Neural Network (Res-Net), Swarm Artificial Neural Network (Sw-ANN), V-shape Neural Network (V-Net), and Xtreme Gradient Boosting (XGBoost).

3.1   Contribution to Diagnosis and Detection of PCa

The 60.4% of the gathered articles proposed methods to improve the diagnosis and detection of PCa [22] with logistic regression to predict biochemical recurrence after surgery for high-risk PCa patients; 29.7% present tools that could be used to perform these tasks and its representative the work as in [23] with a deep learning regression for PCA detection using bi-MRI input. The 7.7% of articles occasionally propose a model or algorithm that improves at least one PCa diagnosis and detection workflow activity. Only 3.3% of the gathered documents presented an improvement directly linked to the metrics used to measure and estimate the presence or absence of PCa, as in [24].

3.2   AI Techniques

In [25], authors present a multi-site network that improves prostate segmentation with heterogeneous MRI data. With the same goal, [26] suggested a 3D adversarial pyramid anisotropic CNN of the prostate on MRI. Automatic histological image processing as in [27]. These works belong to the 36.26% of the articles that implemented a convolutional neural network as a solution to diagnosing and detecting PCa. The 24.17% mentioned U-shape network architectures, being the most cited and viewed Comelli, Albert et al. [28], with a device for prostate segmentation using MRI. The 12.08% the use of a based or combined residual neural network; 6.59% the use of random forest algorithm; 3.29% Naive Bayes, decision trees, and logistic regressions, followed by 2.2% usage of adversarial networks, Lasso regression, Xtreme Gradient Boosting, support vector machines, and deep learning neural networks. The rest mentioned using multivariate risk models, vgg19 architecture, ResNet50, gradient boosting machines, Ridge regression, K-medoids, K-means, IMSLIC algorithm, Adaboost, linear regression, and linear discriminant analysis.

Related image acquisition means, 13.2% mentioned the use of 3D images, 7.7% the use of MRI, 5.5% the use of T2W images, 6.6% MRI, 4.4% transrectal ultrasound, 3.3% multiparametric MRI, dynamic contrast-enhanced, diffusion-weighted images and whole slide histopathology images respectively; 2.2% bi-parametric MRI, TW1, apparent diffusion images, and voxel images each; and 1.0% 2D MRI images and PIRADS version 2 images. Regarding data treatment techniques, 4.4% mentioned transfer learning and 1.0% other strategies like pooling, bi-long short memory, conditional random fields, and one-hot encoding.

In Fig. 3 the reader can see the distribution of the benchmark KPI's values in boxplots detailed by the main architecture technique used and split by patent-base status as follows:
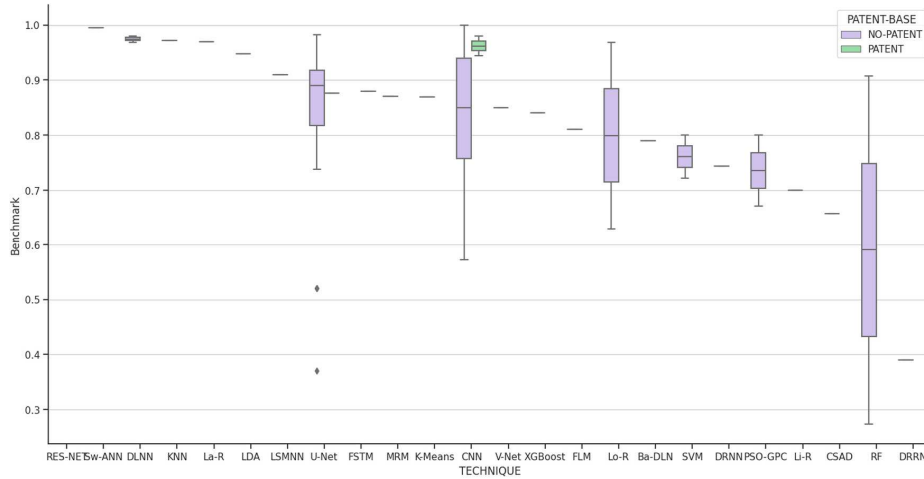
Fig. 3. Distribution of Benchmark KPI values by Technique and Patent-Base status.

The architecture with higher performance for the main KPI mentioned using the median was DLNN (0.9742). In the second place, the patent-related works that used CNN architectures showed a median performance of 0.962. The last group of the architectures with at least two occurrences in median performance descending order were U-Net (0.89), CNN without patent (0.85), Lo-R (0.79), SVM (0.76), PSO-GPC (0.73), and RF (0.59). The rest with one point of observation for median performance and relevant to mention: Res-Net (0.9984), Sw-ANN (0.9948), KNN (0.972), La-R (0.97), LDA (0.948), LSMNN (0.91), FSTM (0.88).

3.3   KPI's and Benchmarks

The most used accuracy testing metric in the analyzed papers was the Dice Score (DS) with the 37.4%, highlighting the work of Zhiqiang Tian et al. [29] with a graph CNN of MRI solution, and Accuracy (ACC.) with 35.2% of the papers, where D. Karimi et al. [30] proposed a deep learning Gleason grading of PCa from histopathology images. The Area Under the ROC Curve (AUC) was founded in (29.7%) of the articles, with artifacts such as 3D CNN with mp-MRI for segmentation [31]. The next step of KPI's, Sensitivity (SENS) and Specificity (SPEC) 14.3% and 13.2%, respectively. Athors did not specified any performance metric in a rate of 9.9%. The Jaccard Similarity Coefficient (JC) and Haussdorff Distance (HD) were cited in 7.7% each. Average Surface Distance (ASD) with 4.4%, Quadratic Kappa Coefficient, Cohen-Kappa Coefficient, Log Rank and F1-Score (3.3% respectively), Contrast group has Noise, Loupas, True Positive Rate, Positive and Negative Prediction Values, Correlation Coefficient Matthews, Root Mean Squared Error (2.2% each). In contrast, the remaining group included Completeness, R Squared, False Positive Rate, Clustering that-Medoids, Precision, and Recall, with 1.0% each. Regarding validation techniques, cross-validation was present in 3.3% of the articles, and 2.2% had to perform data augmentation to have enough information for training.

Regarding the benchmark distribution for the previous techniques architectures, the Fig. 4 presents boxplot distributions for the main architectures.
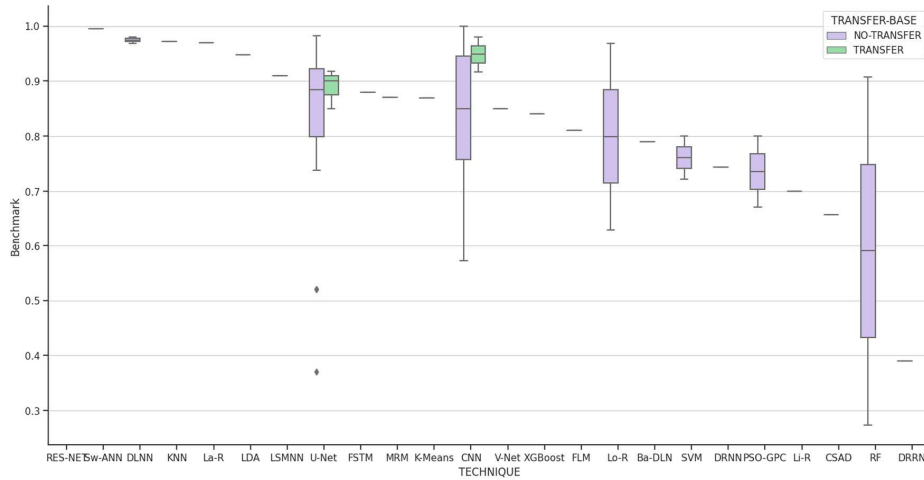
Fig. 4. Distribution of Benchmark KPI values by Technique and Transfer-Base status.

One of the most significant findings in this SLR is related to the KPI metrics in the classification task. The CNN architecture implementing transfer knowledge reported a median of 0.9483. The U-net, also using transfer knowledge, reported a median of 0.8839. Both CNN and U-Net medians were obtained with at least two observation points. The FSTM architecture with transfer knowledge claimed a KPI of 0.8800 and is the only method with a registered patent.

Table 2 indicates the metrics mentioned in at least three articles with the median value calculated. For DS 50% of the articles exceeded 0.8652, and the same proportion for ACC. with 0.92135; AUC 0.876, and SENS. 0.92; as follows:

Table 2. Distribution of frequencies and 50th percentile by metric.

Metric	frequency	50th percentile
DS	34	0.8652
ACC.	30	0.92135
AUC	27	0.876
SENS.	13	0.92
SPEC.	12	0.9091
HD	7	8.1
JC	7	0.77
ASD	4	1.335
LOG RANK	3	24.586

3.4   Data Source and Characteristics

The selected authors claimed to gather data from clinical facilities to which they have access at work.

Regarding public datasets, 15.4% used the Promise12 repository [32] such as He, Kelei et al. [33] within the title synergistic voxel level image processing for prostate segmentation. The 9.9% used the ProstateX dataset [34], and 8.8% of the articles did not precisely mention the data's origin nor provide details about the data's source. The 3.3% of the articles used the NCI-ISBI 2013 and ProstateX2 datasets [35], and 2.2% used PANDA, Prostate3T, CANCER IMAGING ARCHIVE, and The Cancer Genome Atlas, each one. Those that used other lesser-known datasets, with 1% in each case, included PROMIS, PROSTATEX17, UCI, PASCAL VOC 2012, DIAGSET, PRAD, GSE54460, HIPPA, U41RR019703, and Harvard Dataverse. In Summary, 7.7% of the articles combined at least 2 datasets, public or custom, to train and/or test their solutions.

5.5% of articles used whole-slide histopathological images (WSI) and diffusion weight images (DWI), 4.4% had Gleason label info, 3.3% made use of transrectal ultrasound images (TRUS), T1W images, and 2.2% of the articles used scan annotations and dynamic contrast-enhanced images (DCE). The devices used to scan were Phillips, Magnetom, Siemens (4.4%, each), Skyra, and Tesla (3.3% each). Regarding the origin of the custom data, the most frequent facility was Radboud Medical Center with 6.6%, Boston Medical Center, Universitas Indonesia Hospital (UI), and Kaggle, each with 2.2%.

In Table 3 25% of the samples exceeded 51 observations; 50% exceeded 120 observations or patients and the highest 25% of the samples exceeded 225 patients, as follows:

Table 3. Size sample percentile distribution

kth percentile	sample n
25	51
50	120
75	335

3.5   Research Type

According to the type of research, 76% of the articles propose a solution for one of the problems defined within the diagnosis and detection of PCa, such as Duran-Lopez, L. [36] with the contribution CNN based computer-aided diagnosis system for WSI PCa detection artifact. The remaining 24% propose to evaluate a technique, methodology, or approach to contribute to solving the research problem, as in the case of S. Iqbal et al. [37] that performed a comparison of deep learning techniques for PCa detection.

4   Discussion

Most of the reviewed proposals use frameworks or architectures based on deep learning convolutional neural networks to approach PCa Inherent challenges such as prostate segmentation, automatic localization of lesions, and pathologists' flow work. The mechanism for evaluating the general performance of these architectures are Dice Score, accuracy, sensitivity, and specificity since they are transversally related to classification. Most of the selected articles use clinical data from private institutions.

There is a significant drawback regarding the use of all possible available data. Since specialists have found correlations between heritage and other personal factors, such as race with PCa - and other cancer afflictions - one might hypothesize that personal data could be a set of useful features to improve the DS and confusion matrix scores. However, personal data is protected by strict regulations such as HIPAA [38]; therefore, scientists and developers can not include it in their developments. The work presented in [39] and patented [40] proposed a way to avoid this restriction within healthcare facilities. Consequently, personal data might be available, and AI developments can consider personal data while complying with the regulations. Preliminary quantifying attempts compatible with the mentioned fully automated platform for PCa and other cancer types have been reported to the scientific community in [41–44].

Clinical data, in contrast to recruited data, have high variability due to the purpose of the acquisition. Recall that healthcare providers order imaging to suit medical necessities and not research purposes; therefore, the data is acquired with many setups. Consequently, we could not find standard procedures or a baseline from which scientists start their developments. The filtered articles describe unique methods with few methodological coincidences. A good approach for a usable pipeline is to develop a pre-processing stage that allocates the images in a common space regardless of origin.

A second improvement opportunity exists in selecting or designing a common framework with standard tasks, metrics, and benchmark levels. We have identified a set of routine activities that should be standardized. 1. Dimensionality standardization of the image (2D, 3D, pixels, voxels), 2. Prostate segmentation, 3. Tissue classification, depending on the type of image source, 4. GS automatic estimation.

A third opportunity relies on how to merge or incorporate this technology or learning into the instruments (computer-aided, for instance) or procedures used today, aiming to provide a reliable, cheaper, faster, and standardized diagnosis. The database structure that supports the expected massive information should be shareable, available online, and capable of improving verdicts in time, feeding the framework with more observation data points.

A fourth opportunity is the combination of different types of information, tests, results, scenarios, risks, gradings, and stages in a standard way so that a patient with the first screening or another with some previous testing results can get into the pipeline straightforward to be classified and compared with patients having similar characteristics.

5   Future Work

Data standardization through robust pre-processing will be the first goal of the subsequent work. Then, we will focus on improving the quality of the histological information. As mentioned by [27, 30, 45–53], histological image processing currently depends on a series of manual tasks of a high level of difficulty and specialization by pathologists, which require preparation with a high level of meticulousness and attention so as not to lose the value of the information provided by the sample. As they are not obtained automatically or semi-automated, they are considered part of potential new lines of research that provide more accurate results in timely and precise detection.

On the other hand, there is an excellent opportunity for the use of learning transfer techniques and software-patented devices that make it possible to take advantage of the knowledge persisted in a standard data structure (understood as reuse) for its consultation and information retrieval, as well as its retraining capacity and adaptation to subfields or problems of classification or segmentation for all sort of cancer afflictions and several types of tissues other than those related to PCa.

Finally, our work will attain the integration of the standardized data with the most efficient AI-based classification methods, which will be improved with the use of enhanced histological results as supervised factors.

6   Conclusions

We designed a systematic literature review to discover the proposed developments in the context of PCa diagnosis using machine learning or artificial intelligence technologies. The SLR allows us to acknowledge the most accepted techniques of AI and know the metrics and benchmarks used in the PCa diagnosis framework.

The opportunities identified and listed in the discussion section suggest the development of a standard pipeline that could integrate the work reported as the most accurate. Still, we will need to standardize the data along the pipeline and improve the histological results' quality to be used as supervised factors. We will consider features such as data centralization and in-cloud service exploitation as priorities in the design from scratch.

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