A Hybrid Model for Prostate Cancer Detection and Prognosis: A Systematic Review

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A Hybrid Model for Prostate Cancer Detection and Prognosis: A Systematic Review

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Abstract

This study systematically reviews the integration of Interval Type-2 Fuzzy Logic (IT2FL) and XGBoost for prostate cancer detection and prognosis. Prostate cancer is a significant health concern, with existing diagnostic methods often challenged by data uncertainties and accuracy limitations. IT2FL effectively addresses uncertainties in medical data, while XGBoost enhances classification performance. The methodology involved a systematic search across databases, including Google Scholar, IEEE Xplore, Elsevier, and Springer, identifying 121 studies from an initial pool of 500 articles. The review investigates four key aspects: the integration of IT2FL and XGBoost, input parameter significance, the role of linguistic variables, and the impact of XGBoost on diagnostic accuracy. Visualization tools such as VosViewer and Matplotlib facilitated data analysis and presentation. Key findings highlight the hybrid model's ability to enhance diagnostic precision, reduce false positives, and support informed clinical decision-making. However, challenges like data diversity and model interpretability persist. The study highlights the potential of the hybrid model in advancing precision medicine by enhancing the detection and prognosis of prostate cancer. This paper demonstrates the feasibility and effectiveness of combining IT2FL and XGBoost, paving the way for future integration of explainable AI techniques and broader clinical applications.

1. Introduction

Over the past six decades, advancements in prostate cancer diagnostics have significantly improved early detection and treatment outcomes [1]. This malignancy, known as prostate cancer, is the second most frequently diagnosed and has a significant impact on men's health worldwide, presenting significant challenges in early detection and accurate prognosis [2]. Conventional diagnostic methods, including Prostate-Specific Antigen (PSA) testing and Digital Rectal Examination (DRE), frequently encounter challenges related to specificity and sensitivity.

These methods tend to produce high false-positive rates, leading to unnecessary biopsies and overdiagnosis. Moreover, imaging modalities like multiparametric MRI (mpMRI) and ultrasound, while effective, are subject to inter-observer variability and constrained by the quality of imaging data [3]. These limitations hinder the ability to deliver precise, reliable, and early diagnosis, thereby impacting treatment outcomes and patient quality of life [1].

Progress in Machine Learning (ML) and Artificial Intelligence (AI) has led to valuable tools for overcoming these challenges by leveraging computational models to analyze complex, high-dimensional datasets. However, individual ML models often struggle to handle uncertainties inherent in medical data, such as variability in patient demographics and incomplete datasets [4][5]. Despite improvements in predictive accuracy with algorithms like XGBoost and deep learning, the interpretability of these models remains a barrier to clinical adoption. Thus, there is a pressing need for diagnostic frameworks that balance precision, robustness, and transparency. Among AI techniques, Interval Type-2 Fuzzy Logic (IT2FL) from Fuzzy logic systems (FLS), introduced by Zadeh in 1965, offers a robust framework for managing uncertainties and imprecise medical data. IT2FL enhances decision-making by incorporating linguistic variables and fuzzy inference systems, thereby providing a nuanced interpretation of patient data. By extending binary logic to include values between absolute truth and falsehood, fuzzy logic systems map input variables to crisp outputs and simulate human decision-making using linguistic variables and rules [6] . Unlike Type-1 Fuzzy Logic, IT2FL can handle more complex uncertainties, making it particularly suitable for medical applications [6] [7].

Complementing IT2FL, the XGBoost algorithm has gained prominence for its superior performance in classification tasks. Known for its ability to reduce bias and variance, XGBoost delivers high predictive accuracy, This makes it especially well-suited for medical applications that demand high levels of precision. The integration of these two methodologies, IT2FL and XGBoost represents a hybridized model that combines the strengths of uncertainty management and predictive optimization. Artificial Intelligence (AI) has significantly advanced prostate cancer detection and prognosis, particularly in radiology and imaging techniques. AI applications, such as convolutional neural networks (CNNs) and machine learning (ML) models, have improved diagnostic precision and treatment planning. For instance, ML techniques like supervised and unsupervised learning, decision trees, and deep learning have been widely adopted for prostate cancer research [8]. CNNs have been particularly effective in enhancing prostate segmentation and aligning imaging with the Prostate Imaging Reporting and Data System (PI-RADS), as shown by [9]. These advancements surpass traditional diagnostic methods and human interpretation. Comparative studies highlight the superior performance of ML algorithms over conventional approaches. Boosting methods achieved the highest classification accuracy, as reported by [10].

Similarly, studies on hybrid models combining techniques like gradient boosting and fuzzy logic have shown improved reliability in handling medical data uncertainties [11]. The integration of AI in prostate cancer research has also expanded into predictive analytics. For example, hybrid AdaBoost-SVM algorithms have demonstrated exceptional diagnostic accuracy for breast cancer and similar potential for prostate cancer applications. The role of biomarkers and high-dimensional datasets in AI-driven diagnostic tools has grown, emphasizing the need for rigorous experiments to validate model efficacy [12].

Additionally, methods such as multiparametric MRI (mpMRI) and machine learning have enhanced risk stratification and biopsy accuracy, reducing false positives [13] . Challenges remain in implementing these technologies clinically due to data variability, computational requirements, and model interpretability. Future directions emphasize integrating explainable AI for enhanced trustworthiness, federated learning for data privacy, and expanding clinical trials to validate ML models. This comprehensive review identifies the potential of AI and ML in improving prostate cancer care while addressing existing limitations.

[14] conducted an in-depth analysis of segmentation, machine learning, and deep learning methods to enhance the prediction of prostate cancer probability rates. In [15], a reinforcement learning approach was utilized to improve the accuracy of prostate cancer prediction. The study also explored various models and structural frameworks used for the precise identification and classification of prostate cancer. Similarly, [16] examined recent advancements in AI for the development of automated prostate cancer diagnosis systems. AI has demonstrated remarkable accuracy in medical imaging, aiding in the detection of prostate abnormalities and forecasting clinical outcomes such as patient survival and response to treatment.

This systematic review investigates the potential of this hybrid approach, focusing on its application to prostate cancer detection and prognosis. Specifically, it explores the integration flow of IT2FL and XGBoost, evaluates the input parameters influencing model performance, and examines the significance of linguistic variables and XGBoost's implementation. By analyzing existing literature from 2017 to 2024, this review purposes to provide comprehensive insights into the efficacy and applicability of hybrid models in prostate cancer diagnostics, setting the stage for future advancements in precision medicine

The integration of Interval Type-2 Fuzzy Logic (IT2FL) and XGBoost offers a novel approach to address these gaps. IT2FL provides a robust mechanism for managing data uncertainties through its ability to model imprecision and ambiguity using linguistic variables and fuzzy inference systems. This capability is particularly suited for medical applications where patient data often lack exact values. On the other hand, XGBoost, a gradient-boosting algorithm, is renowned for its superior classification performance, scalability, and ability to minimize both bias and variance. By combining these methodologies, the hybrid model hope to enhance diagnostic precision, manage data uncertainty, supports clinical decision-making and bridge theory and practice.

2. Methodology

This section offers an outline of the methodology employed in the literature review, including its objectives, research questions, inclusion and exclusion criteria, and the study framework. Subsection (A) outlines the steps taken during the literature review process. Subsection (B) addresses the formulation of research questions. Subsection (C) details the article selection strategy, while Subsection (D) includes Inclusion and Exclusion Criteria.

A. Methodological Description

Table 1. Tabulated Literature on Detection Problem

S/N	References	Methodology	Description	Dataset	Result	Problem solved
1	[17]	Pixel-wise AI algorithms	AI-powered virtual biopsy enhances MRI-targeted prostate biopsy precision. Pixel-level AI models have been designed for tumor detection and Gleason grading.	A meticulously curated dataset comprising 442 manually annotated slides. A cohort consisting of 115 radical prostatectomy patient cases.	The tumor detection algorithm demonstrated sensitivity/specificity of 0.99/0.90 in the aware version and 0.97/0.97 in the balanced version.	Detection
2	[18]	ANN	Prostate cancer is prevalent in men over 50. ANN model enhances early detection, reducing false positives. Aims for marketable solution in cancer screening.	Four datasets from 1983 patients were used. Variables include age, prostate size, and PSA levels.	Developed ANN model for early prostate cancer detection. Reduced false positive rates in diagnostic methods.	Detection

			Long-term goal: improve patient care and outcomes.			
3	[19]	Deep learning	Deep learning models were developed to identify adverse pathology in prostate cancer. The TransCL model surpassed both the clinical model and radiologists' interpretations in detection accuracy	Radical prostatectomy was performed on 616 men across six institutions. The study included a training cohort of 508 patients and a validation cohort of 108 patients.	TransCL achieved an AUC of 0.813 (95% CI: 0.726–0.882) for detecting AP presence, surpassing TransNet (0.791 [95% CI: 0.702–0.863], P = 0.429) and significantly outperforming CM (0.749 [95% CI: 0.656–0.827]) and RI (0.664 [95% CI: 0.566–0.752]).	Detection
4	[3]	Deep learning	A machine learning-based method identifies high-grade prostate cancer through ultrasound imaging. Combining clinical data with ultrasound imaging enhances detection accuracy.	Clinical datasets were sourced from Nippon Medical School Hospital. Access is restricted, and the data is not publicly available.	The area under the curve (AUC) based on clinical data alone was 0.691, whereas incorporating both clinical and ultrasound imaging data increased the AUC to 0.835 (p = 0.007).	Detection

5	[20]	Deep learning	Machine learning improves prostate cancer detection using PSA kinetics. AUC for machine learning model is 0.886, surpassing traditional methods	PLCO trial data PCPT trial data Contemporary Australian cohort data	The analysis included 10,719 patients. For diagnosing grade group ≥2, the machine learning model achieved an AUC of 0.886, compared to 0.807 for PSA and 0.627 for PSA velocity.	Detection
6	[21]	SVM	S3 spectroscopy detects cancer biomarkers in human prostate tissues label-free. ML algorithms like PCA, NMF, and SVM analyze S3 spectra.	Human cancerous prostate tissue spectra collected label-free. Normal prostate tissue spectra collected label-free.	The classifications NC1vsNC2, NC1vsNC3, and NC2vsNC3 achieved sensitivities 86.7%-100%, specificities 100%, accuracies 93.3%-100%, AUROC values of 1.	Detection
7	[22]	R-CNN	Prostate cancer detection model improves early diagnosis efficiency. Modified ResNet50 architecture	A comprehensive dataset of annotated medical images was utilized. However, specific details regarding the dataset were	The proposed model surpasses both ResNet50 and VGG19 architectures, demonstrating exceptional performance with sensitivity,	Detection

			shows superior performance in medical imaging.	not disclosed in the text.	specificity, precision, and accuracy rates of 97.40%, 97.09%, 97.56%, and 95.24%, respectively.	
8	[23]	Convolutional Neural Networks (CNN), Gradient Boosting, k-Nearest acquaintances (KNN), Ada boosting, (GA-FS).	Optimizes machine learning model for prostate cancer detection accuracy. Uses ensemble learning and feature selection for improved performance.	Publicly available data from the Cancer Genome Atlas. Preprocessed dataset for feature extraction and selection	The proposed model outperforms others with accuracy rates of 93.55%-97.81% across 100-500 rounds, surpassing Boost, KNN, AdaBoost, and GA-FS.	Detection
9	[24]	Fuzzy logic (Mamdani fuzzy inference)	Early cancer diagnosis improves patient survival rates. Fuzzy expert system aids prostate cancer risk assessment.	Clinical data from 119 patients at Ankara University were analyzed. The input variables included Age, PSA, PV, and FPSA.	The FES achieved a 77.05% true positive rate among 119 patients, surpassing Saritas (64.71%), online calculators (62.18%), and the FPSA/PSA ratio (60.50%).	Detection
10	[25]	Logistic regression, decision tree, and random forest	This study designed machine learning models	The study included 200 prostate cancer patients and 200	The random forest model demonstrated the highest performance,	Detection

		models were implemented. Support vector machine and neural network models were also assessed.	for prostate cancer detection, identifying the random forest model as the most effective, achieving 92% accuracy.	healthy control subjects.	achieving 92% accuracy, 95% sensitivity, and 89% specificity, surpassing other machine learning models.	
11	[26]	image registration algorithm developed in MeVisLab	Investigates image registration impact on prostate cancer diagnosis. Deformable registration improves lesion alignment and diagnostic performance slightly.	Three datasets with bpMRI scans for prostate cancer detection. Includes axial T2W, ADC, and HBV imaging.	Deformable registration improved lesion overlap by +10% median Dice score. Diagnostic performance showed a +0.3% AUROC improvement (p=0.18).	Detection
12	[27]	A convolutional neural network (CNN) was utilized for analysis and classification.	An auto-deep learning approach was employed for detecting prostate cancer malignancy from mpMRI. Peripheral zone and central gland detectors efficiently identified	A public cohort of 201 patients was analyzed. Cropped 2.5D slices of prostate glands were utilized for assessment	The CG-detector achieved an AUC of 0.94 when using only T2-ADC pairs as input, whereas the PZ-detector attained an AUC of 0.90 with a mixed-type input pair.	Detection

			suspicious slices.			

Table 2. Summarized Literature on Diagnostic Problems

S/N	References	Methodology	Description	Dataset	Result	Problem solved
1	[28]	Support Vector Machine, Decision Tree, and Naive Bayes were among the models utilized. Additionally, K-Nearest Neighbors, Neural Network, Random Forest, Deep Learning, Auto-MLP, and Rule Induction were implemented.	Study aims to determine best algorithm for diagnosing prostate cancer. Nine data mining techniques used, with K-Nearest Neighbors and Neural Network algorithms showing best performance.	Prostate cancer data was sourced from the Kaggle repository. The dataset included 100 samples with eight distinct features.	The study revealed that the implemented algorithms achieved an accuracy range of 77%–84%. K-Nearest Neighbors and Neural Networks demonstrated the highest accuracy at 84%, with sensitivity rates of 85% and 80%, respectively.	Diagnosis
2	[29]	Support Vector Machine (SVM) and Random Forest (RF) were utilized for	ML models utilizing biparametric MRI were applied for prostate cancer diagnosis. These models	1,368 patients from three tertiary medical centers. Includes cases of csPCa,	ML model and PI-RADS achieved AUCs of 0.869-0.915 for PCa; combining them improved	Diagnosis

		classification and analysis.	demonstrated performance comparable to PI-RADS while enhancing specificity.	ciPCa, and benign lesions.	specificities to 80%-93.3% for diagnosis.	
3	[30]	deep learning, ANNs, and support vector machines (SVMs)	Prostate cancer is common worldwide with high mortality in developing countries. AI and ML improve diagnostic accuracy by reducing inter-individual variation.	SCOPUS, Web of Science, Google Scholar databases used. 293 research papers reviewed for analysis.	AI and ML contribute to improving prostate cancer diagnosis. A comprehensive approach combining demographic details, clinical metrics, serological markers, pathological grading, radiological assessments, and genomic insights enhances non-invasive detection of clinically significant cases.	Diagnosis
4	[31]	DNN. RNN	Early detection of prostate cancer	I2CVB dataset used for training deep	Proposed, DL, approach, achieves, Dice,	diagnosis

			is crucial for treatment. Deep learning automates diagnosis using mpMRI images for better patient care.	learning models. No other datasets mentioned in the study.	coefficient, 0.67, segmentation, task, accuracy, 90.69%, F1-score, 92.09%, classification, metrics, surpassing, state-of-the-art, methods, DNN, Deep, RNN.	
5	[32]	deep convolutional networks, connected neural network (CNNs)	Prostate cancer diagnosis challenges due to early symptom absence. Deep learning improves accuracy using MRI and clinical data.	The dataset was sourced from Trita Hospital in Tehran, encompassing multiparametric MRI images from 343 patients.	The model's accuracy was 88%-96%, sensitivity 94.24%, and specificity 98.62%, with and without clinical and pathological data.	Diagnosis
6	[33]	Deep learning	Multimodal AI improves prostate cancer detection using clinical parameters and MRI.	932 biparametric prostate MRI examinations analyzed retrospectively. Data from two institutions	Multimodal AI demonstrated performance comparable to radiologist assessments, with AUC scores of 0.87	Diagnosis

			Early fusion of features enhances diagnostic accuracy significantly.	included in the study.	vs. 0.88 (internal) and 0.77 vs. 0.75 (external), both showing no statistically significant difference (P > 0.05).	

Table 3. Summarized Literature on Prediction Problems

S/N	References	Methodology	Description	Dataset	Result	Problem solved
1	[34]	Gradient Boosting Survival Analysis (GBSA), Random Survival Forest (RSF), and Extra Survival Trees (EST) were utilized for predictive modeling.	Developed machine learning models for prostate cancer survival prediction. Created a web-based tool for patient prognosis guidance.	3280 prostate cancer patients with lymph node involvement identified from SEER database. Data covers years 2000–2019.	The mean time-dependent AUC values for GBSA, RSF, and EST were 0.782 (95% CI: 0.779–0.783), 0.779 (95% CI: 0.776–0.780), and 0.781 (95% CI: 0.778–0.782), respectively, surpassing the Cox regression model's 0.770 (95% CI: 0.769–0.773).	prediction

2	[35]	Support Vector Machine (SVM) Random Forest (RF)	Developed machine learning model for prostate cancer prediction. Compared diagnostic performance with MRI results. Analyzed data from 501 patients, 276 with cancer. Extracted 851 features from ultrasound video clips. Selected 14 features using LASSO regression. SVM model outperformed senior radiologists' MRI diagnoses. AUC of SVM was 0.78 in validation set.	501 patients: 276 with prostate cancer, 225 benign lesions. Final selection: 231 patients, 118 cancer, 113 benign.	The SVM model achieved AUC 0.78, sensitivity 63%, specificity 80% (validation), and 0.75, 65%, 67% (test), outperforming senior radiologists.	Prediction

			ML models can aid radiologists in diagnosis			
3	[36]	The models are SVC, LR, AdaBoost (Ada B), XG Boost (XGB), KNC, LGBM, GB, DT, and RF	Prostate cancer prevalence is rising globally among men. Machine learning improves diagnostic accuracy and avoids unnecessary biopsies.	Data acquired from Kaggle consists of 100 cases. 10 characteristics used for analysis.	The maximum accuracy achieved was 96.67%, not only for the three models but also for Gradient Boosting (GB) as a whole..	Prediction
4	[37]	Support vector machine (SVM), random forest (RF), adaptive boosting (ADB), and gradient boosting machine (GBM)	ML models using ultrasound and MRI improved diagnosis of prostate cancer. Fusion model of ultrasound and MRI provides complementary information for accurate identification.	383 patients: 187 with prostate cancer, 196 benign lesions. 307 patients for training and validation; 76 for testing.	In the test cohort, RF model achieved AUC 0.85, sensitivity 0.78, specificity 0.84; SVM model fused features yielded AUC 0.87.	prediction
5	[38]	XGBoost	Developed a machine learning model for prostate	Benign prostatic hyperplasia (BPH) data	The XGBoost model had an AUC of 0.82,	prediction

			cancer prediction. XGBoost model outperformed traditional PSA tests in accuracy.	Prostate cancer (PCa) data	outperforming f/tPSA (0.75), tPSA (0.68), and fPSA (0.61).	
6	[39]	KNN	ML used to evaluate prostate cancer, achieving 88% accuracy. Alternative approach to predict cancer besides traditional medicine.	Kaggle dataset retrieved for prostate cancer evaluation Dataset includes 10 numerical attributes and diagnosis result category	The implemented algorithm achieved an accuracy rate of 88%.	prediction
7	[40]	support vector machine (SVM) and random forest (RF)	Developed machine learning algorithm for prostate cancer diagnosis. Achieved over 0.91 sensitivity in Gleason score prediction.	71 patients analyzed in the study. Multiparametric MRI including T2WI and ADC maps.	Combining LASSO, SVM, T2WI, and ADC images achieved AUC 0.92 for predicting Gleason score groups with high sensitivity.	prediction
8	[41]	ANN	Combined PHI and Proclarix	A total of 344 men from two different centers	The model achieved a sensitivity of	prediction

			improve prostate cancer diagnosis accuracy. ANN model predicts clinically significant prostate cancer at initial diagnosis.	were enrolled in the study. The dataset includes biomarkers such as [-2]proPSA, free PSA, total PSA, cathepsin D, and thrombospondin.	78% and a specificity of 62% for all-cancer detection, outperforming PHI and PCLX alone. For clinically significant prostate cancer (csPCa) detection, it demonstrated a sensitivity of 66% (95% CI: 66–68%) and a specificity of 68% (95% CI: 66–68%).	
9	[42]	Fuzzy logic	Systematic review and meta-analysis on diagnostic accuracy of predictive models in prostate cancer. MRI significantly improves detection accuracy and discrimination for biopsy.	25,691 people from thirteen studies included. Data extracted included publication year, sample size, and AUC	Among 25,691 participants, the study reported an overall AUC of 0.78. MRI models achieved 0.88, surpassing Americas (0.73) and Europe (0.80).	predictive

10	[43]	logistic regression, RandomForest, DCA	Developed predictive model for prostate cancer detection. Random Forest model showed best predictive performance and net benefit.	146 patients from Guangxi Medical University. 116 patients from Changhai Hospital.	The Random Forest model demonstrated the highest predictive performance and provided the greatest net benefit among all evaluated algorithms, achieving an area under the curve (AUC) of 0.871	predictive
11	[44]		Machine learning models improve prostate cancer detection using ultrasound. Combined model shows highest predictive efficacy for malignant lesions.	166 men with targeted biopsy-confirmed pathology 72 benign and 94 malignant lesions	The risk factor model incorporating these four predictors demonstrated superior discrimination in the validation cohort (AUC: 0.84) compared to radiomics images (AUC: 0.79 for the B model, 0.78 for the CEUS model, and	prediction

					0.83 for the B-CEUS model). The combined model achieved the highest predictive efficacy with an AUC of 0.89	
12	[45]	machine learning (Fusion gene)	Discovered 8 fusion genes linked to aggressive prostate cancer. Fusion gene model predicts up to 91% clinical outcomes accurately.	271 samples from University of Pittsburgh Medical Center 194 samples from University of Wisconsin, Madison 108 samples from Stanford University	MAN2A1-FER, SLC45A2-AMACR, MTOR-TP53BP1 fusions predict prostate cancer recurrence with 91% accuracy (UPMC), 74% across cohorts, 93% with Gleason.	Prediction
13	[46]	SVM and CNN	Machine learning aids in prostate cancer detection and diagnosis. Study emphasizes ethical aspects and potential for improved	Genetic information datasets Clinical records and medical photographs	The U-Net model achieved AUROC 0.889 and AP 0.732, outperforming Random Forest (AUROC 0.88) and MRI	Prediction

			patient outcomes.		(AUC 0.6269) methods.	
14	[47]	Random Forest (RF) and XGBoost (XGB)	New ML model predicts prostate cancer risk effectively. Targeted and combined biopsies outperform systematic biopsy in detection.	Records from two hospitals in Riyadh, Saudi Arabia. Data on diagnosed prostate cancer from 2019 – 2023.	XGBoost (XGB) and Random Forest (RF) models demonstrated AUC values ranging from 0.94 to 0.97 for both targeted and combined biopsy approaches.	prediction

Table 4. Summarized Literature on Classification Problems

S/N	References	Methodology	Description	Dataset	Result	Problem solved
1	[48]	CNN, SVM, Adaboost, K-NN, and Random Forests	Proposed algorithm for prostate cancer classification using deep learning Achieved high accuracy on ultrasound and MRI images	Ultrasound images dataset for prostate cancer classification. MRI images dataset for prostate cancer classification.	The accuracy from aforementioned 80% to 88% on the MRI dataset.	classification

2	[49]	convolutional neural network (CNN), Logistic regression, Randomforest, XGBoost	Investigates machine learning classifiers for prostate zone detection. Highlights importance of salient features in classification rationale.	T2-weighted images and apparent diffusion coefficient (ADC) map images were utilized	Ensemble algorithms excelled in PZ and TZ zones. CNNs performed best in the AS zone.	classification
3	[50]	unsupervised learning GAEs (graph autoencoders)	Identified biomarkers for prostate cancer using machine learning techniques. Developed a prognostic risk model with four key genes	Multi-database validation performed for diagnostic biomarkers. Literature review conducted for verification of biomarkers.	AUC values of 0.69, 0.58, and 0.61 at 1, 3, and 5 years, respectively	Classification
4	[51]	Random Forest, k-Nearest Neighbors (KNN), Decision Trees, Naïve Bayes, Logistic Regression, Support Vector Machines (SVMs), and XGBoost.	Developed machine learning model for prostate disease early warning. KNN model achieved highest accuracy; ensemble improved results further.	Medical indicator dataset of prostate patients used. No specific dataset names provided in the text.	Ensemble technique increases the accuracy of the model, its accuracy has reached as high as nearly 90%.	classification

5	[52]	Deep learning	DL models outperformed PI-RADS in csPCa detection and classification. DL ensemble model excelled in PSA-stratified csPCa detection.	Training cohort: 1,285 patients External testing cohort: 315 patients	DL-based models achieved higher csPCa detection (AUC: 0.902), outperforming PI-RADS (AUC: 0.759) and excelling in PSA <10 ng/ml assessments.	classification
6	[53]	Support Vector Machines and Balanced Random Forest (BRF)	Non-invasive prostate cancer diagnostic tool using MRI radiomics analysis. Achieved 79% accuracy in identifying clinically significant prostate cancer.	T2 weighted and diffusion weighted images from 1500 patients. Whole prostate gland segmented by deep learning algorithms.	A balanced accuracy of 79% was achieved for the SVM using radiomics from the whole prostate gland.	Classification
7	[54]	artificial neural network	Neural network trained for prostate cancer diagnosis via MRI. Achieved 78% accuracy, surpassing radiologist's 55% accuracy.	MRI data from patients at “Zdorovie” Clinical Center. Histological mapping slides by a morphologist.	Neural network localized prostate cancer in 78% of cases. Radiologist localized prostate cancer	classification

					in 55% of cases.	
8	[55]	DeepNeuralNetwork, Recurrent Neural Network, Convolutional Neural Network	Prostate Cancer detection using CNNs on MRI images. Integrates Conditional Random Fields for improved classification performance. Hybrid end-to-end network enhances XmasNet architecture. Experimental results show accuracy but high variability observed.	MRI dataset from PROSTATEx Challenge 2017. Contains mpMRI studies of 344 subjects.	AlexNet and VGG16 achieve better AUROC and BCE than others; CRF-XmasNet improves performance (AUROC 0.572) with reduced training time	classification
9	[56]	Convolutional Neural Networks and Recurrent Neural Networks	Prostate cancer is a leading cause of male cancer deaths. Hybrid ECNN-ERNN techniques improve cancer detection accuracy significantly.	Size of dataset used: 1.50 GB. No specific dataset details provided.	ECNN achieved 98.34% precision (AUC 0.999); combining features improved accuracy to 99.71% (AUC 1.00), outperforming	classification

					existing systems.	
10	[57]	Support Vector Machine (SVM), AdaBoost, Decision Tree (DT), and Random Forest (RF)	Support vector machines, Radio frequency, Machine learning algorithms, Magnetic resonance imaging, Sociology, Classification algorithms, Reliability	Prostate cancer is a major global health issue. Ensemble models achieved 96% accuracy in MRI detection.	The evaluation showed the ensemble model achieved an impressive 96% accuracy in distinguishing Significant from Non-Significant prostate cancer cases.	Classification
11	[58]	CNN	PCa diagnosis using CNNs and transfer learning on MRI images. Achieved 88.89% accuracy in classifying prostate cancer.	Limited number of MRI images used. Pre-trained on the ImageNet dataset	Our model achieved an impressive accuracy of 88.89% in prostate cancer classification.	classification

Table 7. Gaps of Single Methodology in Previous Studies

S/N	Author	Gaps	Methodology	Tools	Results
1	[59]	Uncertainty was not considered. However, several challenges that exist in the investigation process are the existence of high dimensionality data and less number of training samples	DNN model	Python 3.6.5 tool	the optimal DNN model has provided sensy, specy, precn, accuy, and Fscore of 96.30%, 95.56%, 96.67%, 96.64%, and 96.32%, respectively
2	[60]	The model is applicable to one dataset	Fuzzy logic and associative rules mining	Nil	Upon analyzing the classified subjects, we achieved a specificity of 59.2% and a sensitivity of 90.8%, with negative and positive predictive values of 81.3% and 76.6%, respectively. Notably, for ISUP ≥ 3 prostate cancer, our model accurately predicted biopsy outcomes in 98.1% of cases.
3	[61]	It used only Mamdani Inference Engine	IT2FL	Nil	The true positive prediction rate for biopsy cases is notably high at 73.77%, while the accuracy for negative

					biopsy cases shows a slight deviation

B. Research Questions Steps:

1. Preparation Steps:

The preparation steps are essential for laying the groundwork for formulating well-structured and meaningful research questions. In this phase, the researcher identifies the study's primary focus and determines the investigation's scope.

RQ1: Why is ML relevant in prostate cancer detection and prognosis?

RQ1.1: What ML algorithms are adopted in the studies under review for prostate cancer detection and prognosis?

RQ1.2: Which regions of the world have utilized ML models for prostate cancer research?

RQ1.3: To what extent has the use of machine learning in prostate cancer detection translated into clinical implementation beyond theoretical models

RQ2: How many studies have been conducted on ML for prostate cancer detection and prognosis from 2017 to 2024?

RQ3: What are the most frequently used keywords in research on hybrid models for prostate cancer detection and prognosis?

RQ4 What evaluation metrics are most used to assess detection accuracy in prostate cancer models?

C. Article Selection Strategy

2. Execution Step

The Execution Step is the stage where the planned research activities are implemented, involving data collection and the application of the research design.

a. Search Strategy:

The data collection was carried out using selective, term-based searches across articles from various sources published between 2017 and 2024. We searched research databases such as Google Scholar, IEEE Xplore, Elsevier, and Springer for the specified terms, focusing on titles and abstracts of the articles. The search process was guided by the research questions, and advanced search techniques like "AND" and "OR" were used to narrow down the results.

b. Digital Libraries Resources

Table 8 summarizes the digital library resources utilized for gathering data, with an emphasis on English-language materials obtained via keyword searches. Data collection occurred from January 2017 to September 2024 and included a variety of sources such as peer-reviewed journals, academic articles, e-books, conference proceedings, and online workshops. Major platforms accessed in this research included ACM Digital Library, Elsevier, Google Scholar, IEEE Xplore, Springer, ResearchGate, ScienceDirect, and Systematic Scholar, aided by the Google search engine.

Table 8: Resource Libraries

Language	**Approach**	**Search Engine**	**Duration**	**Type**	**Digital library source**	**Number of Articles**
English	Keywords, Titles	Google	Jan. 2017 to Sept. 2024	scholar articles, scientific journals, e-books, conferences, online workshops	ACM Digital Library	40
					Elsevier	50
					Google Scholar	100
					IEEE Explore	50
					Springer	50
					Research Gate	150
					Science Direct	20
					Systematic Scholar	40
					Total	500

c. Search Terms

Search terms are specific keywords or phrases used in databases, search engines, or digital libraries to find relevant literature, articles, or information related to a research topic. These terms include essential keywords that represent the main concepts of the research, as shown in:

a. (Interval Type-2 Fuzzy Logic OR IT2FL) AND (Prostate Cancer Detection OR Cancer Diagnosis) AND (Hybrid Models OR Fuzzy Logic Systems) AND (Medical Imaging OR MRI and Ultrasound)

b. (Machine Learning OR XGBoost) AND (Prostate Cancer Prognosis OR Cancer Risk Prediction) AND (Hybrid Models OR Integrated Systems) AND (Medical Diagnosis OR Non-Invasive Techniques)

c. (Fuzzy Logic Systems OR IT2FL Applications) AND (Cancer Detection OR Prostate Tumor Localization) AND (XGBoost OR Machine Learning Models) AND (Medical Data Uncertainty OR Diagnostic Accuracy)

d. (AI in Healthcare OR Hybrid AI Models) AND (Prostate Cancer Detection OR Cancer Staging) AND (Interval Type-2 Fuzzy Logic OR IT2FL) AND (XGBoost OR Predictive Models)

e. (Prostate Cancer Screening OR Diagnostic Tools) AND (Machine Learning OR XGBoost Applications) AND (Fuzzy Logic OR Uncertainty Handling) AND (Non-Invasive Imaging OR MRI-Ultrasound Fusion)

D. Study Selection Based on Inclusion and Exclusion Criteria

Figure 1 shows the Prisma flow diagram, illustrating the study selection process, detailing the number of records identified, screened, excluded, and included in the review. Searches were conducted across nine databases, while no records were retrieved from registers, websites, organizations, or citations. A total of 20 duplicates were removed, with 379 records automatically excluded. No records were screened or assessed for retrieval, and no reports were sought out or retrieved from other sources. During the assessment phase, several reports were excluded for specific reasons. Ultimately, 121 new studies and associated reports were included in the final analysis, highlighting the comprehensive effort to identify relevant literature.

The exclusion criteria for studies considered in this review include: i) Sample Size Thresholds - Studies with a sample size of fewer than 50 participants were excluded to ensure statistical reliability and generalizability of results. ii) Publication Quality - Articles published in non-peer-reviewed journals or lacking sufficient methodological rigor were excluded to maintain the credibility of the review. iii) Geographic Limitations - studies restricted to highly localized datasets without diverse demographic representation were excluded to enhance the applicability of findings across broader populations. iv) Timeframe - studies published outside the 2017-2024 window were excluded to focus on the most recent advancements in the field. v) Language - non-English studies were excluded due to resource constraints in translation and validation of findings. vi) Relevance - studies gthat did not specifically address prostate cancer detection or prognosis using machine learning, or that failed to include IT2FL or XGBoost as a component of the methodology, were excluded.

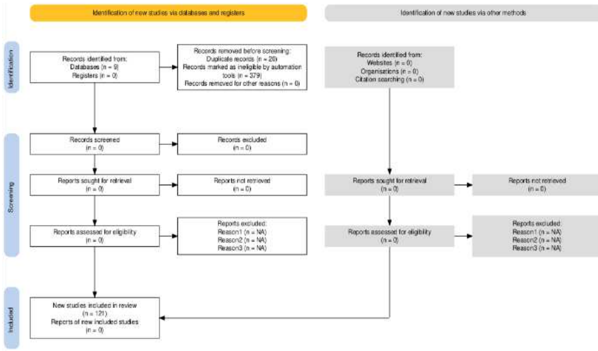

Figure 1: Prisma flow diagram of study selection

3.0 Results and Discussion

RQ1: Why is ML relevant in prostate cancer detection and prognosis?

RQ1 is answered using the sub-questions **RQ1.1 to RQ1.3.**

RQ1.1: What ML algorithms are adopted in the studies under review for prostate cancer detection and prognosis?

This study employs a variety of ML algorithms to enhance diagnostic accuracy and predictive outcomes in prostate cancer research. The models utilized include semi-supervised learning, artificial neural networks (ANN), AdaBoost, boosting techniques, convolutional neural networks (CNN), decision trees, deep learning, fuzzy logic, k-nearest neighbors (KNN), recurrent neural networks (RNN), support vector machines (SVM), naive Bayes (NB), random forests, and XGBoost.

These diverse ML methods highlight the extensive application of advanced computational techniques in the field of prostate cancer research.

RQ1.2: Which regions of the world have utilized ML models for prostate cancer research?

Figure 3 and Figure 4 show that Europe and Asia have the highest number of countries utilizing machine learning models for prostate cancer research, reflecting strong research activity in these regions. North America also has significant involvement, primarily from the U.S. and Canada. Other regions, including the Middle East, Africa, South America, and Oceania, show some engagement but to a lesser extent, indicating that machine learning applications in prostate cancer research are more concentrated in Europe, Asia, and North America. This distribution likely reflects available resources, research funding, and technological advancements in these areas.

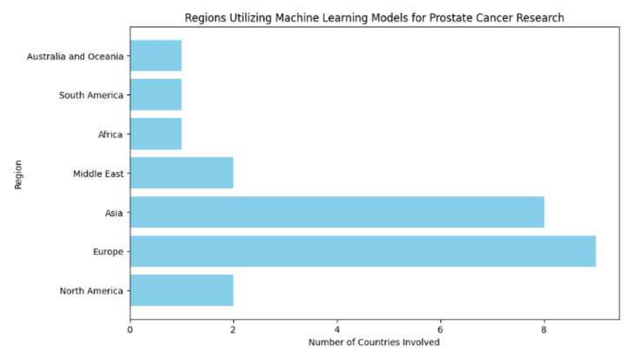

Figure 3: Region of study with several countries

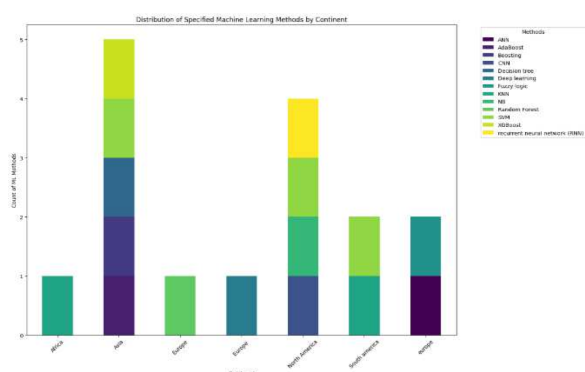

Figure 4: Distribution of specified ML by Continent+

RQ1.3: To what extent has the use of ML in prostate cancer detection translated into clinical implementation beyond theoretical models

The use of ML in prostate cancer detection has shown significant promise, particularly in tasks such as lesion detection, risk stratification, and treatment planning using imaging techniques like MRI. While ML models demonstrate high accuracy and potential for reducing observer variability, their clinical implementation remains limited due to challenges such as the need for extensive validation on diverse datasets, regulatory hurdles, and clinician training. Efforts to address these barriers include integrating ML tools into clinical trials, exploring explainable AI for trust and interpretability, and leveraging federated learning to ensure data privacy. As these advancements continue, the gap between theoretical models and real-world clinical applications is gradually narrowing, paving the way for broader adoption in prostate cancer care.

RQ2: How many studies have been conducted on ML for prostate cancer detection and prognosis from 2017 to 2024?

Figure 5 illustrates the number of studies conducted on ML for detection of prostate cancer and prognosis between 2017 and 2024. The trend shows a gradual increase in the number of studies from 2017, starting with 2 studies, and peaking in 2020 and 2021, with 14 and 13 studies, respectively. Following this peak, there is a decline in the number of studies, with 7 recorded in 2022, 9 in 2023, and 4 in 2024. This pattern indicates growing interest in the field during the earlier years of the period, followed by a tapering off in recent years, possibly due to saturation or shifts in research focus.

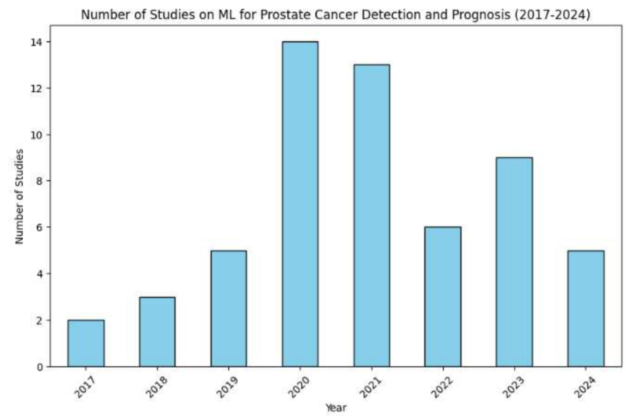

Figure 5: Machine learning used between 2017 and 2024

RQ3: What are the most frequently used keywords in research on hybrid models for prostate cancer detection and prognosis?

Figure 6 present word cloud, showing a visualization of the most frequently used terms in the reviewed literature, highlighting key topics such as "prostate," "cancer," "machine learning," and "diagnosis."

Figure 6: provides a comprehensive visualization of terms frequently associated with research on prostate cancer detection and prognosis. The term "prostate" stands out as the most prominent, reflecting its centrality to the subject matter. Similarly, "cancer" is another dominant term, emphasizing the focus on the identification and treatment of malignant conditions affecting the prostate. The presence of "system" and "biopsy" suggests significant attention to diagnostic systems and procedures, such as biopsies, which remain a critical tool in confirming cancer diagnoses. Terms like "health" and "disease" highlight the broader context of

medical research and the impact of prostate cancer on patient well-being. "Learning" and "artificial" indicate the growing reliance on machine learning and artificial intelligence technologies to enhance predictive models and decision-making processes in prostate cancer management. The appearance of "imaging" points to the pivotal role of medical imaging techniques, such as MRI and ultrasound, in detecting and monitoring the disease.

The frequent occurrence of "therapy," "PSA" (Prostate-Specific Antigen), and "survival" reflects the research interest in therapeutic interventions, biomarker-based screening methods, and survival outcomes. Words like "biomarker," "neural," and "deep" underscore the integration of biomarkers and deep learning techniques in predictive analytics and diagnostics.

Furthermore, the inclusion of terms such as "guidelines," "detection," and "predictive" signifies efforts to establish clinical best practices and improve early detection accuracy. "Radiotherapy," "management," and "decision" suggest a focus on treatment strategies and decision-support systems aimed at optimizing patient outcomes. The presence of words like "fuzzy" and "forest" indicates the adoption of advanced machine learning algorithms such as fuzzy logic and random forest models in research studies.

Additional terms such as "imaging," "Gleason," and "therapy" point to the use of imaging techniques, the significance of the Gleason grading system for classifying tumor severity, and ongoing advancements in therapeutic approaches. Lastly, terms like "survival," "disease," and "care" highlight the overarching goals of improving patient survival rates, understanding disease progression, and enhancing overall healthcare delivery.

In summary, the word cloud reveals a multidisciplinary research approach integrating computational methods, clinical diagnostics, and therapeutic strategies to improve prostate cancer detection, prognosis, and management.

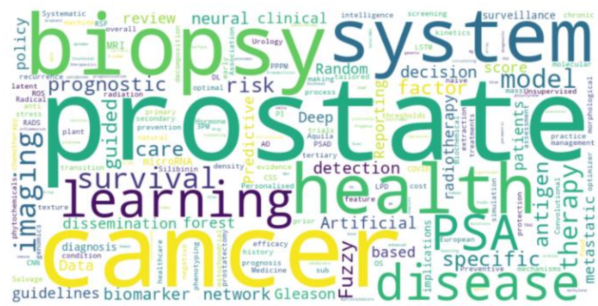

Figure 6: Word cloud visualizing the most frequently used terms in the reviewed literature

RQ4: What evaluation metrics are most used to assess detection accuracy in prostate cancer models?

When assessing detection accuracy in prostate cancer models, several evaluation metrics are commonly employed To provide a thorough assessment of model performance, accuracy is defined as the ratio of correctly classified cases (both true positives and true negatives) to the total number of cases., which is crucial in cancer detection. Specificity, on the other hand, evaluates the model's effectiveness in identifying negative cases, minimizing false positives. The Positive Predictive Value (PPV) indicates the likelihood that patients identified as positive actually have the disease, while the Negative Predictive Value (NPV) reflects the probability that negative predictions are accurate. The F1 Score, the harmonic mean of precision and recall, provides a balance between these metrics, especially in cases with imbalanced datasets. Lastly, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is utilized to assess the model's discriminative ability across various thresholds, offering insight into overall performance. These metrics collectively provide a robust framework for evaluating the effectiveness of prostate cancer detection models.

3.1 Limitations Reported in the Studies

The studies reviewed revealed several significant limitations that affected the performance and applicability of ML models in prostate cancer detection and prognosis. A recurring challenge was the quality and availability of medical data, which is crucial for developing accurate and reliable models. Many studies faced issues such as incomplete, imbalanced, or low-quality datasets, with missing values or a lack of diversity in patient populations. These data deficiencies often led to skewed model outcomes and limited the generalizability of the findings. Additionally, obtaining labeled data for supervised learning tasks was another common obstacle, with the high cost of acquiring detailed medical records or expert annotations being a limiting factor, especially for rare cancer cases. The computational complexity of advanced ML algorithms, particularly when using hybrid or deep learning models, was also highlighted, as these approaches often demand significant computational resources and longer processing times, posing a challenge for real-time clinical application.

Another limitation discussed in the studies was the interpretability of complex models. While advanced algorithms like deep learning offer high accuracy, they often function as "black boxes," making it difficult for healthcare professionals to understand how predictions are made. This lack of transparency raises concerns about the trustworthiness and clinical adoption of these models, as clinicians require an explanation for decisions that could directly impact patient care. Furthermore, the absence of standardized protocols for feature selection, model evaluation, and performance metrics made it challenging to compare the effectiveness of different ML approaches. Some studies also pointed out the need for better integration of these models into clinical workflows, emphasizing the importance of user-friendly interfaces that could help practitioners implement these tools effectively. Finally, the risk of overfitting was identified, particularly when models were trained on small or non-representative datasets, leading to overly optimistic performance estimates that may not reflect real-world conditions.

4.0 Conclusions

This systematic review underscores the effectiveness of a hybrid model integrating Interval Type-2 Fuzzy Logic (IT2FL) and the XGBoost algorithm in enhancing prostate cancer detection and prognosis. IT2FL addresses uncertainties in medical datasets by providing a structured framework for handling complex and imprecise variables, while XGBoost enhances accuracy by reducing bias and variance, ensuring robust and reliable predictions. Together, these technologies create a powerful synergy for improving diagnostic precision and clinical decision-making.

The review analyzed 121 studies published between 2017 and 2024 from reputable digital libraries such as Google Scholar, IEEE Xplore, Elsevier, and Springer, offering key insights into the hybrid model's application. Visualization tools like VosViewer, Matplotlib, and Excel were employed to graphically represent trends and provide a deeper understanding of the field. The hybrid model's ability to handle multidimensional data complexities demonstrates its potential to improve early diagnosis, minimize false positives, and streamline treatment planning for prostate cancer.

This integrative approach advances research in prostate cancer while laying the groundwork for broader applications in precision medicine. Its scalability and adaptability make it particularly valuable for global implementation, including in underserved regions with limited access to expert radiologists and advanced imaging. Furthermore, incorporating explainable AI techniques can enhance the model's interpretability, fostering trust among clinicians and patients and encouraging widespread adoption.

In conclusion, this hybridized approach not only elevates prostate cancer diagnostics but also bridges the gap between innovative research and clinical practice. By addressing critical shortcomings of current methods, it offers a transformative pathway toward more accurate, equitable, and reliable healthcare, marking a significant step forward in precision medicine.

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Ethical Considerations and Safeguards: This study adhered to ethical standards by safeguarding data privacy and anonymity in line with the General Data Protection Regulation and Nigeria's Data Protection Regulation, ensuring that no personally identifiable information from Twitter data was exposed. Also, data authenticity was ensured by filtering bots, spam, and disinformation, thereby preserving the integrity of the electoral discourse analyzed.

Ethics Approval: The study was conducted in compliance with institutional research ethics guidelines.

Competing Interests

The authors confirm that they have no conflicts of interest to disclose.

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