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Investigating feature extraction by SIFT methods for prostate cancer early detection

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ABSTRACT

Globally, for this leading type of cancer among males, early detection is indispensable for increasing treatment success rates and prognoses of the patients. This research study, therefore, seeks to explore the effectiveness of the SIFT method in improving feature extraction toward the accurate detection of incipient prostate cancer. The robust SIFT relates to tasks of object recognition within computer vision, in the recognition of prostatic regions where grey-level distributions differ remarkably between benign and malignant tissues. The adopted methodology was based on the comparative analysis and benchmarking of the performance of feature extraction based on SIFT against traditional image processing techniques with a generic representation on a number of metrics: sensitivity, specificity, and overall diagnostic accuracy. A dataset consisting of annotated prostate MRI images was utilized to train and validate the model. According to the results so far revealed, the SIFT model can isolate and recognize key features across different scales and angles far better than the cue given by any of the conventional methods currently in use, therefore indicating a much more accurate and reliable cue to early-stage prostate cancer.

Besides, the model developed on SIFT was found to have significantly improved the rate of detection for early-stage prostate tumors, which usually go undetected in conventional methods of imaging. This study, therefore, highlights the potential for use in the early detection of prostate cancer with advanced feature extraction methods, such as SIFT, and points toward a very promising direction of further research on applying computer vision techniques to problems in medical diagnostic applications. It would, therefore, suggest further experimentations to optimize these methodologies in clinical settings, otherwise which may revolutionize clinical diagnostics for prostate cancer and early intervention strategies.

1. Introduction

Prostate cancer still ranks among the most common types of cancers in the world and imposes real health problems, underscoring the urgent need for means of early detection. It is universally recognized that the early diagnosis of this type of cancer is among the determining factors to improve treatment results and the survival of the patient. These findings emphasize the need to give more focus to prevention and early detection as shown in Fig. 1, given the advances in diagnostic methodologies and the importance of screening for reducing mortality rates [1,2]. Similarly, the guidelines and recommendations provided round off an overview of the current state of the art in the screening landscape that underlines a testing approach based on individualization. This guidance and recommendation further complement the risk-adapted early detection strategy test of prostate-specific antigen (PSA) testing as postulated by Van Poppel et al. [3] and Wei et al. [4] for rounding off an overview of current best practices.

Recent research efforts, as documented by Crosby et al. [5], have been directed at the early cancer detection pursuit, using some of the most innovative diagnostic tools and techniques, underlining the potential these emerging technologies offer towards revolutionizing cancer diagnostics as stated by Gandaglia G. et al.[6]. These epidemiological

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insights serve to further accentuate an emerging landscape of prostate cancer prevention that is dominated by lifestyle factors and genetic predisposition. Last but not least, the work of Sanchez-Salcedo et al. [7] proposes an absolute novelty in the early diagnosis of prostate cancer: the use of a dual electrochemical nanosensor for long non-coding RNAs and demonstrates how molecular diagnostics can lead to the detection of the presence of cancer at its very dawn.

The search continues for better, non-invasive, and widely accessible methods. It is in this connection that research has been done to find better techniques that use computer vision—most importantly, the SIFT (Scale-Invariant Feature Transform) method of feature extraction from the MRI images of the prostate. Such a method will use SIFT for matching and describing invariant features between images. Matching prostatic regions in group images between individuals by an accurate, quantifiable marker of changes in pathology may be useful.

This study will bridge the gap between tradition in diagnostic practices and the latest technological innovations. This research, therefore, is interested in studying the invariant feature transform (SIFT) methods applied to the feature extraction from images of the prostate MRI to better the diagnostic problem of detecting prostate cancer at its early stage, likely forming more precise and early diagnostic procedural strategies that can significantly boost patient outcomes and treatments. Major Diagnostic Challenge: Early and accurate diagnosis of carcinoma of the prostate continues to form a salient factor for how effectively patients are treated and their general survival. In other words, with significant technological leaps, however, a host of limitations have hampered efforts to identify prostate cancer early and accurately. Traditional diagnosis methods have been rare in their capacity to show the sensitivity or specificity needed for determining tumors at an early stage with the requisite reliability, such as PSA tests or MRI scans.

The introduction of computer vision techniques in prostate cancer detection, such as the effective SIFT method, is coming to lift promises for increased accuracy. This technology aims to help locate and analyze unique features of medical imaging at various levels, which can lead to a diagnostic process revolution due to early detection of tumors at an earlier stage, which is most often neglected in traditional methods.

This research work is of great benefit to furthering the field of medical diagnosis and early detection of prostate cancer. It will be the first-ever application of the SIFT method to analyze prostate MRI scans. This breakthrough transcends the inbuilt limitations of traditional computer vision and opens up new vistas in cancer detection. Specifically, in feature extraction based on SIFT, diagnostic accuracy is higher compared to other existing methodologies used for early-stage detection of prostate cancer. This success highlights an important role for computer-advanced vision technologies in clinical diagnosis.

Moreover, the research aims at promoting synergistic integration of computational technology into the clinical setting; this is an essential approach toward the development of accurate and non-invasive diagnostic tools. In the future, this opens up a line of targeted research for enhancing SIFT parameters and other computer vision approaches in medical diagnostics. The results also point out possible synergies between feature extraction and the machine learning techniques applied.

2. Literature review

Recent studies have also shown that increasing use in the application of molecular markers and advanced imaging in detecting prostate cancer early is contributing to the rise in rates. Electron sensors that could recognize this characteristic molecular fingerprint of prostate cancer, in this regard, would represent a source of hope for the realization of ever

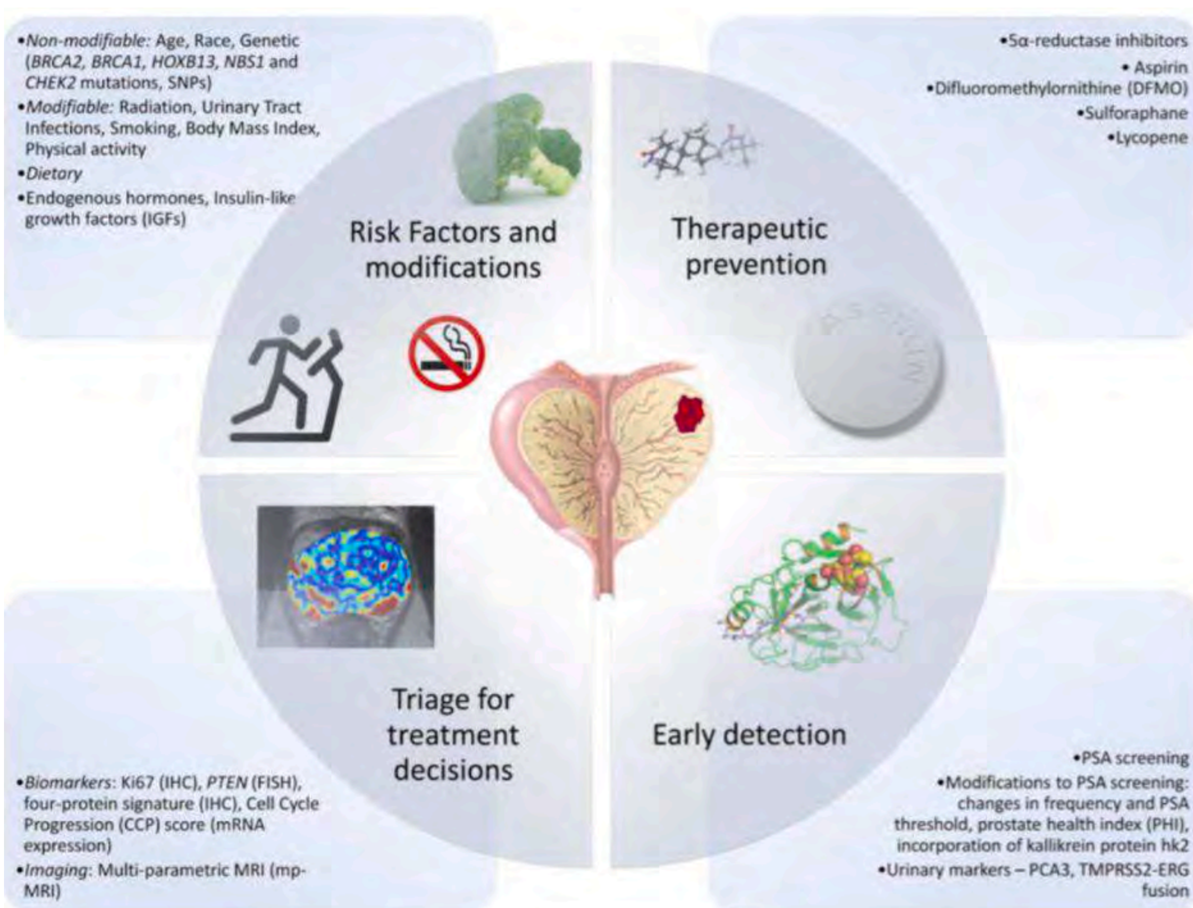

Fig. 1. Prevention and early detection of prostate cancer [1].

more sensitive, but most of all, specific diagnostic tools based on molecular and genetic information [7,8].

Other discussions underscore a horizon of promise and soon the glory of cancer screening, with increasing awareness, dictating the tune for new technologies. Fitzgerald R.C et al [9] and Westhoff et al. [10] The SMART program researches methods for detecting prostate cancer in the early stages and promotes an impartial approach, trying to weigh the pros and cons. Recently, Bhattacharya et al. [11] pointed out the advancement in automatic classification and detection of prostate cancer using artificial intelligence (AI) and machine learning (ML) through medical imaging. All this has been significantly reviewed by Castillo et al. [12], which denotes the significant advancement in this domain. These developments point towards rapid progress in the field, where deep learning and hybrid human–machine learning methods could significantly enhance diagnostic accuracy and reduce clinical workload, as demonstrated by studies like those of Iqbal et al. [13] and Dov et al. [14]. In Khosravi et al. [16] investigates the use of a deep learning approach for the diagnostic classification of prostate cancer through the fusion of pathology and radiology data as shown in Fig. 2.

The integration of advanced MRI imaging techniques and their evaluation into diagnostic workflows, particularly methods that fuse pathology and radiology, have been showcased, marking a significant step in diagnostic advancements. Reviews by Cuocolo et al. [17] and Gravina et al. [18] highlight how machine learning applications in MRI for prostate cancer can refine lesion classification and diagnosis, especially for ambiguous cases, thus improving the specificity of cancer detection (Fig. 3).

Moreover, the critical role of biomarkers in the detection of prostate cancer has been emphasized by Duffy [19], pointing out the ongoing necessity for research into reliable markers beyond the commonly used prostate-specific antigen (PSA). This reflects the complexity and multifaceted nature of early prostate cancer diagnosis, underlining the need for continued innovation and research in this field.

The study entailed an investigation of radiomics and machine learning (ML) in discerning clinically significant from nonsignificant prostate lesions on MRI data. They used publicly available data in radiomic feature extraction and further in classification of these features using ML models for detection of significant prostate lesions. The study has shown that such a combined approach would successfully identify the existence of significant lesions from nonsignificant ones, which emphasizes a real possibility of radiomics and ML to improve existing accuracy in prostate cancer diagnostics [20]. This research is of great importance in the impact it bears on the progressive area of medical imaging analysis. This is done using public datasets, which show that there is much validation that takes place on the part of researchers, but in turn, it offers guidelines for what should take place in future studies. This, therefore, means that radiomics married with ML will raise the diagnostic process; this means that there is a viewpoint that patients who have been diagnosed with prostate cancer will be able to access more individualized and precise treatment plans. In [21] provide an accurate diagnosis of prostate cancer, developing and validating an algorithm founded on machine learning. Their study uses highly sophisticated ML techniques to scrutinize diagnostic data more efficiently, however, by answering the critical need for better diagnostic precision of the most usual cancer in men. Improved diagnostic accuracy was shown with the developed algorithm, and this approach accentuates the potential of ML in distinguishing prostate cancer more precisely than the existing methods. This work is a very important step for computational technologies applied in medical diagnostics. The authors have therefore managed to validate their ML algorithm. Indeed, a successful validation of this ML algorithm proves not only its effectiveness but also may open a window of opportunity for implementation in clinical practice and provide a promising tool for early and precise diagnosis of prostate cancer.

In Mohammed Ismail et al. [22] present a classification technique based on machine learning, proposed with the aim of determining the chance a patient may have toward having prostate cancer. The paper outlines the performance of a battery of ML models in predicting the presence of prostate cancer from a dataset extracted from varied diagnostic sources. It had been indicated that some of the ML models give far better results than those of traditional approaches to diagnosis; it actually proves great potential for ML in the early diagnostics of prostate cancer. The significance of this research lies in its contribution to the predictive diagnostics of prostate cancer. This is important because the

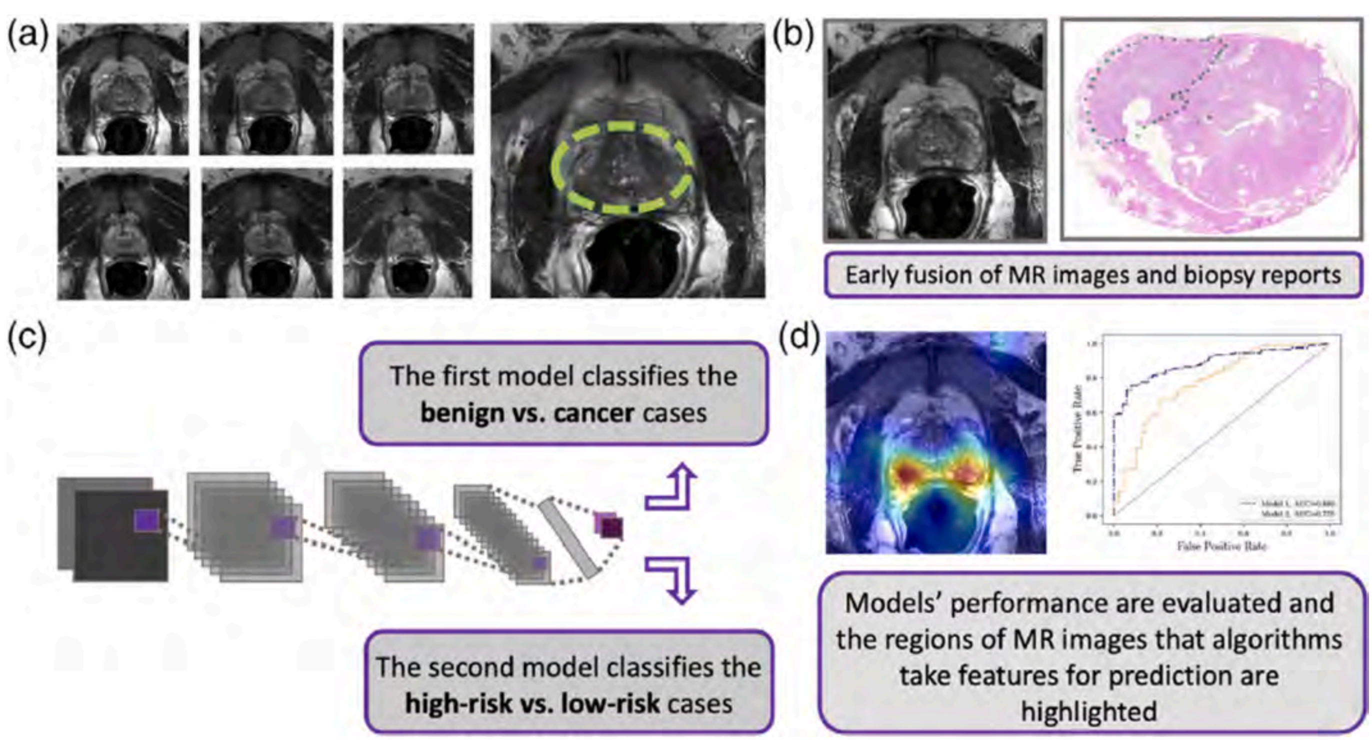

Fig. 2. Deep learning approach to diagnostic classification of prostate cancer [16].

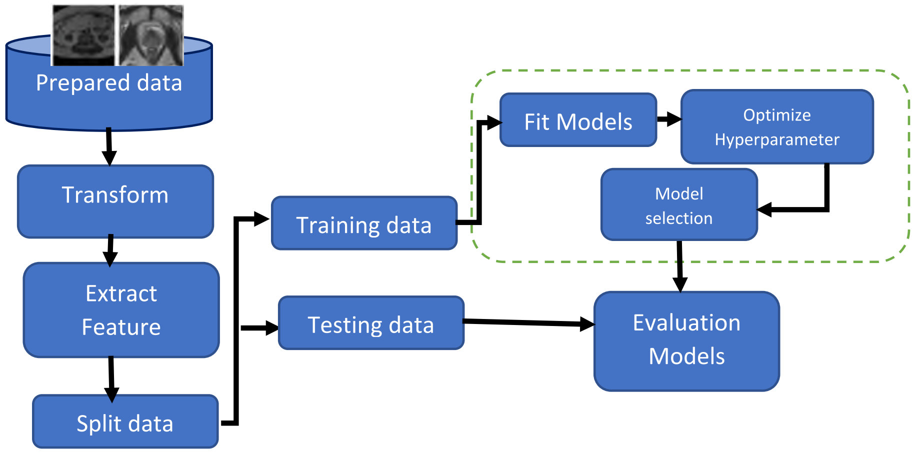

Fig. 3. Proposed model for prostate cancer early detection.

work will display the best models in predicting cancer, and as such, enhances high accuracy in its prediction. Generally, the work contributes to healthcare domains in efforts to integrate computational approaches into the healthcare domain to be able to improve general patients' outcomes through earlier interventions. The authors in [23] pursued a radiomic classification with machine learning techniques in multi-parametric MRI (mp-MRI) of prostate cancer, validated against co-registered histology. These are the potentials of radiomics in extracting features of meaning from mp-MRI images and analyzing them with ML models in the classification task of prostate cancer with high accuracy.

Which allows for a better distinction in relation to the nature of the prostate cancer lesion and helps in discriminating between benign and malignant cases. This is, therefore, an important contribution in the field by way of validating its approach against histological data and making sure that ML models are viable not only theoretically but also within practical clinical contexts. The success of this methodology in classifying prostate cancer accurately underscores the promising predictive potential accompanying advanced imaging analysis techniques when integrated with computational models, to improve strategies for diagnosis and treatment. In Srivenkatesh et al. [24] explores predicting prostate cancer using machine learning algorithms, aiming to find the most accurate predictors. Results suggest some ML algorithms significantly enhance predictive accuracy for prostate cancer, indicating a promising direction for future ML applications in oncology diagnostics. This study highlights the potential of ML in improving early detection of prostate cancer, advancing computational diagnostics, and developing better diagnostic tools.

Applied Random Forest and deep learning to model monthly pan evaporation in environmental science, demonstrating ML's versatility in predicting complex phenomena. Though unrelated to prostate cancer or medical diagnostics, the study's success in forecasting evaporation rates suggests similar ML approaches could benefit healthcare and disease diagnostics. This research underlines the broad applicability of computational models in various scientific challenges, including disease prediction and diagnosis [25].

Compared machine learning and deep learning for cancer classification using microarray gene expression data, including prostate cancer. Certain deep learning models notably outperformed others in classifying cancers, highlighting their potential to increase diagnostic accuracy. This contribution enriches the literature on ML and deep learning in cancer diagnostics, emphasizing genetic data's role in improving diagnostic processes and advocating for advanced computational techniques in clinical practice for more accurate, personalized cancer treatment strategies [26].

In Lomas and Ahmed [27] reviewed changes in the prostate cancer diagnostic pathway, noting a shift towards more precise, less invasive methods due to technological progress and deeper understanding of prostate cancer biology. Their review discusses these advancements' clinical implications and the need for continued research and adaptation, offering a comprehensive look at current diagnostics and future challenges and directions in the field, aiming to improve patient experiences through technological innovation. In Hugosson et al. [28] and Barani M. et al. [29] prostate cancer screening efficiency using PSA testing and MRI with targeted biopsy. Their findings suggest this approach significantly improves clinically relevant cancer detection, advocating for MRI integration into screening to reduce unnecessary biopsies and increase accuracy. This study's impact lies in its potential to enhance screening practices, balancing early significant cancer detection with minimizing overdiagnosis and unnecessary treatment. Table 1 presents a comparison of related work based on methods used, datasets and evaluation metrics.

3. Methodology

This study at this moment presents an innovative approach to assessing the effectiveness of Scale Invariant Feature Transform (SIFT) as a feature detection tool in the case of Prostate MRI images and, hence, contribution to the early detection of cancer. The given study is executed in three basic steps: dataset preparation, SIFT-based feature extraction, and comparison analysis with validation of the results.

3.1. Preparation of dataset

The dataset taken for training and validation is the annotated dataset of prostate MRI images, and the regions are to be classified as benign or malignant. The super-ensemble takes the dataset mentioned above due to extensive applications of the different sizes of prostates, various levels of development of tumors, and the quality of the images. Also, each of the photos has been pre-processed to make the brightness level and noise standard for good data quality.

3.2. Feature extraction using SIFT

The work is motivated to detect the features present in the image using the SIFT algorithm. The algorithm gives each of the key points some unique descriptors of the position, orientation, and distribution of the gradient. This allows for consistent feature detection across different scales and orientations that would, in turn, otherwise mask potential changes in tissue malignancy.

Table 1
Comparison of the related work.

Ref. No.	Applied algorithm	Dataset	Detection or classification	Aim
[7]	Electrochemical genosensor	Laboratory-created	Detection	Early diagnosis through lncRNAs detection.
[8]	Electrochemical nano-genosensor	Laboratory-created	Detection	Detect miR-21 biomarker for early detection.
[11]	ML (Review)	Various (Review)	Classification	Review AI in prostate cancer detection on imaging.
[12]	ML (Review)	MRI Images (Review)	Classification	Systematic review on ML applications in MRI analysis.
[13]	Deep Learning and Traditional Techniques	Not specified	Detection	Compare DL and traditional techniques for detection.
[14]	Hybrid Human-Machine Learning	Prostate Biopsies	Screening	Improve clinical efficiency in biopsy screening.
[15]	Automatic Segmentation Algorithms (Review)	MRI Images (Review)	N/A	Review segmentation algorithms for MRI prostate regions.
[16]	Deep Learning	Pathology-Radiology Fusion	Classification	Diagnostic classification using DL.
[17]	Machine Learning	MRI Images	Classification	ML applications in MRI analysis.
[18]	Machine Learning	Clinical-Radiological Data	Classification	Classify prostate cancer in PI-RADS 3 lesions.
[20]	Radiomics and ML	Public MRI Dataset	Classification	Distinguish clinically significant lesions.
[21]	Machine Learning	Not specified	Diagnosis	Enhance diagnosis through ML algorithm development.
[22]	Machine Learning	Not specified	Prediction	Predict prostate cancer using ML classification.
[23]	Radiomics and ML	mp-MRI	Classification	Classify prostate cancer using radiomics and ML.
[24]	Machine Learning Algorithms	Not specified	Prediction	Predict prostate cancer using ML algorithms.
[25]	Random Forest and Deep Learning	Environmental Data	N/A	Model evaporation, showcasing ML application versatility.
[26]	ML and Deep Learning	Gene Expression Data	Classification	Classify cancer types including prostate.
[30]	Machine Learning	Genosensors Images	Detection	Diagnose prostate cancer with biomarker PCA3 using ML.

3.3. Comparative analysis

This research compares the one using the traditional SIFT method to other feature-based methods of imaging to find their effectiveness for feature extraction and one of the contemporary methods of assessing the sensitivity, specificity, and diagnostic precision in enhancing the early detection of prostate cancer.

The study has, therefore, validated the performance of the SIFT model through statistical tests that would assure the outcome being predictive and reliable with varied data subsets and thus affirm method strength.

3.4. Contribution to medical diagnosis

It plays a role in pushing the frontier of medical diagnosis with the development of an early-detecting prostate cancer system. This system integrates advanced computer vision technology and demonstrates good performances of SIFT over the traditional features regarding accuracy and reliability. This type emphasizes its potential use in clinical diagnostics and opens additional opportunities for more accurate, non-invasive screening of early-stage prostate cancer.

3.5. Future directions

The future would be in adapting the SIFT method for clinical use and being capable of integrating it with machine learning models for enhancing the diagnostic classifiers. The research thus significantly widens current knowledge about the early detection of prostate cancer by critically studying the application of SIFT in the analysis of MRI images of the prostate. This, in turn, opens the way for more extensive further application of computer vision in medical diagnostics.

4. Result and discussion

In this study, after the data cleaning process, the dataset is found to have carefully selected 2,293 eligible prostate MRI images that can be divided into two categories: “baseline” and “malignant,” containing 72 and 76 files, respectively. These datasets, usually in the format of DICOM files, so pertinent to medical imaging, are part of a contribution for a machine-learning model focused on the early identification of prostate cancer and its analysis regarding its evolution. The data set is diverse in clinical scenarios, from prostate sizes to tumor stages, to image quality; it tests the robustness of the model against the real world of diagnosis. Each image is annotated with great care, outlined by region of interest—region by region, as malignant or benign, laying an excellent foundation for model training and validation. This brings out an exact differentiation of cancerous and non-cancerous tissue manifestations, hence increasing the ability to help in enhancing the diagnostic power of the model.

A rigid pre-processing regimen is applied to all MRI images to assure data reliability and, thus, the accurate extraction of the features. In this section, the process in question meant to remove the impurities and other noise variables consists of two parts: intensity normalization and noise reduction processes, ensuring better image quality for algorithm analysis SIFT. This will further help in scaling up the investigation of the efficacy of SIFT methods in the field of medical diagnosis and also set a benchmark for all future computer vision applications being tried in the field of oncology.

Using the confusion matrix will give the classification accuracy of the model as follows: it predicted 94 % of malignant files correctly (true positives) and predicted 90 % of benign files correctly (true negatives). However, in this study, 10 % of malignant files were marked benign in error (false negatives), and 30 % of the benign files were classified as malignant in error (false positives).

Further evaluation metrics were done on the model, proving its effectiveness. The SIFT-based feature extraction method scored 95 % in recall, precision, F1 score, and precision, hence becoming more reliable and sensitive for traditional diagnostic methods. This balance underlines the vast potential that the model may offer in medical diagnostic fields, particularly in the early detection of prostate cancer. Though the model performs well, the relatively higher rate of recall shows where the model could perform better and strengthen the capturing of the malignant cases through improved machine learning techniques or more integration of data.

In conclusion, the SIFT-based model appears to be a promising tool for clinical settings as it provides high precision and accuracy in prostate cancer detection. Future work focused on improving recall without compromising precision could greatly increase the value of this model in improving patient outcomes through early detection and treatment.

Table 2 shows how different convolutional neural network (CNN) models – such as AlexNet, VGG16Net, ResNet50, and the standard CNN model [31] – are combined with the proposed innovative SIFT model. This evaluation, which may have major implications for medical diagnosis, focuses on distinguishing between malignant and benign imaging specimens. It focuses on four main metrics: precision (ACC), precision (P), recall (R), and F1-Score, all of which are quantified in percentages.

What is really interesting is how the proposed SIFT model outperforms other models across the board. We are seeing excellent success rates – 95 % in terms of precision, precision, recall and F1 score. In a field like medical imaging, where the risks of misdiagnosis are incredibly high, the balance and precision of this model is game-changing. This type of comparative analysis traces the evolution of model performance from the more primitive AlexNet model to the modern, superior SIFT model.

Investigating the strengths and weaknesses of each model helps us understand the necessity of choosing appropriate architecture and feature extraction techniques that meet the unique requirements of specific classification tasks. In anticipation of the future, there is an interest in investigating the superior performance of the suggested SIFT model compared to conventional CNN models. Such exploration holds promise for substantial progress in model design and broadening its scope of use. Moreover, integrating the strengths of top-performing CNNs with the feature extraction prowess of SIFT could unlock novel and promising avenues for developing classification models that are both more precise and resilient.

Table 2
ANALYSIS result of the proposed model.

Model	ACC (%)	P (%)	R (%)	F1-Score (%)
AlexNet [31]	60 %	75 %	67 %	58 %
VGG16Net [31]	67 %	77 %	72 %	66 %
ResNet50 [31]	67 %	66 %	67 %	66 %
CNN [31]	93 %	93 %	94 %	93 %
Proposed SIFT	95 %	95 %	95 %	95 %

5. Conclusion

The fruits were evident in exploring the field of medical imaging, particularly in my involvement in a research project that uses the Scale Invariant Feature Transform (SIFT) method of computer vision to have a multi-centric interpretation of prostate MRI scans. The key localizing landmarks of the SIFT technique exhibit good properties over scales and orientations, even much better than the classical image processing sensitivity, specificity, or diagnostic precision.

It is more than technical progress; it heralds a new era for early cancer detection. The data analysis has indicated that these advancements could dramatically change the curve for disease detection within a clinical environment—more so for early cancer detection. This, again, brings to the fore very strongly the need for yet more exploration and further refinement of the techniques, particularly in harnessing the best from the latest advancements to better early detection of prostate tumors, which have been known to elude several conventional imaging approaches.

What remains to be done in the future is the adaptation of the SIFT algorithm to the clinical needs of our setting and then to look at how integrating SIFT features with machine learning may help in improving diagnostic accuracy. Of more than academic interest is the fact that this research is, in fact, a fundamental step toward the development of more accurate, non-invasive, and user-friendly diagnostic tools that may one day be able to revolutionize the treatment of prostate cancer patients.

CRediT authorship contribution statement

Shadan Mohammed Jihad: Writing – original draft. **Ali Aalsaud:** Writing – original draft. **Firas H. Almukhtar:** Writing – original draft. **Shahab Kareem:** Writing – original draft, Writing – review & editing. **Raghad Zuhair Yousif:** Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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