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Category PI-RADS 3: the role of texture analysis in prostate cancer risk stratification (a systematic review)

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ABSTRACT

BACKGROUND: Prostate changes classified as PI-RADS 3 are a clinical situation requiring diagnostic accuracy and minimization of invasive procedures. Exploring the potential value of texture analysis in magnetic resonance imaging for prostate cancer risk stratification is critical in modern medical diagnostics.

AIM: To systematize and analyze current data on the application of texture analysis for prostate cancer risk stratification in patients with PI-RADS 3 and evaluate its diagnostic significance in differentiating clinically significant from clinically insignificant prostate cancer.

MATERIALS AND METHODS: Articles published in the last 7 years were selected and analyzed from research reference and analytical databases (Medline and Scopus) using search engines (PubMed, Google Scholar, and eLibrary). Keywords related to texture analysis and radiomics regarding prostate cancer diagnosis and risk stratification were used.

RESULTS: Analysis of the selected publications showed that machine learning and texture analysis significantly enhance the diagnostic accuracy of prostate cancer. These methods allow for more accurate risk stratification and determination of the actual need for biopsy, potentially leading to a reduction in unnecessary invasive procedures.

CONCLUSION: Texture analysis potentially enhances diagnostic accuracy in cases of prostate gland changes classified as PI-RADS 3. However, further research focused on standardizing techniques and conducting multicenter clinical trials is required for its widespread clinical application.

Keywords: prostate cancer; PI-RADS 3; texture analysis; radiomics; magnetic resonance imaging; clinically significant prostate cancer.

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Категория PI-RADS 3: возможности текстурного анализа в стратификации риска рака предстательной железы (систематический обзор)

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АННОТАЦИЯ

Обоснование. Изменения предстательной железы категории PI RADS 3 — клиническая ситуация, требующая повышения точности диагностики и минимизации применения инвазивных методов. Изучение потенциальной ценности текстурного анализа изображений магнитно-резонансной томографии в стратификации риска рака предстательной железы является актуальной задачей современной медицинской диагностики.

Цель — систематизация и анализ современных данных о применении текстурного анализа для стратификации риска рака предстательной железы у пациентов с категорией PI-RADS 3, а также оценка его диагностической значимости в дифференциации клинически значимого и клинически незначимого рака предстательной железы.

Материалы и методы. Отобраны и проанализированы статьи, опубликованные за последние 7 лет, найденные в базах данных реферативной и аналитической информации о научных исследованиях (Medline, Scopus) с использованием поисковых систем (PubMed, Google Scholar, eLibrary). Применяли ключевые слова, связанные с текстурным анализом и радиомикой в контексте диагностики и стратификации риска рака предстательной железы.

Результаты. Анализ отобранных публикаций показал, что применение машинного обучения и текстурного анализа значительно повышает точность диагностики рака предстательной железы. Эти методы позволяют более точно стратифицировать риски и определять реальную потребность в биопсии при раке предстательной железы, что потенциально ведёт к снижению количества ненужных инвазивных процедур.

Заключение. Текстурный анализ обладает возможностями для улучшения диагностической точности в случае изменений предстательной железы категории PI-RADS 3. Однако для его широкого клинического применения необходимо провести дополнительные исследования, направленные на стандартизацию методик, и мультицентровые клинические испытания.

Ключевые слова: рак предстательной железы; PI-RADS 3; текстурный анализ; радиомика; магнитно-резонансная томография; клинически значимый рак предстательной железы.

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PI-RADS 3 类别：纹理分析在前列腺癌风险分层中的应用（系统性综述）

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摘要

论证。前列腺PI-RADS 3类变化是临床上需要提高诊断精度并最小化侵入性方法应用的情况。研究磁共振成像纹理分析在前列腺癌风险分层中的潜在价值，已成为当前医学诊断中的重要课题。

目的。系统整理和分析关于纹理分析在PI-RADS 3 类别前列腺癌风险分层中的应用的最新数据，评估其在区分临床显著性和临床不显著性前列腺癌中的诊断意义。

材料与方法。选取并分析了过去7年内在科学研究文献数据库（如Medline、Scopus）中找到的文章，通过搜索引擎（PubMed、Google Scholar、eLibrary）查找相关文献。使用与纹理分析和放射组学相关的关键词，研究前列腺癌风险分层和诊断中的应用。

结果。对选定文献的分析表明，机器学习和纹理分析的应用显著提高了前列腺癌的诊断精度。这些方法可以更准确地进行风险分层，判断前列腺癌患者是否需要进行活检，从而有潜力减少不必要的侵入性检查。

结论。纹理分析在PI-RADS 3类前列腺变化的诊断精度提高方面具有潜力。然而，为了广泛应用于临床，仍需进一步研究以标准化方法，并开展多中心临床试验。

关键词：前列腺癌；PI-RADS 3；纹理分析；放射组学；磁共振成像；临床显著性前列腺癌。

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BACKGROUND

Recent studies, particularly by Westphalen et al. [1], demonstrated substantial variability in the prognostic performance of the Prostate Imaging-Reporting and Data System version 2.1 (PI-RADS v2.1) in detecting clinically significant prostate cancer (csPCa). This variability has increased interest in the use of texture analysis in magnetic resonance imaging (MRI). Published data indicate the need for standardized protocols and methods, including texture analysis, to reduce interpretation discrepancies and enhance diagnostic accuracy. This is especially relevant in cases categorized as PI-RADS 3, which indicate an intermediate probability of csPCa—uncertain presence with equivocal findings [2–4].

In recent years, texture analysis, which involves the extraction of quantitative features from medical images, has emerged as a promising approach for the diagnosis and risk stratification of prostate cancer [5–7]. Imaging data may be analyzed by employing machine learning algorithms to identify hidden patterns associated with csPCa. These techniques are used for assessing tumor aggressiveness and predicting treatment response and clinical outcomes [7–11]. A key advantage of texture analysis is its ability to provide clinically significant diagnostic information without the need for invasive procedures such as biopsy, especially critical in scenarios with high diagnostic uncertainty [12, 13].

Texture analysis has gained considerable traction in csPCa diagnosis within the PI-RADS scoring system, particularly for category 3 lesions [3]. Patients with PI-RADS 3 lesions show a diagnostic gray zone. The risk of csPCa is not high enough to warrant immediate biopsy, but not low enough to waive further investigation or monitoring. This creates a clinical dilemma in managing this patient population, as clinicians should balance the risks of over- and underdiagnosis when striving to minimize unnecessary invasive procedures [2, 14].

Thus, texture analysis provides novel opportunities to improve the diagnostic accuracy of csPCa in patients with PI-RADS 3 lesions. It enables more precise risk stratification and facilitates the identification of patients who would benefit from biopsy [13, 15]. Advanced algorithms applied to MRI data can reveal subtle features beyond human visual assessment, thereby informing better clinical decision-making [2, 13, 16]. Considering the increasing relevance of texture analysis in csPCa diagnostics, the present study aimed to evaluate the potential of this technique in enhancing diagnostic accuracy and identify future directions for research in this field.

Despite some studies addressing the application of texture analysis in PCa diagnostics, including PI-RADS 3, current data reveal considerable variability in outcomes and a lack of methodological standardization [2–5, 11, 27]. Therefore, further investigation is required to improve diagnostic precision. This review aimed to clarify the role of texture analysis in risk stratification and in differentiating clinically significant PCa from insignificant ones, thereby enhancing diagnostic accuracy and reducing interpretive ambiguity.

AIM

This study aimed to systematize and analyze current data on the application of texture analysis for PCa risk stratification in patients with PI-RADS 3 lesions and evaluate its diagnostic significance in differentiating clinically significant from clinically insignificant PCa.

METHODS

A comprehensive publication search was conducted to assess the role of texture analysis in diagnosing PCa in patients with PI-RADS 3 lesions. Relevant studies were identified through research reference and analytical databases (Medline and Scopus) using the databases PubMed, Google Scholar, and eLibrary. The following keywords were used: *рак предстательной железы* (*prostate cancer*), *PI-RADS 3*, *текстурный анализ* (*texture analysis*), *радиомика* (*radiomics*), *магнитно-резонансная томография* (*magnetic resonance imaging*), *МРТ* (*MRI*), and *клинически значимый рак предстательной железы* (*clinically significant prostate cancer*).

Inclusion criteria:

- Original studies investigating the application of texture analysis or radiomics in diagnosing PCa in the setting of PI-RADS 3 lesions;
- Studies that underwent internal or external validation and were published over the past 7 years.

Exclusion criteria:

- Publications without accessible full-text versions;
- Abstracts from conference proceedings;
- Comments, editorials, and studies not evaluating the diagnostic performance of texture analysis.

The process of selecting publications for the systematic review involved the following stages:

- Stage 1: Two authors independently analyzed titles and abstracts retrieved by keyword searches.
- Stage 2: Full-text articles meeting the inclusion criteria were independently reviewed by the same authors.
- Stage 3: In cases of disagreement, a consensus-based approach was employed, or a third independent reviewer was consulted to make the final decision.

RESULTS

The search yielded 85 potentially relevant publications, of which 18 studies met the inclusion criteria (Fig. 1). Analysis of these studies revealed current trends and opportunities for enhancing the effectiveness of texture analysis and radiomics in diagnosing PCa in the presence of PI-RADS 3 lesions (Appendix 1).

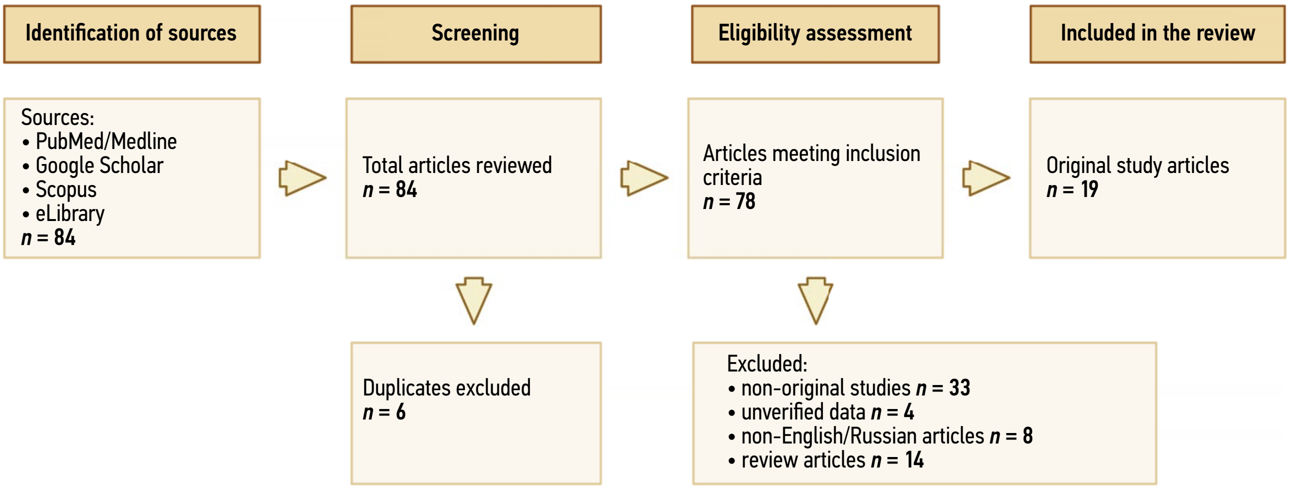

Fig. 1. Flowchart illustrating the article selection process for the systematic review.

Assessment of the Current Issue

Comprehensive evaluation of the diagnostic challenges in identifying clinically significant csPCa in patients with PI-RADS 3 lesions determined several key aspects.

First, the optimal management of patients with PI-RADS 3 lesions is unclear owing to the possibility of missing a small proportion of csPCa cases. This issue was demonstrated by Sonmez et al. [17], who emphasized the need to identify predictive markers for detecting csPCa in patients with prostate-specific antigen (PSA) <10 ng/mL and PI-RADS 3 lesions.

Second, although various diagnostic approaches are available to facilitate clinical decision-making, their efficacy remains limited. Hermie et al. [13] proposed a combined diagnostic strategy involving PSA measurement, multiparametric MRI (mpMRI), and targeted prostate biopsy for cancer screening. Other studies adhered to this approach, indicating that it may improve diagnostic accuracy in cases with PI-RADS 3 lesions [15, 18].

Third, Fang et al. [19] investigated risk factors associated with csPCa in patients with PI-RADS 3 lesions. Notably, the high proportion (33%) of radiologic assessments categorized as PI-RADS 3 reflects considerable interpretive uncertainty, highlighting the need for supportive diagnostic paradigms to assist radiologists [20, 21].

Despite existing strategies to improve diagnostic precision in PI-RADS 3 lesions, there remains a need for more accurate and reliable methods. Texture analysis may be a promising tool in addressing this clinical challenge.

Analysis of Existing Approaches to Addressing the Problem

Review of recent scientific publications on the diagnosis of csPCa in the presence of PI-RADS 3 lesions revealed several key aspects and directions for further investigation.

A proposed strategy involves monitoring patients with PI-RADS 3 lesions over time. However, this approach may miss cases of csPCa. Although studies have emphasized the importance of monitoring and follow-up diagnostics, this strategy is potentially dangerous because of the possibility of overlooking aggressive cancer forms [2, 19, 22].

According to the International Society of Urological Pathology guidelines, further diagnostic interventions, particularly biopsy, are necessary when PCa is suspected in patients with PI-RADS 3 lesions [14]. Nevertheless, invasive procedures are associated with potential complications, require additional time for execution, and may involve hospitalization, imposing an additional burden on the healthcare system [20]. Therefore, it is critical to achieve an optimal balance between diagnostic accuracy and minimally invasive patient management [2, 23].

Serum PSA concentration is a primary biomarker for PCa screening and treatment monitoring. However, PSA testing has limitations, and increased levels do not always indicate the presence of csPCa. Washino et al. [24] showed that PSA increase alone does not guarantee cancer presence. Nevertheless, a comprehensive assessment combining PSA levels, mpMRI findings, and targeted biopsy enables diagnostic precision.

Texture analysis is an innovative method that may improve diagnostic accuracy, reduce the risk of missed csPCa cases, and ease healthcare system burdens by limiting biopsies to well-justified cases [25, 26].

Thus, modern medicine faces the challenge of integrating these technologies into clinical practice to improve accuracy of csPCa detection in PI-RADS 3 lesions while reducing patient risk and conserving healthcare resources.

Review of Texture Analysis Methods

Current initiatives to integrate texture analysis into clinical practice can be categorized into two primary domains based on the principal objectives of the analytical process.

The first domain involves identifying and segmenting areas suspicious for neoplasia. This includes the development and validation of algorithmic solutions for the automated delineation of tissue regions with suspected malignancy to improve diagnostic efficiency [27].

The second domain includes assessing the aggressiveness of prostate carcinoma. Here, the features extracted from tomographic images are analyzed to predict tumor aggressiveness [6, 7]. Texture analysis can uncover latent imaging patterns that are invisible to the human eye [25, 26]. These patterns may correlate with the tumor's genetic and molecular characteristics, revealing its aggressiveness and potential clinical course [28]. This approach can inform treatment decisions by identifying patients who require immediate intervention and those who may be monitored. This is especially critical in PCa cases with PI-RADS 3 lesions, wherein treatment decisions should strike a balance between avoiding unnecessary aggressive diagnostics and ensuring timely treatment to prevent disease progression [3, 25, 29].

Central to both domains is the development and validation of algorithms for clinical integration. This warrants close collaboration among radiologists, oncologists, and information technology experts to ensure that radiomic models are accurate, reproducible, and clinically relevant [27].

The main directions of integration initiatives are classified into six subcategories (Fig. 2).

Development and Validation of Machine Learning Models

Various research groups have developed and validated machine learning models for detecting csPCa in PI-RADS 3 lesions. Kwon et al. [10] developed a classification model for suspicious lesions using machine learning based on mpMRI data. This model comprises transfer learning components to enhance predictive accuracy, including convolutional neural networks for feature extraction and extreme learning machines with weighting coefficients for classification. The study aimed to create a computer-aided diagnostic algorithm based on deep learning principles for PCa verification.

Hectors et al. [29] developed and validated a machine learning model using radiomic features extracted from T2-weighted MRI images to predict csPCa in PI-RADS 3 lesions. This model demonstrated high sensitivity and specificity, outperforming radiologists of varying qualification levels [29].

Furthermore, Jin et al. [16] conducted a retrospective multicenter study to develop a radiomic machine learning model for predicting benign and malignant lesions in PI-RADS 3 cases. This study emphasized the importance of external validation and potential for generalizability to broader populations.

These studies have led to the development of highly accurate models capable of detecting csPCa, offering the potential of reducing the number of unnecessary biopsies, which is an important contribution to clinical practice [16, 23, 29].

However, despite these advances, limitations remain. Deep learning models often lack interpretability, which can hinder understanding of their decision-making processes and complicate clinical adoption without further research and adaptation. Moreover, their effectiveness depends on the volume and quality of training data. In cases of insufficient or poor-quality data, model accuracy and reliability may significantly decrease, highlighting the need to create large, anonymized datasets for training and validating these systems [16, 29, 30].

Analysis of Texture Features and Data Extraction Methodology

Penzias et al. [31] investigated the morphological underpinnings of texture features for PCa stratification based on Gleason score using MRI data. The most predictive features were spectral texture parameters derived using Gabor filters (area under the curve [AUC] = 0.69) and glandular lumen shape patterns (AUC = 0.75), underscoring the diagnostic importance of glandular shape and morphology at the tissue level for differentiating PCa grades on MRI data. These findings provide a new perspective on the use of texture analysis in predicting and identifying csPCa, potentially optimizing diagnostic and

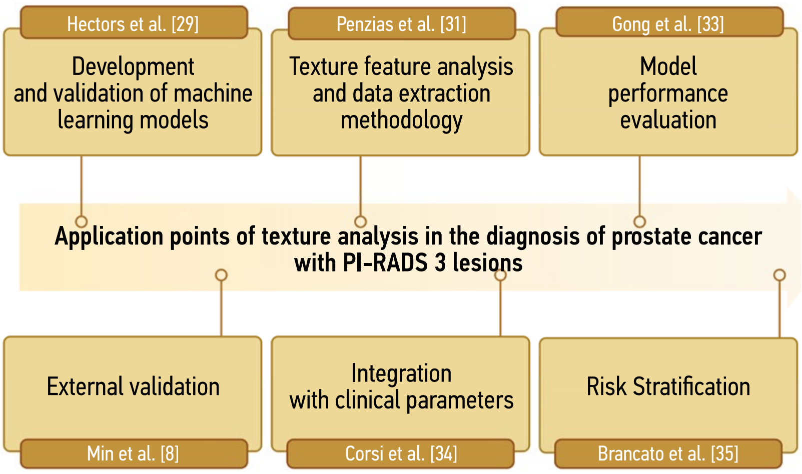

Fig. 2. Research directions for the application of texture analysis in prostate cancer diagnosis with PI-RADS 3 lesions. PI-RADS 3 (Prostate Imaging-Reporting and Data System category 3): an intermediate probability of clinically significant cancer; its presence is equivocal.

treatment strategies. The major advantage of this study is its ability to noninvasively assess tumor aggressiveness based on MRI findings. However, interpretation of radiomic data remains challenging, which is influenced by equipment quality and MRI acquisition parameters.

Giambelluca et al. [25] evaluated the diagnostic performance of texture analysis of prostate MRI images of PI-RADS 3 lesions. They reported strong predictive value for PCa detection, developing models for identifying PCa (Gleason score ⩾6) and csPCa (Gleason score ⩾ 7), with AUCs ranging 0.775–0.821 and 0.749–0.817, respectively. A predictive model combining PSA density[1] and two texture features extracted from MRI images was developed. This model achieved high sensitivity and specificity in identifying csPCa: 80% and 76%, respectively. These results may enhance the effectiveness of texture analysis in early detection, potentially reducing unnecessary biopsies.

Model Performance and Clinical Relevance

A recent study proposed the use of mpMRI findings combined with texture analysis for PCa screening in men with PSA levels of 4–10 ng/mL. The study aimed to predict csPCa based on texture features extracted from mpMRI images, potentially preventing biopsy in low-risk patients. The model's effectiveness depends on adherence to PI-RADS v2.1 protocols and interpretation of texture analysis results [32].

Gong et al. [33] examined the use of different biparametric MRI sequences for the noninvasive detection of high-grade PCa. All radiomic models demonstrated significant predictive performance, enhancing existing screening methods and helping clinicians in selecting appropriate management strategies. Similarly, Wang et al. [34] presented a noninvasive approach to predict csPCa by incorporating radiomic features from MRI, clinical data, and PRKY promoter methylation levels into a machine learning model, achieving high prognostic accuracy. Such predictive radiomic models could improve diagnostic precision and contribute to a more adequate treatment strategy selection. However, these models require complex validation and are limited by disparities in technical capabilities and access to MRI equipment [34, 35].

The studies highlighted the significant potential of advanced imaging and data analysis technologies to enhance diagnostic accuracy and personalize PCa management. Further research is required to confirm their clinical efficacy and safety.

Assessment of Reproducibility and External Validation

Min et al. [8] developed a radiomic model based on features extracted from multiparametric MRI (mpMRI) images for the differential diagnosis of clinically significant and insignificant PCa. Cross-validation of machine learning methods was particularly emphasized to evaluate the model's robustness and reproducibility across heterogeneous datasets. The use of regularized logistic regression and cross-validation techniques enabled the objective assessment of the model's performance, representing a promising strategy for improving diagnostic accuracy in PCa. Integrating cross-validation mechanisms enhances the reliability and generalizability of the model, which is crucial for ensuring its stability and reproducibility in diverse clinical settings. However, despite its strong statistical reliability, the model carries the risk of overfitting and may pose implementation challenges in clinical practice without specialized expertise in machine learning and texture analysis.

Integration of Texture Features with Clinical Parameters in Diagnostic Models

Woźnicki et al. [9] and Corsi et al. [35] have demonstrated that the integration of texture features with clinical parameters enhances PCa diagnostics in patients with PI-RADS 3 lesions.

Woźnicki et al. [9] showed that machine learning models incorporating quantitative radiomic features extracted from mpMRI, combined with clinical data, show significant diagnostic value for csPCa. Their findings highlight the potential of radiomic modeling to improve the diagnostic performance of the PI-RADS v2.1 system and refine PCa risk stratification.

Corsi et al. [35] emphasized the importance of texture analysis in refining assessments under PI-RADS v2.1, particularly in equivocal MRI findings. Their proposed clinical–diagnostic model, which integrates texture features, significantly improves diagnostic accuracy, enabling more precise patient management and reducing unnecessary biopsies.

The main advantages of these approaches include enhanced diagnostic accuracy and specificity, which are critical for optimizing treatment approaches. However, there remain some challenges, particularly regarding standardization, reproducibility, and the need for large datasets to train and validate these models for widespread clinical use.

Risk Stratification

Significant progress has been made in using texture analysis for PCa diagnostics and risk stratification by extracting data from mpMRI images [36–38].

Brancato et al. [36] assessed the role of radiomic features from T2-weighted and contrast-enhanced mpMRI images in detecting PCa in PI-RADS 3 and 4 lesions. Using the PyRadiomics software package, over 290 features selected through the Wilcoxon test and mRMR algorithm were analyzed to extract radiomic features from medical images. Logistic regression models showed high diagnostic performance, outperforming PI-RADS v2.1, with AUC reaching 0.89 for PI-RADS 4 lesions. The study revealed the value of radiomics for improving PCa diagnostics and risk stratification.

[1] PSA density is a diagnostic parameter used in evaluating prostate conditions, including cancer. It is defined as the ratio of serum prostate-specific antigen concentration to prostate volume.

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Hou et al. [37] developed a radiomic model using machine learning to identify csPCa in PI-RADS 3 lesions. Their one-step radiomic model (RML-i) achieved an AUC of 0.89, indicating improved risk stratification accuracy. This model is a machine learning algorithm that processes the entire set of texture features in a single step, without the need for prior feature selection or manual adjustment. It automatically analyzes images and extracts relevant features, streamlining the learning process and increasing predictive precision. Such a model is particularly useful in clinical settings where rapid and accurate decision-making based on complex medical data is critical.

Zhang et al. [38] introduced a novel radiomic nomogram incorporating mpMRI-derived features in distinguishing csPCa from insignificant PCa. The nomogram combines clinical characteristics and radiomic features for precise PCa verification in patients with PSA levels of 4–10 ng/mL.

These studies collectively underscore the significance of texture analysis based on mpMRI in enhancing risk stratification and diagnostic precision in PCa.

Limitations and Future Directions

Despite promising findings on the role of texture analysis in PCa diagnostics, several studies have questioned its clinical benefit [39, 40].

Krauss et al. [40] conducted a study involving 350 patients who underwent mpMRI. They analyzed various texture features, including histogram-based and textural characteristics, to assess their correlation with the presence and aggressiveness of PCa based on follow-up biopsy and clinical outcomes. Although texture analysis was able to differentiate benign and malignant lesions, its integration with traditional MRI parameters and clinical data did not significantly improve predictive accuracy. AUC values for models incorporating texture analysis were not significantly higher than those using conventional inputs alone.

Gresser et al. [39] reported comparable results, highlighting the reproducibility of conclusions on the potential of texture analysis based on MRI data. The study included 142 patients who underwent prostate MRI in different medical centers. Their results showed AUC of 0.78–0.83, underscoring the diagnostic potential of texture analysis. However, the high variability in results—particularly when different bias-correction strategies were applied—indicated the need for further research to improve the consistency of radiomic measurements. Even when advanced machine learning techniques were applied, integration of texture analysis with conventional diagnostic methods such as apparent diffusion coefficient analysis and PI-RADS scoring did not yield substantial improvement in prognostic accuracy.

These findings show that texture features may vary depending on imaging methods, limiting their widespread clinical application. Furthermore, the lack of unified algorithms and variability in imaging protocols across institutions hinders the integration of radiomic prediction models into routine diagnostics [39, 40].

To address existing limitations, ongoing research is focused on developing scientific methods for optimizing procedures in this field. Several studies described efforts to standardize processes and minimize errors at all stages of integrating texture analysis into clinical practice. Huang et al. [41] proposed a set of 16 criteria for effective implementation of texture analysis in clinical testing. These guidelines cover the entire process: from standardization of feature extraction protocols to evaluation of clinical benefit and validity of radiomic tests. The authors proposed key directions for future work in radiomics.

- *Process harmonization and standardization.* Attention should be directed toward the harmonization and standardization of feature extraction and analysis. This includes establishment of standardized operating procedures for image acquisition, feature extraction, and statistical analysis. The authors emphasize the importance of standardization, as it enhances the reliability and reproducibility of radiomics.
- *Model development and validation.* Radiomic models should be developed with measures to prevent overfitting and undergo subsequent validation. This includes the use of external validation data not involved in model development or applying appropriate internal validation methods when external data are unavailable.
- *Iterative refinement and adaptation.* The need for monitoring changes in radiomic tests that may result from updates in hardware and software systems should be emphasized. Any changes unrelated to data drift, such as test application in a different patient population or for different indications, should prompt a return to earlier stages of model development and validation.

These directions represent a comprehensive approach to advancing the clinical applicability of texture analysis and expanding the scope of effective radiomic studies [5, 41].

DISCUSSION

In evaluating the application of texture analysis for PCa diagnosis in patients with PI-RADS 3 lesions, several challenges that are unlikely to be fully addressed in the near future emerged.

Standardization of image acquisition and analysis. Multiple studies highlighted the dependence of texture analysis on the quality and consistency of medical imaging. Notably, different medical institutions use varying MRI protocols and scanning parameters, which affects the reproducibility of texture analysis results. The standardization of imaging acquisition methods remains a major challenge that requires continued efforts to develop universal guidelines and protocols [1].

Interpretability of machine learning models. Although deep learning models based on texture analysis have shown potential in classifying and predicting PCa, their interpretability remains challenging. Thus, the understanding of the nuances behind certain diagnostic decisions may not be readily apparent. This hinders the integration of such technologies into clinical practice, as healthcare professionals should understand how diagnostic tools operate [4].

Overfitting and model generalizability. There is a risk of overfitting in machine learning models, particularly when they are trained using limited or nonrepresentative datasets. Overfitting results in models performing well only on the data used for training. The generalizability of such models to a broader patient population remains uncertain, requiring further studies for external validation and testing on diverse datasets [6].

Unresolved issues in tumor aggressiveness and staging. Texture analysis enables the detection of tumor presence; however, accurate determination of the stage and aggressiveness of the tumor remains challenging. Certain biological characteristics of tumors are not reflected in texture alterations on imaging, limiting the method's ability to accurately stratify risk and guide optimal treatment selection [5].

These issues indicate the complexity and multifaceted nature of PCa diagnosis using texture analysis and machine learning, underscoring the need for further scientific studies and methodological advancements in this field.

CONCLUSION

Texture analysis, particularly when integrated with machine learning techniques, is a promising approach for diagnosing PCa in patients with PI-RADS 3 lesions. These technologies contribute to improved diagnostic model accuracy, enabling more precise risk stratification and better-informed decisions regarding the need for biopsy, potentially preventing unnecessary invasive procedures.

However, several challenges hinder the clinical implementation of these technologies. The main challenges are related to the high variability of texture features, which depend on the technical specifications of the MRI equipment and scanning parameters. This variability may limit the applicability of radiomic models across different clinical settings and reduce their reproducibility. Data extraction and analysis methods should be standardized to ensure consistency of results across different platforms and clinical environments.

Therefore, future research should prioritize the development of standardized protocols for texture analysis that account for variations in imaging hardware and MRI acquisition sequences. Additionally, the creation of large, annotated datasets is crucial for enhancing the training and validation of machine learning models. These efforts are necessary to increase the clinical value of texture analysis in PCa diagnostics.

Thus, despite the significant potential of texture analysis to improve PCa diagnosis, our understanding of how to best implement these technologies in clinical practice remains in its early stages.

ADDITIONAL INFORMATION

Appendix 1. Summary of studies on the application of texture analysis in the diagnosis of clinically significant prostate cancer. doi: 10.17816/DD633500-4272791

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Authors' contribution. A.S. Tyan: data analysis, manuscript writing; E.V. Kondratyev: research concept and design; G.G. Karmazanovsky, N.A. Karelskaya, A.A. Gritskevich: manuscript editing and final approval, advisory support; D.V. Kalinin: advisory support; A.A. Kovalev, A.I. Baeva: data analysis. Thereby, all authors provided approval of the version to be published and agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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