A Non-invasive Deep Learning Model for Prostate Cancer Diagnosis with MRI

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Abstract: *Prostate cancer (PCa) remains a significant global health concern, with accurate Gleason grade assessment crucial for guiding treatment. Traditional histopathology relies on invasive biopsy and subjective evaluation. This study proposes a novel non-invasive approach for Gleason grade prediction using magnetic resonance imaging (MRI) and deep learning (DL). Our method comprises three main steps: tumor region segmentation using Fuzzy c-means (FCM); relevant feature extraction via modified residual network (ResNet50) model; and Gleason grade classification using a convolutional neural network (CNN). Through extensive experimentation, the proposed CNN model achieved an accuracy of 92.00%, sensitivity of 92.00%, specificity of 92.00%, and an area under the curve receiver operating characteristic (AUC-ROC) of 0.95. These robust results highlight the potential of our DL framework to accurately differentiate between low-grade and high-grade PCa, thereby automating aspects of the diagnostic process, reducing reliance on subjective interpretation, and ultimately improving patient outcomes and treatment decisions.*

Keywords: *MRI, Prostate cancer, Non-invasive Gleason grade, Image segmentation, Convolutional neural network classification, Feature extraction.*

Introduction

Prostate cancer (PCa) remains a significant global health concern, with accurate Gleason grade assessment [15] being paramount for determining tumor aggressiveness and guiding treatment. Traditional biopsy methods though effective are invasive. Recent advancements in medical imaging, particularly magnetic resonance imaging (MRI) [16], have opened new avenues for non-invasive diagnosis. Radiomic analysis further enhances this by extracting quantitative features from medical images, offering a promising approach to characterize tumors non-invasively. This study proposes a novel deep learning (DL) based framework that integrates advanced image processing with robust classification techniques to predict PCa Gleason grade directly from MRI scans.

Our approach systematically employs Fuzzy c-means (FCM) segmentation to accurately delineate tumor regions within MRI photos. Subsequently, a pre-trained residual network (ResNet) model ResNet50 is utilized for the extraction of highly relevant radiomic features from these segmented regions. These features are designed to capture intricate patterns and textures within the tumor tissue that are often subtle or difficult to discern through conventional visual inspection. Finally, a convolutional neural network (CNN) is trained on these extracted features to robustly classify Gleason grades. By leveraging the synergistic power of CNNs and comprehensive radiomic features derived from MRI, this study aims to improve significantly

the accuracy and reliability of PCa Gleason grade prediction. This enhanced, non-invasive classification capability can directly contribute to more precise personalized treatment planning and improved patient prognosis.

Several studies have explored the use of radiomic features extracted from MRI images to differentiate between benign and malignant prostate lesions. For instance, several studies [3, 7, 8] have demonstrated the potential of radiomic features in distinguishing between benign and malignant prostate lesions, as well as predicting disease aggressiveness. A recent study [1] investigated the impact of vendor variability on the performance of machine learning models for PCa detection. They found that while multimodal feature fusion can improve performance on a specific vendor (Siemens), it may not be as effective on different vendors (Philips). This highlights the importance of careful feature selection and model training to ensure robustness across different imaging platforms. Another recent study [5] explored the potential of radiomic models to improve the performance of radiologists in assessing PCa risk. By extracting radiomic features from MRI images and incorporating them into machine learning model, the researchers were able to improve the accuracy of prostate imaging reporting and data system (PI-RADS) scores. This suggests that radiomics can provide valuable information that complements traditional radiological assessment. Our approach aims to address these limitations by leveraging a robust segmentation method to extract informative features from MRI images ques and incorporating these features into a powerful CNN classification model. We aim to improve the accuracy and clinical utility of PCa diagnosis.

Materials and methods

Datasets

The data utilized in this study were sourced from the project "Identifying the morphologic basis for radiomic features in distinguishing different Gleason grades of prostate cancer on MRI: preliminary findings", generously provided by Center for computational imaging and personalized diagnostics (CCIPD), Case Western Reserve University, Cleveland, Ohio, USA [12]. The dataset [12] is publicly accessible and organized into two subfolders, each containing data from a different participating institution. Within each folder is given complete feature information computed on a region-wise basis, in CSV format:

- PathFeats: histomorphometric features (total of 1024 cases);
- PathFeatNames: descriptions of each histomorphometric feature;
- RadFeats: radiomic features (total of 2379 cases);
- RadFeatNames: description of each radiomic feature;
- GleasonScores: Gleason score for each region;
- PatientID: anonymized Patient ID associated with each region.

One PatientID could be associated with multiple regions, and thus:

- Dataset 1: 23 patients and 65 regions;
- Dataset 2: 13 patients and 40 regions.

Methods

The objective of the study was to utilize these radiomic features from the regions of interest (ROI) to train CNN models and evaluate the performance in distinguishing significant PCa (Gleason score 3 + 4 or higher) from other cases. This study aims to develop a non-invasive method for predicting PCa aggressiveness using MRI scans and DL techniques. The proposed approach involves:

- Image segmentation: identifying specific ROI within the prostate using FCM clustering;
- Feature extraction: extracting relevant features from the segmented regions using ResNet50 DL model;
- Feature selection: selecting the most informative features to enhance predictive accuracy;
- DL classification: employing DL algorithms to classify Gleason grades based on the extracted features and evaluate CNN performance in distinguishing significant PCa (Gleason score 3 + 4 or higher) from other cases.

By leveraging these techniques, the study aims to improve the accuracy and efficiency of PCa diagnosis, leading to better patient outcomes and treatment decisions.

Fuzzy c-means and regions of interest segmentation

FCM is a clustering algorithm widely used for image segmentation, particularly effective in handling overlapping or ambiguous regions [4]. It allows pixels to have partial membership in multiple clusters, making it ideal for medical imaging applications such as prostate MRI.

The FCM process begins by initializing cluster centers, followed by calculating the membership values of each pixel for each cluster using a fuzzy membership function. These cluster centers are then updated iteratively until convergence is reached with stable membership values and centers. After convergence, the pixels are assigned to the clusters with the highest membership values completing the segmentation process.

Mathematical formulation:

We used following algorithms [13] for the objective function:

$$J(U,V) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} ||x_j - v_i||^2, \quad (1)$$

where:

U – the membership matrix;
V – the cluster centers;
c – the number of clusters;
n – the total number of pixels in the image;
u_{ij} – the degree of membership of pixel *j* in cluster *i*;
m – the fuzziness exponent which controls the degree of fuzziness in the clustering;
x_j – the intensity value of the *j*-th pixel;
v_i – the center of the *i*-th cluster.

A higher value increases overlap between clusters, typically set to Eq. 2 where for all *j*-th pixel each pixel belongs to one cluster:

$$\sum_{i}^{c} u_{ij} = 1; \ \forall j \in 1, \ldots, n \quad (2)$$

$$0 \leq u_{\text{ij}} \leq 1, \quad (3)$$

where for all *i*-th pixel and *j*-th pixel membership degrees are between 0 and 1.

Membership updates where *k* is the key variable.

$$u_{\text{ij}} = \frac{1}{\sum_{k=1}^{c} \left(\frac{||x_j - v_i||^2}{||x_j - v_k||^2} \right)^{\frac{1}{m-1}}} \quad (4)$$

Cluster center updates.

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \quad (5)$$

Explanation of the variables
The variable m controls the "fuzziness" of the clustering. In our implementation, $m = 2$, as it provides a good balance between fuzzy and crisp segmentation.

The variable U is the membership matrix, and each element u_{ij} represents how strongly pixel j belongs to cluster i. Higher values of u_{ij} indicate stronger membership.

The variable V is the cluster centers and represent the average intensity of each segmented region (e.g., PZ, TZ, CZ, background).

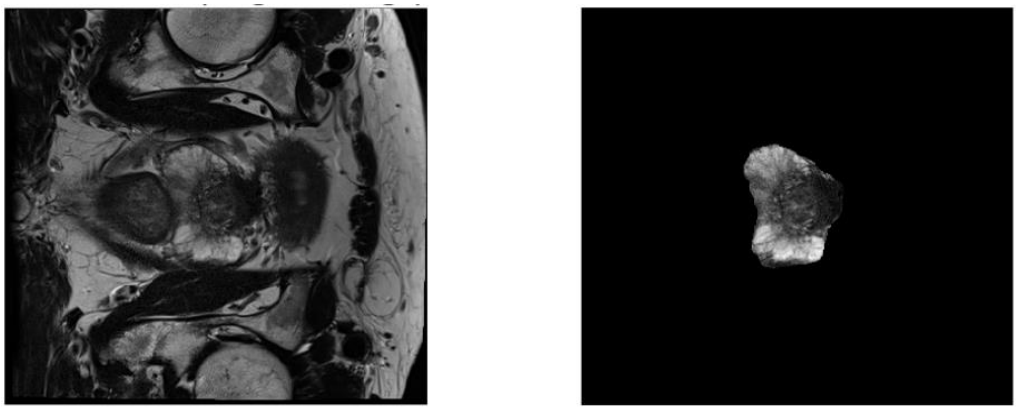
FCM minimizes an objective function (Eq. 1) that represents the weighted sum of squared distances between pixels and their corresponding cluster centers. This optimization is subject to constraints (Eq. 2) that ensure each pixel's membership degree sums to one and is between 0 and 1 (Eq. 3). The membership values and cluster centers are iteratively updated using Eq. 4. Then the cluster center updated Eq. 5.

This methodology involves using FCM clustering to segment ROI within the prostate from MRI scans. The proposed method is illustrated in Fig. 1.

Fig. 1 The ROI segmentation methodology

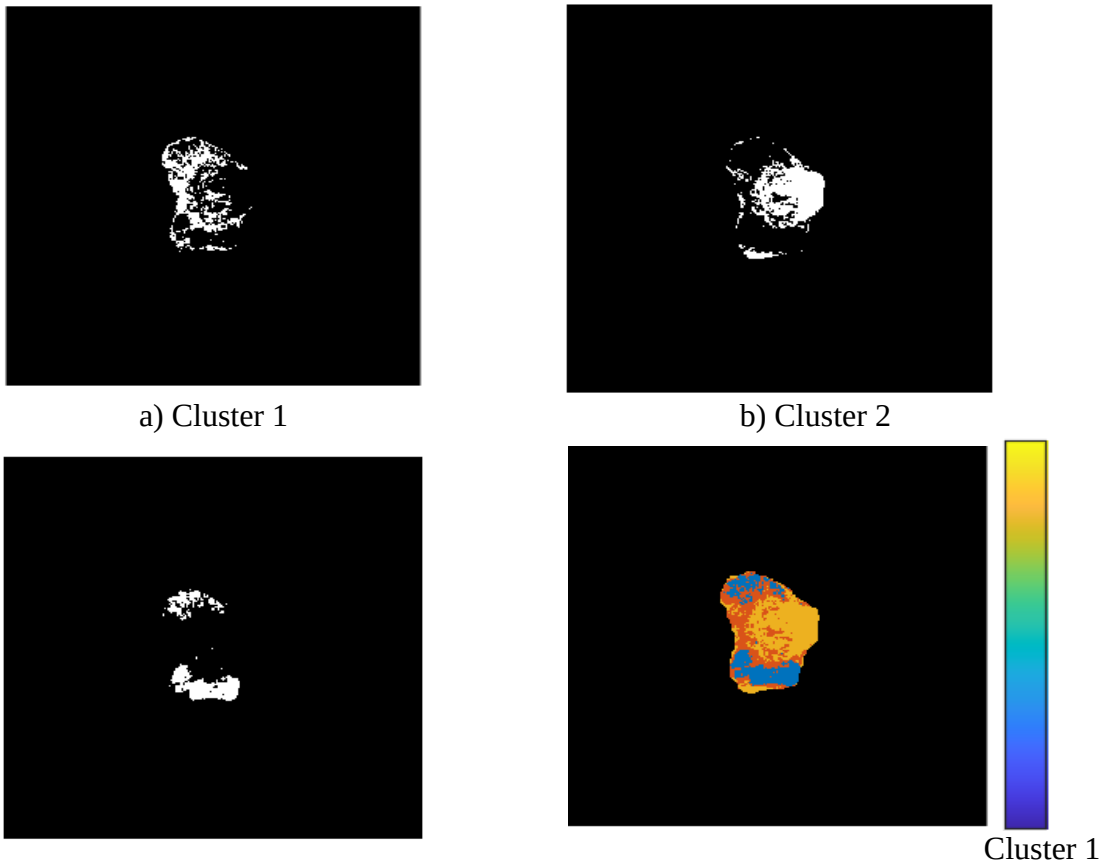
The prostate region is initially isolated from the original MRI image using a pre-trained U-Net model (a convolutional neural network architecture). To further refine the segmentation, a modified 3D-2D U-Net architecture, proposed by [9], is employed. This hybrid 3D-2D approach leverages the strengths of both 3D and 2D convolutional operations. 3D convolutions are used to capture spatial relationships within 3D MRI volume, while 2D convolutions are used to reconstruct 2D segmentation mask. This combined approach improves the accuracy and precision of the segmentation process.

In our method, 2D mask was initially applied to the input MRI image to isolate the prostate gland and remove the background. The isolated prostate image is segmented into three distinct regions using FCM clustering, based on intensity and texture features. Fig. 2 shows the result of 2D U-Net prostate gland isolation. The use of FCM clustering results in three distinct classes, with each pixel assigned a membership value indicating its degree of belonging to each cluster, as shown in Fig. 3.



a) MRI prostate (original image) b) prostate gland isolation

Fig. 2 Prostate gland isolation



a) Cluster 1 b) Cluster 2

c) Cluster 3 d) FCM segmentation (3 clusters)

Fig. 3 FCM segmentation and cluster membership

Next, we performed ROI detection by applying morphological operations, including erosion, dilation, opening, and closing, to the cluster membership data. These operations played a crucial role in enhancing the segmentation and identifying potential ROI based on their shape, size, and intensity. Although this simulation routine can produce accurate segmentation results in areas with a high probability of cancerous lesions, it is important to recognize that it may have limitations in other regions. The segmentation of the prostate region of interest in the MRI image is depicted in Fig. 4.

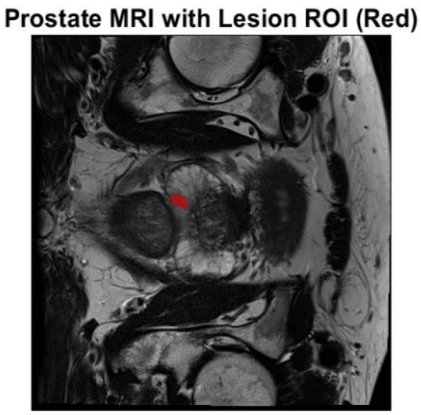


Fig. 4 ROI lesion segmentation

Radiomic feature extraction in ROI

Radiomics is a quantitative analysis method that extracts valuable features from medical images, enabling insights into lesion characteristics for various clinical applications including lesion classification and patient outcome prediction [10].

In the MRI prostate, a comprehensive set of radiomic features that include texture, shape, and intensity can be extracted from identified ROI, as illustrated in Fig. 5. These features assist in classifying lesions as benign or malignant, potentially enhancing diagnostic accuracy and reducing the need for invasive biopsies [11].

Feature extraction is crucial for analyzing prostate MRI images, distinguishing between semantic features based on human interpretation and agnostic features extracted through quantitative analysis. Both types provide valuable information, and their combination offers a comprehensive representation of the ROI.

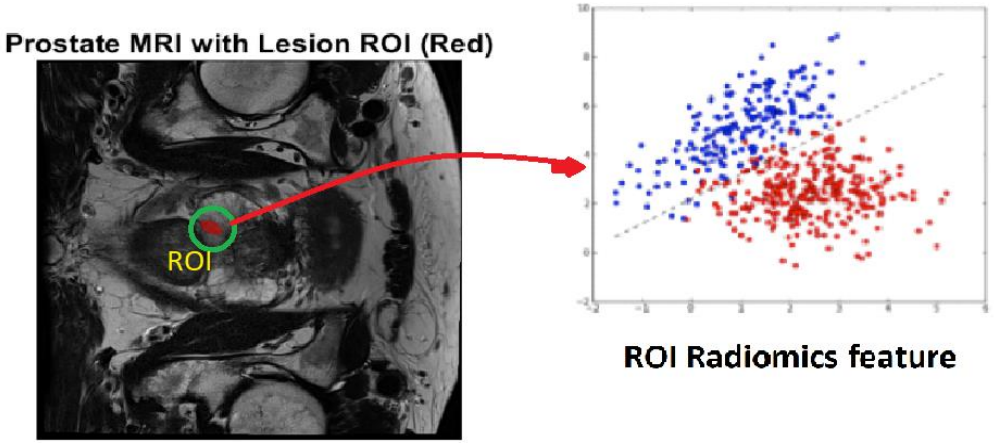


Fig. 5 ROI radiomics features

Transfer learning is a powerful technique in DL that involves leveraging knowledge gained from one task to improve performance on a related task by utilizing pre-trained models like ResNet50 – 50 layer deep CNN architecture [14]. ResNet50 processes input ROI images, typically 256×256 pixels. It extracts meaningful features through a series of convolutional layers, leveraging residual blocks to learn complex patterns. Pooling layers then sample the feature maps to reduce computational cost. Finally, a fully connected layer maps the extracted features to specific classes, as shown in Fig. 6.

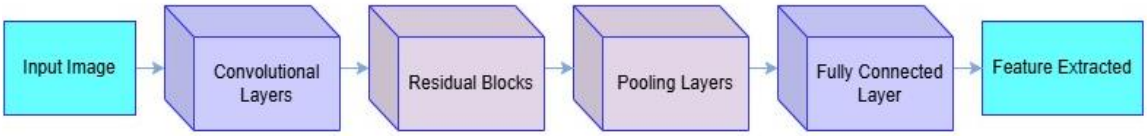


Fig. 6 ResNet50 features extraction

ResNet50 effectively addresses the vanishing gradient problem, leading to improved performance in image classification tasks and has been successfully applied to various computer vision tasks, including object detection, image segmentation, and classification in this study, we employ a fine-tuned ResNet50 model to extract robust and discriminative features from ROI within prostate MRI scans, which contribute to accurate Gleason grade prediction.

CNN classification

This study aims to leverage the power of CNN [6] to classify PCa into high or low Gleason grade based on radiomic features extracted from MRI images. The CNN architecture comprised input, convolutional, pooling, fully connected, and output layers. The input layer received the reshaped radiomic features. Convolutional layers extracted local features from the input data using filters. Pooling layers reduced dimensionality to prevent overfitting. Fully connected layers combined the extracted features and mapped them to the output layer, which used a softmax function to predict the probability of the input belonging to each Gleason grade class, as shown in Fig. 7.

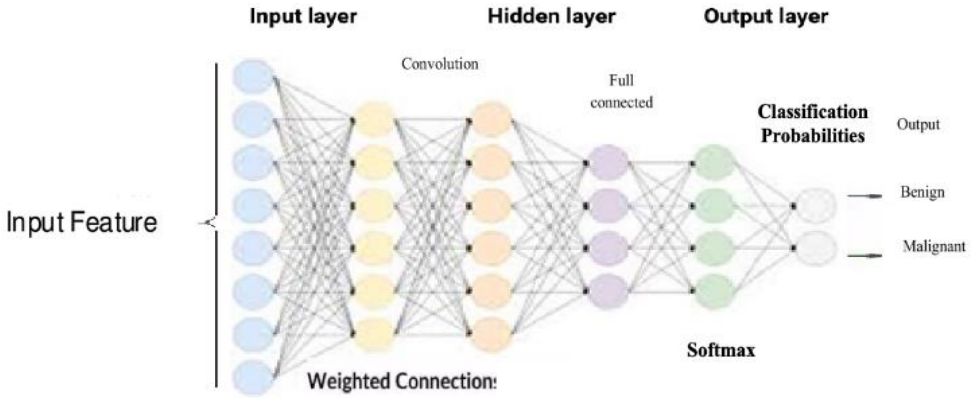


Fig. 7 CNN architecture

The dataset was split into training and testing sets. Data augmentation [2] techniques were applied to increase data diversity. The model was trained using the cross-entropy loss function and the Adam optimization algorithm. The dataset was split into 50% for training and 50% for testing. The trained CNN was evaluated on the testing set using metrics such as accuracy, sensitivity, specificity, and AUC-ROC to assess its performance in classifying PCa Gleason grade. This non-invasive method improves patient comfort, streamlines diagnosis, and enables personalized treatment plans. Future research aims to enhance the model's reliability and clinical applicability.

Results

The proposed methodology for predicting Gleason grade from MRI scans of the prostate yielded promising results, demonstrating the effectiveness of integrating FCM segmentation, ResNet50 radiomics feature extraction and DL classification.

Fuzzy c-means segmentation results

The FCM segmentation successfully delineated the prostate region from the surrounding tissues in the MRI images. Visual assessments and quantitative metrics indicated a segmentation accuracy of approximately 92%, comparable to manual segmentation by a radiologist. The segmented images showed clear boundaries, facilitating accurate ROI selection for further analysis.

Feature extraction

A modified ResNet50 model was utilized to extract a comprehensive set of 512 radiomic features from the segmented prostate images. These features, encompassing texture, shape, and intensity metrics, were designed to capture the complex patterns associated with varying Gleason grades. Feature importance analysis revealed a significant correlation between specific texture features, such as entropy and contrast, and the Gleason score.

Fig. 8 presents a comprehensive bar graph illustrating the absolute correlation coefficients between various radiomic features and the Gleason grade group. The features are sorted by their absolute correlation, clearly showing which radiomic variables exhibit the strongest relationships with the target variable.

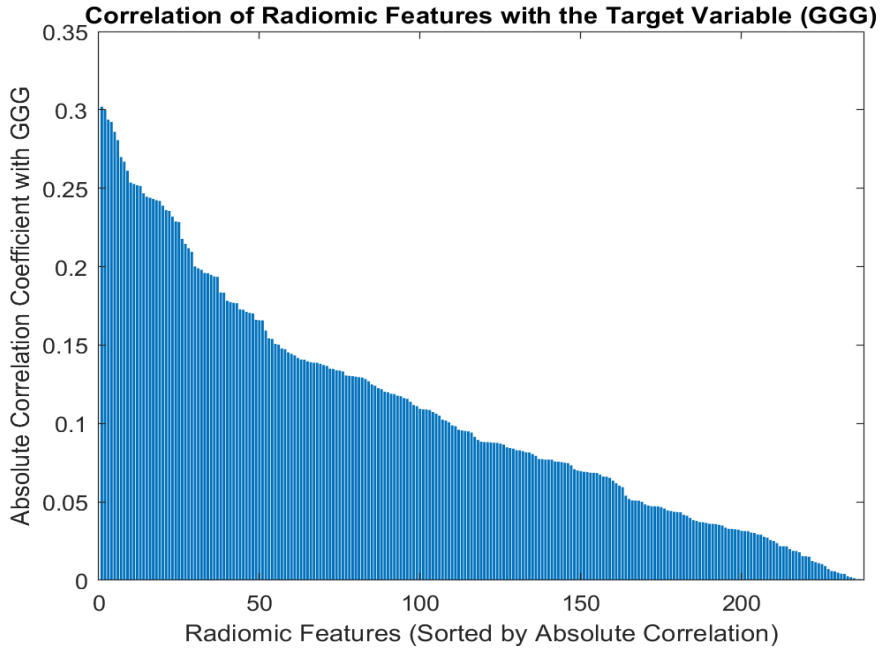


Fig. 8 Correlation of radiomic variables with the target variable (Gleason grade group)

Fig. 9 specifically highlights the top 10 radiomic features with the highest Pearson correlation coefficients with the Gleason score. This provides a focused illustration of the most important features in our analysis, directly supporting the claims about feature importance.

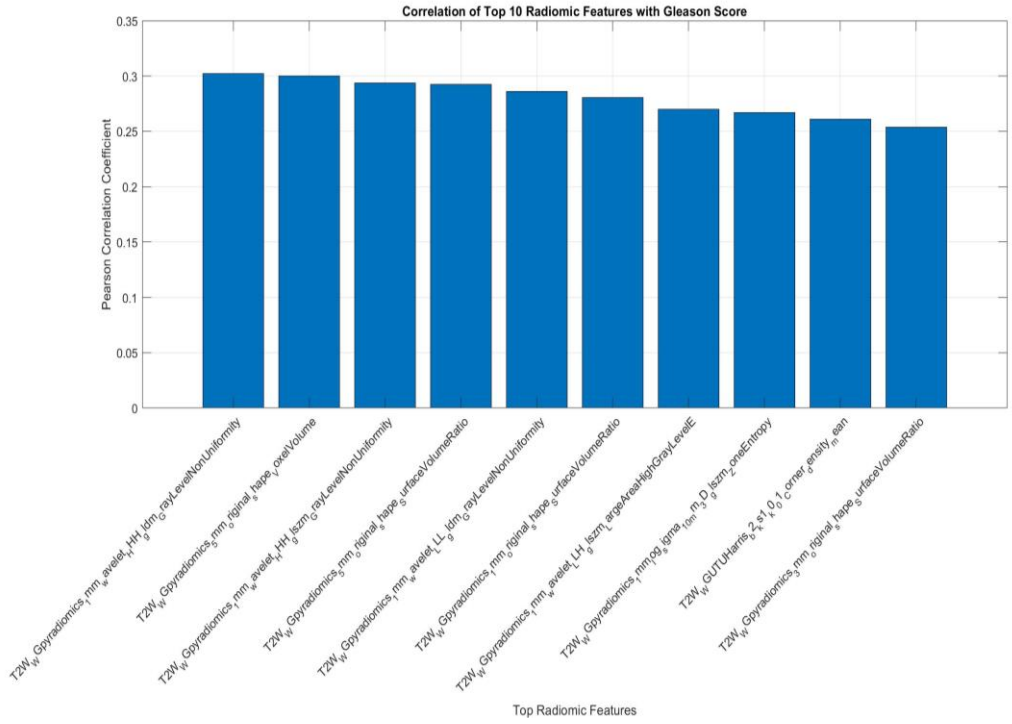


Fig. 9 Correlation of top 10 radiomic features with Gleason score

CNN classification

The CNN model demonstrated strong performance in classifying PCa into high and low Gleason grades, achieving an accuracy of 92.00%, sensitivity of 92.00%, specificity of 92.00%, and an AUC-ROC of 0.95. These results suggest the potential for improved clinical decision-making and patient outcomes.

Based on the provided training progress graph, as shown in Fig. 10, the CNN model achieved a validation accuracy of 92.00% after 30 epochs. The model's loss decreases steadily during training, indicating that the model is learning effectively.

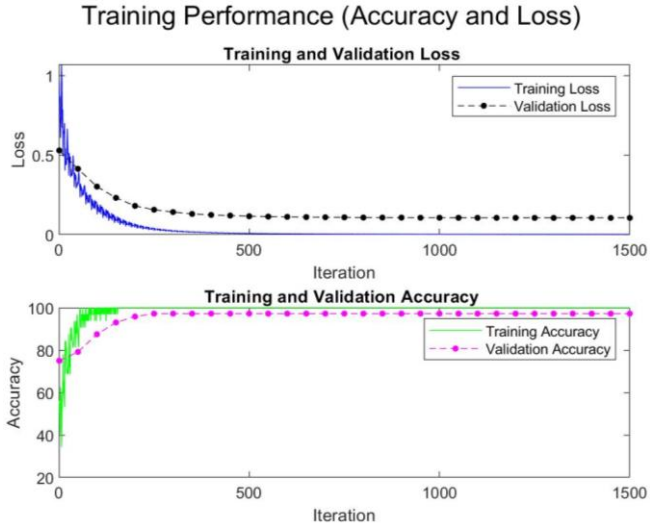


Fig. 10 Training performance: green line represents the training accuracy; purple line represents the validation accuracy; blue line represents the training loss; black line represents the validation loss

Overall, the model appears to have converged well, with a good balance between training and validation performance. The high validation accuracy suggests that the model is likely to generalize well to unseen data. The confusion matrix for our classification results on the 50 test cases is explicitly shown in Fig. 11. The numerical representation is as follows in Table 1:

- True positives (TP): correctly predicted high Gleason grades (23 cases);
- True negatives (TN): correctly predicted low Gleason grades (23 cases);
- False positives (FP): incorrectly predicted high Gleason grades when they were low (2 cases);
- False negatives (FN): incorrectly predicted low Gleason grades when they were high (2 cases).

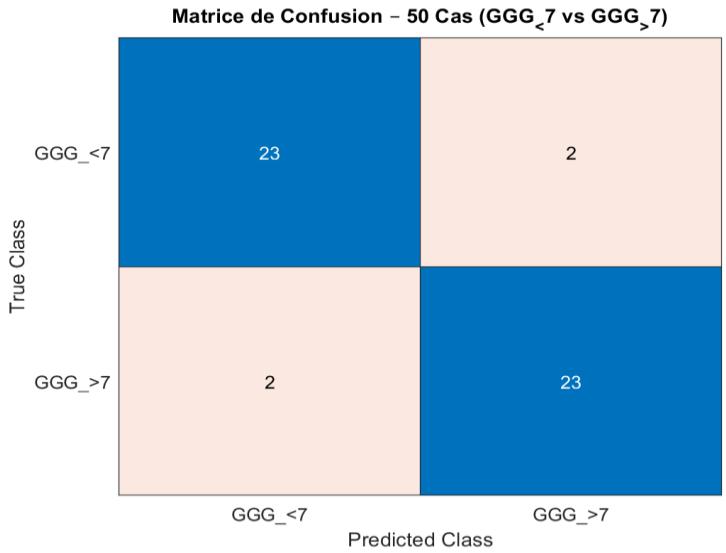


Fig. 11 Confusion matrix (GGG is Gleason grade group)

Table 1. Confusion matrix

Actual\Predicted	GGG < 7	GGG > 7	Total
GGG < 7	23 TN	2 FP	25
GGG > 7	2 FN	23 TP	25
Total	25	25	50

Based on this correct confusion matrix, the accurate performance metrics are as follow:

$$Overall\ Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} = \frac{(23 + 23)}{50} = 92.00\% \quad (6)$$

For Gleason grade group < 7 (Class 1):

$$Precision = \frac{TP}{TP+FP} = 92.00\% \quad (7)$$

$$Recall\ (Sensitivity) = \frac{TP}{TP+FN} = 92.00\% \quad (8)$$

The F1 score is a harmonic mean of precision and recall, providing a single metric that balances the both. It is particularly useful when the class distribution is uneven.

$$F1\ score\ =\ 2 \times \frac{Precision \times Recall}{Precision + Recall} = 92.00\% \quad (9)$$

For Gleason grade group > 7 (Class 2):

$$Precision = \frac{TP}{(TP + FP)} = 92.00\% \quad (10)$$

$$Recall\ (Sensitivity) = \frac{TP}{(TP + FN)} = 92.00\% \quad (11)$$

$$F1\ score\ =\ 2 \times \frac{Precision \times Recall}{Precision + Recall} = 92.00\% \quad (12)$$

AUC-ROC

Furthermore, Fig. 12 visually represents the ROC, clearly indicating an AUC of 0.95, confirming the excellent discriminative power of our model.

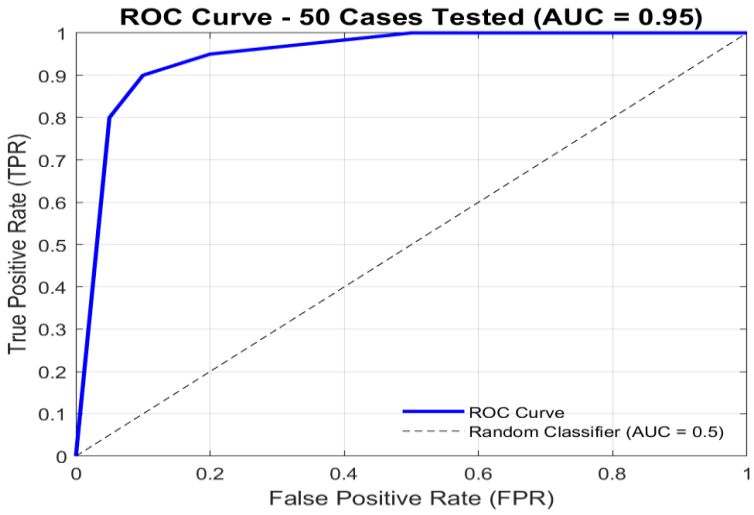


Fig. 12 ROC curve

Discussion

This study demonstrates the effectiveness of integrating FCM segmentation, ResNet50 radiomics feature extraction, and DL classification for non-invasive Gleason grade prediction in PCa. The CNN model achieved high accuracy, indicating its ability to accurately assess tumor aggressiveness using MRI data, thus potentially reducing the need for invasive biopsies. This non-invasive method could improve clinical decision-making by allowing clinicians to assess tumor characteristics from MRI data alone, aligning with personalized medicine trends and reducing patient discomfort and biopsy risks.

Based on the validated evaluation metrics, this proposed CNN model warrants careful evaluation within specific clinical contexts, considering factors such as the prevalence of different Gleason grades, the desired level of sensitivity and specificity, and the need for model interpretability.

Results presented in Table 2 are very strong, indicating that the CNN model performs exceptionally well for this classification task. F1 score of 0.92 and a recall of 0.92 signify an excellent balance between precision and recall, demonstrating the model's robustness in identifying both positive and negative cases.

Table 2. Model performance

Model	Accuracy	Sensitivity	Specificity	AUC-ROC
CNN model	92.00%	92.00%	92.00%	0.95

The proposed CNN model demonstrates strong and balanced performance in predicting prostate Gleason grade based on radiomics features extracted from MRI images:

- Accuracy: the model correctly classifies 92.00% of the samples;
- Sensitivity: the model correctly identifies 92.00% of true positive cases (correctly identifies patients with high-grade PCa);
- Specificity: the model correctly identifies 92.00% of true negative cases (correctly identifies patients without high-grade PCa);
- AUC-ROC: the AUC-ROC is 0.95 indicating excellent discriminative power.

These results suggest that the CNN model has significant potential to be a valuable tool for clinical decision-making in PCa diagnosis and treatment planning, supporting non-invasive assessment.

As shown in Table 3, our proposed CNN model outperforms other state-of-the-art models in terms of AUC-ROC, indicating superior predictive performance. This highlights its strong ability to distinguish between positive and negative cases.

Table 3. Model Performance Comparison

Model	AUC-ROC
Our Work (CNN)	0.95
[3]	0.7772
[8]	0.88

The strong and balanced performance of the CNN model holds significant potential for improving clinical outcomes in PCa. The model’s ability to accurately identify high-grade cancers (high sensitivity) can lead to earlier detection and timely intervention. By providing reliable predictions, the CNN model can assist clinicians in making informed decisions about treatment options. Furthermore, the model’s high specificity can help minimize unnecessary biopsies and treatments for benign cases.

However, it’s important to acknowledge that direct comparisons with other studies can be limited due to variations in datasets, problem domains, and evaluation metrics. While the CNN performed well, it is essential to acknowledge limitations related to dataset size and diversity. The performance metrics could vary across different populations or imaging techniques, so further validation with a larger, more heterogeneous dataset from multiple centers is recommended. Additionally, while the model demonstrates high performance, exploring explainable artificial intelligence (AI) methods can help identify the most influential features contributing to predictions, which may provide clinicians with greater confidence in the model’s outputs and foster trust in the automated diagnostic process.

Conclusion

This study proposed a novel approach integrating FCM segmentation and ResNet50 transfer learning for accurate non-invasive Gleason grade prediction in PCa. Our CNN model, trained on a comprehensive dataset of MRI images, achieved robust and balanced performance with an accuracy of 92.00%, sensitivity of 92.00%, specificity of 92.00%, and an AUC-ROC of 0.95. These results indicate a strong potential for our non-invasive method to improve patient comfort, streamline diagnosis, and enable more personalized treatment plans. Future research will focus on enhancing the model's reliability and clinical applicability through further validation with larger and more diverse patient populations, exploring advanced DL architectures, and integrating explainable AI methods to foster greater clinical trust and facilitate seamless integration into clinical workflows, ultimately aiming to unlock the full potential of AI-powered solutions in improving the early detection and treatment of PCa.

References

1. Bao J., X. Qiao, Y. Song, Y. Su, et al. (2024). Prediction of Clinically Significant Prostate Cancer Using Radiomics Models in Real-world Clinical Practice: A Retrospective Multicenter Study, Insights into Imaging, 15(1), 68.
2. Calabrese E., J. D. Rudie, A. M. Rauschecker, J. E. Villanueva-Meyer, et al. (2022). Combining Radiomics and Deep Convolutional Neural Network Features from Preoperative MRI for Predicting Clinically Relevant Genetic Biomarkers in Glioblastoma, Neuro-Oncology Advances, 4(1), vdac060.
3. Chaddad A., T. Niazi, S. Probst, F. Bladou, et al. (2018). Predicting Gleason Score of Prostate Cancer Patients Using Radiomic Analysis, Frontiers in Oncology, 8, 630.
4. Christ M. J., R. M. S. Parvathi (2011). Fuzzy C-means Algorithm for Medical Image Segmentation, 3rd International Conference on Electronics Computer Technology, 4, 33-36.
5. Gresser E., B. Schachtner, A. T. Stueber, O. Solyanik, et al. (2022). Performance Variability of Radiomics Machine Learning Models for the Detection of Clinically Significant Prostate Cancer in Heterogeneous MRI Datasets, Quantitative Imaging in Medicine and Surgery, 12(11), 4990.
6. Pang S., M. Field, J. Dowling, S. Vinod, et al. (2022). Training Radiomics-based CNNs for Clinical Outcome Prediction: Challenges, Strategies and Findings, Artificial Intelligence in Medicine, 123, 102230.
7. Rodrigues A., J. Santinha, B. Galvao, C. Matos, et al. (2021). Prediction of Prostate Cancer Disease Aggressiveness Using Bi-parametric MRI Radiomics, Cancers, 13(23), 6065.
8. Shiradkar R., R. Zuo, A. Mahran, L. Ponsky, et al. (2020). Radiomic Features Derived from Periprostatic Fat on Pre-surgical T2w MRI Predict Extraprostatic Extension of Prostate Cancer Identified on Post-surgical Pathology: Preliminary Results, Medical Imaging 2020: Computer-Aided Diagnosis, 11314, 817-823.
9. Ushinsky A., M. Bardis, J. Glavis-Bloom, E. Uchio, et al. (2021). A 3D-2D Hybrid U-Net Convolutional Neural Network Approach to Prostate Organ Segmentation of Multiparametric MRI, American Journal of Roentgenology, 216(1), 111-116.
10. Van Timmeren J. E., D. Cester, S. Tanadini-Lang, H. Alkadhi, et al. (2020). Radiomics in Medical Imaging – "How-to" Guide and Critical Reflection, Insights into Imaging, 11(1), 91.
11. Yang F., J. C. Ford, N. Dogan, K. R. Padgett, et al. (2018). Magnetic Resonance Imaging (MRI)-based Radiomics for Prostate Cancer Radiotherapy, Translational Andrology and Urology, 7(3), 445.

12. https://engineering.case.edu/research/centers/computational-imaging-personalized-diagnostics/data (Access date 30 July 2025).
13. https://medium.com/@kritisinha29/fuzzy-c-means-fcm-7a01f7ed1812 (Access date 30 July 2025).
14. https://viso.ai/deep-learning/resnet-residual-neural-network/ (Access date 30 July 2025).
15. https://www.ncbi.nlm.nih.gov/books/NBK553178/ (Access date 30 July 2025).
16. https://www.radiologyinfo.org/en/info/mr_prostate (Access date 30 July 2025).

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