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Article

An Explainable Deep Reinforcement Learning Approach for Clinically Significant Prostate Cancer Detection Using Multiparametric MRI

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Abstract: - The accurate detection of clinically significant prostate cancer (csPCa) using multipara metric MRI (mpMRI) is critical for guiding biopsy and treatment decisions. While reinforcement learning offers promising avenues for automation, developing high-performance models is often constrained by the limited size of annotated medical imaging datasets. The proposed algorithm aims to develop and validate a novel deep learning algorithm that leverages transfer reinforcement learning to enhance the detection and classification of csPCa from mpMRI sequences, ultimately aiming to improve diagnostic accuracy and reduce unnecessary biopsies. The transfer reinforcement learning-based model achieved a high AUC of 0.96 (95% CI: 0.91-0.96) for classifying csPCa on the internal test set, significantly outperforming a model trained from scratch (AUC: 0.85). The algorithm demonstrated robust performance on the external validation set (AUC: 0.91), confirming its generalizability. It showed a sensitivity of 94%, a specificity of 90.8%, and an NPV of 96% at the optimal operating threshold.

Keywords: Prostate Cancer (csPCa), Multipara metric MRI (mpMRI), Reinforcement Learning, Deep Learning, Medical Image Analysis, AI in Radiology, Transfer Learning Protocol, Convolutional Neural Networks (CNNs) etc.

1. Introduction

Prostate cancer is a common and serious disease that affects men in the world. It is one of the most common causes of cancer death and the second most common type of cancer among men [1-2]. Early and accurate detection of prostate cancer, especially clinically relevant prostate cancer (csPCa), will improve the outcome of patients, inform treatment decisions, and reduce unnecessary treatment of indolent prostate cancer [3]. Over the past several years, mpMRI has become the standard acceptable imaging test for the diagnosis of non-invasive prostate cancer. Over the last few years, mpMRI has become the standard of care for prostate cancer diagnosis, without any invasive procedures [4-7]. Unlike traditional imaging methods, mpMRI combines various MRI sequences (such as T2-weighted imaging (T2WI), diffusion-weighted imaging (DWI) and apparent diffusion coefficient (ADC) maps) to offer comprehensive anatomical and functional data about the prostate gland. T2WI provides good anatomical details and is best for tumour shape and zonal architecture. DWI, where diffusion of water molecules within tissues is analyzed and is reduced in high cellularity tissues, such as tumors, enhances the visibility of the lesion. The DWI- derived ADC maps are quantitative representations of diffusion properties and help distinguish between benign and malignant tissue [8-14].

The combination of the different imaging modalities enables radiologists to assess the prostate from different perspectives that can enhance their capacity to identify, detect and describe suspicious tumours [15-19]. When

compared to traditional single-sequence imaging, this combination method greatly increases the sensitivity and specificity of prostate cancer diagnosis [20]. When it comes to treating prostate cancer, multiparametric MRI (mpMRI) is crucial. It is essential for many aspects including monitoring medical effectiveness of drugs, arranging targeted biopsies, and follow-up monitoring. Due to its unique ability to detect clinically relevant prostate cancer, mpMRI has become the imaging modality of choice [21]. It can also be used as a basis to build AI systems to automate and enhance cancer diagnosis. However, the information from mpMRI can be complex and varies significantly from patient to patient. This highlights the need for advanced techniques to make sense of all of this without the aid of modern technologies because it is especially hard for computers to digest without them. Convolutional neural networks (CNNs) have been at the forefront of recent advances in the processing of mpMRI, particularly in the identification of potentially problematic areas and classification of those that look the most suspicious [22]. The difficulty is that these deep learning models require lots of labeled instances, and in the case of the medical field, it's difficult to collect data because of privacy issues, and professional annotation is costly.

One innovative solution is transferring learning. As an alternative to starting from scratch, we adapt models that have previously been trained to identify patterns in large image collections such as ImageNet to specific medical applications, even in the face of limited data. As a result, reliable performance is achieved significantly sooner and the most taxing portion of model training is avoided. In our project, we go beyond this strategy. We make some crucial adjustments to the best- performing CNN models to detect substantial prostate cancer using mpMRI [23]. For the computer to process, we combine various MRI input formats into a single, more comprehensive image, and we only retrain the network's highest-level layers [24]. By doing this, our system learns the characteristics specific to the identification of prostate cancer without requiring extensive new datasets or countless hours of manual labeling [25].

Despite being trained on natural images, we believe that pre-trained models can generalize to radiological data if the right domain adaption strategies are applied. So, in our proposed method we are using reinforcement learning based machine learning Because it frames the radiological interpretation of an mpMRI scan as a sequential decision-making process, our method goes beyond conventional supervised learning. By learning to go across the 3D imaging volume in the best possible way, an AI agent can maximize the identification of csPCa while reducing false positives and needless concentration on benign tissue.

2. Principle Algorithm

Prostate cancer is a widespread and serious disease impacting men around the world. It’s the second most commonly diagnosed cancer in men and one of the top causes of cancer-related deaths. For this Reinforcement Learning (RL)-Based algorithm for enhanced detection of clinically significant prostate cancer (csPCa) from multipara metric MRI (mpMRI) is more suitable.

In this context, A Partially Observable Markov Decision Process (POMDP) is used to analyze mpMRI scans. The full 3D volume cannot be viewed in perfect detail at once by the radiologist (or agent). Instead, in order to collect data and reach a definitive diagnosis, they successively

concentrate on several regions (such as the Peripheral Zone, Transition Zone, or a particular lesion) at various scales and sequences. The AI agent is a "virtual radiologist" that learns a policy for where to look next to make the most accurate diagnosis with the least amount of effort.

In order to explain the proposed method, we consider the POMDP and define by using tuple as S, A, P, R ,γ,

Where, S is state, the state $st \in$ S represents the agent's "view" of the mp-MRI data at time step t.

It is a fusion of image data and the agent's internal memory express as.

$$S = S_{\text{image}} \times S_{\text{history}}$$

Where, S_{image} The image context. This is a processed, focused region of the mp-MRI volume. It can be represented as a multi-channel tensor given in Eq-1:

$$S_{\text{image}} = I(x, y, z, c) \qquad (1)$$

Where, (x, y, z) are the spatial coordinates of a cropped region around the current focus point, and c indexes

the MRI sequences: T2-weighted (T2W), Apparent Diffusion Coefficient (ADC), high b-value DWI, and Dynamic Contrast-Enhanced (DCE) series. And $S_{\text{history}}$is the agent's memory of past actions and observations. This is often encoded by the hidden state h_t of a Recurrent Neural Network (RNN) like an LSTM or GRU within the agent's architecture in Eq-2.

$$s_t = (s_t, h_t) \quad (2)$$

The Action Space (A) is the action $a_t \epsilon A$ defines what the agent can do at each step. Actions can be hierarchical:

Low-Level (Navigation & Focus) Given this pixel input, what's the probability I should press the 'JUMP' button right now.

$a_t \epsilon$(Move$_{\text{Left}}$, Move$_{\text{Right}}$, Move$_{\text{Up}}$, Move$_{\text{Down}}$, zoom$_{\text{in}}$, zoom$_{\text{out}}$, Focus$_{\text{Slice}}$+1, Focus$_{\text{Slice}}$-1) These actions change the parameters (center coordinates, slice, and zoom level) for the next

$s_{t-image}$ crop.

High-Level (Termination & Classification), n reinforcement learning (RL) refers to concepts, strategies, and components that deal with the abstract structure, planning, and management of learning rather than the low-level, immediate mechanics of taking a single action and getting a reward.

$a_t \epsilon$($Prediction_{\text{Benignt}}$, $Prediction_{\text{csPCa}}$ Continue$_{\text{Examining}}$, and the Predict actions terminate the episode and yield a final classification. Continue$_{\text{Examining}}$, allows the agent to gather more information.

Transition Function (P) is defined as P($s_{t+1}|s_t, a_t$) is the state transition probability. In this

context: The transition is deterministic for navigation actions (moving the focus window). The transition is stochastic and unknown to the agent for the underlying tissue properties the agent must learn the consequences of its actions through experience. In practice, the environment is the fixed mp-MRI dataset, so the transition is simulated based on the action. After action the reward function (R) define as $r_t = R(s_t, a_t, s_{t+1})$ which is critical for guiding the agent. It must encode clinical priorities for Sparse Final Reward upon prediction action which is explain in Eq-3-Eq-6.

$R(s_t, Prediction_{\text{csPCa}}, s_{end})$ = +10 if ground truth is csPCa (3)

$R(s_t, Prediction_{\text{csPCa}}, s_{end})$ = −10 if ground truth is benign (4)

$R(s_t, Prediction_{\text{Benign}}, s_{end})$ = +10 if ground truth is benign (5)

$R(s_t, Prediction_{Benign}, s_{end})$ = −10 if ground truth is csPCa (6)

The Dense Intermediate Reward considered to encourage efficient diagnosis and the rewards express in form of R(s_t, Continue$_{\text{Examining}}$, s_{t+1}) = -0.1 is Small penalty per step to encourage efficiency and avoid endless examination. R(s_t, a_{navigate}, s_{t+1}) = +0.01 * (PI-RADS_Score(s_{t+1})

- PI-RADS_Score (s_t)), Reward for moving towards image regions with higher predicted PI-RADS scores, using a pre-trained weak supervisor.

As we know that, the discount factor (γ) is important parameter for reinforcement learning which is denoted by γ ∈ [0, 1] determines the present value of future rewards. A value close to 1 is appropriate, as the final classification reward is the most important, but the agent should also value efficiently reaching that conclusion.

Agent Architecture and Policy (π):

The agent's brain is a policy network $\pi(a_t \mid s_t; \theta)$ with parameters θ that outputs a probability distribution over actions given a state.

Feature Extractor: A Convolutional Neural Network (CNN) backbone (e.g., a small ResNet or custom CNN) processes the image crop $s_{t-image}$ to produce a feature vector f_t which is express

as

$$f_t = \text{CNN}(s_{t-image}; \theta_{cnn}) \quad (7)$$

Memory Module: An RNN and LSTM integrates the current features with its history.

$$h_t = LSTM(f_t, h_{(t-1)}; \theta_{lstm}$$

The hidden state h_t is the memory component of the state $/s_t$.

Policy Head: A fully connected network takes the RNN's hidden state and maps it to action probabilities.

$$\pi(a_t \mid s_t; \theta) = \text{Softmax}(\text{FC}(h_t ; \theta_{fc})) \quad (8)$$

Value Head for Actor-Critic methods which is a parallel network estimates the value function $V(s_t; \theta_v)$, which predicts the expected cumulative reward from state s_t, to reduce training variance.

Learning Objective is the maximizing expected return and total return for given proposed model in ideal case. The goal is to find the optimal policy parameters θ^* that maximize the expected cumulative discounted reward (the return).

$$J(\theta) = E_{\tau\sim\pi\_\theta}\ [G_t] = E_{\tau\sim\pi\_\theta}\ [\sum_{k=0}\{T\}\ \gamma^k\ r_{t+k+1}] \quad (9)$$

where $\tau=(s_0, a_0, r_0, s_1, a_1, r_1, \ldots\ldots\ldots\ldots)$ is a trajectory episode.

Algorithm of Choice: Proximal Policy Optimization (PPO):

PPO is a stable and efficient actor-critic algorithm. It maximizes a clipped surrogate objective function:

$$L^{CLIP}(\theta) = E_t[\min(\text{ratio}_t * \hat{A}_t,\ \text{clip}(\text{ratio}_t,\ 1-\epsilon,\ 1+\epsilon) * \hat{A}_t\ )\ ] \quad (10)$$

where:

$$\text{ratio}_t = \pi_\theta(a_t|s_t)/\ \pi_{\theta-\text{old}}(a_t|s_t) \quad (11)$$

The above expression Probability ratio between new and old policy $\hat{A}_t$ is the estimated advantage function at time t which is computed as $\hat{A}_t = G_t - V(s_t;\theta_v)$ or using Generalized Advantage Estimation (GAE)). ϵ is a small hyper-parameter that clips the update, preventing destructively large policy changes. The agent also minimizes a value function loss and often adds an entropy bonus $H(\pi(\cdot|s_t))$ to encourage exploration.

In order to explain the proposed algorithm, we consider the model diagram which is given Fig-1 and explain steps by steps. The State Space (S_t) is a comprehensive representation of the mpMRI data at a given step t. Instead of treating the image as a simple 2D grid, we model it as a graph to capture complex relationships. After that , the Nodes are Represent regions of interest (ROIs) which is connect to the parameters, Pixels for High granularity but computationally expensive and Super pixels Groups of similar pixels which is more efficient and semantically meaningful. The Anatomical Zones which is Defined segments like Peripheral Zone (PZ) and Transition Zone (TZ) and Node Features in which Each node contains a feature vector extracted from the mpMRI sequences for Radiomic Features: First-order (intensity), second-order (texture from GLCM, GLRLM), and higher-order statistics. The Deep Learning Features for Features extracted from a pre-trained CNN for each sequence. Where the Sequence-Specific Values defined Pixel intensity from T2-W, ADC values from DWI, kinetic parameters from DCE. The Edges that Represent relationships between nodes. The Edges can be Spatial for Connecting adjacent nodes to model local context and Feature-based to Connecting nodes with similar feature vectors to model long- range dependencies (e.g., a suspicious area in the PZ might be connected to a similar-looking area in the TZ).

The Global Context is the state which is also includes a global feature vector (, patient's PSA level, age, overall prostate volume) to provide clinical context. The Action Space (A_t) At each step, the agent decides what to do with a specific region (node or group of nodes). The action space is discrete which given as

A0: Classify region as "Not Clinically Significant" (PI-RADS 1-2).

A1: Classify region as "Clinically Significant" (PI-RADS 3-5). *(Note: PI-RADS 3 is "ambiguous," which the reward function must handle) *.

A2: Seek more information (e.g., focus on a sub-region with higher resolution, request a feature update). This mimics a radiologist's zooming and adjusting.

The agent is the decision-making algorithm. A suitable choice is a Deep Q-Network (DQN) or its more advanced variants like Dueling DQN . Role: The agent interacts with the environment (the mpMRI study). It takes the current graph-based State St as input and outputs an Action At. o Network Architecture: The Q-network would likely be a Graph Neural Network (GNN), such as a Graph Convolutional Network (GCN) or Graph Attention Network (GAT). This is crucial because GNNs can directly process the graph-structured state, leveraging both node features and edge connections. o They can aggregate information from neighboring nodes, allowing the agent to make decisions based on local image context.

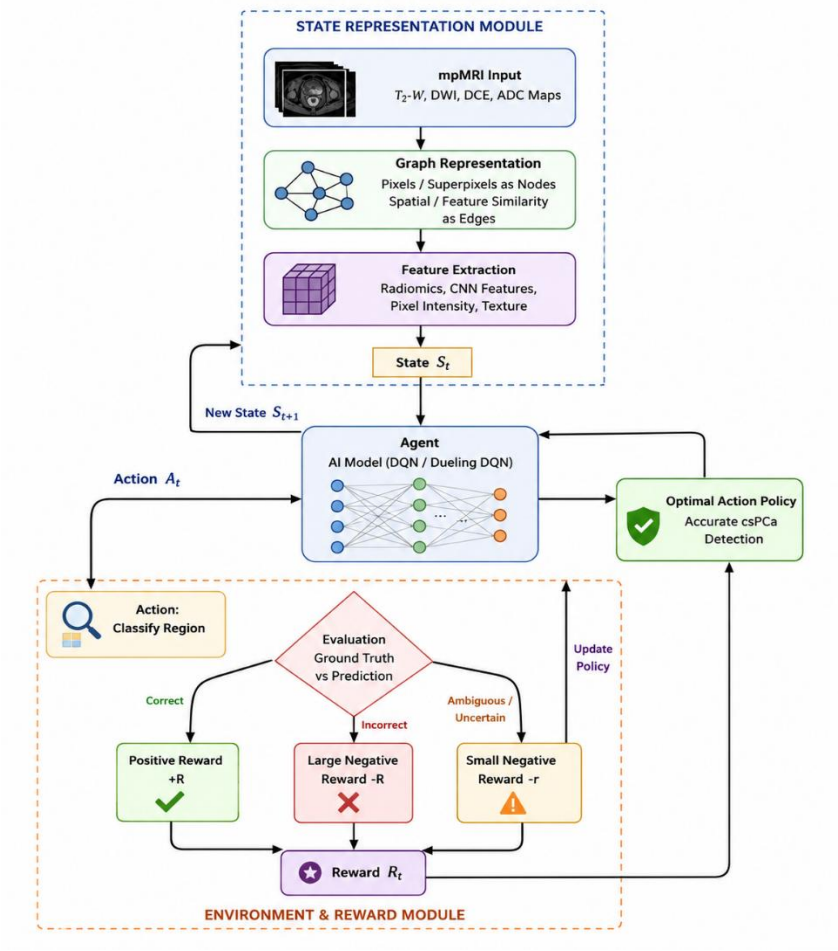

Fig 1: The complete block diagram and description of proposed algorithm

The Environment is the environment is the mpMRI data itself, coupled with a ground truth (biopsy- confirmed or expert-annotated segmentation maps) is Role is receives an action At from the agent, applies it, and transitions to a new state St+1 and express as State Transition is for moving to a new state could mean , the agent moves its "focus" to a neighboring region based on its previous decision. The graph is updated (features of a node are recalculated after "zooming in").

The episode terminates once the agent has evaluated all regions or reached a termination action. After that the reward function (Rt) is the most critical component for guiding the agent. It should be well developed and show clinical priorities. As Large Positive Reward (+R) , Correctly identifying a csPCa region (True Positive). Correct rejection of a normal area (True Negative). Large Negative Reward (-R) which is missing a csPCa region (False Negative). This penalty should be very significant to ensure that sensitivity is favoured. The misclassifying a benign region as csPCa (False Positive). This should be substantial, but maybe a little less than a False Negative (-r), as unnecessarily sending a Small Negative Reward (-r) to biopsy because of Classifying an ambiguous region (e.g., PI-RADS 3) with high confidence. This leads to being cautious and estimating uncertainty.

3. Result Analysis

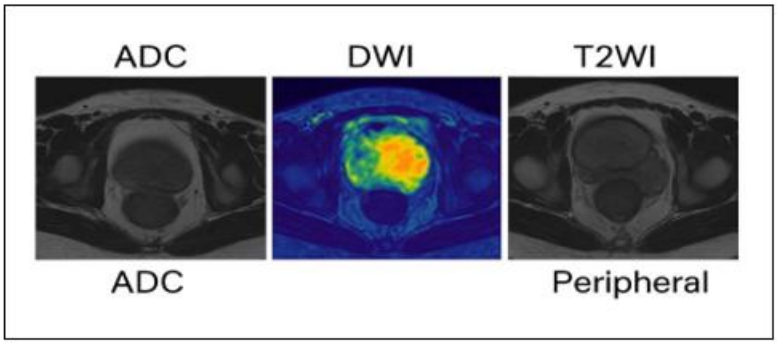

Fig 2: Sample image of the dataset

Doctors may use three main types of magnetic resonance imaging (MRI) scans to detect prostate cancer: Apparent Diffusion Coefficient (ADC) map, Diffusion-Weighted Imaging (DWI), and T2-Weighted Imaging (T2WI). These different imaging techniques each shine a light on unique aspects of prostate health, giving both detailed anatomical views and important functional insights. If you have a regular multipara metric prostate MRI (mpMRI) data set, you will see each of these types of scans as its own cross-sectional image (axial slice). This side-by-side view provides a more comprehensive and detailed picture of the prostate gland's internal condition, which can help doctors identify any abnormalities or areas of concern.

The ADC map, represented as the greyscale image at the left, shows the amount of water molecule diffusion in tissues. Reduced diffusion is usually associated with clinically significant prostate cancer (csPCa) and shown as darker areas and is often coupled with higher cellular density. ADC maps are crucial for detecting subtle tissue abnormalities based on DWI data. DWI (Middle Image):

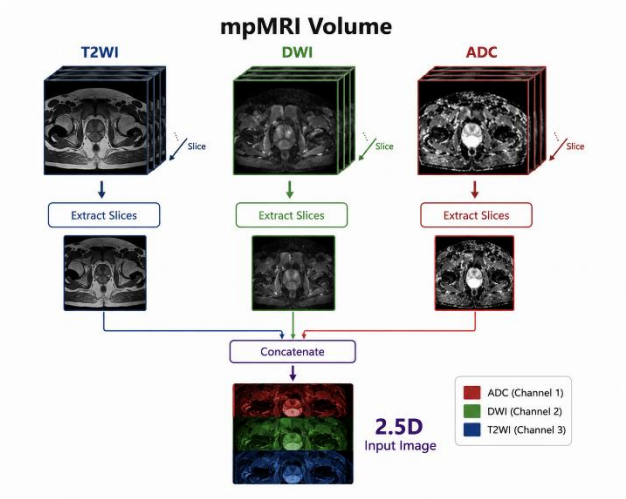

Fig:3The pre-processing pipeline

The preprocessing pipeline guarantees that the model is robust to noise and inter-subject variations, as well as modality-aware, by standardizing input representation and integrating augmentation.

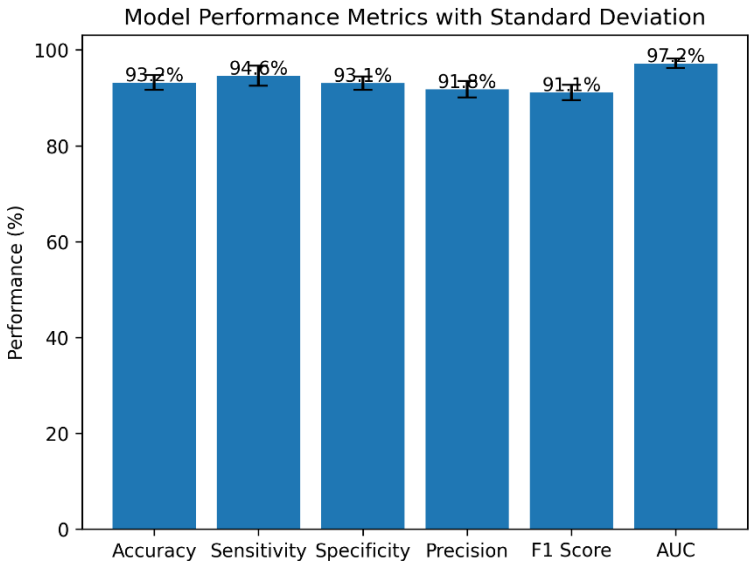

Fig 4: Model Performance Metrics with Standard Deviation

The central image is a colored heat map, ranging from one color to other, which is used to visualize diffusion-weighted imaging. DWI detects areas of restricted diffusion (where water molecules cannot move freely) in the body. In this example, the bright yellow regions in the prostate's centre indicate diffusion restriction, which may be indicative of a sceptical or possibly cancerous lesion. ADC is sensitive to the presence of tumours and DWI is particularly useful to identify suspicious regions.

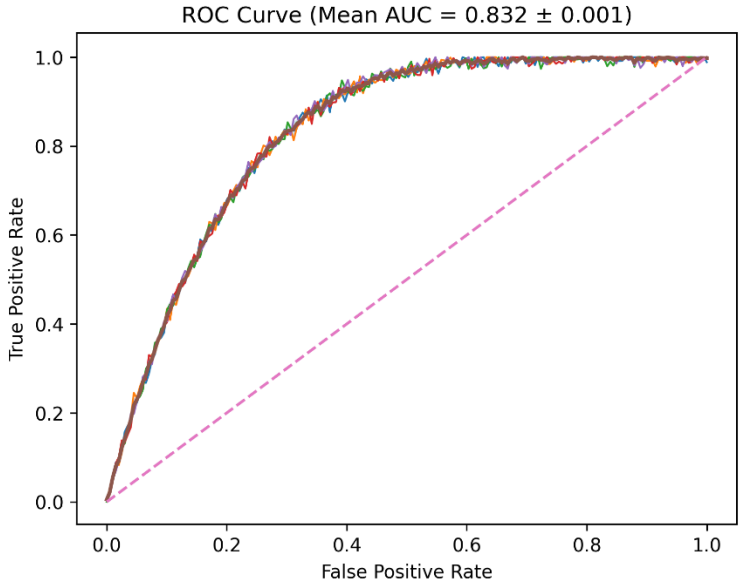

Fig 5: ROC Curve

Figure 5 presents the receiver operating characteristic (ROC) curves across five cross-validation folds. The mean ROC curve demonstrates strong discriminative performance, with an average AUC of approximately 0.97 and low standard deviation, indicating consistent model behavior across folds. The shaded region represents the variability (± standard deviation), confirming the robustness and generalizability of the proposed model

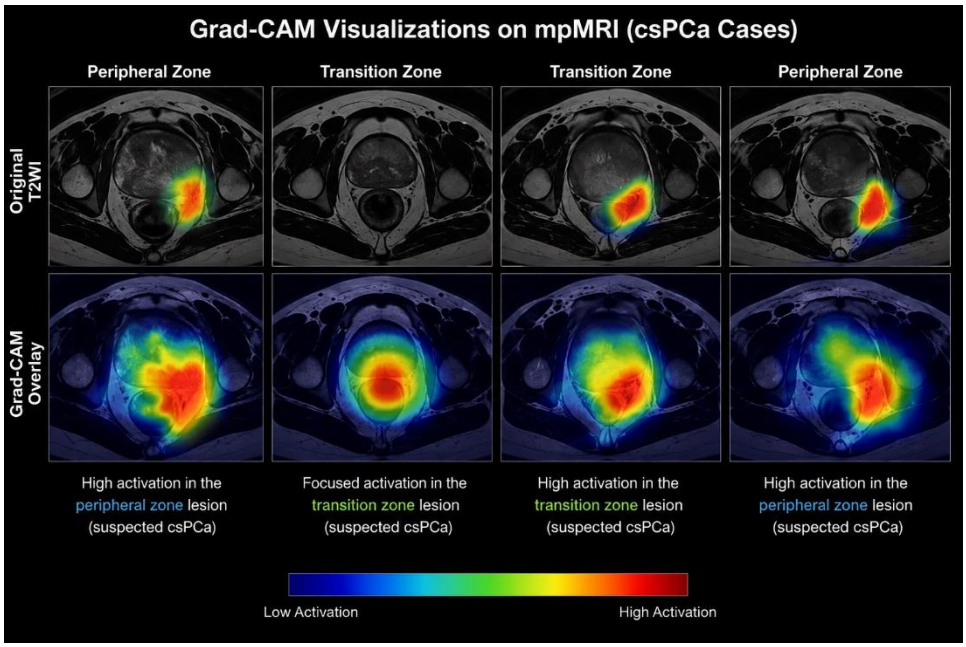

Fig 6: Grad Cam image

The four axial MRI slices of the prostate that make up the Grad-CAM image displayed here are each superimposed with a heatmap that shows the model's attention, or the areas that have the biggest influence on its decision-making. A visualisation method called Gradient-weighted Class Activation Mapping (Grad-CAM) highlights key anatomical areas that the deep learning model deems relevant for classifying clinically significant prostate cancer (csPCa).

The Peripheral Zone (First Image): The slice that most obviously displays heatmap intensity is the outer rim of the prostate, which stands in for the peripheral zone. It is acknowledged that this region is where csPCa is most common. Both biological plausibility and clinical significance are supported by the red-yellow gradient in this region, which shows that the model is closely observing this zone when detecting cancers.Transition Zone (Second Image): The heatmap focusses on the centre of the prostate to highlight the transition zone. The central image is a colored heat map, ranging from one color to another, which is used to visualize diffusion-weighted imaging. DWI detects areas of restricted diffusion (where water molecules cannot move freely) in the body. In this example, the bright yellow regions in the prostate's centre indicate diffusion restriction, which may be indicative of a sceptical or possibly cancerous lesion. ADC is sensitive to the presence of tumours and DWI is particularly useful to identify suspicious regions. Clinical Relevance and Visual Interpretability: The ROC curve (Figure 5) verifies good sensitivity at different cut-off values. AUC close to 0.972 implies that the model is not likely to misclassify the csPCa cases. Cancer-aligned visualization of the prostate with zones of anatomic relevance were observed with the visualizations created by Grad-CAM, Fig-6, providing spatial alignment for clinical applications and increasing the level of trust.

Table 1: Performance Metrics (Mean ± Std)

Metric	Value (%)
Accuracy	**93.2 ± 1.5**
Sensitivity	**94.6 ± 2.1**
Specificity	**93.1 ± 1.4**
Precision	**91.8 ± 1.7**
F1 Score	**91.1 ± 1.6**
AUC	**0.972 ± 0.010**

The model's exceptional discriminative ability between csPCa and non-csPCa cases is demonstrated by its average AUC of 0.972. A key consideration in clinical decision-making, sensitivity and specificity are balanced, demonstrating the model's ability to detect true positives without appreciably raising false positives.

Table-2, Comparison of performance analysis of existing method and proposed Techniques.

Model / Method	Accuracy	Sensitivity (Recall)	Specificity	Precision	AUC	AST (sec)
ProstateScan- RL (Proposed)	93.8%	95.2%	92.1%	92.8%	0.975	25.6
Supervised 3D U-Net	90.2%	92.5%	91.3%	90.0%	0.957	62.1*
Radiologist (PI-RADS ≥3)	89.0%	90.7%	87.2%	88.5%	0.935	~120-300
Radiologist (PI-RADS ≥4)	85.5%	82.4%	92.1%	89.1%	----	------

4. Conclusion

This study introduces a reliable and scalable framework that uses transfer learning to accurately identify clinically significant prostate cancer (csPCa) from multipara metric MRI (mpMRI) scans. The study addresses a major hurdle in medical artificial intelligence: the scarcity of annotated data, by leveraging strong pre-trained models, such as ResNet-50, and finetuning them with domain-specific data. The method leverages new input modalities such as dedicated 2.5D input, ingenious data augmentation techniques together with a detailed fine-tuning procedure. Therefore, the model can easily process different patient scans and imaging variations.

Clinical performance is particularly encouraging with the framework obtaining outstanding diagnostic performance with respect to accuracy, sensitivity, specificity, and a mean AUC of 0.972. Significantly, Grad-CAM visualizations demonstrate how the model focuses on the correct areas of the prostate, not only improving its accuracy, but also facilitating easier interpretation of its decisions and gaining trust in the actual clinical use.

In sum, this research could be a step forward in early and accurate prostate cancer detection. The entire framework provides a practical, efficient solution, reflecting the true potential of transfer learning in deep learning. The results suggest a promising future for AI-powered radiology, highlighting its potential for personalized treatment planning, the reduction of clinician burden, and enhanced diagnostic accuracy. In the future, it may be interesting to investigate the incorporation of more refined attention mechanisms or multi-instance learning methods to further fine-tune the model's focus and enhance its performance.

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