Deep-Learning Based Classification of Clinical Significance for Prostate Cancer

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***Abstract*—This study developed a new model for assessing the risk of prostate cancer, combining artificial intelligence with MRI data features. Through a neural network with three hidden layers and detailed analysis of MRI and PSA data, along with the use of Leave-One-Out Cross Validation and multidimensional performance metrics, the model's effectiveness has been proven, especially with a Youden's Index of 0.616, indicating strong classification capability. This research provides new tools and methods for the medical community, with the hope of offering more accurate prostate cancer risk assessments in the future, thereby further advancing the application of artificial intelligence in medical diagnostics.**

Keywords—Prostate Cancer, Artificial Intelligence, Artificial Neural network, MRI

I. MOTIVATION

This study is motivated by addressing a significant issue in global male health: prostate cancer. According to the World Health Organization's data from 2019 [1], prostate cancer ranks at the forefront of incidence rates among male cancers, highlighting its severe impact on global male health. The currently widespread diagnostic methods for prostate cancer, such as Prostate-Specific Antigen testing (PSA), Digital Rectal Examination (DRE), Transrectal Ultrasound-Guided Prostate Biopsy (TRUS-Guided Prostate Biopsy), Transrectal Ultrasound (TRUS), and Magnetic Resonance Imaging (MRI), are extensively used but present numerous issues regarding sensitivity, specificity, cost, and patient comfort. Notably, some invasive examinations can cause discomfort or pain for patients, reducing their willingness to undergo these tests. Therefore, developing new diagnostic methods that are both patient-friendly and highly accurate is especially important.

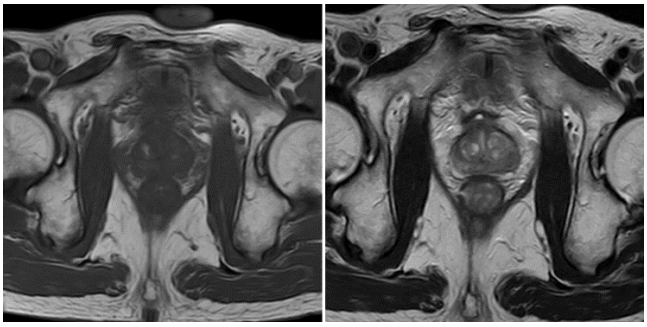

Fig. 1. The left image is a eT1-weighted image, and the right image is a eT2-weighted image

Although the use of artificial intelligence in prostate cancer research has shown progress and good developmental potential [2], the current technologies for rapid diagnosis and economic risk assessment are still not mature enough. Thus, this study aims to explore and develop an evaluation model that combines artificial intelligence with prostate imaging data features, particularly through magnetic resonance imaging of eT1w and eT2w images, as shown in Fig. 1. By developing this system, we hope to assist physicians in making accurate and rapid diagnoses.

II. METHOD

This research aims to utilize deep learning, specifically artificial neural networks [3], to increase the precision in assessing prostate cancer risk, structured into two primary phases: data feature extraction and model prediction analysis.

A. Dataset

Data was gathered using 1.5T MRI from Tainan Hospital, Ministry of Health and Welfare, involving 40 patients, with the distribution across various risk types provided in Table I.

TABLE I. NUMBER OF PATIENTS BY RISK CLASSIFICATION

Rick Level	Number of patients
Low	9
Intermediate	7
High	14
Regional	4
Metastatic	6

B. Disadvantages of Traditional Medicine

Conventional prostate cancer detection methods exhibit significant limitations. For instance, digital rectal exams focus on the prostate's posterior part, potentially missing anterior tumors [4]. Transrectal ultrasound-guided prostate biopsies, although providing the gold standard Gleason Score, are invasive and may lead to complications such as bleeding [5].

C. Feature Extraction & One-Hot Encoding

This study emphasizes integrating MRI image features with PSA level analysis, particularly extracting detailed features from MRI images across the entire prostate location, resulting in 12 indicators as listed in Table II. Based on PSA data according to the D'Amico Risk standards, one-hot encoding was conducted, as shown in Table III.

TABLE II. DATA FEATURE LIST

No.	Feature name	Description
01	Mean	The sum of all values divided by the number of values.
02	Median	The largest value in a dataset.
03	Max	The smallest value in a dataset
04	Variance	The average of the squared differences from the mean.
05	Standard Deviation	The square root of the variance
06	Range	The difference between the largest and smallest values.
07	Q1	The value below which 25% of the falls.
08	Q2	The median of the dataset.
09	Q3	The value below which 75% of the data falls
10	IQR	The range between the first and third quartiles
11	Skewness	Measure of the asymmetry of the probability distribution
12	Kurtosis	Measure of the "tailedness" of the probability distribution

TABLE III. SCHEMATIC DIAGRAM OF CONVERTING PSA LEVELS TO ONE-HOT ENCODING

PSA level	One-Hot Encoding
<10 ng/mL	[1, 0, 0]
10-20 ng/mL	[0, 1, 0]
>20 ng/mL	[0, 0, 1]

D. Patient Risk Stratification and Grouping

To address varied clinical needs, patients were categorized into two groups based on their risk levels: Low Risk and Non-Low Risk, to facilitate appropriate clinical guidance and treatment options for patients with different risk levels. This categorization, discussed and confirmed by a team of doctors, aims to support physicians in making quick and professional clinical decisions. Detailed classification data is available in Table IV.

TABLE IV. NUMBER OF PATIENTS WITH LOW & NON-LOW RISK

Risk Level	Number of patients
Low	9
Non Low	31

E. Model

In this study, we used an artificial neural network model with three hidden layers, integrating 25 features from MRI scans and the PSA indicator to predict prostate cancer risk. The ReLU function was selected to enhance training efficiency and address the vanishing gradient issue [6], while the output layer's Sigmoid function ensures suitability for binary classification. To speed up training and improve model generalization, batch normalization [7] was applied in each layer to maintain output distribution stability during training.

III. EXPERIMENT

A. Leave-One-Out Cross Validation (LOOCV)

This study employed LOOCV to evaluate the model, allowing full utilization of all data for testing and training to ensure accurate and fair assessment.

B. Performance Metrics

We assessed our model's performance using metrics such as area under the ROC curve (AUC), Accuracy (Acc.), F1 Score (F1.), and Youden's Index (*J*) for a comprehensive evaluation from various angles, especially useful in data imbalance scenarios. The Youden's Index above 0.6 indicates the model has effective classification ability [8].

$$J = Sensitivity + Specificity - 1 \quad (1)$$

C. Result

The experimental results demonstrated that our model performed excellently in classifying low and non-low risk categories, assessed using metrics such as AUC, Acc., Prec., Rel., F1., and *J*. It achieved good standards on all metrics, with the Youden's Index reaching 0.616, proving the model to be an effective classifier.

TABLE V. EXPERIMENTAL RESULTS

Acc.	Prec.	Rel.	F1.	AUC	J
0.825	0.583	0.777	0.666	0.874	0.616

IV. CONCLUSION

This study developed a new model combining AI with MRI data to enhance the accuracy of prostate cancer risk assessment. Experimental results show that a simple three-layer neural network model is effective and can quickly operate on standard hardware. We hope this model will support clinical decisions in the future. With technological advancements, the application of AI in diagnosing prostate cancer is expected to increase.

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