MRI Based Artificial Neural Network Model Used in Prostate Cancer Detection

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Purpose:

Prostate cancer (PCa) is the second most frequently diagnosed cancer of men (899 000 new cases, 13.6% of the total) and the fifth most common cancer overall [1, 2]. Prostate specific antigen (PSA) is presently the most widely used tumor marker for early detection of prostate cancer, and MR imaging plays an increasingly important role in the detection and staging of prostate cancer [3, 4]. Howerver, applicable detection model combining both clinical and MR information has not been proposed for prostate cancer detection. In this study, we devised an artificial neural network (ANN) model integrating clinical data and MR images in detection of prostate cancer, and compared the performance of this model with clinical-only model and MRI-only model.

Materials and Methods :

Data source: A total of 512 patients (mean age 71±8 years, range 27-91 years) were recruited in this study. All of the patients (with raised serum PSA level) were highly suspected of prostate cancer by urologist, and were performed MR examinations before biopsy. Among them, 270 patients (mean PSA 30.28 ng/ml, range 0.15-148.40 ng/ml) were confirmed to be prostate caner by biopsy or surgery, the other 242 patients (mean PSA 10.11 ng/ml, range 0.07-65.22 ng/ml) were not deteted of prostate cancer by serial biopsy and at least 3 years of follow-up. Each patient had clinical examinations containing total PSA value (tPSA), free/total PSA ratio (f/tPSA), age and a multiparametric MRI examination including T2 weighted images (T2WI)，diffusion weighted images (DWI), dynamic contrast enhanced images (DCE) and MR spectroscopy (MRS). MR images of the prostate cancer were acquired on clinical 1.5/3T scanners (Signa TM; GE Medical Systems, Milwaukee, WI).

Detection model: A back-propagation based multi-layer perceptron (MLP) network with 3 layers (input layer, hidden layer and output layer) was used as a detection model (Fig.1). Three clinical indicators (tPSA, f/tPSA and age, purple circles) along with MR images (blue circles) were chosen to be the inputs of the system, and the output was a probability for prostate cancer (black circles). After changing the number of neurons in the hidden layer (2–20, green circles), 14 neurons was chosen for the hidden layer, and Levenberg–Marquardt (LM) algorithm was used as learning rule. At the first stage, all data belonging to the 512 patients were included in two sets for ANN model(training set and testing set). At the second stage, 360 data (70% of the total data) randomly selected from the database were used for training and the remaining 152 data (30% of the total data) were used for test.

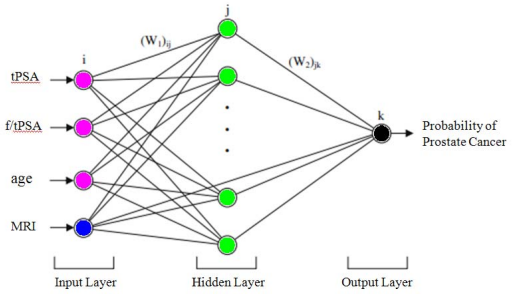

Fig.1. Schematic diagram of ANN model with 3 layers (input layer, hidden layer and output layer), both clinical indicators (purple circles) and MR images (blue circles) are used as inputs, each of them are richly interconnected by weighed connection lines.

Results:

At the first stage in Fig.2a, the areas under ROC curve (AUCs) were 0.81±0.02 for group A (ANN model based on clinical indicators only), 0.85±0.02 for group B (ANN model based on MR images only) and 0.91±0.01 for group C (ANN model based on both clinical and MR information), respectively. Good AUC performance was achieved through proper training, which suggested the effectiveness of this model. From the ROC curves of each ANN model in Fig.2b, it is observed that the model with both clinical and MR information produces better AUC (Group C, AUC= 0.86, 95%, CI= 0.81, 0.92) than that with either clinical indicators (Group A, AUC= 0.76, 95%, CI= 0.68, 0.83) or MR images only (Group B, AUC= 0.84, 95%, CI= 0.80, 0.92). The statistical results of the second stage model are shown in Table 1. AUCs in all three groups exhibited statistically significance (P< 0.01) when compared to that of random classifier. In Group C, 81% accuracy and 0.86 AUC can been obtained by using 2-fold cross validation method (50 times). Group C has significantly better AUC when compared to Group A (p< 0.01), better but not significant difference is detected when compared to Group B (p= 0.081).

Table 1. Summary of the detection performance and statistical testing carried out on prostate cancer using ANN analysis*.

Subject	Specificity	Sensitivity	Accuracy	AUC	P value
Group A	0.78±0.06	0.65±0.07	0.71±0.03	0.76±0.03	<0.01
Group B	0.78±0.08	0.82±0.08	0.79±0.03	0.84±0.02	<0.01
Group C	0.84±0.07	0.78±0.07	0.81±0.03	0.86±0.03	<0.01

* P values calculated by Mann Whitney U test were used to indicate the significance of the difference between estimated AUC and AUC of random classifier. Data are mean ± SD (n= 50).

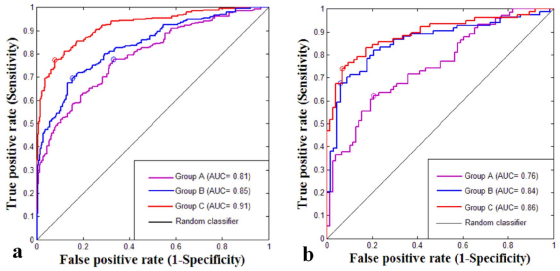

Fig.2. ROC curves for three ANN models based on clinical indicators (group A, purple curve), MR images (group B, blue curve) and both clinical and MR information (group C, red curve) with

a) All 512 samples used as training group as well as testing group (left);

b) 360 samples used for training, the remaining 152 used for testing (right).

Conclusions:

In the present study, this proposed ANN model could be used in prostate cancer detection with high accuracy, on condition that both clinical and MRI information were integrated. The model integrating both clinical and MR information is able to provide better AUC and accuracy in detection of PCa than the other two models, which further demonstrates the feasibility of MRI for computer-aided prostate cancer identification. In conclusion, this ANN model utilizing quantitative features of both clinical and MR information has the potential for prostate cancer detection.

References:

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