Developing Bayesian Networks based Prognostic Radiomics Model for Clear Cell Renal Cell Carcinoma Patients

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***Abstract*– Clear cell renal cell carcinoma (ccRCC) is one of the most aggressive histologic subtype of RCC. In this study, we developed and evaluated a Bayesian network as a prognostic model using computed tomography (CT) radiomic features and clinical information to predict the risk of death within 5 years for ccRCC patients. Seventy patients who had abdominal CT scans with delayed post-contrast phase and outcome data were enrolled. 3D volumes of interest (VOIs) covering the whole tumor on CT images were manually delineated. Image preprocessing techniques including, wavelet, Laplacian of Gaussian, and resampling of the intensity values to 32, 64 and 128 bin levels were applied on all VOIs. Different radiomic features, including shape, first-order, and texture features were extracted from the VOIs. For features selection, we first used the z-score method to normalize all image features, then the relevant features were selected based on mutual information (MI) criteria. The patients were divided into a low- and high-risk group based on survival or death at 5 years after surgery, respectively. Bayesian networks were used as a classifier for risk stratification. The model was evaluated using the area under the curve (AUC), sensitivity, specificity, and accuracy by 1000 bootstra resampling. The Bayesian model with Laplacian of Gaussian (LOG) filter showed the best predictive performance in this cohort with an AUC, sensitivity, specificity, and accuracy of 0.94, 85 %, 94%, and 89%, respectively. The results of the current study indicated that prognostic models based on radiomic features are very promising tools for risk stratification for ccRCC patients.**

***Index Terms*— ccRCC, Radiomics, Byesian Network, CT**

I. Introduction

Renal cell carcinoma (RCC) with 403,000 new cases and 175,000 mortality annually forms 2-3% of all cancer diagnoses and death worldwide [1, 2]. Clear cell renal cell carcinoma (ccRCC) is one of the most aggressive histologic subtype of RCC [3-5]. For ccRCC patients, some clinical prognostic models by the International Union Against Cancer (UICC) and American Joint Committee on Cancer (AJCC) were proposed and developed [6]. Nevertheless, due to limited accuracy, their clinical application was not promising [7].

Also, biopsy-based genes analysis to predict prognosis due to intra-tumor heterogeneity, invasive approches and availability is limited [8]. Radiomics is a new concept in precision medicine to quantitative analysis of medical images enabling non-invasively to characterize tumor phenotype for diagnostic and prognostic models [9-16]. In this study, we developed and evaluated a Bayesian network as a prognostic model using computed tomography (CT) radiomic features and clinical information to predict the risk of death within 5 years for ccRCC patients.

II. Materials and Methods

In this retrospective study, seventy patients who had abdominal CT with delayed post-contrast phase and outcome data from the cancer image archive (TCIA) [17] dataset were provided. The 3D region of interest (VOI) covering the whole tumor on CT images was manually segmented slice by slice by an experienced radiologist using the 3D slicer software package.

Image preprocessing techniques including, wavelet, Laplacian of Gaussian, and resampling of the intensity values to 32, 64 and 128 bin levels were applied on all VOIs.The radiomics features were extracted from each VOI on CT images using an open-source package PyRadiomics [18]. Extracted features included shape features (n = 16), intensity first-order features (n=19), intensity histogram features (n = 18), grey level co-occurrence matrix (GLCM) features (n = 22), gray level run-length matrix (GLRLM) features (n=11), gray-level size zone matrix (GLSZM) features (n=13), and neighboring gray tone difference matrix (NGTDM) features (n=9) [18].

For features selection, first we used z-score method to normalize all image features, then relevant features are selected based on mutual information (MI) criteria. Patients divided into a low and high-risk group based on survival or death at 5 years after surgery, respectively. In this study, we used Bayesian network as a classifier for risk stratification. Model evaluated by area under the curve (AUC), sensitivity, specificity, and accuracy by 1000 bootstrapping resample.

III. RESULT

Table 1 summarizes the results of the all models for different data set. As shown, Bayesian model with Laplacian of Gaussian (LOG) filter showed the best predictive performance in the cohort, with an AUC, sensitivity,

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specificity, and accuracy of 0.94, 85 %, 94%, and 89%, respectively.

Fig 1. compare the AUC of different preprocessing images

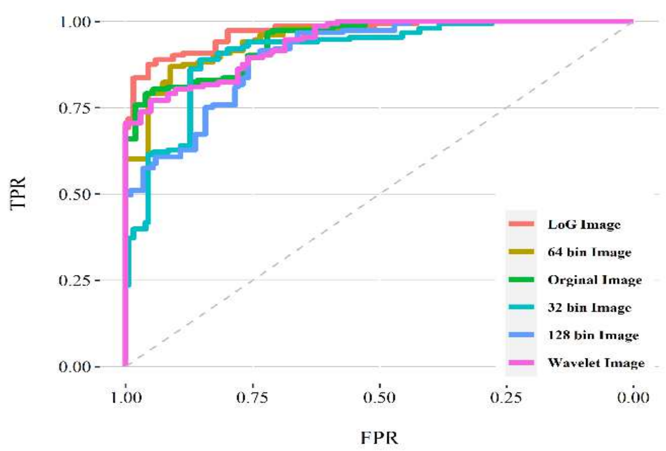

Fig. 1. AUC of different image data sets.

Radiomic models in this study was constructed using different image filter and various features including shape features, first-order feature, and texture features.

TABLE I. models performance for different image data set.

Original Images			
AUC	Sensitivity	Specificity	Accuracy
0.92	0.73	0.91	0.81
32 Bin Images			
AUC	Sensitivity	Specificity	Accuracy
0.91	0.77	0.90	0.80
64 Bin Images			
AUC	Sensitivity	Specificity	Accuracy
0.93	0.82	0.92	0.83
128 Bin Images			
AUC	Sensitivity	Specificity	Accuracy
0.9	0.71	0.88	0.79
Wavelet Images			
AUC	Sensitivity	Specificity	Accuracy
0.92	0.83	0.91	0.82
LoG Images			
AUC	Sensitivity	Specificity	Accuracy
0.94	0.85	0.94	0.89

IV. DISCUSSION AND CONCLUSION

Our study accompanied by previous research [6], demonstrated the prognostic power of CT image biomarker in risk stratification, despite intra- and inter-tumor heterogeneity most ccRCC tumors. However, future studies with larger sample sizes are needed to validate the finding of this study with reproducible and robust features [19, 20].

Prognostic models are the most important tools that can aid healthcare to guided therapy in cancer patients. The results of current study indicated that prognostic model based on radiomics features are very promising tools for risk stratification for ccRCC patients.

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