

The Radionics Features Could Be Used to Predict the Distinct Metastases in Nasopharyngeal Carcinoma Patients

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Abstract

Objectives

For NPC patients, distant metastasis is now the main reason for treatment failure. The patients with distinct metastases need different therapeutic regimen and have distinct prognosis. Radiomics might help us predict the type of metastases effectively.

Methods

The MRI data of seventy non-metastatic NPC patients who develop distant metastasis within five years after treatment were collected and 4410 radiomics features for each patient were extracted by PyRadiomics. Every radiomics feature were compared among patients with distinct metastases and tested by the receiver operating characteristic curve.

Results

Twenty features have significant differences between the bone metastases cohort and lung metastases cohort, two features have significant differences between the bone metastases cohort and liver metastases cohort, one feature has significant differences between the bone metastases cohort and multiple metastases cohort and sixty-seven features have significant differences between the lung metastases cohort and liver metastases cohort. Six T2WI features could identified lung metastases from bone metastases and liver metastases effectively (AUC = 0.851 ~ 0.896), two T1WI features and one CE T1WI feature could respectively identified bone metastases from liver metastases and multiple metastases effectively (AUC = 0.779 ~ 0.821).

Conclusion

The results indicate that the radionics features could reflect some of the characteristics of distinct metastases and have potential to be used as predictor of distinct metastases.

Introduction

Nasopharyngeal carcinoma (NPC) has a unique geographical distribution, with the highest incidence in southeast Asia. More than 70% of NPC patients are diagnosed as locoregionally advanced disease due to its hidden pathogenic site [1–4]. Currently the standard treatment for advanced NPC patients is radiotherapy combined with chemotherapy. Locoregional control has improved substantially due to the use of intensitymodulated radiotherapy and combined chemoradiotherapy[5]. Moreover, approximately 30–40% of advanced NPC patients eventually develop distant metastasis after treatment and distant metastasis is now the main reason for treatment failure[6]. For advanced NPC patients, the common

metastases were bone metastases, lung metastases, liver metastases, mediastinal metastases and multiple metastases[6]. The patients with distinct metastases need different therapeutic regimen and have distinct prognosis.

The tumour–node–metastasis (TNM) staging system is the key determinant for prognostic prediction and risk stratification for treatment decisions. Even though NPC patients with the same TNM stage receive similar treatments, their clinical outcomes vary greatly. Hence, the current anatomical-based staging system is not sufficient to predict the site of metastases. If we could predicted the site of the metastases and prevent before the occurrence of metastases, the patients would benefit from it and the survival time of the advanced NPC patients would be Prolonged.

Recently, the radiomics emerged and it enables image features to be extracted from standard-of-care medical imaging and applied within clinical-decision support systems and has significantly improved the diagnostic, prognostic, and predictive accuracy of various tumors[7–17]. Therefore, we wanted to see if radiomics could help us predict the site of the metastases in patients with advanced nasopharyngeal carcinoma.

In this study, we collected the MRI data of seventy non-metastatic NPC patients who develop distant metastasis within five years after treatment and extracted 4410 radiomics features for each patient by PyRadiomics. We compared the radiomics features among patients with distinct metastases and found that radiomics features have significant differences among these groups and some features could be used to predict the type of metastases effectively. These results indicate that the radionics features have potential to be used as predictor of distinct metastases in NPC patients.

Materials And Methods

Patients

This study included 70 non-metastatic NPC patients who were treated at the Affiliated Foshan Hospital of Sun Yat-Sen University from January 2009 to December 2012 and finally developed distant metastasis during the 5-year follow-up. All patients underwent a pretreatment evaluation, which included MRI (T1, T2, and Contrast-enhanced T1 scans) of the neck and nasopharynx, chest radiography, abdominal sonography and whole-body bone scan. All patients were treated with intensity-modulated radiation therapy (IMRT) with or without chemotherapy. This study was approved by the ethics committee of the Affiliated Foshan Hospital of Sun Yat-Sen University. All the participants provided written informed consent. The research protocol complied with the guidelines outlined in the Declaration of Helsinki. The 8th AJCC staging system was used as a standard manual for tumor staging and the related clinical characteristics were collected such as age, gender, T stage, N stage, C-reaction protein, Epstein-Barr virus DNA copy number before treatment, lactate dehydrogenase and so on.

Follow-up and clinical endpoint

After completion of radiation and chemotherapy, all patients were followed up every 3 months in the first 2 years, every 6 months from year 3 to year 5, and annually thereafter. Follow-up was performed with endoscopy, head and neck computed tomography, or MRI. The follow-up period was defined as the time from the date of diagnosis to the date of the last follow-up or death.

Imaging protocol and Image assessment

T1-weighted images (T1WI), contrast-enhanced T1-weighted images (CE T1WI), and T2-weighted images (T2WI) were retrieved from the picture archiving and communication system (PACS) and loaded in AnalyzePro (<https://analyzedirect.com/analyzepro/>) for manual segmentation. The MRI scans were evaluated by two independent radiologists (G.Y.Z, L.Z.L) with over 10 years' experience in MRI of patients with NPC. Differences were resolved by consensus.

Radiomics features extraction

Radiomics features extraction was performed using PyRadiomics, which is a flexible open-source platform capable of extracting a large number of engineering features from medical images (<http://www.radiomics.io/pyradiomics.html>)[18, 19]. In total, we extracted 4410 (1470×3) radiomics features for each patient from axial T1WI, T2WI, and CE T1WI scans, The list of the radiomics features was available in supplement tables.

Statistical analysis

The clinical characteristics of the cohorts were compared using the Mann-Whitney U test for continuous variables and Chi-square test for categorical variables and two-sided P values < 0.05 were considered to be statistically significant. The receiver operating characteristic (ROC) curve was used to illustrate the diagnostic ability of a binary classifier system. The area under the curve (AUC) was calculated by the Hanley and McNeil method. These analyses were performed using Graphpad Prism software (version 5.1) and SPSS (version 20.0).

Result

Clinical Characteristics

The clinical and pathological features are listed in Table 1. The median follow-up period was 40.5 months (range: 6.2–72.2 months) for all patients. All patients finally developed distant metastasis during the 5-year follow-up, twelve of them developed bone metastases, sixteen of them developed lung metastases, thirteen of them developed liver metastases, three of them developed mediastinal metastases and the other developed multiple metastases.

Table 1
The clinical characteristic of the NPC patients in this study.

Characteristic	bone metastases(n = 12)	other metastases(n = 58)	P value
Age			0.751
< 50	7	37	
≥ 50	5	21	
Sex			1.0
Male	9	43	
Female	3	15	
T stage			0.166
T1	4	6	
T2	1	8	
T3	2	21	
T4	5	23	
N stage			0.796
N0	1	6	
N1	5	28	
N2	5	16	
N3	1	8	
TNM stage			0.134
I	1	0	
II	2	7	
III	3	23	
IV	6	28	
VCA-IgA			1
< 1:80	1	9	
≥ 1:80	11	49	
EA-IgA			1
< 1:10	3	14	

IC, induction chemotherapy; CC, concurrent chemoradiotherapy; AC, adjuvant chemotherapy.

Characteristic	bone metastases(n = 12)	other metastases(n = 58)	P value
≥ 1:10	9	44	
EBV DNA copy number			0.485
< 1000	4	11	
1000–9999	2	22	
10000–99999	4	18	
100000–999999	2	7	
≥ 1000000	0	0	
LDH concentration (U/L)			1
< 245	11	54	
≥ 245	1	4	
C-reactive protein concentration (mg/L)			0.436
< 8.2	11	45	
≥ 8.20	1	13	
WBC, 10 ⁹ /L			0.299
< 4	0	2	
4–10	12	48	
≥ 10	0	8	
PLT, 10 ⁹ /L			0.851
< 100	0	1	
100–300	10	46	
≥ 300	3	11	
LYM			1
< 0.8	0	0	
0.8–4, 10 ⁹ /L	12	58	
≥ 4	0	0	
MONO, 10 ⁹ /L			1
< 0.12	0	0	

IC, induction chemotherapy; CC, concurrent chemoradiotherapy; AC, adjuvant chemotherapy.

Characteristic	bone metastases(n = 12)	other metastases(n = 58)	P value
0.12–0.8	10	49	
≥ 0.8	2	9	
HBsAg			1
0	10	47	
1	2	11	
Treatment			1
IMRT alone	1	2	
IC + IMRT	2	8	
CC + IMRT	2	26	
AC + IMRT	1	0	
IC + CC + IMRT	6	22	
IC, induction chemotherapy; CC, concurrent chemoradiotherapy; AC, adjuvant chemotherapy.			

Radiomics features have significant differences among the patients with distinct metastases.

Radiomics features (1470 × 3) for each patient were extracted from MRI scan (T1WI, T2WI, and CE T1WI). We compared these radiomics features among patients with distinct metastases and found that twenty features have significant differences between the bone metastases cohort and lung metastases cohort (Fig. 1B), two features have significant differences between the bone metastases cohort and liver metastases cohort (Fig. 1C), one feature has significant differences between the bone metastases cohort and multiple metastases cohort (Fig. 1D) and sixty-seven features have significant differences between the lung metastases cohort and liver metastases cohort (Fig. 1A). Moreover, one feature called “T2_log-sigma-5-0-mm-3D_glcm_ClusterShade” was higher in bone metastases cohort than other metastases cohort significantly (Fig. 1E). These results indicated that MRI features could reflect some of the characteristics of distinct metastases and they might classify distinct metastases effectively.

Radiomics features could be used to classify distinct metastases

In order to explore which radiomics feature could classify distinct metastases, we performed ROC curve analysis and found that radiomics features could be used to classify distinct metastases effectively. As shown in Table 2 and Fig. 2, six T2WI features could identified lung metastases from bone metastases and liver metastases effectively (AUC = 0.851 ~ 0.896), two T1WI features and one CE T1WI feature could respectively identified bone metastases from liver metastases and multiple metastases effectively (AUC = 0.779 ~ 0.821). Moreover, one T2WI feature could identified bone metastases from other metastases

(AUC = 0.739). These results indicate that the radiomics features have potential to be used as predictor of distinct metastases and help to the interfere treatment before metastases in NPC patients.

Table 2
The Radiomics features which could classify the metastases effectively.

Comparison	Sig.(2-tailed)	AUC
Lung metastases vs Bone metastases		
T2_log-sigma-5-0-mm-3D_firstorder_Minimum	< 0.001	0.896
T2_log-sigma-5-0-mm-3D_glszm_HighGrayLevelZoneEmphasis	0.001	0.865
T2_log-sigma-5-0-mm-3D_glszm_LowGrayLevelZoneEmphasis	0.001	0.865
Lung metastases vs Liver metastases		
T2_exponential_firstorder_Mean	0.001	0.851
T2_exponential_firstorder_RootMeanSquared	0.001	0.851
T2_square_glrIm_GrayLevelNonUniformityNormalized	0.001	0.851
Bone metastases vs Liver metastases		
T1_log-sigma-3-0-mm-3D_glszm_SmallAreaEmphasis	0.007	0.821
T1_wavelet-HHH_firstorder_Median	0.007	0.821
Bone metastases vs Multiple metastases		
T1C_logarithm_glcm_MaximumProbability	0.006	0.779
Bone metastases vs Other metastases		
T2_log-sigma-5-0-mm-3D_glcm_ClusterShade	0.0097	0.739
glszm, gray Level size zone matrix; glcm, gray level co-occurrence matrix		

Discussion

We undertook this study to explore the value of radiomics in predicting the site of distant metastasis in NPC patients. We collected the MRI data of seventy non-metastatic NPC patients who develop distant metastasis within five years after treatment and 4410 radiomics features were extracted from each MRI. All of the features were compared among cohorts with distinct metastases and we found that radiomics features have significant differences among the patients with distinct metastases and they have potential to be used as predictor of distinct metastases in NPC patients.

Currently, several studies have assessed the performance of radiomics signature in clinical staging, prognostic prediction, response to treatment, and discrimination of phenotype for several types of tumors [8–12, 14–16]. For Nasopharyngeal carcinoma patients, distant metastasis after treatment is one of the

most pressing issues and predicting the site of distant metastasis could be benefit to scheme of treatment. In 2018, a study reported a gene expression-based signature to predict distant metastasis in locoregionally advanced nasopharyngeal carcinoma [5] and they develop a nomogram to predict an individual's risk of distant metastasis. In that study they focused on the risk of distant metastasis and didn't group the patients according to the site of metastasis. Our study indicated that radiomics signature might be a good choice for predicting the site of metastasis because it allowed high dimensional, noninvasive, and quantitative characterization of the tumor.

We collected the MRI data of 778 NPC patients who were treated at Sun Yat-Sen University Cancer Center from January 2009 to December 2012. Seventy patients developed distant metastasis during the 5-year follow-up. Limited by the number of patients, we couldn't validated the selected features in independent cohorts. We didn't know whether the features have the similar efficiency in distinct hospitals. We are trying our best to build cooperation with other radiologists and looked forward to getting diverse data to calibrate the findings in this study.

In this study we focus on the radiomics features of distinct metastases and found significant differences. They even could be used to predict the type of metastases effectively. These results indicate that the radionics features have potential to be used as predictor of distinct metastases in NPC patients.

Declarations

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

ETHICS STATEMENT

This study was approved by the ethics committee of the Affiliated Foshan Hospital of Sun Yat-Sen University. All the participants provided written informed consent. The research protocol complied with the guidelines outlined in the Declaration of Helsinki.

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AUTHOR CONTRIBUTIONS:

Guoyi Zhang designed and supervised the study. Meige Li and Haiwen Ye collected follow-up data. Ziyou Feng and Zejiang Zhan performed the statistical analysis. Meige Li, Ziyou Feng and Guoyi Zhang wrote the manuscript. Guoyi Zhang carried out an extensive revision. All authors participated in the writing and approval of the manuscript.

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Figures

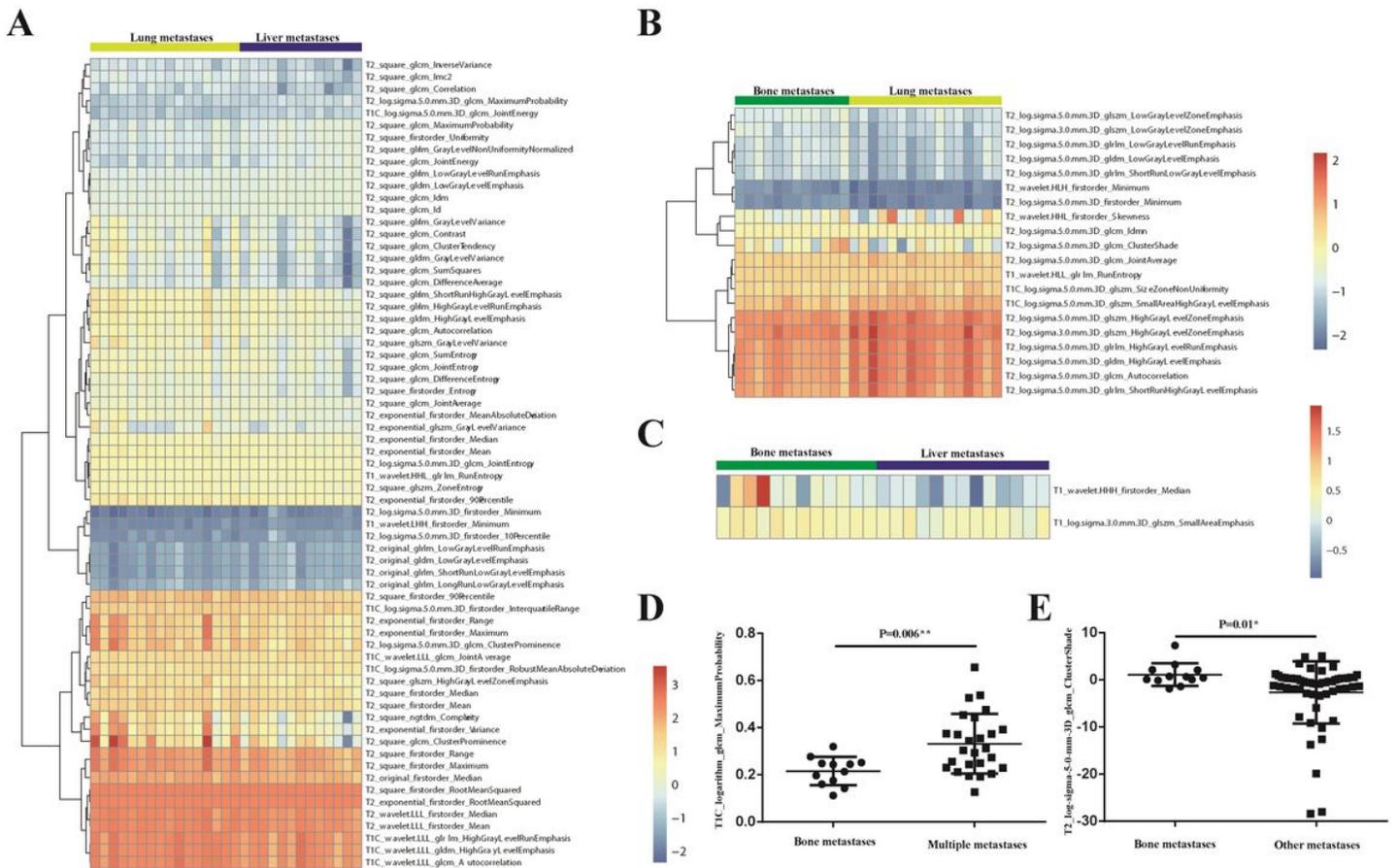


Figure 1

The radiomics features which have significant differences between (A) the lung metastases cohort and liver metastases cohort, (B) the bone metastases cohort and lung metastases cohort, (C) the bone metastases cohort and liver metastases cohort, (D) the bone metastases cohort and multiple metastases cohort, (E) bone metastases cohort and other metastases cohort.

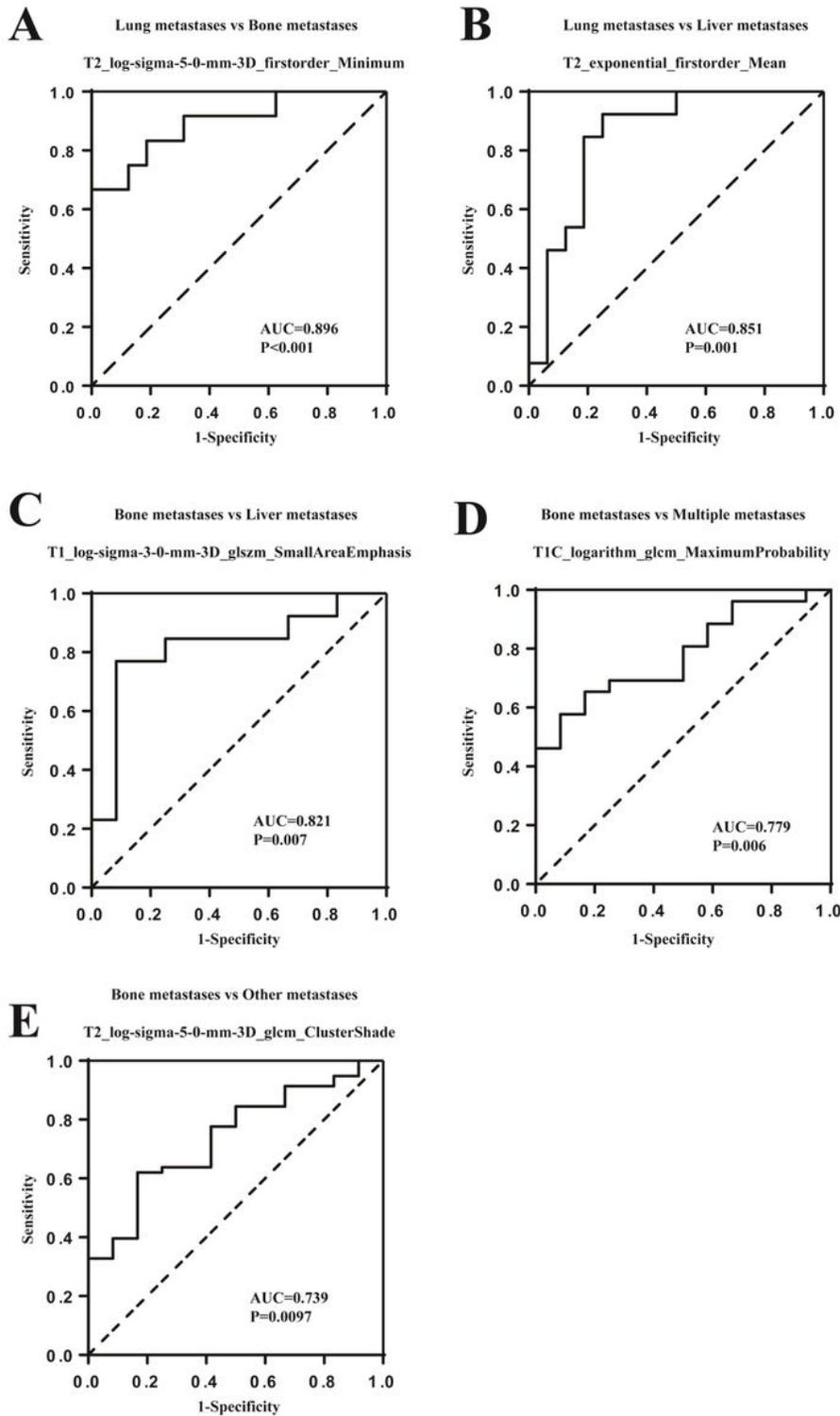


Figure 2

The ROC curves of the radiomics features which could be used to classify distinct metastases effectively. (A) the bone metastases cohort and lung metastases cohort, (B) the lung metastases cohort and liver metastases cohort, (C) the bone metastases cohort and liver metastases cohort, (D) the bone metastases cohort and multiple metastases cohort, (E) bone metastases cohort and other metastases cohort.