Assessing the Application of Radiomics on Post Radio-iodine Therapy Whole body Scan – A Preliminary Study

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ABSTRACT

Purpose: Radiomics has been principally applied for characterization of tumor heterogeneity which by virtue of its predictive power in the prognostication, claims further implication in the management. As a practitioner of radioactive iodine therapy, we have observed the characteristic of radiomic features extracted from post radioiodine therapy whole body scan.

Patients and methods: Anterior planar images from 39 patients who underwent radioiodine therapy after thyroidectomy due to differentiated papillary thyroid carcinoma were analyzed in LIFEX software to generate radiomic feature (RF) data from two regions of interest (ROI): neck and liver per patient. Correlation of the RF was checked against two demographic variables, patient's body weight and patient's age and three clinical variables, administered radioiodine dose during therapy, pre therapy TSH level, pre therapy thyroglobulin level. After discovering features with significant correlation with demographic and clinical variables, the RF that correlated in each of the two ROI were shortlisted.

Results: A total of 141 RF per ROI per patient were extracted using LIFEX while 32 Radiomics features from neck ROI and 15 radiomic features from liver ROI were discovered to have significant correlation with two demographic variables and three clinical variables (R ranged from -0.5 to 0.49, $p < 0.05$). Four radiomic features were common for both neck and liver ROI that have significant correlations. Among those four, one was correlated with body weight and three were with therapy dose. Pre therapy TSH level was found to have correlation with 10 features from neck ROI and no feature from liver ROI. Pre therapy Tg level was found to have correlation with two features from neck ROI and one feature from liver ROI.

Conclusions: With further exploration, the RF from post radioiodine therapy whole body scan may evolve as a useful aid to the management of differentiated thyroid cancer by providing prediction about clinical outcome as well as by playing as surrogates of histopathological and immunohistochemical markers.

Keywords: Radiomics, Differentiated thyroid cancer, Post radioiodine therapy whole body scan.

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INTRODUCTION

The application of radiomics feature (RF) extraction has been largely applied to volumetric medical imaging data to characterize tumor heterogeneity and predict treatment outcome (1-3). However, prediction of clinical outcome is also possible using RF from two-dimensional imaging data (4-6) as well as histopathological data (7). Application of radiomic for the prediction of metastasis, tumor progression, treatment response, and gene mutation in differentiated thyroid cancer has been reported using ultrasound X-ray computed tomography and magnetic resonance imaging data (8) and recently using whole-body post radioiodine therapy scans (9). Some important facts that are taken into consideration during administration of radioactive iodine therapy include, patients age, body weight, pre therapy levels of thyrotropin (TSH) and thyroglobulin (Tg) (10). This retrospective cross-sectional study was done to explore the correlation of those basic demographic and clinical variables with RF extracted from whole-body post radioiodine therapy scan.

PATIENTS AND METHODS

Images of whole-body post radioiodine therapy scans were selected. The scans were performed on patients who underwent total thyroidectomy with a diagnosis of differentiated thyroid papillary carcinoma. The DICOM image data from anterior whole body sweep images was used for the analysis. First, the DICOM images were loaded to freeware, Local Image Feature Extraction (LIFEX). Thereafter, region of interest (ROI) was drawn on neck and liver using the planar anterior whole body sweep images to generate radiomic feature (RF) output data. The output data were then complied and compared to two demographic variables and three clinical variables of the patients to find those RFs with significant correlation, using corrplot package on R. A p-value < 0.05 was considered significant.

RESULTS

Analysis was done on 39 anterior planar images from whole body post radioiodine therapy scan. A total of 141 radiomic features per ROI per patient were extracted using LIFEX. Among the RF, categorically 31 were morphological, 54 were intensity based, 24 were Gray-Level Co-occurrence Matrix (GLCM) based, 11 were Gray-Level Run-Length Matrix (GLRLM) based, five were Neighboring Gray Tone Difference Matrix (NGTDM) based, and 16 were Gray Level Size Zone (GLSZM) based.

Out of those 141 features per ROI per patient, a total of 32 Radiomics features from neck ROI (table 1 and 2) and 15 radiomic features from liver ROI (table 3 and 4) were discovered to have significant correlation with two demographic variables and three clinical variables.

Six features from neck ROI and one feature from liver ROI were found to have significant correlation with age. One common feature from both neck and liver ROI and six additional features from the liver ROI were found to have significant correlation with body weight.

Therapy dose of radioiodine was found to have correlation with three features that were common from both neck and liver ROI, additional 10 features from neck ROI and another three features from liver ROI.

Altogether, four radiomic features were common for both neck and liver ROI that have significant correlations with demographic and clinical variables. Among those four, one was correlated with body weight and three were with therapy dose.

Pre therapy TSH level was found to have correlation with 10 features from neck ROI and no feature from liver ROI. Pre therapy Tg level was found to have correlation with two features from neck ROI and one feature from liver ROI.

DISCUSSION

The observed correlation of RF with body weight and therapy dose is partly explainable by the retention of larger amount of radioactivity during post radioiodine therapy scan happened in larger amount of tissue in larger patients as well as due to the larger amount of dose administered. Thus, these findings may seem rational. At the same time these findings may create an opportunity to use the radiomic features as a surrogate for dosiomics (11) to conduct dosimetry and that may in turn have an implication in the management of patients who require more than one episode of radioiodine therapy.

There remains scope for further exploration of eligibility of the RF from planar whole-body post radioiodine therapy scans as a surrogate for histopathological and immunohistochemical markers (12). Further study on larger group of patients with inclusion of long-term prognostic data will aid in the formation of radiomics based risk prediction models in differentiated thyroid cancer. The correlation of pre therapy level of TSH and Tg to RF indicates the possibility of finding RF surrogates that may predict patients who may later evolve as positive Tg but negative iodine scan, using RF features from the first post radio-iodine therapy scan.

CONCLUSION

This cross-sectional study on a small group of patients have found a set of RF that correlates with basic demographic and clinical variables. Further exploration of capability of the RF in the prediction of clinical outcome as well as by a candidate for playing as surrogates of histopathological and immunohistochemical markers, will facilitate their incorporation in the management of differentiated thyroid cancer.

Table 1. Discovered seven radiomic features from neck ROI that had significant correlation with demographic variables.

Demographic variable	Radiomic feature	Correlation coefficient (Pearson's R)	p-value
Age (years)	GLCM contrast	0.32	0.046
	GLCM difference average	0.36	0.023
	GLCM dissimilarity	0.36	0.023
	GLRLM long run low grey level emphasis	-0.32	0.049
	GLRLM low grey level Run Emphasis	-0.33	0.043
	GLRLM Short run low grey level emphasis	-0.33	0.042
Weight (Kg)	Morphologic Radius Sphere Normalized-Maximum Intensity Coordinate-ROI Centroid Coordinate-Distance*	-0.33	0.04

*Radiomic feature that showed significant correlation from liver ROI as well

Table 2. Discovered 25 radiomic features from neck ROI that had significant correlation with clinical variables.

Clinical variable	Radiomic feature	Correlation coefficient (Pearson's R)	p-value
Therapy dose of radioiodine (mCi)	Morphologic Voxel count*	0.49	0.001
	Intensity histogram Maximum Histogram Gradient	-0.5	0.001
	GLCM inverse difference	0.4	0.012
	GLCM inverse difference moment	0.4	0.01
	GLCM joint maximum	0.36	0.025
	GLRLM grey level non uniformity	0.41	0.009
	GLRLM long run emphasis	0.36	0.023
	GLRLM run length non-uniformity*	0.45	0.004
	GLRLM run percentage	-0.35	0.03
	NGTDM busyness	0.34	0.032
	NGTDM coarseness	-0.34	0.033
	NGTDM strength	-0.44	0.005
	GLSZM grey level non uniformity*	0.43	0.007
Pre therapy TSH (µIU/mL)	Morphologic integrated intensity	0.37	0.021
	10th intensity centile	0.34	0.034
	25th intensity centile	0.34	0.033
	75th intensity centile	0.32	0.047
	Intensity based Robust Mean Absolute Deviation	0.32	0.048
	Intensity based minimum intensity	0.43	0.006
	Intensity histogram minimum grey level	0.44	0.006
	Intensity histogram 10th centile	0.34	0.033
	Intensity histogram 10th centile	0.34	0.034
	GLSZM grey level non uniformity	-0.37	0.02
Pre therapy Tg (ng/mL)	Intensity based minimum intensity	0.46	0.003
	Intensity histogram minimum grey level	0.46	0.003

*Radiomic feature that showed significant correlation from liver ROI as well

Table 3. Discovered eight radiomic features from liver ROI that had significant correlation with demographic variables

Demographic and clinical variable	Radiomic feature	Correlation coefficient (Pearson's R)	p-value
Age (years)	Intensity histogram skewness	-0.32	0.046
Weight (Kg)	Morphologic Approximate volume	0.36	0.026
	Morphologic Surface area	0.37	0.019
	Morphologic Radius Sphere Normalized-Maximum Intensity Coordinate-ROI Centroid Coordinate-Distance*	-0.37	0.02
	Morphologic RadiusSphereNormalized- CentroidCoordinate-Weighted Centroid Coordinate-Distance	-0.35	0.029
	Morphologic Maximum 3D Diameter	0.38	0.017
	Morphologic Sphere Diameter	0.33	0.037
	Intensity based Minimum Histogram Gradient	-0.34	0.036

*Radiomic feature that showed significant correlation from neck ROI as well

Table 4. Discovered seven radiomic features from liver ROI that had significant correlation with clinical variables.

Clinical variable	Radiomic feature	Correlation coefficient (Pearson's R)	p-value
Therapy dose of radioiodine (mCi)	Morphologic Voxel count*	0.41	0.009
	Intensity based Intensity skewness	-0.35	0.027
	Intensity based Intensity kurtosis	-0.38	0.016
	Intensity based Intensity histogram kurtosis	-0.36	0.023
	GLRLM run length non-uniformity*	0.44	0.005
	GLSZM Grey level non-uniformity*	0.47	0.002
Pre therapy TSH (µIU/mL)	-	-	-
Pre therapy Tg (ng/mL)	Maximum Intensity Coordinate-ROI Centroid Coordinate-Distance	0.32	0.049

*Radiomic feature that showed significant correlation from neck ROI as well

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