Machine Learning based on CT Radiomic features can predict Residual Tumor from Radiation Changes in Head and Neck cancer patients treated with definitive Chemoradiotherapy

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INTRODUCTION

Surveillance images used in patients treated with definitive chemoradiotherapy (chemoRT) are known to have inherent difficulties in differentiating residual disease from radiation changes. These image deficiencies can lead to unnecessary interventions, including rescue surgery, resulting in a poorer quality of life for patients and increased healthcare expenses. On the other hand, the early detection of residual disease is particularly important since it would make it possible to identify patients who need to undergo rescue surgery as a priority.

AIM

This study aims to assess the response and progress of head and neck cancer patients treated with definitive chemoRT with the purpose of predicting residual tumor from radiation changes and inflammation by machine learning (ML) models based on radiomic features (RadFs) extracted from surveillance pre- and post-treatment CT images.

METHODS

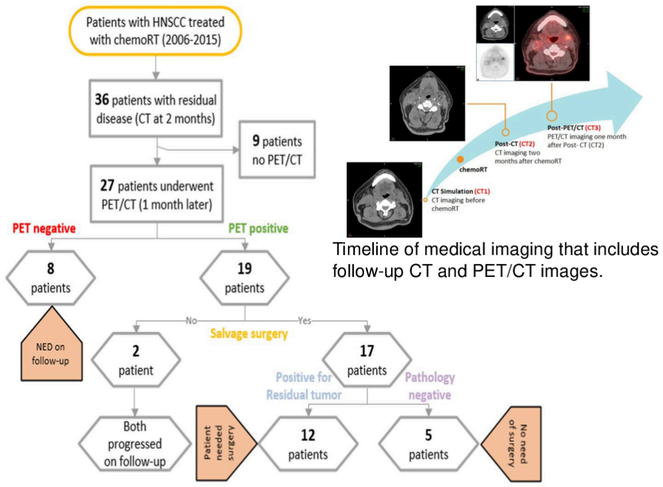
HIPPA-compliant, IRB-approved retrospective analysis of patients with squamous cell carcinoma of the head and neck (HNSCC) treated with chemoRT at UMMC. Thirty-six patients (n=36) with residual disease on CT scan performed in 2 months interval- either in primary site, nodal station or both were enrolled.

All gross tumor volumes (GTVs) were transferred from the treatment planning CT scan (CT1) to a DICOM viewer (MIM® Software Inc., v6.9.6). Then, an experienced radiologist contoured the tumors in 2 months follow-up CT scan (CT2) and in the CT portion (CT3) of the 3 months follow-up PET/CT scan using MIM's tools.

Next, the segmented GTVs from CT images were exported to MatLab® (The MathWorks, Inc., R2017a) where RadFs were extracted through different approaches: (a) from the region of interest (ROI) which best represented the GTV ($RadF_{2D}$=280 features), (b) from the volume of interest (VOI) of the GTV ($RadF_{3D}$=455 features).

Finally, ML models such as support vector machine (SVM), neural network (NN) and, random forest (RF) were used to predict changes and progress in HNSCC cancer patients treated with chemoRT.

RESULTS



Timeline of medical imaging that includes follow-up CT and PET/CT images.

Figure 1. Flowchart of treatment decision sequences for the patients with HNSCC treated with chemoRT in this study.

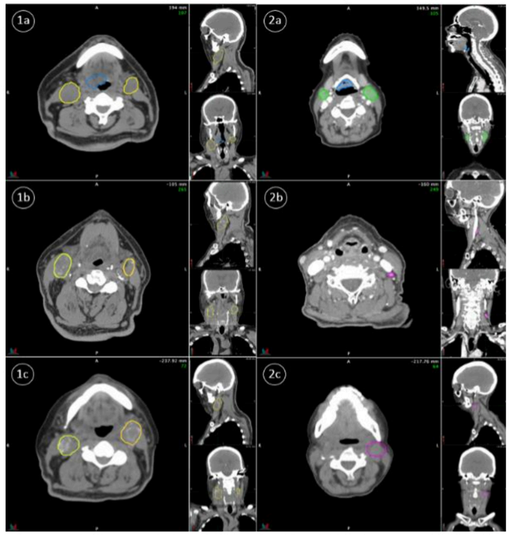


Figure 2. Segmentation process of HNSCC tumors performed for all subjects enrolled in the study.

Table 1. Patient demographic information.

Demographic Information	Numbers (%)
Total patients enrolled	36
Gender	
Male	27(75)
Female	9(25)
Age	
Both sexes	59 ± 6.25
Male	58 ± 6.18
Female	60 ± 6.77
Race	
White or Caucasian	21(58)
Black or African American	14(39)
Not registered	1(3)
Primary Site	
Oropharynx	26(72)
Larynx	8(22)
Hypopharynx	2(6)

Table 2. Set of RadFs in each scheme (2D and 3D) with variable importance > 80. Those features made the largets contributions to the predictive ability of the different ML models to identify residual tumor in head and neck cancer patients treated with chemoRT.

Scheme	Positive PET from CT2	Positive Path from CT2	Positive Path from PET/CT (CT3)*
2D	GLCM Correlation (d=4, θ=135°)†	Autoregressive Model θ_3†	GLCM Variance (d=5, θ=135°)†
	Histogram Mean	Histogram Skewness	GLCM Difference Variance (d=5, θ=135°)
	GLCM Correlation (d=5, θ=135°)	GLCM Difference Variance (d=5, θ=0°)	GLCM Contrast (d=5, θ=135°)
	Wavelet Energy HH s-2		GLCM Sum Variance (d=5, θ=135°)
	GLCM Correlation (d=3, θ=135°)		GLCM Difference Entropy (d=5, θ=135°)
	Wavelet Energy HL s-2		GLCM Entropy (d=5, θ=135°)
	Histogram Percentile 50		GLCM Sum Entropy (d=5, θ=135°)
			GLCM Correlation (d=5, θ=135°)
3D	GLZLM Long Zone Emphasis†	Shape Volume (voxels)†	Histogram Skewness†
	GLRLM Run Length Non-uniformity		GLCM Homogeneity (d=2, θ=ALL‡)
			GLCM Correlation (d=2, θ=ALL‡)

* The radiomic features were extracted from the CT volume of post-treatment PET/CT scan.

† The most predictive radiomic feature to identify residual tumor in head and neck cancer patients treated with chemoRT.

‡ All 13 orientations were computed using the mean value for more stable models.

RESULTS (CONT.)

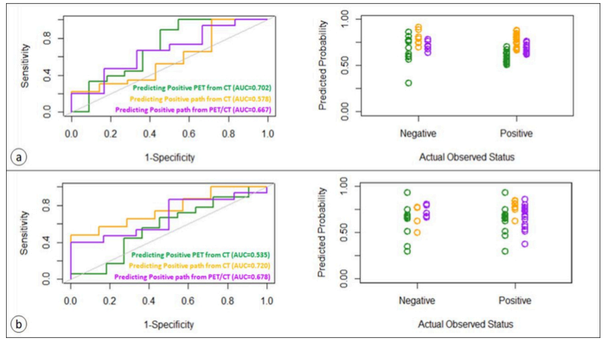


Figure 3. AUCs and the predicted probabilities for the different ML models: (a) for the 2D scheme and, (b) for the 3D scheme.

CONCLUSIONS

RadFs extracted from both pre- and post-treatment CT data using ML prediction models were able to discriminate between residual tumor and radiation changes in a small group of HNSCC cancer patients treated with chemoradiotherapy.

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