Preliminary Report

Quantitative radiomic phenotyping of cervix cancer

Abstract

Radiomics aims to extract huge amount of quantifiable features from medical images with data-characterization algorithms.1–5 Radiologists cannot appreciate all the disease characteristics in generic diagnostic images.6 Using these radiomic features, it is possible to uncover the physiognomies of disease progression. The hypothesis of radiomics is that the distinctive imaging features between disease forms may be useful for predicting prognosis and therapeutic response for various conditions, thus providing valuable information for personalized therapy.1,7,8 Radiomics emerged from oncology3 is the most cutting-edge innovation. However, the technique can be useful in any medical study involving tomographic imaging. This article analyzes currently available phenotyping algorithms for Lung and Head & Neck malignancies. And It can help researchers to understand the concept to apply the same for cervix cancer.

Keywords: radiomics, feature selection, cervix cancer

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Introduction

Radiomics process comprises of following five major levels.

i. Image acquisition (Computed Tomography imaging)

ii. Developing algorithms for image segmentation (Automatic/Semi automatic).

iii. Extraction and feature quantification

iv. Analysis and creation of database

v. Developing retrospective/prognostic models for personalized therapy.

Large volumes of raw scan images are stored in DICOM RT format in Picture Archiving and Communication System in imaging department. Thus, it is made available to data mining procedures. Raw data does not contain any tumor volumes defined. Hence the transverse CT images are segmented slice by slice using any automatic or semiautomatic algorithms. Many radiomic features are computed from the images after segmentation. The features range from volume, shape, surface density and intensity, texture, tumor location, relations with the surrounding tissues. Redundant information can be eliminated by proper quantification of data acquired. A feature selection algorithm accelerates the evaluation of these features. The data in the radiomic features were compared for any similarity. The repetition of similarity is evaluated when occurs in the same time frame. An outcome variable is defined in supervised analysis of data points to create a predictive model. Graphical representation of final results is deduced from unsupervised analysis. Now the new patient CT data is given as inputs in an radiomic algorithm, that returns a value for tumor growth and disease free survival. Radiomic features can be grouped into five important characteristics such as;

i. Size and shape based–features, image intensity histogram descriptors,

ii. Image-voxels descriptors (e.g. Gray-level co-occurrence matrix (glcm), run length matrix (rlm), size zone matrix (szm),

iii. And neighborhood gray tone difference matrix (ngtdm) derived textures,

iv. Filtered images textures, and

v. Fractal features.

The mathematical definitions (algorithms) of these radiomic features are independent of imaging modality (suitable for ultrasound, MRI imaging etc.).10–14 A detailed description of texture features for radiomics can be found in Depeursinge et al.15

Methods

A retrospective data collection of CT images of 22patients treated in the clinic from the year 2015 to 2017. Our article outlines the design of radiomics study of cervix cancer. Patients were included based on specific selection criteria as mentioned as follows;

Inclusion criteria

i. Histopathological confirmed locally advanced Squamous intra epithelial cell carcinomas of Cervix

ii. Age<65years

iii. ECOG performance status of 0-2.

iv. Hematological parameters with total leukocyte count of >4000cells/mm^3 ,

v. platelet counts of >1.5lakh/mm^3

vi. Renal parameters with Serum creatinine

vii. Patients with an informed consent.

Exclusion criteria

i. Tumors of non - squamous histology.

ii. Age>65years.

iii. Performance status ECOG PS>2.

iv. Any prior treatment received for the tumor.

v.   Patients with abnormal cardiac function, renal, hematological parameters or co-morbid illness.

vi.   Patients who do not give an informed consent.

vii.   Patients unavailable for follow up

CT images archived from PACS were contoured with normal structures such as Rectum, Urinary Bladder, Intestines, Left and right femoral bones using an automatic edge detection algorithm using 3D slicer software in an independent system (Figure 1). And the Gross tumor volume, Clinical Target Volume, high risk/low risk tumor volumes were delineated with semi automatic algorithm under the supervision of experienced radiation oncologists. A Combined (MATLAB and C++) code was generated using grey scale differentiations and contoured volumes to extract the features. These features can be used as predictive models for outcome prediction, distant metastasis risk analysis and genetics assessment, when a new patient data was given as input (Figure 2).
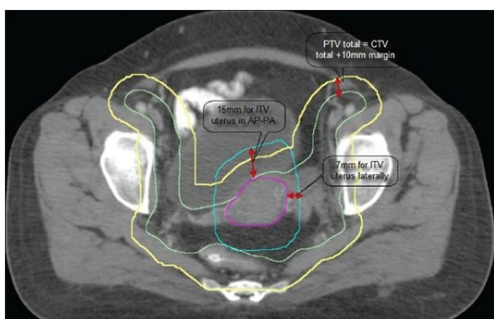

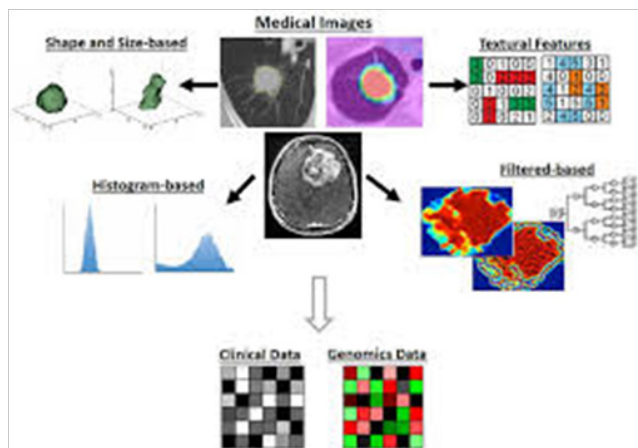**Figure 1** Gross tumor volume.

Figure 2 Patient data was given.

Discussion

Clinical outcome prediction was first performed by Aerts et al.[1] It was a large-scale radiomic study that included three lung and two head-and-neck cancer cohorts with 1000patients. They evaluated the predictive values of more than 400 textural and shape- and intensity-based features extracted from the computed tomography (CT) images acquired before treatment. Tumor volumes were delineated either by radiation oncologists or using semiautomatic segmentation methods.[16,17] A subset of radiomic features were identified for predicting patient survival and describing intra-tumoral heterogeneity.

It was confirmed that the prognostic ability of these radiomics features may also be used for head-and-neck cancer. But later it was found that prognostic value of some radiomic features may be cancer type dependent.[18] Not every radiomic feature that significantly predicted the survival of lung cancer patients could also predict the survival of head-and-neck cancer patients and vice versa. Radiomic features are better at predicting treatment response than conventional measures, such as tumor volume and diameter, and the maximum radiotracer uptake on positron emission tomography (PET) imaging.[19–25] Metastatic latency of tumors could also be predicted by radiomic features.[26–27] For example, 35 CT-based radiomic features were recognized to be predictive of distant metastasis of lung cancer[26] Thus it guides physicians to select the effective treatment for individual patients with a risk of developing distant metastasis. Cancer genetics Assessment associated with biological gene sets, such as cell cycle phase, DNA recombination, immune system regulatory process.[1] Moreover, various mutations of glioblastoma (GBM), such as 1p/19q deletion, MGMT methylation, TP53, EGFR, and NF1, were predicted by magnetic resonance imaging (MRI) volumetric measures, including tumor volume, necrosis volume, and contrast enhancing volume.[28–30] Radiomic feature extracted with FDG PET scan of cervix cancer deals with the Texture analysis of tumor.[15,29,30] But, in our study we have extracted tumor signatures using computed tomography images.

Conclusion

We developed an empirical algorithm for feature extraction with CT data sets of 22 cervix cancer patients. A preliminary development of algorithm was done in a stand-alone computer system with MATLAB and C++ environment. Radiomic features extracted to define squamous cell carcinoma of cervix phenotype were: Textural feature, Tumor size and heterogeneity. Outcome and metastatic risk prediction models could be generated further with these radiomic features.

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Conflict of interest

Authors declare that there is no conflict of interest.

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