Dosiomics-based comparison of dose distributions in nasopharyngeal cancer patients: 3D-CRT versus Tomotherapy

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ABSTRACT

Original article

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Background: This research was conducted to compare dosiomics features extracted from planning target volume (PTV) between the two three-dimensional conformal radiation therapy (3D-CRT) and helical tomotherapy (HT) techniques in nasopharyngeal cancer. Materials and Methods: 3D-CRT plans were designed for ten nasopharyngeal patients previously treated with HT. For both treatment techniques, the total prescription dose was 70 Gray in 33 fractions. At first, the dosimetric parameters, including mean dose, conformity index (CI), and homogeneity index (HI), were calculated for two techniques. Then, using 3D-Slicer software, dosiomics features were extracted from the dose matrix of PTV. Results: In comparing the plans regarding dosimetric parameters, HT plans had a lower mean dose and higher CI (p-value <0.01 and <0.001, respectively). HI had no statistically difference between the two groups (p>0.9). Among 93 features extracted from PTV70, only 40 features including eight features from the first-order group, ten features from the gray-level co-occurrence matrix group (GLCM), seven features from the gray-level dependence matrix group (GLDM), ten features from the gray-level run-length matrix group (GLRLM), four features from the gray-level size-zone matrix group (GLSZM), and one feature from the neighboring gray-tone difference matrix group (NGTDM) were found to be significantly different between the two groups. Conclusion: According to the results, the dosiomics features can distinguish the differences between dose distributions in different studied plans. However, more studies should be done in selecting the most suitable features for use in evaluating the quality of the treatment plans.

However, due to the lack of spatial information in

DVH, plans with different dose characteristics may

result in the same DVH curve and, subsequently the same NTCP value (2, 4). In addition, dose-volume

parameters and patient-related clinical factors

include the main structure of current models (5). The

current models have been obtained using the data of

patients of one or several centers despite the

different conditions of the patients and the different

types of complications. These models cannot fully

explain the response to treatment outcomes and the

complications caused by radiation among people ⁽⁶⁾.

Therefore, introduction of new factors to investigate

patient-specific responses to radiation therapy,

optimization of TCP models, and better evaluation of

calculated dose distributions in planning are

needed. Recently, in studies related to radio-oncology

and medical physics, to purposefully determine the

relationship between the personal information of the

patient and the outcome of the treatment, the use of

spatial characteristics of patient-specific medical

images under the name of radiomics features or

imaging biomarkers is one of the most interesting

methods introduced in targeted therapy (7, 8). The

extraction of radiomics features from the image

Currently, treatment plans in radiation oncology are often optimized and evaluated based on dose-volume histogram (DVH), and other factors related to planning are not considered ⁽¹⁾. Dosimetric factors such as $V_{D\%}$ (volume exposed to dose equal to or higher than D Gray) and $D_{V\%}$ (the dose received by V percent of volume) use only partial information in the dose distribution. They are calculated based on DVHs ^(1,2). However, a known limitation of DVH-based dosimetric factors is that it incorporate a threedimensional dose distribution into a two-dimensional curve and loses spatial information of 3D dose distribution. It may not be sufficient to predict radiation complications. DVH may not always provide sufficient data from the dose distribution or may not distinguish slight differences in the dose distribution ⁽³⁾. Another method of evaluating patients' plans is based on normal tissue complication probability (NTCP) and tumor control probability (TCP) models. NTCP models, converting the entire DVH curve into a single parameter, use all the information of the DVH curve and have better prediction capabilities than dosimetric factors ⁽²⁾.

INTRODUCTION

allows the conversion of different image modalities into powerful quantitative data and the identification of correlations between voxels.

Radiomics can provide rich information about tumors or normal tissue and can also be used to build predictive or prognostic models (1, 5, 7, 9-14). Recently, a new method called dosiomics, derived from the radiomics method, has attracted the attention of researchers in this field (8). Dosiomics features are extracted from the dose matrix instead of medical images (10) to obtain information about the correlation of voxels on dose distribution. The dosiomics features allow a better description of the dose distribution than DVHs (3, 4, 8, 9, 15). Integrating dosiomics with DVH can be an advanced tool for evaluation of radiotherapy treatment planning. Dosiomics features can improve the performance of NTCP and TCP models. Several studies have been conducted to compare the dosimetric and radiobiological factors of modern radiation therapy methods and the three-dimensional conformal radiation therapy (3D-CRT) method (16-22). Also, recently, it has been proved that the dosiomics features can work better than the factors based on DVH and NTCP, as factors for the prognosis and prediction of damage caused by radiation therapy (2, 3, 8, 10, 15)

Nevertheless, it seems that according to the results of recent research to improve the performance of dosiomics features compared to DVHbased factors in predicting treatment outcomes, these new dosiomics features can be used in the future along with DVH factors to evaluate treatment plans. Until now, there is no reported study on comparing a dosiomics-based 3D dose distribution in patients with nasopharyngeal cancer treated by helical tomotherapy (HT) and 3D-CRT techniques. Therefore, the purpose of this study was dosimetric and dosiomics-based comparison of treatment planning between 3D-CRT and HT techniques in nasopharyngeal cancer patients.

MATERIALS AND METHODS

Patient characteristics and CT simulation

Ten retrospective patients with nasopharyngeal cancer (NPC) treated with HT in our hospital (Seyed Alshohada Hospital, Isfahan, Iran) between December 2021 and December 2023 were selected for this research. A summary of patients' information is given in table 1. All patients were immobilized in the supine position to obtain a 3 mm slice thickness CT images using a SOMATOM Definition AS or SOMATOM Confidence CT scanner (Siemens, Germany).

Target delineation

All CT images were imported to the Precision treatment planning system (TPS) (Accuray, USA,

version 2.0.1.1) for contouring. Clinical target volume (CTV₇₀) was defined as gross tumor volume (GTV₇₀) and highly positive lymph nodes (GTV_{nd}) as any lymph nodes >1 cm or nodes with necrotic cancer. CTV_{59.4} was delineated as the area at high risk of microscopic involvement. PTV₇₀ and PTV_{59.4} was defined as CTV₇₀ and CTV_{59.4} with a margin of 3 mm. Also, PTV-node was defined as neck lymph nodes. Figure 1 shows the image of an axial cut of a patient and the contouring of the target volume.

Table 1	Clinical	information	of	patients.

Patients	Sex		Age	Pathology	Clinical stage	AJCC prognostic stage groups
P 1	Male	15		Metastatic SCC	Tx N2	Stage Ш
P 2	Male	39	Average: 46	Undifferentiated Carcinoma	T2 N2	Stage Ш
P 3	Male	47		Metastatic Carcinoma	T3 N2	Stage Ш
P 4	Female	69		SCC	T1 N2	Stage Ш
P 5	Female	64		Poorly Differentiated Carcinoma	T1 N2	Stage Ш
P 6	Male	43		Non Keratinizing Carcinoma	T1 N2	Stage Ш
P 7	Male	35		Undifferentiated Carcinoma	T2 N1	Stage П
P 8	Male	52		Not Available	Not Available	Not Available
Р9	Female	36		Non Keratinizing SCC	T2 N3	Stage IVA
P 10	Male	58		Carcinoma	T1 N1	Stage П

Abbreviations: AJCC: American Joint Committee on Cancer.



Figure 1. Target volumes delineated by the physician as defined in the method section. Pink: PTV-node (in the right), red: PTV-59.4 (in the left), blue: PTV-70 (in the left)

Planning techniques and prescribed dose 3D-CRT plans

Treatment planning for 3D-CRT were performed using the TIGRT TPS (Lina Tech – Treatment Planning System, version: 1.0.10.573, USA), for execution using a Siemens Primus equipped with a 6 MV photon beam (Siemens, Germany). The plans were designed to deliver the dose in two steps: in the first step, a prescribed dose of 59.4 Gy in 33 fractions for the PTV₇₀, PTV-node, and PTV_{59,4}, and in the second step, a dose of 10.6 Gray was considered as a

boost for the PTV₇₀ in 10 fractions, which covered more than 95% of PTV₇₀ volume. In practice, the prescribed dose of 70 Gy to the primary tumor and 59.4 to the high-risk areas and the neck lymph nodes is not applicable in the 3D-CRT method. Nevertheless, we wanted the dosiomics features extracted from the dose distribution to be independent of the total prescribed dose and only the treatment modality and, subsequently the type of TPS to be influential in the dose matrix calculations. To solve that issue, the prescription dose was considered the same in both treatment techniques. The plans were designed using two lateral parallel opposed beams for the head and two parallel opposed anterior/posterior beams for the neck. The match line of beams was made by giving an angle to the couch for lateral beams. An example of 3D-CRT planning for a patient is shown in figure 2.





Figure 2. An example of three-dimension conformal radiation therapy planning for patient number 1.

HT plans

Treatment planning of HT was performed using the Precision TPS (Accuray Precision 2.0.1.1, USA). Three main parameters were set by the operator: field width 2.5-5 cm, pitch 0.434-0.440, and modulation factor 3-3.8. A Convolution-Superposition algorithm was used for dose calculation with a grid size of (X, Z): 0.8-0.98 and (Y): 2-5 mm. The prescribed dose for $PTV_{59,4}$ and PTV-node was 59.4 Gy, and a simultaneously boosting dose for PTV_{70} was 70 Gy.

Dosimetric investigation and extraction of dosiomics features

At first, for the dosimetric evaluation of plans, the parameters such as mean dose, homogeneity index (HI), and conformity index (CI) $^{(16,20)}$ for PTV₇₀ were obtained for two treatment methods. The CI was used to assess the conformity of the dose distribution. The CI is defined according to the equation 1:

$$CI = \frac{v_{t:ref}}{v_t} \times \frac{v_{t:ref}}{v_{ref}} \tag{1}$$

 V_{tref} , V_t , and V_{ref} represent the volume of the target that received the prescribed dose, the target volume, and the total volume that received the prescribed dose, respectively. According to the range of 0 to 1 for CI values, the higher the CI value, the higher the conformity of the dose to the target. HI was calculated using the equation 2:

$$HI = \frac{D_{206} - D_{9806}}{D_{5006}} \tag{2}$$

Where $D_{98\%}$, $D_{50\%}$, and $D_{2\%}$ represent the dose received by 98%, the dose received by 50%, and the dose received by 2% of the PTV volume. HI was used to assess the homogeneity of the dose distribution. The lower the value of HI means the dose distribution has good homogeneity for the target volume.

Then, using the SlicerRadomics module (a Python scripted loadable module bundled in the SlicerRadomics extension) in 3D Slicer (23), a total of 93 dosiomics features were extracted from the PTV70 for each of the 3D-CRT and HT plans. The different families of extracted dosiomics features from area of PTV₇₀ included first-order dosiomics features of the dose matrix (18 features) and 75 texture features (including the Gray Level Co-occurrence Matrix (GLCM) (24 features), Gray Level Dependence Matrix (GLDM) (14 features), Gray Level Run Length Matrix (GLRLM) (16 features), Gray Level Size Zone Matrix (GLSZM) (16 features), and Neighborhood Gray Tone Difference Matrix (NGTDM) (5 features). The dosiomics features used in this research have already been explained in references ^(1,3). 3D-Slicer software version 5.3.0 was used to extract the features of dosiomics. To extract the features after treatment design, CT images and 3D dose matrix in DICOM format were exported from TPSs and imported into 3D Slicer software. Before the extraction of dosiomics features, 1×1×1 mm³ resampling was performed for all dose distributions. Then, the discretization of the resampled dose distribution between the minimum and maximum dose was performed with a fixed bin width of 1 Gray. An overview of the study is given in figure 3.



Figure 3. Overall workflow of the study. Abbreviations: HT = Helical Tomotherapy; 3D-CRT = Three-dimensional Conformal Radiotherapy.

Statistical analyzes

To compare dosimetric factors and dosiomics

features of 3D-CRT plans versus HT, paired *t-test* and Wilcoxon statistical tests were performed for parametric and non-parametric data, respectively. A P-value<0.05 was considered statistically significant. IBM SPSS version 19.0 software was used to perform all statistical analyses (SPSS, Inc., Chicago, IL, USA).

RESULTS

The plans of 10 patients with NPC were designed using TIGRT and Precision TPSs. Compared with 3D-CRT plans, HT plans showed superior CI (p<0.001). 3D-CRT and HT plans had mean doses to PTV of 71.5 \pm 0.7 Gray and 70.1 \pm 1.3 Gray, respectively (p<0.01). In addition, for 3D-CRT and HT plans, CI and HI were 0.12 \pm 0.06, 0.77 \pm 0.12 (p < 0.001), and 0.1 ± 0.03 , 0.1 ± 0.03 (p > 0.937), respectively. Figure 4 shows the logarithmic diagram for comparing the mean values of 93 dosiomics features extracted from 3D-CRT and HT plans; among the 93 features extracted from PTV₇₀, only 40 features (including: seven features from the first-order group, ten features from the GLCM group, seven features from the GLDM group, ten features from the GLRLM group, four features from the GLSZM group, and one feature from the NGTDM group) were found to be significantly different between the two groups. Table 2 shows the information related to the statistically significant results of the features mentioned above. Only the features with a statistical difference between the two groups are reported in this table. Also, figure 5 shows the difference in dose distribution between plans 3D-CRT and HT.

 Table 2. The values of dosiomics features extracted from 3D-CRT and HT plans (only the features that are statistically significantly different between the two radiotherapy techniques).

		, , ,		
	3D-CRT	HT	P-Va	lue
Dosiomics Features Name	Mean ±SD	Mean ±SD	paired t-test	Wilcoxon
First order group				
10Percentile	69.48±0.84	67.84±1.64	0.004	
90Percentile	74.11±1.13	71.96±1.03	0.000	0.007
Energy	(0.77±0.99)×10 ⁹	(0.73±0.93)×10 ⁹	0.058	0.007
Maximum	79.97±6.58	75.22±1.74	0.029	0.012
Mean	71.73±0.68	70.18±1.15	0.001	0.007
Median	71.81±0.75	70.58±1.1	0.006	0.017
RootMeanSquared	71.76±0.7	70.2±1.14	0.001	0.007
TotalEnergy	(0.77±0.99)×10 ⁹	(0.73±0.93)×10 ⁹	0.058	0.007
GLCM group				
Correlation	0.92±0.03	0.86±0.07	0.044	0.047
DifferenceAverage	0.3±0.16	0.47±0.08	0.007	0.012
DifferenceEntropy	0.9±0.28	1.2±0.12	0.003	
ld	0.87±0.03	0.78±0.03	0.000	
Idm	0.87±0.03	0.77±0.03	0.000	
Idn	0.98±0.00	0.97±0.01	0.001	
Imc1	-0.62+0.04	-0.41+0.06	0.000	0.005
Imc2	0.98+0.01	0.91+0.06	0.006	0.005
InverseVariance	0.21+0.03	0.36+0.05	0.000	0.005
MCC	0.95+0.01	0.88+0.07	0.011	0.005
GLDM group	0.000_0.001	0.0020107	0.011	0.000
DependenceNonUniformity	$(13.77+16.21)\times10^3$	$(69.9+87.93)\times10^{2}$	0.018	0.005
DependenceNonUniformityNormalized	0 1+0 02	0.04+0.00	0.000	0.005
Gravl evelNonUniformity	$(21.01+22.53)\times10^3$	$(28.17+30.47)\times10^3$	0.059	0.028
LargeDependenceEmphasis	412.75±33.32	282.12±48.19	0.000	
LargeDependenceLowGravLevelEmphasis	15.3±17.59	3±5.04	0.038	0.028
LowGravLevelEmphasis	0.03±0.04	0.01±0.01	0.056	0.047
SmallDependencel owGravLevelEmphasis	0.00+0.00	0.00+0.00	0.237	0.047
GLRLM group				
GravLevelNonUniformity	$(54.72\pm56.23)\times10^{2}$	$(94.16\pm102.22)\times10^{2}$	0.025	0.005
LongRunEmphasis	33.08±10.09	11.29±3.71	0.000	0.005
LongRunHighGravLevelEmphasis	$(264.88\pm92.23)\times10^{2}$	$(40.34\pm41.73)\times10^{2}$	0.080	0.047
LongRunLowGravLevelEmphasis	1.32±1.68	0.13±0.25	0.046	0.022
RunEntropy	5.83±0.38	4.87±0.37	0.000	
RunLengthNonUniformity	$(130.8\pm92.23)\times10^{2}$	$(24.97\pm32.89)\times10^{3}$	0.011	0.005
RunLengthNonUniformityNormalized	0.2±0.06	0.35±0.05	0.000	
RunPercentage	0.29±0.04	0.44±0.05	0.000	
RunVariance	14.39±3.6	5.61±2.07	0.000	0.005
ShortRunEmphasis	0.39±0.11	0.6±0.05	0.000	
GLSZM group				
GravLevelNonUniformity	54.23±96.46	118.43±108.42	0.004	0.005
GravLevelNonUniformityNormalized	0.1±0.06	0.16±0.06	0.021	
LargeAreaHighGrayLevelEmphasis	(922.33±92.23)×10 ²	(14.63±20.18)×10 ²	0.048	0.005
LargeAreaLowGravLevelEmphasis	(922.33±92.23)×10 ²	(174±92.23)×10 ²	0.074	0.047
NGTDM group		,		
Coarseness	0.5×10 ⁻³ ±0.00	0.3×10 ⁻³ ±0.00	0.025	0.007

Abbreviations: 3D-CRT: Three-Dimension Conformal Radiation Therapy, HT: Helical Tomotherapy, SD: Standard Deviation, GLCM: Gray Level Cooccurrence Matrix, GLDM: Gray Level Dependence Matrix, GLRLM: Gray Level Run Length Matrix, GLSZM: Gray Level Size Zone Matrix, NGTDM: Neighborhood Gray Tone Difference Matrix. Other information about the names of each feature is referenced in the previous articles in the method section.



Figure 4. An overview of the comparison of all dosiomics features. Abbreviations: Gray Level Co-occurrence Matrix (GLCM), Gray Level Dependence Matrix (GLDM), Gray Level Run Length Matrix (GLRLM), Gray Level Size Zone Matrix (GLSZM), and Neighborhood Gray Tone Difference Matrix (NGTDM);



Figure 5. A view of difference in the dose distribution of three-dimension conformal radiation therapy and helical tomotherapy.

DISCUSSION

In the last decade, the use of dosiomics features was introduced as an option to improve the evaluation of treatment plans and the prediction of treatment outcomes ^(2,3,8,15). Several studies have been conducted on the limitations of dosimetric factors extracted from DVH ^(1,2). Dosiomics features extraction is a new method for three-dimensional investigation of dose distribution in the radiotherapy treatment planning. The extraction of dosiomics features from the dose matrix considers complex spatial information for the designed plans, which is not present in the DVH-based dosimetric factors ⁽⁸⁾.

In this research, in addition to comparing dosimetric factors, we examined and compared 93 dosiomics features extracted from PTV in plans designed for 3D-CRT and HT. Until now, no study has been done to compare the dosiomics features between plans designed for different radiation therapy techniques.

Nevertheless, some studies have been conducted on the ability of dosiomics features to predict treatment outcomes after radiation therapy. In the study of Wu et al. (15), by investigating whether dosiomics can be helpful in predicting local recurrences (LR) of patients with NPC treated with IMRT, they have shown that dosiomics can be helpful in predicting LR. According to table 2, five of the dosiomics features (First order: 90th percentile, GLRLM: Long Run Low Gray Level Emphasis, GLDM: Large Dependence Low Gray Level Emphasis and Low Gray Level Emphasis, GLSZM: Large Area Low Gray Level Emphasis) reported with significant differences are the same as the features noted in Wu study. Another study by Murakami et al. (1) has been conducted to investigate the dosiomics features in predicting biological recurrence after prostate radiation therapy. Despite the difference in the type of disease in present study and their study (NPC versus prostate cancer), none of the features reported in table 2 were consistent with their study ⁽¹⁾. Also, several studies have been conducted on dosiomics as a parameter for predicting radiation damage to normal tissue. For example, some studies for predicting lung pneumonia ^(2, 3, 8) and one study for predicting hypothyroidism (4) have used dosiomics features. These studies have examined the features obtained from normal tissue. However, the three features given in table 2 are consistent with the results of their research (First order: 90th percentile, GLRLM: RunEntropy and RunLengthNonUniformityNormalized)^(4,8).

It seems that dosiomics features with significant differences in our research can detect the difference in 3D dose distribution between the two techniques. Of course, it should be pointed out whether the reason for the difference is only the differences resulting from the different treatment techniques and TPS. That is why several studies have been carried out in investigating the stability and reproducibility of features against some parameters influencing the extraction of dosiomics features. For example, stability studies have been done against the types and versions of dose calculation algorithms (24), calculation grid size ⁽²⁵⁾, radiation therapy techniques and modalities, and different treatment planning systems ⁽²⁶⁾. According to the results of these studies, the textural features have the most variability, especially in target volume compared to other region of interests. In consistent with this studies, the highest number of features with significant differences in the two groups were: GLCM and GLRLM (10 times), GLDM and First-Order (7 times), GLSZM (4 times), and finally NGTDM (1 times). Of course, in this work, only the difference of dosiomics features between the two methods was evaluated, and the variability of the features were not investigated.

CONCLUSION

According to the results of our study, some dosiomics features have the ability to distinguish dose distribution between different plans. It seems that more studies in this field may lead to the introduction of some of these dosiomics features as factors for evaluating and comparing treatment planning quality. Of course, before doing this, it is necessary to check the extraction of dosiomics features in terms of stability and other issues to select the appropriate dosiomics features for use.

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REFERENCES

- Murakami Y, Soyano T, Kozuka T, et al. (2022) Dose-based radiomic analysis (Dosiomics) for intensity modulated radiation therapy in patients with prostate cancer: Correlation between planned dose distribution and biochemical failure. Int J Radiat Oncol Biol Phys, 112(1): 247–259.
- Liang B, Yan H, Tian Y, et al. (2019) Dosiomics: Extracting 3D spatial features from dose distribution to predict incidence of radiation pneumonitis. Front Oncol, 9: 1–7.
- Adachi T, Nakamura M, Shintani T, et al. (2021) Multi-institutional dose-segmented dosiomic analysis for predicting radiation pneumonitis after lung stereotactic body radiation therapy. *Med Phys*, 48(4): 1781–1791.
- Ren W, Liang B, Sun C, et al. (2021) Dosiomics-based prediction of radiation-induced hypothyroidism in nasopharyngeal carcinoma patients. Phys Medica, 89: 219–225.
- Pota M, Scalco E, Sanguineti G, et al. (2017) Early prediction of radiotherapy-induced parotid shrinkage and toxicity based on CT radiomics and fuzzy classification. Artif Intell Med, 81: 41–53.
- Trott KR, Doerr W, Facoetti A, et al. (2012) Biological mechanisms of normal tissue damage: Importance for the design of NTCP models. Radiother Oncol, 105(1): 79–85.
- Giraud P, Giraud P, Gasnier A, et al. (2019) Radiomics and machine learning for radiotherapy in head and neck cancers. Front Oncol, 9: 1–13.
- Puttanawarut C, Sirirutbunkajorn N, Khachonkham S, et al. (2021) Biological dosiomic features for the prediction of radiation pneumonitis in esophageal cancer patients. Radiat Oncol, 16: 1–9.
- Gabryś HS, Buettner F, Sterzing F, et al. (2018) Design and selection of machine learning methods using radiomics and dosiomics for normal tissue complication probability modeling of xerostomia. *Front Oncol*, 8: 1–20.
- van Dijk LV, Brouwer CL, van der Schaaf A, et al. (2017) CT image biomarkers to improve patient-specific prediction of radiationinduced xerostomia and sticky saliva. *Radiother Oncol*, 122: 185– 191.
- 11. Sheikh K, Lee SH, Cheng Z, *et al.* (2019) Predicting acute radiation induced xerostomia in head and neck Cancer using MR and CT

Radiomics of parotid and submandibular glands. *Radiat Oncol,* **14**: 1–11.

- 12. Bruixola G, Remacha E, Jiménez-Pastor A, et al. (2021) Radiomics and radiogenomics in head and neck squamous cell carcinoma: Potential contribution to patient management and challenges. Cancer Treat Rev, 99.
- Hirose T aki, Arimura H, Ninomiya K, et al. (2020) Radiomic prediction of radiation pneumonitis on pretreatment planning computed tomography images prior to lung cancer stereotactic body radiation therapy. Sci Rep, 10: 1–9.
- Krafft SP, Rao A, Stingo F, et al. (2018) The utility of quantitative CT radiomics features for improved prediction of radiation pneumonitis. *Med Phys*, 45(11): 5317–5324.
- Wu A, Li Y, Qi M, *et al.* (2020) Dosiomics improves prediction of locoregional recurrence for intensity modulated radiotherapy treated head and neck cancer cases. *Oral Oncol*, **104**(2): 104625.
- Tai DT, Oanh LT, Phuong PH, et al. (2022) Dosimetric and radiobiological comparison in head-and-neck radiotherapy using JO-IMRT and 3D-CRT. Saudi J Biol Sci, 29(8): 103336.
- Ibrahim MS, Attalla EM, El Naggar M, et al. (2019) Dosimetric comparison between three-dimensional conformal radiotherapy (3D-CRT) and intensity-modulated radiotherapy (IMRT) in the treatment of different stages of nasopharyngeal carcinoma. J Radiother Pract, 18(1): 16–20.
- Bišof V, Rakušić Z, Bibić J, et al. (2018) Comparison of intensity modulated radiotherapy with simultaneous integrated boost (IMRT-SIB) and a 3-dimensional conformal parotid gland-sparing radiotherapy (ConPas 3D-CRT) in treatment of nasopharyngeal carcinoma: a mono-institutional experience. *Radiol Medica*, **123** (**3**): 217–226.
- Gabryś HS, Buettner F, Sterzing F, et al. (2017) Parotid gland mean dose as a xerostomia predictor in low-dose domains. Acta Oncol (Madr), 56(9): 1197–1203.
- Lu S, Fan H, Hu X, et al. (2021) Dosimetric comparison of helical tomotherapy, volume-modulated arc therapy, and fixed-field intensity-modulated radiation therapy in locally advanced nasopharyngeal carcinoma. Front Oncol, 11: 1–10.
- Chen W, Yang X, Jiang N, et al. (2017) Intensity-modulated radiotherapy, volume-modulated arc therapy and helical tomotherapy for locally advanced nasopharyngeal carcinoma: A dosimetric comparison. Transl Cancer Res, 6(5): 929–939.
- 22. Zhou L, Chen J, Shen W, et al. (2020) Thyroid V50 is a risk factor for hypothyroidism in patients with nasopharyngeal carcinoma treated with intensity-modulated radiation therapy: A retrospective study. Radiat Oncol, 15(1): 1–8.
- Fedorov A, Beichel R, Kalpathy-Cramer J, et al. (2012) 3D Slicer as an image computing platform for the Quantitative Imaging Network. Magn Reson Imaging, 30(9): 1323–1341.
- Sun L, Smith W, Kirkby C (2023) Stability of dosiomic features against variations in dose calculation: An analysis based on a cohort of prostate external beam radiotherapy patients. J Appl Clin Med Phys, 24(5): 1–14.
- Placidi L, Lenkowicz J, Cusumano D, et al. (2020) Stability of dosomics features extraction on grid resolution and algorithm for radiotherapy dose calculation. *Phys Medica*, 77(3): 30–35.
- Placidi L, Gioscio E, Garibaldi C, et al. (2021) A multicentre evaluation of dosiomics features reproducibility, stability and sensitivity. *Cancers (Basel)*, 13(15).