

Head Neck Cancer Locoregional Recurrence Prediction Using Delta-radiomics Feature

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INTRODUCTION

Head and Neck Squamous cell cancer (HNSCC) is one of the most common cancers worldwide. Patients with HNSCC can be successfully treated in many cases, and radiation therapy is often required as part of their management. However, even after therapy with curative intent, 15% to 50% of HNSCC patients will experience locoregional recurrence (LRR), most of them occur within the first 3 years after treatment. Patients usually undergo post-treatment surveillance in the form of clinical examinations and imaging studies with the aim of identifying asymptomatic recurrences at an earlier stage, when further treatment may be more successful. Therefore, a strategy that can timely and accurately identify patients with high risk of HNSCC LRR is of great value to guide physicians making more effective treatment plan for patients and potentially support personalized treatment.

Radiomics is a technique that extract handcrafted quantitative features from radiological images to help cancer diagnosis, treatment outcome prediction and survival analysis. In recent years, radiomics-based method has been successfully conducted on different cancer types. Besides, changes in radiomics features, in terms of delta-radiomics features, have also been studied for predicting the response or outcome of treatment.

In this work, we have focused on building a multiple-classifier, multi-objective and multiple-modality (mCOM) model for HNSCC LRR prediction. In mCOM, the features from multiple modalities at pre and post treatment stages are utilized as training, validation and testing data, multiple classifiers are used for building the model and a iterative multi-objective immune algorithm is used for training the model.

AIM

This work aims to develop a multiple-classifier, multi-objective and multiple-modality (mCOM) model for HNSCC LRR prediction, and to investigate whether the therapy induced changes characterized by radiomics features can help improve the accuracy of LR prediction.

DATASETS

224 HNSCC patients received radiation treatment between September 2005 to November 2015 from the University of Texas Southwestern Medical Center (UTSW) were included in this study, 57 of them experienced LRR. The median follow-up duration for this study is 37 months. All of these patients have FDG-PET/CT images acquired from both pre-treatment and post-treatment scanning, and Gross tumor volumes (GTVs) were directly drawn on the CT of the FDG-PET/CT scan by expert radiation oncologists. Clinical information of these patients comprising gender, HPV status, primary tumor site, T-stage, N-stage and treatment method were also collected to help build the outcome prediction model.

For each imaging modality acquired either before or after RT, 257 radiomics features were extracted, including 9 intensity features, 8 geometry features, and 240 texture features. The delta-radiomics features of PET and CT were calculated by direct subtraction of pre- and post-treatment radiomics features after feature normalization. The conjunction of pre-, post- treatment radiomics feature and delta-radiomics feature is utilized as the model input.

METHODS

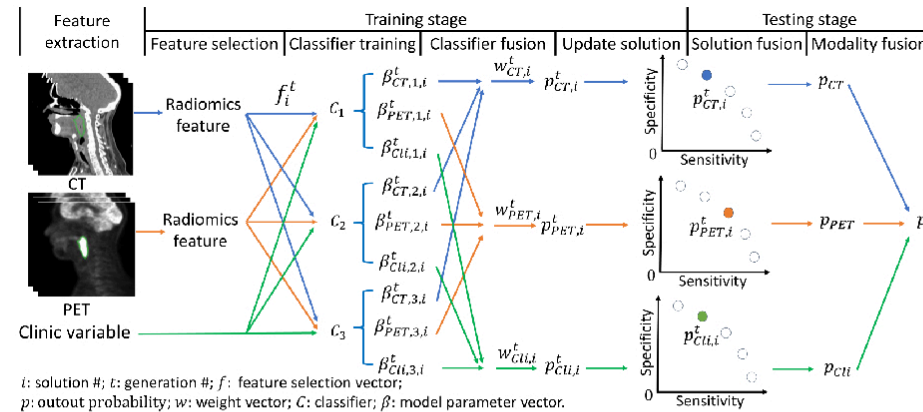


Fig. 1. The overall framework of the mCOM model.

The implementation of mCOM consists of training stage and testing stage. During the training stage, training and validation data are utilized to train the predictive model. For each modality, a multi-classifier multi-objective immune algorithm (mCOIA) based on our previous work is utilized to optimize the model through iteratively feature selection, classifier training, evidential reasoning (ER) fusion of output probabilities of classifiers and Pareto-optimal solution set update. Here, for each modality, each individual solution θ_i is defined as a group of parameters which contains feature selection vector f_i , classifier hyperparameter vector β_i and weighting factor vector w_i . f_i is a binary vector, a value of '1' indicates that the corresponding feature has been selected, while '0' is not. β_i is the vector containing all the parameter including hyperparameter to train different classifiers, and w_i is the weights used in classifier fusion to fuse the output probabilities of multiple classifiers to a single value. The three classifiers used in this study are support vector machine (SVM), logistic regression (LR) and discriminant analysis (DA), which are commonly utilized in radiomics methods.

After the model is well trained, the final output probabilities of testing samples are calculated by a two-step automatic weighted ER fusion method (solution fusion and modality fusion) in the testing stage.

RESULTS

The results show that post-treatment prediction using mCOM with delta-radiomics features yielded better AUC, accuracy and sensitivity, and specificity than all other models trained with features from single modality or single image scan. Compared with radiomics models built with base classifiers, multi-classifier (MC) model achieved better accuracy and AUC for both CT and PET.

CONCLUSIONS

We developed a multiple-classifier multi-objective multiple-modality predictive (mCOM) model for HNSCC LRR prediction using delta-radiomics features. The experimental result demonstrated that therapy induced change on radiomics features can help improve LRR prediction accuracy, and the fusion of multiple classifiers and multiple modalities can improve the robustness of the predictive model.

RESULTS

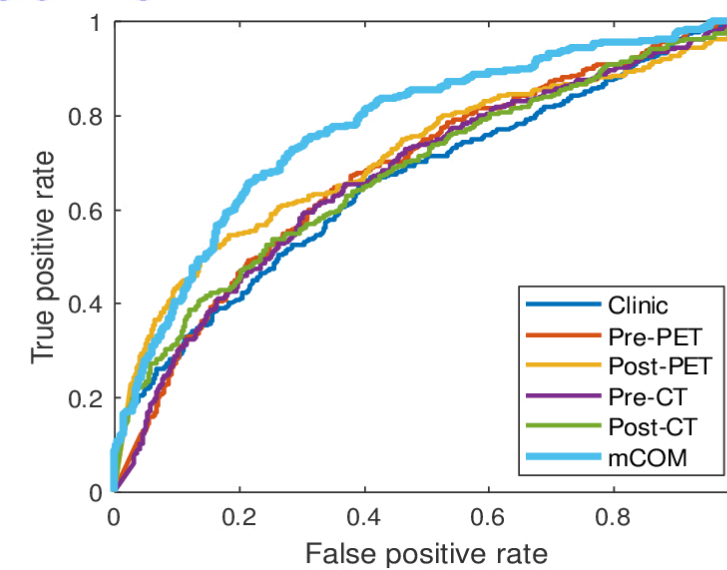


Fig. 2. ROC curves of models built with features of different modality.

Table 1. Results of delta-radiomics models built with different classifiers.

Modality	Classifier	Sensitivity	Specificity	Accuracy	AUC
CT	SVM	0.63±0.07	0.72±0.03	0.69±0.03	0.72±0.05
	LR	0.68±0.05	0.69±0.04	0.69±0.03	0.73±0.04
	DA	0.67±0.06	0.66±0.04	0.66±0.04	0.71±0.04
	MC	0.73±0.02	0.70±0.04	0.70±0.03	0.74±0.03
PET	SVM	0.69±0.02	0.70±0.03	0.70±0.02	0.74±0.01
	LR	0.72±0.05	0.68±0.02	0.69±0.01	0.75±0.02
	DA	0.69±0.04	0.66±0.03	0.65±0.03	0.72±0.03
	MC	0.72±0.05	0.71±0.03	0.71±0.02	0.75±0.02

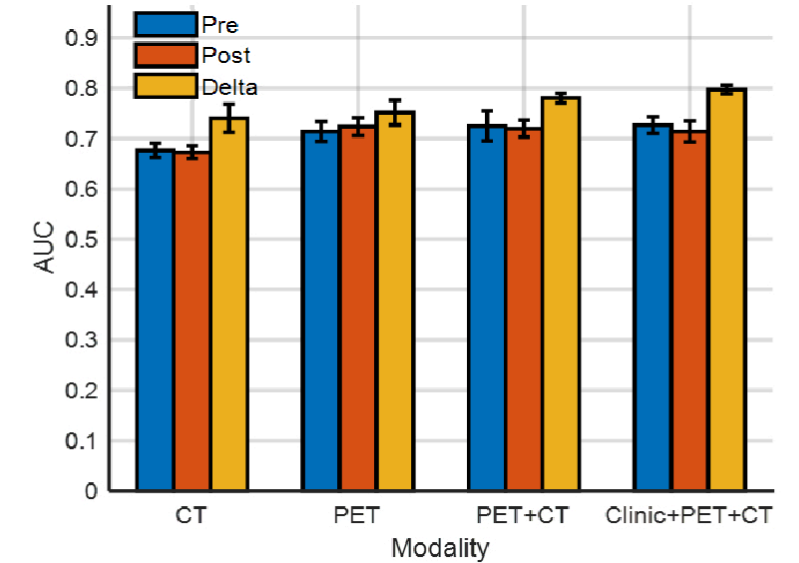


Fig. 3. AUCs of models built with different radiomics features.

Table 2. Results of models built with features from different modalities and scans.

Modality	Feature	Sensitivity	Specificity	Accuracy	AUC
Clinic		0.64±0.05	0.62±0.03	0.62±0.02	0.67±0.03
CT	Pre	0.69±0.03	0.62±0.02	0.64±0.01	0.69±0.02
	Post	0.62±0.03	0.62±0.04	0.62±0.03	0.67±0.01
	Delta	0.73±0.02	0.70±0.04	0.70±0.03	0.74±0.03
PET	Pre	0.65±0.04	0.66±0.02	0.66±0.02	0.72±0.02
	Post	0.65±0.03	0.65±0.01	0.65±0.01	0.72±0.02
	Delta	0.72±0.05	0.71±0.03	0.71±0.02	0.75±0.02
CT/PET	Pre	0.67±0.07	0.70±0.05	0.69±0.03	0.74±0.02
	Post	0.67±0.01	0.68±0.03	0.68±0.02	0.73±0.02
	Delta	0.71±0.03	0.71±0.02	0.71±0.02	0.78±0.01
CT/PET/Clinic	Pre	0.71±0.06	0.67±0.02	0.69±0.02	0.75±0.03
	Post	0.69±0.02	0.68±0.03	0.68±0.02	0.73±0.02
	Delta	0.75±0.04	0.72±0.01	0.73±0.01	0.80±0.01

REFERENCES

- Chang, J.H., et al., Locoregionally recurrent head and neck squamous cell carcinoma: incidence, survival, prognostic factors, and treatment outcomes. *Oncotarget*, 2017. 8(33): p. 55600-55612.
- Lambin, P., et al., Radiomics: the bridge between medical imaging and personalized medicine. *Nature Reviews Clinical Oncology*, 2017. 14(12): p. 749-762.
- Fave X, Zhang L, Yang J, Mackin D, Balter P, Gomez D, et al. Delta-radiomics features for the prediction of patient outcomes in non-small cell lung cancer. *Scientific Reports*. 2017;7(1):588.
- Zhou Z, Folkert M, Iyengar P, Westover K, Zhang YY, Choy H, et al. Multi-objective radiomics model for predicting distant failure in lung SBRT. *Physics in Medicine and Biology*. 2017;62(11):4460-78.

