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Using MRI Radiomics and Machine Learning Algorithms in Noninvasive Biopsy of Brain Tumor

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ABSTRACT

Brain cancer is diagnosed samples acquired from a tumor biopsy; using AI-based technologies may also speed up picture processing and analysis. Radiomics is a particular application within the vast subject of AI that involves computing, identifying, and extracting picture features. Radiomic analysis includes data gathering, segmentation, feature extraction, exploratory analysis, and modeling. We think that novel diagnostic examination and machine-learning algorithms may improve predictive cancer diagnosis and speed up the practical use of quantitative cancer imaging data.

Keywords: Radiomics; Machine Learning; MRI Images

Introduction

Brain cancer is diagnosed via samples acquired from a tumor biopsy. Since the 1970s, anatomical imaging methods (CT, MRI, PET/CT, and PET/MRI) have been employed for brain tumor diagnosis, treatment planning, and follow-up studies. Recent technology such as PET/CT and PET/MRI scanners created a significant quantity of detailed neuroimaging data in patients with brain tumors [1-3]. Using AI-based technologies may also speed up picture processing and analysis, enhancing productivity. Radiomics is a particular application within the vast subject of AI that involves computing, identifying, and extracting picture attributes. An overview of feature-based radiomics and machine learning algorithms in noninvasive biopsy of brain tumor using MRI image is presented [2,3].

Radiomics

Robert Gillies and colleagues provide a clear and concise description of radiomics. Radiomics is a high-throughput method that converts medical pictures into radiomics characteristics. This quantitative link may help improve early diagnosis and prognosis prediction in some illnesses, therefore enhancing treatment options. Radiomic analysis includes data gathering, segmentation, feature extraction, exploratory analysis, and modeling [4-6].

Data Selection and Image Preprocessing

Radiomics starts with digital imaging, and MRI is the most often utilized imaging modality; radiomics analysis can be performed on MRI, CT, PET, and ultrasound. Having enough imaging data is helpful for statistical inference, but variation in imaging procedures might impact the quality of retrieved features and radiomics models. Recent research shows that radiomics in MRI are substantially affected by image collection and reconstruction conditions, making them less reproducible. Many studies have demonstrated that many variations exist in radiomics, and preprocessing (normalization, voxel, and pixel resampling) could improve and solve this problem [7,8].

Segmentation

Segmentation approaches are a crucial part of the radiomics process that separates a lesion from normal tissue. There are three types of segmentation (Manual, semi-automatic, and fully automated). Manual segmentation needs a skilled physician to reduce variability. It is attractive to use semi- or completely automatic segmentation to observe robust characteristics from a particular ROI [9,10]. Nowadays, machine learning softwares (3D-Slicer,Lifx, IBEX) can semi-automatically segment the lesion on MR images [6,11,12].

Feature Extraction

Numerous quantitative radiomics features, such as size and shape-based, histogram, matrix feature (run-length matrix (RLM), size zone matrix (SZM), gray-level co-occurrence matrix (GLCM), and neighborhood gray-tone difference matrix (NGTDM), wavelet feature base could be extracted from the medical images [8,10,12].

Feature Selection

All quantitative features collected from imaging data are not essential for predictive or prognostic models. Also, overfitting occurs when a created model closely fits the test data set; it makes the dependent model more susceptible to noise. Pre-selection of features reduces the probability of overfitting [5]. Radiomics uses both unsupervised and supervised reduction dimensions. The first methods try to remove unnecessary features; the two unsupervised feature selection approaches in radiomics are principal component analysis (PCA) and clustering [5]. There are three popular ways to reduce supervised feature sets:

Filter Techniques

Filter techniques often used include Wilcoxon rank-sum, Fisher score, Chi-squared score, Student's t-test, and minimal redundancy maximum relevance [13-15]. These approaches investigate the full feature space, considering feature relations to other features in the dataset, and the prediction model is used to score a subset of characteristics [13,14].

Wrapper

Wrapper techniques are hence greedy algorithms. These are forward and backward feature selection, comprehensive feature selection, and search [14,15].

Embedded Approaches

Embedded techniques, mixed filter, and wrapper methods are more accurate than filter methods, quicker than wrapper methods, and less prone to overfitting data. (Regression, tree-based techniques like random forest classifier, or the least absolute shrinkage and selection operator (LASSO)) [15-17].

Modeling and Evaluating

Depending on the study's goal, after feature selection, a model may be created to predict tumor types, machine learning algorithms may develop predictive models. The decision trees and random forest are the most used radiomics algorithms for predicting tumor type. Creating and testing models on the same dataset is a methodological error that leads to overfitting; the train and test datasets and K-fold are in machine learning models can solve this problem [2,16,17].

Conclusion

Radionics is a new imaging biomarker that combines information from radiology, computer vision, and machine learning. With the growth of imaging examination datasets, emerging computational models, there are more demand to use radiomics biopsy in brain tumors. We think that novel diagnostic hypothesis in conjunction with machine-learning algorithms may improve predictive cancer diagnosis and speed up the practical use of quantitative cancer imaging data**.**

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