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Mini review

Prospects for the use of Radiomics in Brain Tumors

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Abstract

Radiomics is a new direction in diagnostics that can ensure more efficient use of medical equipment, reduce the time that a physician spends on a patient, and also increase the accuracy of differential diagnosis in various fields of medicine. The review provides general information about radiomics and radiogenomics in oncology with the results of research in this area obtained in recent years, with special attention to the role of these methods in neuro-oncology, as well as solving the problems of brain tumors diagnosing. The above research results on radiomics and radiogenomics in neuro-oncology indicate the undoubted promise of these techniques, however, as in other fields of medicine and biology, errors cannot be completely excluded, and the task of the team of specialists involved in it is to minimize this probability.

Introduction

The latest advances in diagnostic radiology are intended to help solve the numerous problems facing neurooncology. Among the most notable of them is the creation of a whole new direction in the early 2010s - radiomics. It is based on the identification using computer processing of medical images of a wide range of signs that are not visible to the eye and not obvious to the radiologist. Further analysis is based on the determination of clinically significant signs as a result of comparison with the data of the clinical picture, biochemical and molecular biological studies [1]. One of the definitions of radiomics: "Radiomics is the extraction of quantitative characteristics from medical images, followed by linking these characteristics to biological markers and clinical outcomes," resulting in such significant features sometimes referred to as "image biomarkers." Studies that have discovered the relationship between radiomics and molecular genetic parameters fall under the definition of radiogenomics [2-7]. The research results accumulated to date indicate that radiomics and radiogenomics can ensure more efficient use of medical equipment, reduce the time a doctor spends on a patient, and increase the accuracy of differential diagnosis in various fields of medicine. It is especially important that radiomics is designed to help individualize treatment and, consequently, increase its effectiveness, ideally avoiding a number of invasive procedures [2,7–9].

The development and subsequent improvement of radiomics is also based on the achievements of radiation diagnostics.:

1. Creation of highly informative methods of radiation diagnostics: multi-slice CT, dual-energy CT, hybrid methods (PET-CT) [10-14]

2. Development of new radiopharmaceuticals for PET, for example, markers of hypoxia [15]

3. Improvement and widespread dissemination of standardized radiological examination protocols (in particular, for CT and MRI)[16]

4. Implementation of computer detection systems (computer-assisted detection – CAD systems) [17]

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The process of obtaining and processing information in radiomics includes several stages. First, a high-quality, standardized diagnostic image is obtained, and in some cases, a process of standardization or normalization of images is used. Next, the area of interest is highlighted in the image; in oncological practice, the visible boundaries of the tumor are determined (by automatic segmentation or "manually"). Then, quantitative characteristics of the image of the tumor area determined in this way are collected. These include the distribution of signal intensity (or density), features describing the contours of the formation, its effect on surrounding tissues, etc. Of these signs, the most informative ones are distinguished, in terms of independence from other signs, reproducibility and degree of manifestation. Based on the analysis of the texture of a 2D or 3D picture of a tumor, radiomics sets itself the task of highly reliable differentiation of benign and malignant tumors, acting as a "virtual biopsy". In radiomics, image analysis typically uses over 200 features, all of which are presented in quantitative terms. These signs are stored in the form of large databases, which make it possible to significantly automate the diagnostic process, identify new prognostic signs, and, consequently, more accurately predict the course and outcome of the disease. The next stage is to assess the relationship of the observed radiological characteristics of the pathological process with clinical outcomes, with the genetic profile and with other characteristics of patients. The so-called biomarkers of images (BMIs) are determined [4]. They are also called quantitative imaging biomarkers, which are objective characteristics obtained from in vivo images, measured in a ratio or interval scale as indicators of normal biological processes, pathogenic processes, or reactions to therapeutic intervention. A biomarker is a measurable parameter whose qualitative or quantitative characteristics indicate the presence or absence of a disease or condition. Biomarkers of images obtained by machine learning (ML) methods are selected automatically by algorithms. The most commonly used ML algorithms for analyzing radiomics data are regression, various types of decision trees, and deep neural networks. Using mathematical statistics, the most informative BMI is selected from the entire set of calculated features. Removing uninformative features makes the prediction results more stable and prevents random "noise" in the data from influencing the decision. The ultimate goal of these actions is to create mathematical models and algorithms for certain groups of diseases that allow the doctor to understand the disease in a particular patient more deeply and comprehensively and choose the most effective plan for its further management [2-6,18].

One of the difficult tasks facing radiomics is related to the fact that solid malignant tumors, including brain tumors, are characterized by heterogeneity, both spatially and temporally. This heterogeneity is difficult, and perhaps often impossible, to assess using histological and molecular studies of the material obtained during invasive biopsy. At the same time, medical imaging techniques are able to reflect the heterogeneity of neoplasms, and this ability has increased significantly over the past decades. [2,19]

Results of the application of radiomic analysis in clinical trials.

The possibilities of radiomic analysis are being actively explored in the field of neuro-oncology. Thus, in the work of Zhang Y. et al. [20] retrospectively analyzed the MRI data of 261 adult patients; of these, 97 patients had glioblastoma, 92 had primary CNS lymphoma, and 72 had demyelinating tumor-like lesion. The U-Net 3D segmentation model was trained to visualize the affected area. The level of accumulation of contrast agent in this area and in unaffected tissues was analyzed. This information was used for deep learning of the 3D model of differential diagnosis (Resnet). Of the entire cohort studied, 182 patients formed a group to train the model, while the rest formed a group to test it. The overall accuracy, sensitivity, and specificity were calculated, as well as the area under the receiver operating characteristic curve (AUC). The results of the differential diagnosis obtained by the model turned out to be more accurate than the conclusions of highly qualified radiologists. After using the deep learning model, the AUC was 1.00 (1,000–1,000) for glioblastoma, 0.96 (0.923–1,000) for primary CNS lymphoma, and 0.95 (0.904–1,000) for demyelinating tumor lesion. The merit of the authors of this work can be seen, in particular, in the fact that they were able to apply their model not only to single, but also to multiple pathological zones.

Cao et al. [21] studied not images, but texts describing the MRI of patients with gliomas. The following algorithms were used to train the model: Random forest, k-nearest neighbors, and the Support Vector Machine. A fairly high AUC (0.89) of their model was obtained in determining the IDH mutation status. Relatively recently, it was found that mutant forms of gliomas in the IDH1 gene progress slowly, have a lower risk of malignancy, and generally have a pronounced anti-oncogenic effect [22].

Dong et al. [23] successfully used the ADC analysis system (it allows converting analog data to digital - analog-to-digital converters) to differentiate between ependymoma and medulloblastoma in 51 children (AUC 0.91). One of the important criteria in the differential diagnosis of these tumors in their work was the assessment of fluid diffusion into the tumor using MRI.

Importantly, radiomics techniques can significantly help a radiotherapist in planning the treatment plan of brain tumors, as well as in subsequent follow-up of the patient,

especially in differentiating the progression of the neoplasm from pseudoprogression and from radiation damage [24]. To date, the most reliable systems for automatic tumor contouring have been obtained using systems based on convolutional neural networks) with a sensitivity of 0.85 [25].

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