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Роль системы контроля качества лучевой диагностики онкологических заболеваний в радиомике

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АННОТАЦИЯ

Современные методы медицинской визуализации дают возможность качественно и количественно оценить как ткани опухоли, так и пространство вокруг неё. Прогресс в информатике, особенно с участием методов машинного обучения в анализе медицинских изображений, позволяет преобразовывать любые радиологические исследования в поддающиеся анализу наборы данных. Среди этих наборов данных затем можно искать статистически значимые корреляции с клиническими событиями, чтобы впоследствии оценивать их прогностическую значимость и способность предсказывать тот или иной клинический исход. Эта концепция впервые была описана в 2012 г. и получила название «радиомика». Особую значимость она представляет для онкологии, поскольку известно, что каждый тип опухоли может подразделяться на множество различных молекулярно-генетических подтипов, и просто визуальной характеристики сейчас уже недостаточно. А радиомика при абсолютной неинвазивности способна обеспечить врача-радиолога информацией, которую порой может дать только гистологическое исследование биопсийного материала. Однако, как и в любой методике, основанной на использовании больших данных, здесь остро встаёт вопрос о качестве исходной информации данных, потому как это прямым образом может повлиять на исход анализа и дать неверную диагностическую информацию.

В литературном обзоре мы анализируем возможные подходы к обеспечению качества исследований на всех этапах — от технического контроля за состоянием диагностического оборудования до извлечения маркеров визуализации в онкологии и вычисления их корреляции с клиническими данными.

Ключевые слова: радиомика; лучевая диагностика; контроль качества; стандартизация; опухоли; онкологические заболевания.

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The role of the quality control system for diagnostics of oncological diseases in radiomics

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ABSTRACT

Modern medical imaging methods allow for both qualitative and quantitative evaluations of tumors and issues surrounding them. Advances in computer science and big data processing are transforming any radiological study into analytic datasets, especially with the use of machine learning in medical image analysis. Among these datasets, statistically significant correlations with clinical events can then be searched for to subsequently assess their predictive value and ability to predict a particular clinical outcome. This concept, known as "radiomics," was first described in 2012. It is particularly important in oncology because each type of tumor can be subdivided into many different molecular genetic subtypes, and simple visual characteristics are no longer sufficient. Moreover, as an absolutely noninvasive method, radiomics can provide a radiologist with additional information that would otherwise be unavailable without a histological examination of biopsy material. However, as with any methodology based on the use of big data, the question of the quality of the initial data becomes critical, because this can directly affect the outcome of the analysis and provide incorrect diagnostic information.

In this literature review, we examine potential approaches to ensuring the quality of research at all stages, from technical control of the state of diagnostic equipment to the extraction of imaging markers in oncology and the calculation of their correlation with clinical data.

Keywords: radiomics; radiology; quality assurance; quality control; tumors; cancer; standardization.

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肿瘤疾病放射诊断质量控制系统在放射组学中的作用

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简评

现代医学成像方法可以定性和定量地评估肿瘤组织及其周围的空间。计算机科学的进步，特别是机器学习方法在医学图像分析中的参与，允许将任何放射学研究转变为可分析的数据集。在这些数据集中，可以寻找有统计学意义夫人相关性与临床事件，以便随后评估其预后意义和预测不同临床结果的能力。 这个概念在2012年首次被描述并称为»放射组学»。这对于肿瘤学特别重要，因为已知每种类型的肿瘤可以分为许多不同的分子遗传亚型，而仅仅是视觉特征已经不够了。在绝对非侵入性的情况下，放射组学能够为放射科医生提供有时只有活检材料的组织学检查才能提供的信息。然而，正如在任何基于使用大数据的方法中一样，存在关于初始数据信息的质量的尖锐问题，因为这可能直接影响分析的结果并给出不正确的诊断信息。

在文献综述中，我们分析了确保各个阶段研究质量的可能方法 – 从诊断设备状态的技术控制到提取肿瘤学中的成像标记并计算其与临床数据的相关性。

关键词：放射学；放射诊断；质量控制；标准化；肿瘤；肿瘤疾病。

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INTRODUCTION

Advances in the field of radiation imaging significantly expanded their role in the entire range of methods for tumor processes management, from diagnosing primary foci and detecting metastases to monitoring treatment response and predicting individual patient outcomes. However, a simple visual analysis of tumor using radiation diagnostics is no longer sufficient, since each type of tumor is known to subdivide into many different molecular genetic subtypes. Accordingly, each tumor requires its own therapeutic and diagnostic approach. Here from the side of diagnostics, radiomics can be of great help.

Radiomics represents a method not just for visual analysis of medical images, but for large number extraction of quantitative signs, which allow deeper analysis and comprehensive assessment, such as tumor phenotypes and other pathological properties of affected tissues, as well as tumor biological characteristic assessment and treatment response prediction [1, 2]. For example, solid cancer is heterogeneous in time and space, which limits the use of molecular analysis based on invasive biopsy but offers great potential for medical imaging and enables non-invasive detection of intratumoral heterogeneity [3–5].

Quantitative analysis transition requires the development of automated and reproducible analysis methodologies to extract additional information from images [6]. Hence, a question in initial data quality arises, since this can affect the analysis outcome and provide incorrect diagnostic information, which will affect the clinical significance of detected indicators and patient health [7, 8].

Therefore, this literature review aimed to analyze possible approaches to ensure the quality of radiation diagnostics studies at all stages, from technical control over the state of diagnostic equipment to extracting imaging markers in oncology and calculating their correlation with clinical data.

Literature search was performed in the PubMed, GoogleScholar, and eLibrary databases in English and Russian languages. Requests such as “radiomics,” “cancer and tumors,” “standardization,” and “quality assurance or quality control” were used for PubMed and GoogleScholar.

METHODOLOGY OF RADIOMICS

Image acquisition

The step 1 in radiomics consists obtaining images using radiology methods, namely magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography combined with computed tomography (PET/CT) (Fig. 1). Radiology methods provide various and often complementary information about physical and kinetic properties of tissues, metabolism, etc. For example, analysis based on the size or volume of the pathological structure can be obtained using anatomical MRI or CT. Perfusion can be determined by a series of dynamic MRI or contrast-enhanced CT scans. Diffusion-weighted MRI can be used to assess tissue microcirculation and assess cellularity. Metabolic changes such as glucose metabolic rate can be measured using PET/CT and fluorodeoxyglucose. In addition, other additional biomarkers may be proposed in the course of clinical trials [9, 10].

Historically, imaging devices were developed for subjective interpretation of images, for clinicians to determine the presence of lesion and its location. Subsequent technical innovations are focused on image quality improvement, scan times reduction, or processing machines integration. These devices were not primarily intended to provide quantitative measurement in a reproducible manner. Standardization protocols for image acquisition are unavailable. In addition, significant differences may be present in reconstruction

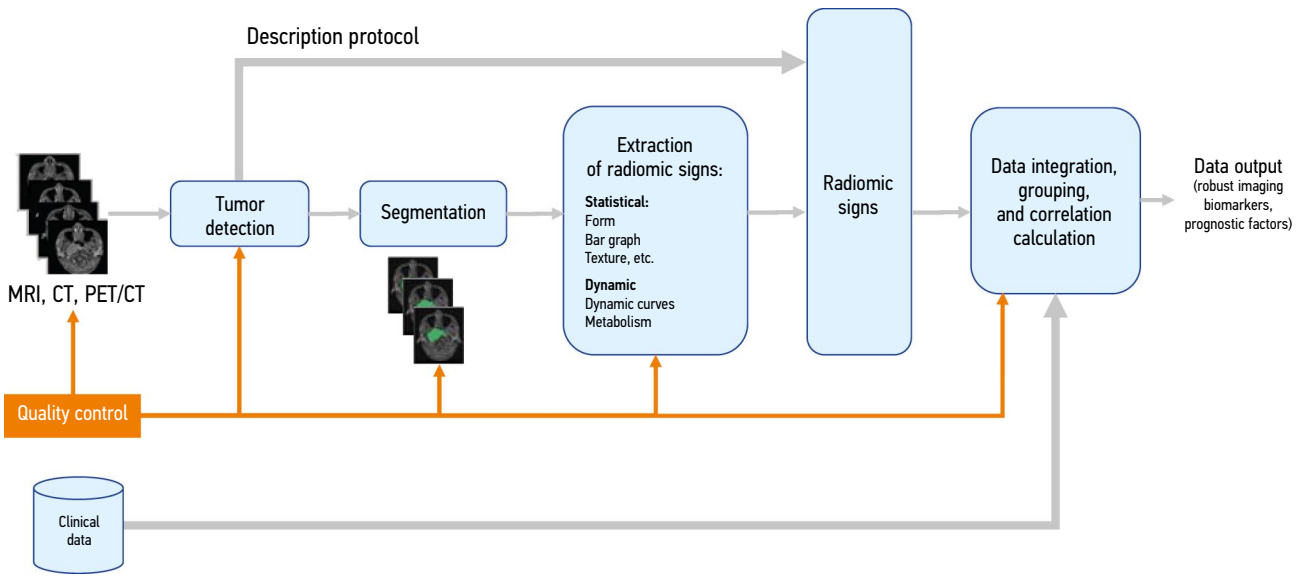

Fig. 1. Scheme of radiomics analysis of radiation diagnostic images indicating the role of quality control system.

parameters. H. Kim et al. [11] studied the effect of reconstruction filters on radiomic signs identified from CT images of patients with lung cancer and concluded that the relationship was statistically significant and reconstruction settings should not be used interchangeably. N. Ohri et al. [12] assessed the variability of radiomic characteristics obtained from PET/CT under different modes of data collection, algorithms reconstruction, post-filtration, and number of iterations. A total of 40 out of 50 signs were demonstrated to have significant (up to 30%) variability. Variability of signs can vary more significantly when performing MRI due to the amplitude of the scanner gradient magnetic field, used pulse sequence, contrast agent administration method, trajectory sampling in k-space, and other factors [13]. Data quality depends on reliability of data collection protocols used in clinical centers, thus the effect of these changes on the stability of radiomic signs needs to be carefully investigated and analyzed in future studies.

New methods of image processing

Image processing is the next step in radiomic signs extraction. Thus, identification of a region of interest (ROI) and volume of interest (VOI) is a fundamental task in oncological practice [14]. Manual description by experienced roentgenologists or radiologists is considered the gold standard, but is time-consuming with a high degree of inter- or even intra-operator variability. Automated or semi-automated methods are often used, such as determining threshold values, classifiers, clustering, Markov models of random fields, artificial neural networks, deformable models, and some others to determine ROI [15].

Automation can provide new opportunities for segmentation techniques standardization; however, problems associated with complex anatomy or areas of low soft tissue contrast are still present, therefore manual adjustments by an experienced physician are often required. One of the methods of semi-automatic segmentation, which avoids errors, is the use of digital biopsy, in which only certain segments are sampled based on intensity and texture values [16]. For segmentation or selection of images, advanced machine learning methods also emerged and used [17].

Several major initiatives aimed to develop automatic segmentation solutions using deep learning. These include, Google DeepMind, Microsoft Project InnerEye, and Mirada DLCExpert. These automated segmentation tools showed to increase efficiency in structure reconstruction, especially for organs at risk [18, 19]. In the near future, deep learning-based segmentation tools may become reliable enough for routine research.

Extraction of signs, grouping, and data integration

Extraction of multidimensional datasets (radiomics signs) is the main stage of radiomics to quantify the VOI highlighted in the image [20]. Signs extracted from images can be divided into static and dynamic groups.

Characteristics of static signs. Static signs multitude comprises two categories, morphological and statistical [21]. Morphological signs are used to define three-dimensional (3D) shape characteristics such as volume and surface area, as well as sphericity (the extent a 3D volume resembles a sphere). Statistical signs are used to mathematically evaluate the distribution of grayscale within an ROI or VOI. Therefore, the first-order signs include the mean value, standard deviation, percentiles, kurtosis, and asymmetry, which are used to characterize the overall variability in intensity. Second-order signs characterize the texture of selected area by analyzing the relationship between individual voxels within the ROI or area, i.e., exhibit local distribution.

Aspects of dynamic signs. Pharmacokinetic modeling is commonly used to quantify the dynamic distribution of a contrast agent or other indicator within a region (which may be one or more voxels). In general, pharmacokinetic modeling considers the contrast agent concentration as a function of arterial input and residual contrast agent decay within the ROI. The intravascular and interstitial space can be modeled under different assumptions. For example, the most widely used kinetic model, the Toft model, assumes instant mixing of contrast in the intravascular and interstitial space, whereas the extended Toft model takes into account the effect of delayed contrast agent concentration in tissue. The model of homogeneity of adiabatic tissue is explained by the fact that contrast agent concentration in distribution volume outside the vessels changes more slowly compared to the intravascular space concentration. Thus, the model assumes a finite transit time for contrast agents from arterial phase to venous phase.

In general, existing analytical pipeline typically includes thousands of extracted radiomics characteristics, and this number is expected to grow with new available data. However, clinically significant signs include not all selected ones, but the most reliable signs, correlating with clinical data for the possibility of disease course prediction.

Calculation of correlations, identification of prognostic factors

As in many other fields where the -omics suffix is used, the number of input variables often far exceeds the number of patients. In order to reduce the probability of false positive results, specific sign selection or search area size reduction is required, and filter-based scoring approaches are commonly used, such as Wilcoxon analysis and principal component analysis. This can be implemented using either one-dimensional methods, when the evaluation criterion depends only on the object relevance, or multivariate methods, when a weighted sum is used to maximize relevance and minimize redundancy [22–25]. Object selection can also be combined with object classification into one model.

Once a set of characteristics is obtained, a data-driven model can be created. These models include controlled and

uncontrolled approaches [21, 26]. Unmanaged analysis does not provide a result variable, but rather a summary of information. Most often, a thermal map is used for its graphical display, on which cluster structures in data matrix are simultaneously detected. In contrast, in the course of monitored analysis, models are created, that attempt to divide the treatment outcome data. Typical classification methods include traditional logistic regression or more advanced machine learning methods.

Isolated radiomic signs that correlate closely with clinical data and molecular analysis results can be classified as imaging biomarkers, whereas classical biomarkers are obtained by histological and molecular examination of tumor tissues, i.e., using invasive method, imaging biomarkers provide non-invasive characterization of the pathology. In addition, reliable indicators of normal or pathological processes in tissues or tumor responses are available for any intervention.

QUALITY CONTROL AND STANDARDIZATION OF PARAMETERS IN RADIOMICS

Measurement accuracy improvement is necessary (Fig. 2) to ensure radiomic signs quality and imaging biomarkers reliability, which is determined by the magnitude of bias or absolute error of obtained data and variability of values (repeatability and reproducibility, defined as dispersion of measured values). These indicators are achieved by introducing quality control tests in radiation diagnostic departments, namely acceptance tests, periodic, and internal control tests (tests for parameter constancy) [27]. Acceptance tests are performed during equipment installation to establish the compliance of tested characteristics with the manufacturer's limit values. In case of confirmation of parameter conformity, the medical organization personnel perform the first tests for parameter constancy, during which base values are established for further quality control. Internal control or parameter constancy testing is essential in the quality control system as it predicts deterioration in diagnostic image quality. In Russia, periodic tests include monitoring of extended list of parameters, and are performed by certified testing laboratories.

In international practice, inclusion of technical personnel in the staff of MRI, CT, PET/CT offices is common. For example, a large role is assigned to medical physicists, whose important task consist research optimization and standardization, as well as radiation diagnostics equipment quality monitoring and safe system organization during research [28]. In Russia presence of such personnel in the staff of radiation diagnostics rooms are currently not required, and competencies to implement quality control for radiomics are unnecessary for medical personnel.

Measures to ensure quality control of radiological diagnostic equipment are required to achieve reliability and clinically acceptable repeatability of measurements, which is supported by the Radiological Society of North America (RSNA), the European Society of Radiology, etc. Thus, collaboration between members of the Quantitative Imaging

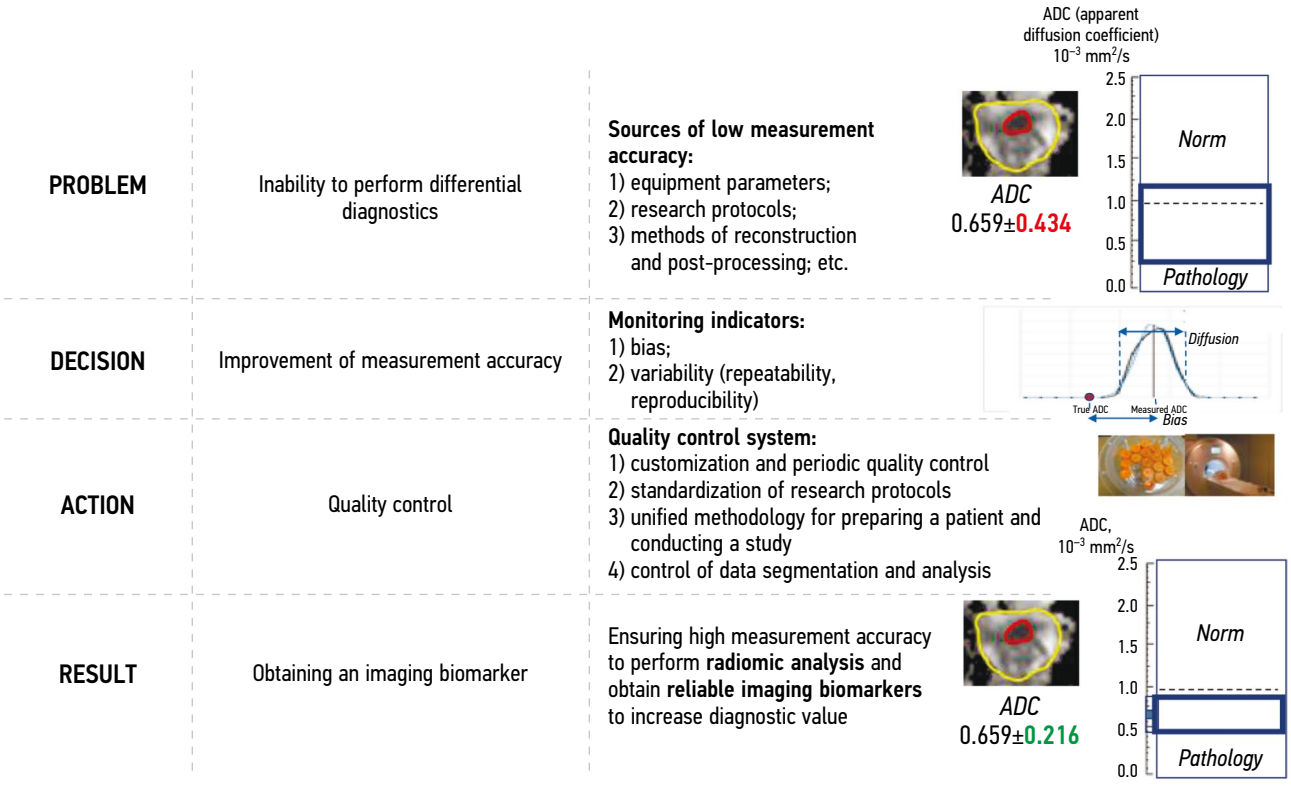

Fig. 2. Justification for quality control system implementation in radiomics.

Network (QIN; USA) and National Institute of Standards and Technology phantoms was developed for quality control in clinical trials [29, 30].

Relationships are formed between revealed signs and clinical data as a result of radiomic analysis to check the model constructed and assess output information reliability; it is validated for new patients [31, 32]. Literature data are used, as well as dataset validation testing, or data from other healthcare organizations to gain generalization possibility [31].

Standardization of study protocols

Following the standard methods of examination preparation, namely exclude foreign objects from the scan area that contribute to distortion is necessary since MRI, CT, and PET/CT images are susceptible to artifacts and noise; make sure that the established rules for positioning the patient are followed for better visualization. The patient should feel comfortably motionless for a long time.

In addition, the voxel size and signal intensity have a great influence on radiomic signs, therefore, ensuring the standardization of protocols is important when setting up the scan [32, 33]. The effect of reconstruction filters on image quality and signal intensity should also be taken into account, namely a filter should be chosen that does not lose the useful signal and ensure high reproducibility of radiomic signs when performing PET/CT and CT [34].

The image matrix is scaled and reduced to an isotropic (square) form as part of image preprocessing [35]. Signal intensity normalization to one scale is also recommended, especially for MRI. For this purpose, statistical methods are used, for example ANTsR and WhiteStripe [36]. Signal intensity inhomogeneity phenomena may be encountered when performing MRI, which are caused not by biological properties of tissues, but by technical factors. In such cases, correction for this heterogeneity is required, which should be included in the quality control system of performed procedures.

Post-processing control

Tools and algorithms with proven accuracy of their work should be used for post-processing process [36]. For example, for the subsequent correct analysis of radiomic signs, it is important to use high-quality tools at the segmentation stage. Previously semi-automatic algorithms with manual segmentation correction were used, but now more and more algorithms based on artificial intelligence technologies [37] appear, which must undergo appropriate tests [38].

Monitoring of isolated radiomic signs and validation of imaging biomarkers

Principles of standardization and quality control of studies and procedures for pre- and post-processing of images are required to ensure the quality (bias and variability) of radiomic signs, as well as reliability of imaging biomarkers [39].

At this stage, quality control tools are used, such as phantoms, which enable the assessment of bias and reproducibility of distinguished signs. Phantoms can be both digital and physical, made using substances of specified parameters [40, 41]. For example, for multicenter studies of breast cancer, an appropriate phantom is used, which enables the evaluation of study reproducibility and accuracy [42].

The phantom is scanned repeatedly under different conditions, after which the variability of measurements is calculated and compared with the threshold value that the European Medicines Agency recommends, which is no more than 15% to analyze the effect of the scanning parameters on variability and methodology of study and post-processing performance [39].

Accuracy is assessed in the process of studies on phantoms or on tissue samples and corresponds to the relative error when the true value of signs (ground truth) and measured ones are compared. Setting the threshold value for successful completion of assessment at the level of 15% is recommended in the process of imaging biomarker validation [39].

This field of radiomics is under development, which may become an effective method for diagnosing tumors and predicting process analysis in the near future. We believe that the number of studies in this field will increase with the introduction of artificial intelligence algorithms to create relationships between the selected signs and clinical data. However, without the implementation of the described quality control approaches at all stages, obtaining a solid evidence is impossible, i.e., data reproducible on other populations, other equipment with a bias indicators within the established limit. Phantoms were previously developed for monitoring quantitative modes of MRI (with diffusion indicators) and CT (with indicators of bone mineral density) at the Center for Diagnostics and Telemedicine. From our point of view, interaction with technical specialists (medical physicists, engineers) and medical personnel is necessary to develop phantoms with specified measurement accuracy in planning a study of radiomic signs and further obtaining imaging biomarkers in this work.

ROLE OF DEVELOPMENT OF VISUALIZATION BIOMARKERS

In recent years, efforts were made to improve approaches to standardization of radiomic signs by defining standard data collection protocols. Particular efforts for this were made by the QIN created by the National Cancer Institute (NCI), as well as RSNA, the Quantitative Imaging Biomarkers Alliance (QIBA) and others. In 2010, NCI launched an initiative of the Cancer Institute Centers for Quantitative Image Excellence, and the creation of a National Clinical Trials Network has become a key focus of this effort [43]. Centers for

quantitative image improvement create PET/CT, CT, and MR phantoms, as well as protocols for standardization, and QIBA provides consensus decisions on the accuracy of quantitative biomarker imaging measurements and requirements/procedures necessary to achieve this level of accuracy [29, 35, 36, 44, 45].

Since the term "radiomics" appeared in the scientific literature, hundreds of published radiomics studies aimed to improve the quality of diagnostics, treatment, and prognosis of cancer. An increasing number of works demonstrate the value of imaging biomarkers as an additional tool for clinical decision-making and role of machine learning algorithms in it [46].

One of the earliest applications of the radiomics-based method is the successful detection of tumors in the imaging of lung and breast cancers.

Breast cancer is a pathology that most often occurs in women worldwide. Accurate diagnosis and early prediction of treatment response are key aspects in clinical practice since it is a well-known heterogeneous disease [47]. Several studies used radiomics to predict breast cancer subtype or ER, PR, Ki67, and HER2 status on mammography [48], PET/CT [49, 50], and MRI [51, 52]. In addition to characterizing breast cancer, radiomics may also provide a non-invasive approach to predict metastases in the sentinel lymph nodes [53].

Most radiological research on breast cancer focuses on therapy response evaluation. H.M. Chan et al. [54] developed an automated method using MRI to predict the absence or insufficient response to treatment in patients with early breast cancer. Most other studies attempted to obtain a pathologic complete response (pCR) biomarker with neoadjuvant chemotherapy, a hot topic of discussion in studies on breast cancer. Thus, N.M. Braman et al. [55] revealed that intra- and peri-tumor characteristics found on dynamic contrast-enhanced MRI can predict pCR prior to treatment. Other studies also showed that T1WI, T2WI, and DWI can aid in pCR detection [56, 57].

Radiological studies focused on the prognosis of breast cancer are performed more and more frequently. For example, H. Park et al. [58] developed an algorithm combining MRI imaging biomarkers and clinical information to individually assess the survival ability of patients with breast cancer.

Lung cancer is the most dangerous type of cancer, and its prevalence also continues to increase worldwide. Lung cancer screening is one of the most important diagnostic applications of radiomics. N. Nasrullah et al. [59] proposed a deep learning model based on chest CT studies from the LIDC-IDRI dataset and achieved good results in detecting malignant lung nodules with a sensitivity of 94% and specificity of 91%. B.W. Carter et al. [60] conducted a screening study of patients diagnosed with lung cancer in the National Lung Screening Trial dataset using low-dose CT. They were able to obtain predictive accuracy of 80% and 79% for nodules that develop into malignant neoplasms in one or two years, respectively.

Radiomics enables the determination at the preoperative stage in staging lung cancer by tumor nodules metastasis (TNM) [61, 62], which is important for making a decision about surgical intervention. In addition, the technique can be used to detect specific genetic mutations in lung cancer, such as the status for the *Estimated glomerular filtration rate* gene [63] which can help medical specialists choose the optimal therapeutic approach. X. Fave et al. used delta-radiomic characteristics to predict outcomes in patients with stage III non-small cell lung cancer during radiation therapy [64]. Their results suggest that changes in radiomic characteristics due to radiation therapy will be indicative of tumor response. T.P. Coroller et al. [65] established that radiomic signs of CT before treatment can predict a pathological response after neoadjuvant chemoradiation therapy in patients with advanced non-small cell lung cancer.

In recent years, radiomics are increasingly used for diagnostics, treatment response prediction, and long-term outcomes of tumors of the nervous system [26, 66, 67], head and neck [68, 69], gastrointestinal tract [70, 71], prostate cancer [72, 73], and some other forms of oncological diseases [74].

CONCLUSION

Early detection and identification of tumors, their heterogeneity, and phenotypic signs can be invaluable in patient stratification, subsequent treatment options determination, and effects prediction. Radiomic analysis of diagnostic studies provides information necessary for this, but only under conditions of high-quality collected and processed data. All of these processes need to be standardized and optimized using a variety of quality control methods, and at each stage, from image acquisition to validation of imaging biomarkers. In addition, clinical information must be taken into account, based on which the search for clinical correlations is performed to establish the prognostic value of biomarkers. Only the qualitative fulfillment of all these criteria can make the biomarker imaging tool really useful for doctors and necessary for patients.

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REFERENCES

1. Kumar V, Gu Y, Basu S, et al. Radiomics: The process and the challenges. *Magn Reson Imaging*. 2012;30(9):1234–1248. doi: 10.1016/j.mri.2012.06.010

2. Papanikolaou N, Matos C, Koh DM. How to develop a meaningful radiomic signature for clinical use in oncologic patients. *Cancer Imaging*. 2020;20(1):33. doi: 10.1186/s40644-020-00311-4

3. Aerts HJ, Grossmann P, Tan Y, et al. Defining a radiomic response phenotype: A pilot study using targeted therapy in NSCLC. *Sci Rep*. 2016;6:33860. doi: 10.1038/srep33860

4. Coroller TP, Grossmann P, Hou Y, et al. CT-based radiomic signature predicts distant metastasis in lung adenocarcinoma. *Radiother Oncol*. 2015;114(3):345–350. doi: 10.1016/j.radonc.2015.02.015

5. Lopez CJ, Nagornaya N, Parra NA, et al. Association of radiomics and metabolic tumor volumes in radiation treatment of glioblastoma multiforme. *Int J Radiat Oncol Biol Phys*. 2017;97(3):586–595. doi: 10.1016/j.ijrobp.2016.11.011

6. De Souza NM, Achten E, Alberich-Bayarri A, et al. Validated imaging biomarkers as decision-making tools in clinical trials and routine practice: current status and recommendations from the EIBALL* subcommittee of the European Society of Radiology (ESR). *Insights Imaging*. 2019;10(1):87. doi: 10.1186/s13244-019-0764-0

7. Jones EF, Buatti JM, Shu HK, et al. Clinical trial design and development work group within the quantitative imaging network. *Tomography*. 2020;6(2):60–64. doi: 10.18383/j.tom.2019.00022

8. European Society of Radiology (ESR). ESR statement on the validation of imaging biomarkers. *Insights Imaging*. 2020;11(1):76. doi: 10.1186/s13244-020-00872-9

9. Grimm LJ, Zhang J, Mazurowski MA. Computational approach to radiogenomics of breast cancer: Luminal A and luminal B molecular subtypes are associated with imaging features on routine breast MRI extracted using computer vision algorithms. *J Magn Reson Imaging*. 2015;42(4):902–907. doi: 10.1002/jmri.24879

10. Nie K, Shi L, Chen Q, et al. Rectal cancer: Assessment of neoadjuvant chemoradiation outcome based on radiomics of multiparametric MRI. *Clin Cancer Res*. 2016;22(21):5256–5264. doi: 10.1158/1078-0432.CCR-15-2997

11. Kim H, Park CM, Lee M, et al. Impact of reconstruction algorithms on ct radiomic features of pulmonary tumors: analysis of intra- and inter-reader variability and inter-reconstruction algorithm variability. *PLoS One*. 2016;11(10):e0164924. doi: 10.1371/journal.pone.0164924

12. Ohri N, Duan F, Snyder BS, et al. Pretreatment 18F-FDG PET textural features in locally advanced non-small cell lung cancer: Secondary analysis of ACRIN 6668/RTOG 0235. *J Nucl Med*. 2016;57(6):842–848. doi: 10.2967/jnumed.115.166934

13. Zhang B, Tian J, Dong D, et al. Radiomics features of multiparametric MRI as novel prognostic factors in advanced nasopharyngeal carcinoma. *Clin Cancer Res*. 2017;23(15):4259–4269. doi: 10.1158/1078-0432.CCR-16-2910

14. Nakatsugawa M, Cheng Z, Goatman KA, et al. Radiomic analysis of salivary glands and its role for predicting xerostomia in irradiated head and neck cancer patients. *Int J Radiat Oncol Biol Phys*. 2016;96(2 suppl):S217. doi: 10.1016/j.ijrobp.2016.06.539

15. Shafiee MJ, Chung AG, Khalvati F, et al. Discovery radiomics via evolutionary deep radiomic sequencer discovery for pathologically proven lung cancer detection. *J Med Imaging*. 2016;4(4):041305. doi: 10.1117/1.JMI.4.4.041305

16. Echegaray S, Nair V, Kadoch M, et al. A rapid segmentation-insensitive «Digital Biopsy» method for radiomic feature extraction: method and pilot study using ct images of non-small cell lung cancer. *Tomography*. 2016;2(4):283–294. doi: 10.18383/j.tom.2016.00163

17. Li H, Galperin-Aizenberg M, Pryma D, et al. Unsupervised machine learning of radiomic features for predicting treatment response and overall survival of early stage non-small cell lung cancer patients treated with stereotactic body radiation therapy. *Radiother Oncol*. 2018;129(2):218–226. doi: 10.1016/j.radonc.2018.06.025

18. Tajbakhsh N, Shin JY, Gurudu SR, et al. Convolutional neural networks for medical image analysis: full training or fine tuning? *IEEE Transactions on Medical Imaging*. 2016;35(5):1299–1312. doi: 10.1109/TMI.2016.2535302

19. Elguindi S, Zelefsky MJ, Jiang J, et al. Deep learning-based autosegmentation of targets and organs-at-risk for magnetic resonance imaging only planning of prostate radiotherapy. *Phys Imaging Radiat Oncol*. 2019;12:80–86. doi: 10.1016/j.phro.2019.11.006

20. Gillies RJ, Kinahan PE, Hricak H. Radiomics: images are more than pictures, they are data. *Radiology*. 2016;278(2):563–577. doi: 10.1148/radiol.2015151169

21. Buckler AJ, Bresolin L, Dunnick NR, et al. Quantitative imaging test approval and biomarker qualification: Interrelated but distinct activities. *Radiology*. 2011;259(3):875–884. doi: 10.1148/radiol.10100800

22. Alobaidli S, McQuaid S, South C, et al. The role of texture analysis in imaging as an outcome predictor and potential tool in radiotherapy treatment planning. *Br J Radiol*. 2014;87(1042):20140369. doi: 10.1259/bjr.20140369

23. Li H, Giger ML, Lan L, et al. Comparative analysis of image-based phenotypes of mammographic density and parenchymal patterns in distinguishing between BRCA1/2 cases, unilateral cancer cases, and controls. *J Med Imaging*. 2014;1(3):031009. doi: 10.1117/1.JMI.1.3.031009

24. Goh V, Ganeshan B, Nathan P, et al. Assessment of response to tyrosine kinase inhibitors in metastatic renal cell cancer: CT texture as a predictive biomarker. *Radiology*. 2011;261(1):165–171. doi: 10.1148/radiol.11110264

25. Yip C, Davnall F, Kozarski R, et al. Assessment of changes in tumor heterogeneity following neoadjuvant chemotherapy in primary esophageal cancer. *Dis Esophagus*. 2015;28(2):172–179. doi: 10.1111/dote.12170

26. Park JE, Kim HS. Radiomics as a quantitative imaging biomarker: practical considerations and the current standpoint in neuro-oncologic studies. *Nucl Med Mol Imaging*. 2018;52(2):99–108. doi: 10.1007/s13139-017-0512-7

27. Sergunova KA, Akhmad ES, Semenov DS, et al. Medical physicist's participation in quality assurance and safety in magnetic resonance imaging. *Medical physics*. 2020;(3):78–85. (In Russ).

28. Clements JB, Baird CT, de Boer SF, et al. AAPM medical physics practice guideline 10.a.: Scope of practice for clinical medical physics. *J Appl Clin Med Phys*. 2018;19(6):11–25. doi: 10.1002/acm2.12469

29. Shukla-Dave A, Obuchowski NA, Chenevert TL, et al. Quantitative imaging biomarkers alliance (QIBA) recommendations for improved precision of DWI and DCE-MRI derived biomarkers in multicenter oncology trials. *J Magn Reson Imaging*. 2019;49(7):e101–e121. doi: 10.1002/jmri.26518

30. Russek SE, Boss M, Jackson EF, et al. Characterization of NIST/ISMRM MRI System Phantom. *Proc Intl Soc Mag Reson Med*. 2012;20:2456.
31. Kuo MD, Jamshidi N. Behind the numbers: Decoding molecular phenotypes with radiogenomics –guiding principles and technical considerations. *Radiology*. 2014;270(2):320–325. doi: 10.1148/radiol.13132195
32. Narang S, Lehrer M, Yang D, et al. Radiomics in glioblastoma: current status, challenges and potential opportunities. *Transl Cancer Res*. 2016;5(4):383–397. doi: 10.21037/tcr.2016.06.31
33. O'Connor JP, Aboagye EO, Adams JE, et al. Imaging biomarker roadmap for cancer studies. *Nat Rev Clin Oncol*. 2017;14(3):169–186. doi: 10.1038/nrclinonc.2016.162
34. Buizza G, Toma-Dasu I, Lazzeroni M, et al. Early tumor response prediction for lung cancer patients using novel longitudinal pattern features from sequential PET/CT image scans. *Phys Med*. 2018;54:21–29. doi: 10.1016/j.ejmp.2018.09.003
35. Raunig DL, McShane LM, Pennello G, et al. Quantitative imaging biomarkers: a review of statistical methods for technical performance assessment. *Stat Methods Med Res*. 2015;24(1):27–67. doi: 10.1177/0962280214537344
36. Obuchowski NA, Reeves AP, Huang EP, et al. Quantitative imaging biomarkers: a review of statistical methods for computer algorithm comparisons. *Stat Methods Med Res*. 2015;24(1):68–106. doi: 10.1177/0962280214537390
37. Elguindi S, Zelefsky MJ, Jiang J, et al. Deep learning-based autosegmentation of targets and organs-at-risk for magnetic resonance imaging only planning of prostate radiotherapy. *Phys Imaging Radiat Oncol*. 2019;12:80–86. doi: 10.1016/j.phro.2019.11.006
38. Morozov SP, Vladzimirsky AV, Klyashtorny VG, et al. Clinical trials of software based on intelligent technologies (radiation diagnostics). Methodological recommendations. Moscow; 2019. 33 p. (In Russ).
39. Sullivan DC, Obuchowski NA, Kessler LG, et al. Metrology standards for quantitative imaging biomarkers. *Radiology*. 2015;277(3):813–825. doi: 10.1148/radiol.2015142202
40. Shur J, Blackledge M, D'Arcy J, et al. MRI texture feature repeatability and image acquisition factor robustness, a phantom study and in silico study. *Eur Radiol Exp*. 2021;5(1):2. doi: 10.1186/s41747-020-00199-6
41. Bane O, Hectors SJ, Wagner M, et al. Accuracy, repeatability, and interplatform reproducibility of T1 quantification methods used for DCE-MRI: Results from a multicenter phantom study. *Magn Reson Med*. 2018;79(5):2564–2575. doi: 10.1002/mrm.26903
42. He Y, Liu Y, Dyer BA, et al. 3D-printed breast phantom for multipurpose and multi-modality imaging. *Quant Imaging Med Surg*. 2019;9(1):63–74. doi: 10.21037/qims.2019.01.05
43. Scheuermann JS, Reddin JS, Opanowski A, et al. Qualification of national cancer institute-designated cancer centers for quantitative PET/CT imaging in clinical trials. *J Nucl Med*. 2017;58(7):1065–1071. doi: 10.2967/jnumed.116.186759
44. Obuchowski NA, Barnhart HX, Buckler AJ, et al. Statistical issues in the comparison of quantitative imaging biomarker algorithms using pulmonary nodule volume as an example. *Stat Methods Med Res*. 2015;24(1):107–140. doi: 10.1177/0962280214537392
45. Kessler LG, Barnhart HX, Buckler AJ, et al. The emerging science of quantitative imaging biomarkers terminology and definitions for scientific studies and regulatory submissions. *Stat Methods Med Res*. 2015;24(1):9–26. doi: 10.1177/0962280214537333
46. Napel S, Mu W, Jardim-Perassi BV, et al. Quantitative imaging of cancer in the postgenomic era: Radio(geno)mics, deep learning, and habitats. *Cancer*. 2018;124(24):4633–4649. doi: 10.1002/cncr.31630
47. Rozhkova NI, Bozhenko VK, Burdina II, et al. Radiogenomics of breast cancer as new vector of interdisciplinary integration of radiation and molecular biological technologies (literature review). *Medical alphabet*. 2020;(20):21–29. (In Russ). doi: 10.33667/2078-5631-2020-20-21-29
48. Antropova N, Huynh BQ, Giger ML. A deep feature fusion methodology for breast cancer diagnosis demonstrated on three imaging modality datasets. *Med Phys*. 2017;44(10):5162–5171. doi: 10.1002/mp.12453
49. Antunovic L, Gallivanone F, Sollini M, et al. [^{18}F]FDG PET/CT features for the molecular characterization of primary breast tumors. *Eur J Nucl Med Mol Imaging*. 2017;44(12):1945–1954. doi: 10.1007/s00259-017-3770-9
50. Ha S, Park S, Bang JI, et al. Metabolic radiomics for pretreatment ^{18}F-FDG PET/CT to characterize locally advanced breast cancer: histopathologic characteristics, response to neoadjuvant chemotherapy, and prognosis. *Sci Rep*. 2017;7(1):1556. doi: 10.1038/s41598-017-01524-7
51. Guo W, Li H, Zhu Y, et al. Prediction of clinical phenotypes in invasive breast carcinomas from the integration of radiomics and genomics data. *J Med Imaging (Bellingham)*. 2015;2(4):041007. doi: 10.1117/1.JMI.2.4.041007
52. Saha A, Harowicz MR, Grimm LJ, et al. A machine learning approach to radiogenomics of breast cancer: a study of 922 subjects and 529 DCE-MRI features. *Br J Cancer*. 2018;119(4):508–516. doi: 10.1038/s41416-018-0185-8
53. Dong Y, Feng Q, Yang W, et al. Preoperative prediction of sentinel lymph node metastasis in breast cancer based on radiomics of T2-weighted fat-suppression and diffusion-weighted MRI. *Eur Radiol*. 2018;28(2):582–591. doi: 10.1007/s00330-017-5005-7
54. Chan HM, van der Velden BH, Loo CE, Gilhuijs KG. Eigentumors for prediction of treatment failure in patients with early-stage breast cancer using dynamic contrast-enhanced MRI: a feasibility study. *Phys Med Biol*. 2017;62(16):6467–6485. doi: 10.1088/1361-6560/aa7dc5
55. Braman NM, Etesami M, Prasanna P, et al. Intratumoral and peritumoral radiomics for the pretreatment prediction of pathological complete response to neoadjuvant chemotherapy based on breast DCE-MRI. *Breast Cancer Res*. 2017;19(1):57. doi: 10.1186/s13058-017-0846-1
56. Chamming's F, Ueno Y, Ferré R, et al. Features from computerized texture analysis of breast cancers at pretreatment MR imaging are associated with response to neoadjuvant chemotherapy. *Radiology*. 2018;286(2):412–420. doi: 10.1148/radiol.2017170143
57. Partridge SC, Zhang Z, Newitt DC, et al. Diffusion-weighted MRI findings predict pathologic response in neoadjuvant treatment of breast cancer: the ACRIN 6698 multicenter trial. *Radiology*. 2018;289(3):618–627. doi: 10.1148/radiol.2018180273
58. Park H, Lim Y, Ko ES, et al. Radiomics signature on magnetic resonance imaging: association with disease-free survival in patients with invasive breast cancer. *Clin Cancer Res*. 2018;24(19):4705–4714. doi: 10.1158/1078-0432.CCR-17-3783
59. Nasrullah N, Sang J, Alam MS, et al. Automated lung nodule detection and classification using deep learning combined

with multiple strategies. *Sensors (Basel)*. 2019;19(17):3722. doi: 10.3390/s19173722
60. Carter BW, Godoy MC, Erasmus JJ. Predicting malignant nodules from screening CTs. *J Thorac Oncol*. 2016;11(12):2045–2047. doi: 10.1016/j.jtho.2016.09.117
61. Aerts HJ, Velazquez ER, Leijenaar RT, et al. Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach. *Nat Commun*. 2014;5:4006. doi: 10.1038/ncomms5006
62. Zhou H, Dong D, Chen B, et al. Diagnosis of distant metastasis of lung cancer: based on clinical and radiomic features. *Transl Oncol*. 2018;11(1):31–36. doi: 10.1016/j.tranon.2017.10.010
63. Liu Y, Kim J, Balagurunathan Y, et al. Radiomic features are associated with EGFR mutation status in lung adenocarcinomas. *Clin Lung Cancer*. 2016;17(5):441–448.e6. doi: 10.1016/j.cllc.2016.02.001
64. Fave X, Zhang L, Yang J, et al. Delta-radiomics features for the prediction of patient outcomes in non-small cell lung cancer. *Sci Rep*. 2017;7(1):588. doi: 10.1038/s41598-017-00665-z
65. Coroller TP, Agrawal V, Narayan V, et al. Radiomic phenotype features predict pathological response in non-small cell lung cancer. *Radiother Oncol*. 2016;119(3):480–486. doi: 10.1016/j.radonc.2016.04.004
66. Kickingereder P, Neuberger U, Bonekamp D, et al. Radiomic subtyping improves disease stratification beyond key molecular, clinical, and standard imaging characteristics in patients with glioblastoma. *Neuro Oncol*. 2018;20(6):848–857. doi: 10.1093/neuonc/nox188
67. Pérez-Beteta J, Molina-García D, Ortiz-Alhambra JA, et al. Tumor surface regularity at MR imaging predicts survival and response to surgery in patients with glioblastoma. *Radiology*. 2018;288(1):218–225. doi: 10.1148/radiol.2018171051
68. Zhou Z, Chen L, Sher D, et al. Predicting lymph node metastasis in head and neck cancer by combining many-objective radiomics and 3-dimensioal convolutional neural network through evidential reasoning. *Annu Int Conf IEEE Eng Med Biol Soc*. 2018;2018:1–4. doi: 10.1109/EMBC.2018.8513070
69. Wang G, He L, Yuan C, et al. Pretreatment MR imaging radiomics signatures for response prediction to induction chemotherapy in patients with nasopharyngeal carcinoma. *Eur J Radiol*. 2018;98:100–106. doi: 10.1016/j.ejrad.2017.11.007
70. Chen X, Oshima K, Schott D, et al. Assessment of treatment response during chemoradiation therapy for pancreatic cancer based on quantitative radiomic analysis of daily CTs: An exploratory study. *PLoS One*. 2017;12:e0178961. doi: 10.1371/journal.pone.0178961
71. Huang YQ, Liang CH, He L, et al. Development and validation of a radiomics nomogram for preoperative prediction of lymph node metastasis in colorectal cancer. *J Clin Oncol*. 2016;34(18):2157–2164. doi: 10.1200/JCO.2015.65.9128
72. Lin YC, Lin G, Hong JH, et al. Diffusion radiomics analysis of intratumoral heterogeneity in a murine prostate cancer model following radiotherapy: Pixelwise correlation with histology. *J Magn Reson Imaging*. 2017;46(2):483–489. doi: 10.1002/jmri.25583
73. Chaddad A, Kucharczyk MJ, Niazi T. Multimodal radiomic features for the predicting gleason score of prostate cancer. *Cancers (Basel)*. 2018;10(8):249. doi: 10.3390/cancers10080249
74. Ognerubov NA, Shatov IA, Shatov AV. Radiogenomics and radiomics in the diagnostics of malignant tumours: a literary review. *Tambov University Reports*. Series: Natural and Technical Sciences. 2017;22(6):1453–1460. (In Russ). doi: 10.20310/1810-0198-2017-22-6-1453-1460

СПИСОК ЛИТЕРАТУРЫ

1. Kumar V., Gu Y., Basu S., et al. Radiomics: The process and the challenges // Magn Reson Imaging. 2012. Vol. 30, N 9. P. 1234–1248. doi: 10.1016/j.mri.2012.06.010
2. Papanikolaou N., Matos C., Koh D.M. How to develop a meaningful radiomic signature for clinical use in oncologic patients // Cancer Imaging. 2020. Vol. 20, N 1. P. 33. doi: 10.1186/s40644-020-00311-4
3. Aerts H.J., Grossmann P., Tan Y., et al. Defining a radiomic response phenotype: A pilot study using targeted therapy in NSCLC // Sci Rep. 2016. Vol. 6. P. 33860. doi: 10.1038/srep33860
4. Coroller T.P., Grossmann P., Hou Y., et al. CT-based radiomic signature predicts distant metastasis in lung adenocarcinoma // Radiother Oncol. 2015. Vol. 114, N 3. P. 345–350. doi: 10.1016/j.radonc.2015.02.015
5. Lopez C.J., Nagornaya N., Parra N.A., et al. Association of radiomics and metabolic tumor volumes in radiation treatment of glioblastoma multiforme // Int J Radiat Oncol Biol Phys. 2017. Vol. 97, N 3. P. 586–595. doi: 10.1016/j.ijrobp.2016.11.011
6. De Souza N.M., Achten E., Alberich-Bayarri A., et al. Validated imaging biomarkers as decision-making tools in clinical trials and routine practice: current status and recommendations from the EIBALL* subcommittee of the European Society of Radiology (ESR) // Insights Imaging. 2019. Vol. 10, N 1. P. 87. doi: 10.1186/s13244-019-0764-0
7. Jones E.F., Buatti J.M., Shu H.K., et al. Clinical trial design and development work group within the quantitative imaging network // Tomography. 2020. Vol. 6, N 2. P. 60–64. doi: 10.18383/j.tom.2019.00022
8. European Society of Radiology (ESR). ESR Statement on the validation of imaging biomarkers // Insights Imaging. 2020. Vol. 11, N 1. P. 76. doi: 10.1186/s13244-020-00872-9
9. Grimm L.J., Zhang J., Mazurowski M.A. Computational approach to radiogenomics of breast cancer: Luminal A and luminal B molecular subtypes are associated with imaging features on routine breast MRI extracted using computer vision algorithms // J Magn Reson Imaging. 2015. Vol. 42, N 4. P. 902–907. doi: 10.1002/jmri.24879
10. Nie K., Shi L., Chen Q., et al. Rectal cancer: Assessment of neoadjuvant chemoradiation outcome based on radiomics of multiparametric MRI // Clin Cancer Res. 2016. Vol. 22, N 21. P. 5256–5264. doi: 10.1158/1078-0432.CCR-15-2997
11. Kim H., Park C.M., Lee M., et al. Impact of reconstruction algorithms on ct radiomic features of pulmonary tumors: analysis of intra- and inter-reader variability and inter-reconstruction algorithm variability // PLoS One. 2016. Vol. 11, N 10. P. e0164924. doi: 10.1371/journal.pone.0164924
12. Ohri N., Duan F., Snyder B.S., et al. Pretreatment 18F-FDG PET textural features in locally advanced non-small cell lung cancer: Secondary analysis of ACRIN 6668/RTOG 0235 // J Nucl Med. 2016. Vol. 57, N 6. P. 842–848. doi: 10.2967/jnumed.115.166934

13. Zhang B., Tian J., Dong D., et al. Radiomics features of multiparametric MRI as novel prognostic factors in advanced nasopharyngeal carcinoma // Clin Cancer Res. 2017. Vol. 23, N 15. P. 4259–4269. doi: 10.1158/1078-0432.CCR-16-2910
14. Nakatsugawa M., Cheng Z., Goatman K.A., et al. Radiomic analysis of salivary glands and its role for predicting xerostomia in irradiated head and neck cancer patients // Int J Radiat Oncol Biol Phys. 2016. Vol. 96, N 2, Suppl. P. S217. doi: 10.1016/j.ijrobp.2016.06.539
15. Shafiee M.J., Chung A.G., Khalvati F., et al. Discovery radiomics via evolutionary deep radiomic sequencer discovery for pathologically proven lung cancer detection // J Med Imaging. 2016. Vol. 4, N 4. P. 041305. doi: 10.1117/1.JMI.4.4.041305
16. Echegaray S., Nair V., Kadoch M., et al. A rapid segmentation-insensitive "Digital Biopsy" method for radiomic feature extraction: method and pilot study using ct images of non-small cell lung cancer // Tomography. 2016. Vol. 2, N 4. P. 283–294. doi: 10.18383/j.tom.2016.00163
17. Li H., Galperin-Aizenberg M., Pryma D., et al. Unsupervised machine learning of radiomic features for predicting treatment response and overall survival of early stage non-small cell lung cancer patients treated with stereotactic body radiation therapy // Radiother Oncol. 2018. Vol. 129, N 2. P. 218–226. doi: 10.1016/j.radonc.2018.06.025
18. Tajbakhsh N., Shin J.Y., Gurudu S.R., et al. Convolutional neural networks for medical image analysis: full training or fine tuning? // IEEE Transactions on Medical Imaging. 2016. Vol. 35, N 5. P. 1299–1312. doi: 10.1109/TMI.2016.2535302
19. Elguindi S., Zelefsky M.J., Jiang J., et al. Deep learning-based auto-segmentation of targets and organs-at-risk for magnetic resonance imaging only planning of prostate radiotherapy // Phys Imaging Radiat Oncol. 2019. Vol. 12. P. 80–86. doi: 10.1016/j.phro.2019.11.006
20. Gillies R.J., Kinahan P.E., Hricak H. Radiomics: images are more than pictures, they are data // Radiology. 2016. Vol. 278, N 2. P. 563–577. doi: 10.1148/radiol.2015151169
21. Buckler A.J., Bresolin L., Dunnick N.R., et al. Quantitative imaging test approval and biomarker qualification: Interrelated but distinct activities // Radiology. 2011. Vol. 259, N 3. P. 875–884. doi: 10.1148/radiol.10100800
22. Alobaidli S., McQuaid S., South C., et al. The role of texture analysis in imaging as an outcome predictor and potential tool in radiotherapy treatment planning // Br J Radiol. 2014. Vol. 87, N 1042. P. 20140369. doi: 10.1259/bjr.20140369
23. Li H., Giger M.L., Lan L., et al. Comparative analysis of image-based phenotypes of mammographic density and parenchymal patterns in distinguishing between BRCA1/2 cases, unilateral cancer cases, and controls // J Med Imaging. 2014. Vol. 1, N 3. P. 031009. doi: 10.1117/1.JMI.1.3.031009
24. Goh V., Ganeshan B., Nathan P., et al. Assessment of response to tyrosine kinase inhibitors in metastatic renal cell cancer: CT texture as a predictive biomarker // Radiology. 2011. Vol. 261, N 1. P. 165–171. doi: 10.1148/radiol.11110264
25. Yip C., Davnall F., Kozarski R., et al. Assessment of changes in tumor heterogeneity following neoadjuvant chemotherapy in primary esophageal cancer // Dis Esophagus. 2015. Vol. 28, N 2. P. 172–179. doi: 10.1111/dote.12170
26. Park J.E., Kim H.S. Radiomics as a quantitative imaging biomarker: practical considerations and the current standpoint in neuro-oncologic studies // Nucl Med Mol Imaging. 2018. Vol. 52, N 2. P. 99–108. doi: 10.1007/s13139-017-0512-7
27. Сергунова К.А., Ахмад Е.С., Семенов Д.С., и др. Участие медицинских физиков в обеспечении контроля качества оборудования и безопасности пациентов при магнитно-резонансной томографии // Медицинская физика. 2020. № 3. С. 78–85.
28. Clements J.B., Baird C.T., de Boer S.F., et al. AAPM medical physics practice guideline 10.a.: Scope of practice for clinical medical physics // J Appl Clin Med Phys. 2018. Vol. 19, N 6. P. 11–25. doi: 10.1002/acm2.12469
29. Shukla-Dave A., Obuchowski N.A., Chenevert T.L., et al. Quantitative imaging biomarkers alliance (QIBA) recommendations for improved precision of DWI and DCE-MRI derived biomarkers in multicenter oncology trials // J Magn Reson Imaging. 2019. Vol. 49, N 7. P. e101–e121. doi: 10.1002/jmri.26518
30. Russek S.E., Boss M., Jackson E.F., et al. Characterization of NIST/ISMRM MRI System Phantom // Proc Intl Soc Mag Reson Med. 2012. Vol. 20. P. 2456.
31. Kuo M.D., Jamshidi N. Behind the numbers: Decoding molecular phenotypes with radiogenomics –guiding principles and technical considerations // Radiology. 2014. Vol. 270, N 2. P. 320–325. doi: 10.1148/radiol.13132195
32. Narang S., Lehrer M., Yang D., et al. Radiomics in glioblastoma: current status, challenges and potential opportunities // Transl Cancer Res. 2016. Vol. 5, N 4. P. 383–397. doi: 10.21037/tcr.2016.06.31
33. O'Connor J.P., Aboagye E.O., Adams J.E., et al. Imaging biomarker roadmap for cancer studies // Nat Rev Clin Oncol. 2017. Vol. 14, N 3. P. 169–186. doi: 10.1038/nrclinonc.2016.162
34. Buizza G., Toma-Dasu I., Lazzeroni M., et al. Early tumor response prediction for lung cancer patients using novel longitudinal pattern features from sequential PET/CT image scans // Phys Med. 2018. Vol. 54. P. 21–29. doi: 10.1016/j.ejmp.2018.09.003
35. Raunig D.L., McShane L.M., Pennello G., et al. Quantitative imaging biomarkers: a review of statistical methods for technical performance assessment // Stat Methods Med Res. 2015. Vol. 24, N 1. P. 27–67. doi: 10.1177/0962280214537344
36. Obuchowski N.A., Reeves A.P., Huang E.P., et al. Quantitative imaging biomarkers: a review of statistical methods for computer algorithm comparisons // Stat Methods Med Res. 2015. Vol. 24, N 1. P. 68–106. doi: 10.1177/0962280214537390
37. Elguindi S., Zelefsky M.J., Jiang J., et al. Deep learning-based auto-segmentation of targets and organs-at-risk for magnetic resonance imaging only planning of prostate radiotherapy // Phys Imaging Radiat Oncol. 2019. Vol. 12. P. 80–86. doi: 10.1016/j.phro.2019.11.006
38. Морозов С.П., Владзимирский А.В., Кляшторный В.Г., и др. Клинические испытания программного обеспечения на основе интеллектуальных технологий (лучевая диагностика). Методические рекомендации. Москва, 2019. 33 с.
39. Sullivan D.C., Obuchowski N.A., Kessler L.G., et al. Metrology standards for quantitative imaging biomarkers // Radiology. 2015. Vol. 277, N 3. P. 813–825. doi: 10.1148/radiol.2015142202
40. Shur J., Blackledge M., D'Arcy J., et al. MRI texture feature repeatability and image acquisition factor robustness, a phantom study and in silico study // Eur Radiol Exp. 2021. Vol. 5, N 1. P. 2. doi: 10.1186/s41747-020-00199-6
41. Bane O., Hectors S.J., Wagner M., et al. Accuracy, repeatability, and interplatform reproducibility of T1 quantification methods used for DCE-MRI: Results from a multicenter phantom study // Magn Reson Med. 2018. Vol. 79, N 5. P. 2564–2575. doi: 10.1002/mrm.26903

42. He Y., Liu Y., Dyer B.A., et al. 3D-printed breast phantom for multi-purpose and multi-modality imaging // Quant Imaging Med Surg. 2019. Vol. 9, N 1. P. 63–74. doi: 10.21037/qims.2019.01.05
43. Scheuermann J.S., Reddin J.S., Opanowski A., et al. Qualification of national cancer institute-designated cancer centers for quantitative PET/CT imaging in clinical trials // J Nucl Med. 2017. Vol. 58, N 7. P. 1065–1071. doi: 10.2967/jnumed.116.186759
44. Obuchowski N.A., Barnhart H.X., Buckler A.J., et al. Statistical issues in the comparison of quantitative imaging biomarker algorithms using pulmonary nodule volume as an example // Stat Methods Med Res. 2015. Vol. 24, N 1. P. 107–140. doi: 10.1177/0962280214537392
45. Kessler L.G., Barnhart H.X., Buckler A.J., et al. The emerging science of quantitative imaging biomarkers terminology and definitions for scientific studies and regulatory submissions // Stat Methods Med Res. 2015. Vol. 24, N 1. P. 9–26. doi: 10.1177/0962280214537333
46. Napel S., Mu W., Jardim-Perassi B.V., et al. Quantitative imaging of cancer in the postgenomic era: Radio(geno)mics, deep learning, and habitats // Cancer. 2018. Vol. 124, N 24. P. 4633–4649. doi: 10.1002/cncr.31630
47. Рожкова Н.И., Боженко В.К., Бурдина И.И., и др. Радиогеномика рака молочной железы — новый вектор междисциплинарной интеграции лучевых и молекулярно-биологических технологий (обзор литературы) // Медицинский алфавит. 2020. № 20. С. 21–29. doi: 10.33667/2078-5631-2020-20-21-29
48. Antropova N., Huynh B.Q., Giger M.L. A deep feature fusion methodology for breast cancer diagnosis demonstrated on three imaging modality datasets // Med Phys. 2017. Vol. 44, N 10. P. 5162–5171. doi: 10.1002/mp.12453
49. Antunovic L., Gallivanone F., Sollini M., et al. [^{18}F]FDG PET/CT features for the molecular characterization of primary breast tumors // Eur J Nucl Med Mol Imaging. 2017. Vol. 44, N 12. P. 1945–1954. doi: 10.1007/s00259-017-3770-9
50. Ha S., Park S., Bang J.I., et al. Metabolic radiomics for pretreatment ^{18}F-FDG PET/CT to characterize locally advanced breast cancer: histopathologic characteristics, response to neoadjuvant chemotherapy, and prognosis // Sci Rep. 2017. Vol. 7, N 1. P. 1556. doi: 10.1038/s41598-017-01524-7
51. Guo W., Li H., Zhu Y., et al. Prediction of clinical phenotypes in invasive breast carcinomas from the integration of radiomics and genomics data // J Med Imaging (Bellingham). 2015. Vol. 2, N 4. P. 041007. doi: 10.1117/1.JMI.2.4.041007
52. Saha A., Harowicz M.R., Grimm L.J., et al. A machine learning approach to radiogenomics of breast cancer: a study of 922 subjects and 529 DCE-MRI features // Br J Cancer. 2018. Vol. 119, N 4. P. 508–516. doi: 10.1038/s41416-018-0185-8
53. Dong Y., Feng Q., Yang W., et al. Preoperative prediction of sentinel lymph node metastasis in breast cancer based on radiomics of T2-weighted fat-suppression and diffusion-weighted MRI // Eur Radiol. 2018. Vol. 28, N 2. P. 582–591. doi: 10.1007/s00330-017-5005-7
54. Chan H.M., van der Velden B.H., Loo C.E., Gilhuijs K.G. Eigentumors for prediction of treatment failure in patients with early-stage breast cancer using dynamic contrast-enhanced MRI: a feasibility study // Phys Med Biol. 2017. Vol. 62, N 16. P. 6467–6485. doi: 10.1088/1361-6560/aa7dc5
55. Braman N.M., Etesami M., Prasanna P., et al. Intratumoral and peritumoral radiomics for the pretreatment prediction of pathological complete response to neoadjuvant chemotherapy based on breast DCE-MRI // Breast Cancer Res. 2017. Vol. 19, N 1. P. 57. doi: 10.1186/s13058-017-0846-1
56. Chamming's F., Ueno Y., Ferré R., et al. Features from computerized texture analysis of breast cancers at pretreatment MR imaging are associated with response to neoadjuvant chemotherapy // Radiology. 2018. Vol. 286, N 2. P. 412–420. doi: 10.1148/radiol.2017170143
57. Partridge S.C., Zhang Z., Newitt D.C., et al. Diffusion-weighted MRI findings predict pathologic response in neoadjuvant treatment of breast cancer: the ACRIN 6698 multicenter trial // Radiology. 2018. Vol. 289, N 3. P. 618–627. doi: 10.1148/radiol.2018180273
58. Park H., Lim Y., Ko E.S., et al. Radiomics signature on magnetic resonance imaging: association with disease-free survival in patients with invasive breast cancer // Clin Cancer Res. 2018. Vol. 24, N 19. P. 4705–4714. doi: 10.1158/1078-0432.CCR-17-3783
59. Nasrullah N., Sang J., Alam M.S., et al. Automated lung nodule detection and classification using deep learning combined with multiple strategies // Sensors (Basel). 2019. Vol. 19, N 17. P. 3722. doi: 10.3390/s19173722
60. Carter B.W., Godoy M.C., Erasmus J.J. Predicting malignant nodules from screening CTs // J Thorac Oncol. 2016. Vol. 11, N 12. P. 2045–2047. doi: 10.1016/j.jtho.2016.09.117
61. Aerts H.J., Velazquez E.R., Leijenaar R.T., et al. Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach // Nat Commun. 2014. Vol. 5. P. 4006. doi: 10.1038/ncomms5006
62. Zhou H., Dong D., Chen B., et al. Diagnosis of distant metastasis of lung cancer: based on clinical and radiomic features // Transl Oncol. 2018. Vol. 11, N 1. P. 31–36. doi: 10.1016/j.tranon.2017.10.010
63. Liu Y., Kim J., Balagurunathan Y., et al. Radiomic features are associated with EGFR mutation status in lung adenocarcinomas // Clin Lung Cancer. 2016. Vol. 17, N 5. P. 441–448.e6. doi: 10.1016/j.cllc.2016.02.001
64. Fave X., Zhang L., Yang J., et al. Delta-radiomics features for the prediction of patient outcomes in non-small cell lung cancer // Sci Rep. 2017. Vol. 7, N 1. P. 588. doi: 10.1038/s41598-017-00665-z
65. Coroller T.P, Agrawal V., Narayan V., et al. Radiomic phenotype features predict pathological response in non-small cell lung cancer // Radiother Oncol. 2016. Vol. 119, N 3. P. 480–486. doi: 10.1016/j.radonc.2016.04.004
66. Kickingereder P., Neuberger U., Bonekamp D., et al. Radiomic subtyping improves disease stratification beyond key molecular, clinical, and standard imaging characteristics in patients with glioblastoma // Neuro Oncol. 2018. Vol. 20, N 6. P. 848–857. doi: 10.1093/neuonc/nox188
67. Pérez-Beteta J., Molina-García D., Ortiz-Alhambra J.A., et al. Tumor surface regularity at MR imaging predicts survival and response to surgery in patients with glioblastoma // Radiology. 2018. Vol. 288, N 1. P. 218–225. doi: 10.1148/radiol.2018171051
68. Zhou Z., Chen L., Sher D., et al. Predicting lymph node metastasis in head and neck cancer by combining many-objective radiomics and 3-dimensioal convolutional neural network through evidential reasoning // Annu Int Conf IEEE Eng Med Biol Soc. 2018. Vol. 2018. P. 1–4. doi: 10.1109/EMBC.2018.8513070
69. Wang G., He L., Yuan C., et al. Pretreatment MR imaging radiomics signatures for response prediction to induction chemotherapy in patients with nasopharyngeal carcinoma // Eur J Radiol. 2018. Vol. 98. P. 100–106. doi: 10.1016/j.ejrad.2017.11.007

70. Chen X., Oshima K., Schott D., et al. Assessment of treatment response during chemoradiation therapy for pancreatic cancer based on quantitative radiomic analysis of daily CTs: An exploratory study // PLoS One. 2017. Vol. 12. P. e0178961. doi: 10.1371/journal.pone.0178961
71. Huang Y.Q., Liang C.H., He L., et al. Development and validation of a radiomics nomogram for preoperative prediction of lymph node metastasis in colorectal cancer // J Clin Oncol. 2016. Vol. 34, N 18. P. 2157–2164. doi: 10.1200/JCO.2015.65.9128
72. Lin Y.C., Lin G., Hong J.H., et al. Diffusion radiomics analysis of intratumoral heterogeneity in a murine prostate cancer model following radiotherapy: Pixelwise correlation with histology // J Magn Reson Imaging. 2017. Vol. 46, N 2. P. 483–489. doi: 10.1002/jmri.25583
73. Chaddad A., Kucharczyk M.J., Niazi T. Multimodal radiomic features for the predicting gleason score of prostate cancer // Cancers (Basel). 2018. Vol. 10, N 8. P. 249. doi: 10.3390/cancers10080249
74. Огнерубов Н.А., Шатов И.А., Шатов А.В. Радиогеномика и радиомика в диагностике злокачественных опухолей: обзор литературы // Вестник Тамбовского университета. Серия: Естественные и технические науки. 2017. Т. 22, № 6-2. С. 1453–1460. doi: 10.20310/1810-0198-2017-22-6-1453-1460

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