Systematic Review

Radiomics in Oncological PET Imaging: A Systematic Review—Part 1, Supradiaphragmatic Cancers

David Morland 1,2,3,4,*, Elizabeth Katherine Anna Triumbari 1, Luca Boldrini 5, Roberto Gatta 5,6,7, Daniele Pizzuto 1 and Salvatore Annunziata 1

Abstract: Radiomics is an upcoming field in nuclear oncology, both promising and technically challenging. To summarize the already undertaken work on supradiaphragmatic neoplasia and assess its quality, we performed a literature search in the PubMed database up to 18 February 2022. Inclusion criteria were: studies based on human data; at least one specified tumor type; supradiaphragmatic malignancy; performing radiomics on PET imaging. Exclusion criteria were: studies only based on phantom or animal data; technical articles without a clinically oriented question; fewer than 30 patients in the training cohort. A review database containing PMID, year of publication, cancer type, and quality criteria (number of patients, retrospective or prospective nature, independent validation cohort) was constructed. A total of 220 studies met the inclusion criteria. Among them, 119 (54.1%) studies included more than 100 patients, 21 studies (9.5%) were based on prospectively acquired data, and 91 (41.4%) used an independent validation set. Most studies focused on prognostic and treatment response objectives. Because the textural parameters and methods employed are very different from one article to another, it is complicated to aggregate and compare articles. New contributions and radiomics guidelines tend to help improving quality of the reported studies over the years.

Keywords: radiomics; artificial intelligence; brain tumors; head and neck tumors; lung tumors; breast tumors; thyroid nodules; thymic tumors

1. Introduction

The strive for personalized medicine, particularly in the oncological field, has led to the need to consider an ever-increasing amount of data to propose the most appropriate treatment at the most appropriate timing for each patient, so as to increase survival outcomes. Some recently arisen scientific fields are based on the measurement of biological molecules in a high-throughput way and attempt to comprehensively understand the underlying biology of systems of interest at the highest resolution possible [1]. The rationale of these so-called “omics” disciplines is to generate a reliable prognostic or predictive model for a certain condition, which should be more accurate than already existing models that were constructed based on conventionally collected clinical data [1]. The first “omic”
disciplines were born in the late 1980s and were represented by genomics, proteomics, and metabolomics. Their importance was soon so well acknowledged that an “Omics era” was recognized existing from the end of the twentieth century. Taking advantage of the digital transformation in healthcare, medical imaging also contributed to the edifice by proposing its own “omic” field, that went under the name of “radiomics”. Radiomics corresponds to the extraction of a high number of quantitative features from medical images, beyond the dimensional, uptake, or volume parameters traditionally used in radiology and nuclear medicine. Their extraction is based on a rigorous processing chain where each step can greatly influence the result [2] and hinder the reproducibility of the findings. Interestingly, a recent study aimed to evaluate 77 oncology-related radiomics studies by proposing an objective measurement of radiomics research quality and concluded that the overall scientific quality and reporting of radiomics was insufficient [3]. It highlighted the frequent absence of a validation cohort and underlined that the most frequent limitations to reproducibility were represented by frequently missing data, insufficient reporting of study objectives, blind assessment, and sample size. Moreover, a major criticism was addressed to the low frequency in which demonstration of clinical utility was explained in those onco-radiomics articles.

The large amount of data generated by radiomics can be difficult to handle for traditional statistical approaches. Artificial intelligence (AI), with its ability to identify patterns within a massive dataset, is highly useful in this setting. This term covers several interrelated categories, including machine learning, which refers to all modeling and prediction applications based on training data (e.g., logistic regression), and deep learning, a subcategory of machine learning based on a neural network that is supposed to reproduce—on a smaller scale—the functioning of a human brain [4]. One of the key points of AI is the training base, which must be large enough to avoid overfitting issues [5], or, in other words, to avoid that the model becomes too attuned to the training data and loses its applicability to any other dataset.

As a result of the increasing number of articles on radiomics in oncological Positron Emission Tomography (PET) imaging, we here provide a systematic review of the literature, with a particular focus on assessing the quality of articles. In this first part, we will consider only supradiaphragmatic malignancies, other cancers will be treated in part 2.

2. Materials and Methods

This systematic review of published literature was performed according to the reporting standards of the PRISMA-P statement [6]. It was not registered.

2.1. Search Strategy, Inclusion and Exclusion Criteria

We performed a literature search in the PubMed database to identify all eligible articles using the following formula:

(“PET” OR “positron”) AND (radiomics” OR “radiomic” OR “texture” OR “textural”) (1)

Results were admitted from 1 January 1990 up to and including 18 February 2022. Reviews were automatically identified using the article type options and removed from the extracted database.

Inclusion criteria were (Table 1): (1) studies based on human data, (2) studies specifying at least one supradiaphragmatic tumor type, and (3) studies performing radiomics on PET imaging. Exclusion criteria were: (1) studies not related to medical topics, (2) reviews, posters, editorials, comments, cases reports, (3) duplicates, (4) studies outside the oncological field or radiomics not performed on PET, (5) studies only based on phantom or animal data, (6) technical articles (optimization, robustness), without a clinically oriented question, (7) studies including fewer than 30 patients in the training cohort (for studies including multiple types of cancers, each cancer type was considered separately), (8) not strictly supradiaphragmatic malignancy (e.g., esophagus), (9) studies not in English, and (10) full text not available (Table 1).
Table 1. Inclusion and exclusion criteria (PICOS systematization).

| Parameter     | Inclusion Criteria                                                                 | Exclusion Criteria                                                                 |
|---------------|------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Patients      | Patients with any supradiaphragmatic cancer                                         | Patients with a not strictly supradiaphragmatic malignancy                          |
| Intervention  | Radiomics analysis on PET studies                                                   | Reviews, expert opinions, comments, letters to editor, case reports, studies on animals or phantoms, conference reports. Fewer than 30 patients. Studies with no outcomes reported. Published in any language other than English |
| Comparator    | Diagnostic performances                                                             |                                                                                     |
| Outcome       | Primary outcome measures, diagnostic accuracy, area under curve                     |                                                                                     |
| Study design  | Any trials, retrospective, prospective or concurrent cohort studies. At least 30 patients. Published in English. |                                                                                     |

2.2. Quality Assessment

Studies were assessed for quality based on three items:

1. The number of patients, estimating the risk of bias and overfitting: fewer than 50 patients (score 0), 50 to 100 patients (score 1), more than 100 patients (score 2);
2. The retrospective (score 0) or prospective (score 2) nature of the collection of data;
3. The use of a completely independent cohort for validation: no or k-folding—as it can expose to data leakage—(score 0), partition of the cohort between completely separated training and test set (score 1), external validation cohort (score 2).

A simple quality score (QS), consisting in the sum of the 3 previously stated items, was calculated. A maximum possible score of 6 meant high quality study design of the article. Mean and 95% confidence intervals (CI) of the quality scores were calculated for all database articles divided by year of publication.

Results from articles with a QS strictly lower than 3 were not considered in the result section.

2.3. Textural Parameters Used

The number of textural parameters that can be extracted in an image is huge. They can be grouped into several categories, which were assessed in this review [7,8]:

- Shape features: it is a purely geometric description of the segmented volume (metabolic tumoral volume, sphericity).
- First order features (also called histogram-based features): these parameters are based on the value of each voxel included in the segmented region without taking into account their spatial inter-relationships (maximum, minimum, average, standard deviation, etc.).
- Second order features: these parameters take into account the spatial interrelations between groups of pixels and are computed from texture matrices, calculated from the segmented region of interest [9]. Let us mention as an example Gray-level co-occurrence matrix (GLCM), which represents the frequency of occurrence of two intensity levels in neighboring voxels within a specific distance along a fixed direction or Gray-level run-length matrix (GLRLM), which encodes the size of homogenous runs for each image intensity.
- Higher order features: higher-order statistics features are computed after the application of specific mathematical transformations or filters [8].

2.4. Data Collection and Review

An Excel review database was generated. The database was filled in completely three times (two readings one week apart by one author and a second reading by a second one). Any discrepancies were corrected by consensus. The following parameters were extracted from each article:
3. Results

3.1. Discrepancies between the Two Reading Sessions

Eleven discrepancies between the two reading sessions of the database were encountered and led to a third reading: one duplicate was identified, two articles were misclassified regarding cancer subtype, eight discrepancies concerned patient number and presence of a validation cohort.

3.2. Searching Results

A total of 1180 studies were identified in the PubMed database, 239 of which were reviews and therefore automatically excluded. Of the remaining 941 studies, 537 more were excluded as 111 were off topic, 57 articles corresponded to undetected reviews or editorials, 7 were duplicates, 176 articles were not oncological or based on PET-radiomics, 27 were not human-based, 89 were technical articles, and 70 included fewer than 30 patients in the training cohort. A total of 404 articles were then sought for retrieval: 5 were not written in English, 17 articles had no full text available, and 162 studies dealt with non-supradiaphragmatic malignancies and were therefore excluded. Finally, 220 studies were included in this review (Figure 1). A study characteristics table is available in a separate file (Supplementary Table S1).

Figure 1. Flowchart of literature search and article selection.
3.3. Quality Assessments

Mean quality score of the articles was 2.05/6, with a constant improvement over the years (from 0.80 in 2014, to 1.96 in 2018, to 2.33 in 2021), as displayed in Table 2. A total of 119 (54.1%) studies included more than 100 patients each, 21 studies (9.5%) were based on prospectively acquired data, 91 (41.4%) articles described an independent validation set. The number of publications was found to increase each year (Table 2).

Table 2. Mean quality scores and number of publications per year on PET(CT) radiomics.

| Year | Quality Score (Mean-95%CI) | Number of Publications |
|------|---------------------------|------------------------|
| 2013 | 1 [-]                     | 2                      |
| 2014 | 0.80 [0;2.44]             | 5                      |
| 2015 | 1.33 [0;4.28]             | 6                      |
| 2016 | 1.86 [0;4.49]             | 7                      |
| 2017 | 1.72 [0;4.48]             | 18                     |
| 2018 | 1.96 [0;4.71]             | 28                     |
| 2019 | 1.88 [0;4.29]             | 42                     |
| 2020 | 2.31 [0.34;4.27]          | 50                     |
| 2021 | 2.33 [0.11;4.55]          | 52                     |
| 2022 *| 2.40 [0.29;4.51] *        | 10 *                   |

* partial data.

3.4. Textural Parameters Used

The vast majority of the included studies (n = 189, 85.9%) used both first and second-order textural parameters. Eight studies (3.6%) used only first-order parameters. Finally, 23 studies (10.5%) used higher order textural parameters.

3.5. Brain Cancers

A total of 23 of the 220 studies focused on oligodendrogliomas, gliomas, and glioblastomas [10–32] employing several PET tracers: 11C-Metionine (n = 7), 18F-FET (n = 7), 18F-FDG (n = 4), 18F-FDOPA (n = 3), 18F-FMISO (n = 1). These studies included an average of 78.4 patients (range: 32–160), 6/23 (26.1%) including more than 100 patients, 3/23 (13.0%) with prospective data and 8/23 (34.8%) with validation sets. Main subjects included mutations and phenotyping (9/23, 39.1%), prognosis assessment (7/23, 30.4%), and differentiation between progression and radionecrosis (4/23, 17.4%).

In particular, three studies describing more than 100 patients used radiomics to predict O6-methylguanine-DNA methyltransferase promoter methylation status [12], isocitrate dehydrogenase phenotype [15], and mutations in the telomerase reverse transcriptase promoter status [28], with encouraging results. As for differentiation between progression and radionecrosis, studies showed heterogeneous results both in terms of tracer and performance. Wang et al. [22] reported promising results with 11C-Metionine (160 patients—112 of which in the training cohort, AUC of 0.914), whereas Ahrari [31] noted a poor added value of PET radiomics using 18F-FDOPA PET in patients with high-grade glioma.

Finally, 2 additional studies [33,34] focused on brain metastases, QS was however low.

3.6. Head and Neck Cancer including Salivary Gland Cancers

A total of 48 articles met the inclusion criteria in the group of head and neck malignancies [35–82], 46/48 (95.8%) using 18F-FDG. Only 1 study out of 48 (2.1%) used 18F-FMISO [36] and 1/48 (2.1%) [42] used 18F-FLT. However, the conclusions of these two articles remain limited due to the small number of patients studied (between 30 and 35). Included articles had an average of 155.5 patients (range 30–707) with 24/48 (50.0%) studies including more than 100 patients and 24/48 (50.0%) using an independent validation cohort.

A vast majority of these articles (37/48, 77.1%) focused on prognostic issues by offering various and heterogeneous models. In a vast retrospective study on patients with nasopharyngeal carcinoma (470 patients in the training set and 237 in the test set),
Peng et al. [61] used a deep-learning approach to predict disease-free survival with a C-index of 0.754 (95% CI: 0.709–0.800) and potentially guide the induction chemotherapy. Notably, the only negative study was conducted by Ger et al. on a large monocentric population of 686 head and neck cancer patients, with the conclusion that radiomic features were not consistently associated with survival, neither in CT or PET images and even within patients undergoing the same imaging protocol [68].

Other articles focused on indirect prognosis factors such as human papillomavirus (HPV) positivity, as HPV-positive cancers have longer overall survival than HPV-negative ones [50]. In particular, Haider et al. tried to correlate radiomics findings with HPV-positivity in oropharyngeal squamous cell carcinoma: using 435 primary tumors (326 of which for training and the other 109 for validation), his model achieved an AUC of 0.83 [50].

One paper studied radiomics as a potential tool to assess node status: Chen et al. [39] used a model associating deep learning and radiomics to classify lymph nodes as normal, suspicious or involved, with a reported accuracy of 0.88.

For salivary gland cancers, radiomics was also studied for local control and overall survival, with good preliminary results [80–82]. However, the QS were low, ranging from 0 to 2.

3.7. Lung Cancer

PET radiomics in pulmonary oncology gathered 107 articles [83–189], all employing 18F-FDG. Only 8 studies included prospective cohorts (7.5%). The average number of patients included was 191.3 (range 30–1419) with 68/107 (63.6%) studies including more than 100 patients; 51/107 (47.7%) studies used dedicated validation cohorts. The main investigated topics were prognostic evaluation (50/107, 46.7%), benign versus malignant nodule characterization (13/107, 12.1%), epidermal growth factor receptor (EGFR) gene mutation prediction (12/107, 11.2%) and histological subtype prediction (9/107, 8%).

Among the most salient publications about tumor characterization, in a large study including 1419 patients (283 of whom in the testing set), Han et al. [131] developed a deep convolution neural network algorithm which achieved an accuracy of 0.841 for histologic subtype classification of non-small cell lung cancer. EGFR mutation detection, which conditions the use of dedicated targeted therapies, also benefitted from radiomics in a model developed by Chang et al. [90] on 583 patients (AUC: 0.84).

Radiomics was used for staging purposes by Zheng et al. [154], who used a radiomics-based model to predict mediastinal lymph node metastases in a population of 716 patients (501 of which included in the training cohort and the other 215 in the testing set): in the testing cohort, performances of the radiomics approach were significantly higher than clinical node staging (p = 0.037).

On the prognostic side, most studies focused on local control and treatment response prediction. Among them, a study on prospectively acquired data conducted by Mattonen et al. [88] (training: n = 145 patients; validation: n = 146 patients) was used to build a model that predicted recurrence/progression in non-small cell lung cancer (concordance of 0.74 in the testing set). A few studies have focused on the prediction of treatment side effects, especially radiation pneumonitis [93,139]. In the study conducted by Cui et al. [139], an externally validated deep learning model outperformed traditional normal tissue complication probability models in a multi-omics actuarial neural network architecture for prediction of radiation pneumonitis of grade 2 or higher.

3.8. Breast Cancer

We screened 32 publications on breast cancer [190–221], all employing 18F-FDG. The average number of enrolled patients was 126.8 (range 35–435), 18/32 (56.3%) studies including more than 100 patients; 3 studies (9.3%) were based on prospectively acquired data and 6/32 used an internal independent validation cohort (18.8%). Part of these studies was dedicated to investigating the correlation between texture parameters and immunohistochemical subtypes of breast cancer, in particular Liu et al. [210]. However,
in a prospective study including 171 patients, Groheux et al. [202] did not find a high discriminative power for PET-derived texture metrics.

Other studies [190,214] have investigated the added value of texture parameters for predicting response to neoadjuvant chemotherapy and suggest a trend toward improved prediction models. In the largest study included for breast cancer, Lee et al. [214] concluded that the predictive power of a model incorporating both clinicopathological and texture factors was significantly higher than that of a model with clinicopathological factors only (AUC 0.80 vs. 0.73 \( p = 0.007 \)).

3.9. Thyroid and Thymus

Six studies were available for thyroid tumors [222–227], all using 18F-FDG. The average number of patients was 89.0 (range 55–123); 3/6 (50.0%) studies included more than 100 patients, 1 was prospective and 1 used a validation cohort. Among them, 3/6 (50.0%) studies focused on 18F-FDG thyroid incidentalomas, 2 studies were interested in risk stratification in indeterminate thyroid nodules. The only study with a QS above 3, a prospective study of 123 patients conducted by de Koster et al. [225], reported no added value of radiomics for that purpose in 18F-FDG positive nodules.

Two retrospective studies were available for thymic epithelial tumors and 18F-FDG PET/CT [228,229], both including fewer than 50 patients and without validation cohorts.

4. Discussion

4.1. Quality Assessment and Textural Parameters Used

In this work, we considered 220 publications related to radiomics in supradiaphragmatic malignancies. Our composite score for the evaluation of the quality of the publications was low, estimated at 2.05/6, in good agreement with a previous work reporting low quality of radiomics publications [3]. Almost half of the publications had fewer than 100 patients, a number often cited as a threshold to avoid overfitting [230]. About 60% of the studies did not use an independent data set for model validation. This phenomenon, although explained by the difficulty of collecting data, limits the generalizability of the conclusions, as radiomics is dependent on acquisition protocols [2]. Although there are reserves about the quality of the work in previous publications, we observe an improvement over the years on our composite criterion combining the number of patients, the presence of a validation cohort, and the presence of prospective data. This improvement is probably due to the publication of guidelines and dedicated checklists to ensure proper methodology (e.g., the Image Biomarker Standardization Initiative [231] and the Radiomics Quality Score Checklist [232]).

In this review, most papers consider textural parameters up to second order. The consideration of higher order parameters is less frequently encountered (about 10%).

4.2. Trends and Topics

The number of studies on radiomics is exponentially increasing, relying on both machine learning and deep learning approaches. The most studied supradiaphragmatic cancers are, in order of frequency, lung cancer, head and neck cancers, and breast cancers. The majority of the studies here described focus on prognostic and treatment response objectives. 18F-FDG remains the most studied tracer, as expected due to its wide clinical use.

About brain tumors, PET radiomics and AI analysis could lead to a gain in more specific information on diagnosis and prognosis. Brain cancer patients usually have poor prognosis and new therapeutic strategies are needed to improve their outcomes [27]. PET radiomics and AI could help in the diagnosis of brain diseases with non-invasive methods and in the stratification of more aggressive histology at baseline, helping personalized and precision medicine in these conditions. Aminoacidic tracers [22,27] (e.g., 18F-DOPA, 11C-Methionine) and new targeted tracers could also increase the specificity of PET radiomics in certain diseases.
About lung tumors, PET radiomics and AI analysis have been widely evaluated in several settings. The number and the quality of available studies in the literature could help introducing these advanced systems in clinical practice. Probably, new studies should be focused on external validation cohorts to clearly assess the clinical usefulness of PET radiomics and AI in lung cancer, such as in distinguishing lung metastases and primary tumors with different histology and prognosis.

Similarly, for head and neck tumors, PET radiomics and AI analysis should spread in a clinical routine evaluation to definitively allow personalized and precision medicine for these patients. Some limitations emerged in 18F-FDG PET/CT applications in head and neck tumors for not being able to distinguish between inflammatory activation in some tissues and the localization of the tumor [47]. PET radiomics and AI analysis could help physicians to overcome these limitations.

In breast cancer, PET/CT has a great value for staging and restaging purposes [191]. The limited avidity of 18F-FDG in some primary breast tumors could be a limitation in the application of PET radiomics and AI analysis. Nevertheless, new tracers such as 18F-FAPI and monoclonal antibodies could be used in the near future to study the textural heterogeneity in primary breast tumors, thanks to PET radiomics and AI analysis. 18F-FDG PET/CT still has limited indications in thyroid cancer [226], mainly for restaging of differentiated carcinomas and staging of anaplastic carcinomas. Therefore, PET radiomics and AI analysis should be further evaluated.

Given the increasing number of immunotherapies in metastatic cancer from different primary tumors, PET radiomics and AI analysis may be considered to better evaluate cases of stable disease or pseudo-progression due to inflammatory reaction to immunomodulators, such as in lung cancer or breast cancer.

4.3. Limitations

Our review has a certain number of limitations: first, we set an arbitrary threshold of 30 patients to eliminate studies that were too exposed to an overfitting bias. One of the disadvantages of this selection is the potential elimination of rare pathologies from this review, as previously reported [233].

The scale used to assess the quality of the articles was practical but rather simplistic. This score made it possible to evaluate a large number of articles with a fairly high reproducibility (11 discrepancies between the reading sessions) at the expense of a thorough analysis of the methods.

Finally, and because the textural parameters and methods used are very different from one article to another, even for similar subjects or cancers it was challenging to aggregate and compare the articles between them.

5. Conclusions

Radiomics and AI are upcoming fields in nuclear oncology, especially in brain, head and neck, thyroid, and breast cancers. Although technically demanding, new contributions with robust validation cohorts and guidelines for clinical practice applications will surely continue helping to improve the quality and the impact of the reported studies over the years.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/diagnostics12061329/s1, Table S1: A study characteristics table.

Author Contributions: Conceptualization, D.M. and E.K.A.T.; methodology, D.M.; validation, D.M., E.K.A.T., L.B., R.G., D.P. and S.A.; resources, S.A.; data curation, D.M.; writing—original draft preparation, D.M.; writing—review and editing, E.K.A.T., L.B., R.G., D.P. and S.A.; supervision, S.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.
Data Availability Statement: The datasets generated during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Micheel, C.M.; Institute of Medicine (Eds.) Omics-Based Clinical Discovery: Science, Technology, and Applications. In Evolution of Translational Omics: Lessons Learned and the Path Forward; National Academies Press: Washington, DC, USA, 2012; pp. 33–63. ISBN 978-0-309-22418-5.

2. van Timmeren, J.E.; Cester, D.; Tanadini-Lang, S.; Alkadhi, H.; Baesler, B. Radiomics in Medical Imaging—“How-to” Guide and Critical Reflection. Insights Imaging 2020, 11, 91. [CrossRef] [PubMed]

3. Park, J.E.; Kim, D.; Kim, H.S.; Park, S.Y.; Kim, J.Y.; Cho, S.J.; Shin, J.H.; Kim, J.H. Quality of Science and Reporting of Radiomics in Oncologic Studies: Room for Improvement According to Radiomics Quality Score and TRIPOD Statement. Eur. Radiol. 2020, 30, 523–536. [CrossRef] [PubMed]

4. Shiyam Sundar, L.K.; Muzik, O.; Buvat, I.; Bidaut, L.; Beyer, T. Potentials and Caveats of AI in Hybrid Imaging. Methods 2021, 188, 4–19. [CrossRef] [PubMed]

5. Hatt, M.; Cheze Le Rest, C.; Antonorsi, N.; Tixier, F.; Tankyevych, O.; Jaouen, V.; Lucia, F.; Bourbonnais, V.; Schick, U.; Badic, B.; et al. Radiomics in PET/CT: Current Status and Future AI-Based Evolutions. Semin. Nucl. Med. 2021, 51, 126–133. [CrossRef]

6. PRISMA-P Group; Moher, D.; Shamseer, L.; Clarke, M.; Ghersi, D.; Liberati, A.; Petticrew, M.; Shekelle, P.; Stewart, L.A. Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) 2015 Statement. Syst. Rev. 2015, 4, 1. [CrossRef]

7. Papadimitroulas, P.; Brocki, L.; Christopher Chung, N.; Marchadour, W.; Vermet, F.; Gaubert, L.; Eleftheriadis, V.; Plachouris, D.; Visvikis, D.; Kagadis, G.C.; et al. Artificial Intelligence: Deep Learning in Oncological Radiomics and Challenges of Interpretablity and Data Harmonization. Phys. Med. 2021, 83, 108–121. [CrossRef]

8. Lohmann, P.; Bousabarah, K.; Hoevels, M.; Treuer, H. Radiomics in Radiation Oncology—Basics, Methods, and Limitations. Strahlenther. Onkol. 2020, 196, 848–855. [CrossRef]

9. Haralick, R.M.; Shanmugam, K.; Dinstein, I. Textural Features for Image Classification. IEEE Trans. Syst. Man Cybern. 1973, 3SC-3, 610–621. [CrossRef]

10. Zhao, K.; Yu, P.; Xue, Z.; Liu, J.; Yao, A.; Zhao, Y.; Yang, F.; Tian, J.; Xu, B.(11)C-Methionine Integrated PET/MRI-Based Texture Analysis May Have a Potential Ability to Distinguish Oligodendroglioma (IDH-Mutant and 1p/19q-Codeleted) from Varied Gliomas. Acad. Radiol. 2020, 27, e159–e167. [CrossRef]

11. Kong, Z.; Jiang, C.; Zhu, R.; Feng, S.; Wang, Y.; Li, J.; Chen, W.; Liu, P.; Zhao, D.; Ma, W.; et al. (18)F-FDG-PET-Based Radiomics Features to Distinguish Primary Central Nervous System Lymphoma from Glioblastoma. NeuroImage Clin. 2019, 23, 101912. [CrossRef]

12. Kong, Z.; Lin, Y.; Jiang, C.; Li, L.; Liu, Z.; Wang, Y.; Dai, C.; Liu, D.; Qin, X.; Wang, Y.; et al. (18)F-FDG-PET-Based Radiomics Signature Predicts MGMT Promoter Methylation Status in Primary Diffuse Glioma. Cancer Imaging Off. Publ. Int. Cancer Imaging Soc. 2019, 19, 58. [CrossRef]

13. Zaragori, T.; Oster, J.; Roch, V.; Hossu, G.; Chawkli, M.B.; Grignon, R.; Pouget, C.; Gauchotte, G.; Rech, F.; Blonski, M.; et al. (18)F-FDOPA PET for the Noninvasive Prediction of Glioma Molecular Parameters: A Radiomics Study. J. Nucl. Med. Off. Publ. Soc. Nucl. Med. 2022, 63, 147–157. [CrossRef]

14. Hotta, M.; Minamimoto, R.; Miwa, K. 11C-Methionine-PET for Differentiating Recurrent Brain Tumor from Radiation Necrosis: Potential Grading Discrimination Using a Machine Learning Model. Curr. Oncol. Tor. Ont. 2021, 28, 5318–5331. [CrossRef]

15. Li, L.; Mu, W.; Wang, Y.; Liu, Z.; Liu, Z.; Wang, Y.; Ma, W.; Kong, Z.; Wang, S.; Zhou, X.; et al. A Non-Invasive Radiomic Method Using (18)F-FDG PET Predicts Isocitrate Dehydrogenase Genotype and Prognosis in Patients With Glioma. Front. Oncol. 2019, 9, 1183. [CrossRef]

16. Muzi, M.; Wolsztynski, E.; Fink, J.R.; O’Sullivan, J.N.; O’Sullivan, F.; Krohn, K.A.; Mankoff, D.A.; Assessment of the Prognostic Value of Radiomic Features in (18)F-FMISO PET Imaging of Hypoxia in Postsurgery Brain Cancer Patients: Secondary Analysis of Imaging Data from a Single-Center Study and the Multicenter ACRIN 6684 Trial. Tomogr. Ann. Arbor. Mich. 2020, 6, 14–22. [CrossRef]

17. Russo, G.; Stefano, A.; Alongi, P.; Comelli, A.; Catalfamo, B.; Mantarro, C.; Longo, C.; Altieri, R.; Certo, F.; Cosentino, S.; et al. Feasibility on the Use of Radiomics Features of 11C-MET PET/CT in Central Nervous System Tumours: Preliminary Results on Potential Grading Discrimination Using a Machine Learning Model. Curr. Oncol. Tor. Ont. 2021, 28, 5318–5331. [CrossRef]

18. Lohmann, P.; Elahmadawy, M.A.; Gutsche, R.; Werner, J.-M.; Bauer, E.K.; Ceccon, G.; Kocher, M.; Lerche, C.W.; Rapp, M.; Fink, G.R.; et al. FET PET Radiomics for Differentiating Pseudoprogression from Early Tumor Progression in Glioma Patients Post-Chemoradiation. Cancers 2020, 12, 3835. [CrossRef]

19. Carles, M.; Popp, I.; Starke, M.M.; Mix, M.; Urbach, H.; Schimek-Jash, T.; Eckert, F.; Niyazi, M.; Baltas, D.; Grosu, A.L. FET-PET Radiomics in Prognostic Recursive Outcome for After Re-Irradiation? Radiat. Oncol. 2021, 16, 46. [CrossRef]

20. Papp, L.; Pötsch, N.; Grahovac, M.; Schmidbauer, V.; Woehrler, A.; Preussner, M.; Mitterhauser, M.; Kiesel, B.; Wadsak, W.; Beyer, T.; et al. Glioma Survival Prediction with Combined Analysis of In Vivo (11)C-MET PET Features, Ex Vivo Features, and Patient Features by Supervised Machine Learning. J. Nucl. Med. Off. Publ. Soc. Nucl. Med. 2018, 59, 892–899. [CrossRef]
21. Yu, P.; Ning, J.; Xu, B.; Liu, J.; Dang, H.; Lin, M.; Feng, X.; Grimm, R.; Tian, J. Histogram Analysis of 11C-Methionine Integrated PET/MRI May Facilitate to Determine the O6-Methylguanayethyltransferase Methylation Status in Gliomas. *Nucl. Med. Commun.* **2019**, *40*, 850–856. [CrossRef]

22. Wang, K.; Qiao, Z.; Zhao, X.; Li, X.; Wang, X.; Wu, T.; Chen, Z.; Fan, D.; Chen, Q.; Ai, L. Individualized Discrimination of Tumor Recurrence from Radiation Necrosis in Glioma Patients Using an Integrated Radiomics-Based Model. *Eur. J. Nucl. Med. Mol. Imaging* **2020**, *47*, 1400–1411. [CrossRef]

23. Zhou, W.; Huang, Q.; Wen, J.; Li, M.; Zhu, Y.; Liu, Y.; Dai, Y.; Guan, Y.; Zhou, Z.; Hua, T. Integrated CT Radiomics Features Could Enhance the Efficacy of (18)F-PET PET for Non-Invasive Isoitcinate Dehydrogenase Genotype Prediction in Adult Untreated Gliomas: A Retrospective Cohort Study. *Front. Oncol.* **2021**, *11*, 772073. [CrossRef]

24. Mitamura, K.; Yamamoto, Y.; Kudomi, N.; Maeda, Y.; Norikane, T.; Miyake, K.; Nishiya, Y. Intratumoral Heterogeneity of (18)F-FLT Uptake Predicts Proliferation and Survival in Patients with Newly Diagnosed Gliomas. *Ann. Nucl. Med.* **2017**, *31*, 46–52. [CrossRef]

25. Haubold, J.; Demircioglu, A.; Gratz, M.; Glas, M.; Wrede, K.; Sure, U.; Antoch, G.; Keyvani, K.; Nittka, M.; Kannengiesser, S.; et al. Non-Invasive Tumor Decoding and Phenotyping of Cerebral Gliomas Utilizing Multiparametric (18)F-PET-MRI and MR Fingerprinting. *Eur. J. Nucl. Med. Mol. Imaging* **2020**, *47*, 1435–1445. [CrossRef]

26. Lohmann, P.; Lerche, C.; Bauer, E.K.; Steger, J.; Stoffels, G.; Blau, T.; Dunkl, V.; Kocher, M.; Viswanathan, S.; Filss, C.P.; et al. Predicting IDH Genotype in Gliomas Using Radiomics. *Acta Oncol.* **2020**, *48*, 1339–1346. [CrossRef]

27. Qian, J.; Herman, M.G.; Brinkmann, D.H.; Laack, N.N.; Kemp, B.J.; Hunt, C.H.; Lowe, V.; Pafundi, D.H. Prediction of MGMT Status for Glioblastoma Patients Using Radiomics Feature Extraction from (18)F-DOPA PET Imaging. *Int. J. Radiat. Oncol. Biol. Phys.* **2020**, *108*, 1339–1346. [CrossRef]

28. Li, Z.; Kaiser, L.; Holzgreve, A.; Ruf, V.C.; Suchorska, B.; Wenter, V.; Quach, S.; Herms, J.; Bartenstein, P.; Tonn, J.-C.; et al. Prediction of TERTp-Mutation Status in IDH-Wildtype High-Grade Gliomas Using Pre-Treatment Dynamic [(18)F]FET PET Radiomics. *Eur. J. Nucl. Med. Mol. Imaging* **2021**, *48*, 4415–4425. [CrossRef]

29. Manabe, O.; Yamaguchi, S.; Hirata, K.; Kobayashi, K.; Kobayashi, H.; Terasaka, S.; Toyonaga, T.; Magota, K.; Kuge, Y.; Tamaki, N.; et al. Preoperative Texture Analysis Using (11)C-Methionine Positron Emission Tomography Predicts Survival after Surgery for Gliomas. *Diagnoses* **2021**, *11*, 189. [CrossRef]

30. Kong, Z.; Li, J.; Liu, Z.; Liu, Z.; Zhao, D.; Cheng, X.; Li, L.; Lin, Y.; Wang, Y.; Tian, J.; et al. Radiomics Signature Based on FDG-PET Predicts Proliferative Activity in Primary Glioma. *Clin. Radiol.* **2019**, *74*, 815.e15–815.e23. [CrossRef]

31. Ahrari, S.; Zaragori, T.; Rozenblum, L.; Oster, J.; Imbert, L.; Kas, A.; Verger, A. Relevance of Dynamic (18)F-DOPA PET Radiomics for Differentiation of High-Grade Glioma Progression from Treatment-Related Changes. *Biomedicines* **2021**, *9*, 1924. [CrossRef]

32. Pyka, T.; Gempt, J.; Hiobi, D.; Ringel, F.; Schlegel, J.; Bette, S.; Wester, H.-J.; Meyer, B.; Förster, S. Textural Analysis of Pre-Therapeutic [(18)F]-FET-PET and Its Correlation with Tumor Grade and Patient Survival in High-Grade Gliomas. *Eur. J. Nucl. Med. Mol. Imaging* **2016**, *43*, 133–141. [CrossRef] [PubMed]

33. Lohmann, P.; Kocher, M.; Ceccon, G.; Bauer, E.K.; Stoffels, G.; Viswanathan, S.; Ruge, M.I.; Neumaier, B.; Shah, N.J.; Fink, G.R.; et al. Combined PET/CT/MRI Radiomics Differentiates Radiation Injury from Recurrent Brain Metastasis. *Neuroimage Clin.* **2018**, *20*, 537–542. [CrossRef] [PubMed]

34. Lohmann, P.; Stoffels, G.; Ceccon, G.; Rapp, M.; Sabel, M.; Filss, C.P.; Kamp, M.A.; Stegmayr, C.; Neumaier, B.; Shah, N.J.; et al. Radiation Injury vs. Recurrent Brain Metastasis: Combining Textural Feature Radiomics Analysis and Standard Parameters May Increase (18)F-PET PET Accuracy without Dynamic Scans. *Eur. Radiol.* **2017**, *27*, 2916–2927. [CrossRef] [PubMed]

35. van Dijk, L.V.; Noordzij, W.; Brouwer, C.L.; Boellaard, R.; Burgerhof, J.G.M.; Langendijk, J.A.; Sijtsema, N.M.; Steenbakkers, R.J.H.M. (18)F-FDG PET Image Biomarkers Improve Prediction of Late Radiation-Induced Xerostomia. *Radiother. Oncol. J. Eur. Soc. Ther. Radiol. Oncol.* **2018**, *126*, 89–95. [PubMed]

36. Carles, M.; Fechter, T.; Grosu, A.L.; Sörensen, A.; Thomann, B.; Stoian, R.G.; Wiedenmann, N.; Rühle, A.; Zamboglou, C.; Ruf, J.; et al. (18)F-FMISO-PET Hypoxia Monitoring for Head-and-Neck Cancer Patients: Radiomics Analyses Predict the Outcome of Chemo-Radiotherapy. *Cancers* **2021**, *13*, 3449. [CrossRef]

37. Wang, K.; Zhou, Z.; Wang, R.; Chen, L.; Zhang, Q.; Sher, D.; Wang, J. A Multi-Objective Radiomics Model for the Prediction of Locoregional Recurrence in Head and Neck Squamous Cell Cancer. *Med. Phys. 2020*, *47*, 5392–5400. [CrossRef]

38. Chen, R.-Y.; Lin, Y.-C.; Shen, W.-C.; Hsieh, T.-C.; Yen, K.-Y.; Chen, S.-W.; Kao, C.-H. Correlation of Pretreatment (18)F-FDG PET Tumor Textural Features with Gene Expression in Pharyngeal Cancer and Implications for Radiotherapy-Based Treatment Outcomes. *Eur. J. Nucl. Med. Mol. Imaging* **2017**, *44*, 567–580. [CrossRef]
42. Ulrich, E.J.; Menda, Y.; Boles Ponto, L.L.; Anderson, C.M.; Smith, B.J.; Sunderland, J.J.; Graham, M.M.; Buatti, J.M.; Beichel, R.R. FLT PET Radiomics for Response Prediction to Chemoradiation Therapy in Head and Neck Squamous Cell Cancer. *Tomography* 2019, 5, 161–169. [CrossRef]

43. Shiri, I.; Arabi, H.; Sanaat, A.; Jenabi, E.; Becker, M.; Zaidi, H. Fully Automated Gross Tumor Volume Delineation From PET in Head and Neck Cancer Using Deep Learning Algorithms. *Clin. Nucl. Med.* 2021, 46, 872–883. [CrossRef]

44. Fujima, N.; Hirata, K.; Shiga, T.; Li, R.; Yasuda, K.; Onimaru, R.; Tsuchiya, K.; Kano, S.; Mizumachi, T.; Homma, A.; et al. Integrating Quantitative Morphological and Intratumoral Textural Characteristics in FDG-PET for the Prediction of Prognosis in Pharynx Squamous Cell Carcinoma Patients. *Clin. Radiol.* 2018, 73, 1059.e1–1059.e8. [CrossRef]

45. Choi, J.W.; Lee, D.; Hyun, S.H.; Han, M.; Kim, J.-H.; Lee, S.J. Intratumoural Heterogeneity Measured Using FDG PET and MRI Is Associated with Tumour-Stroma Ratio and Clinical Outcome in Head and Neck Squamous Cell Carcinoma. *Clin. Radiol.* 2017, 72, 482–489. [CrossRef]

46. Lafia, K.J.; Chang, Y.; Wang, C.; Mowery, Y.M.; Vergalasova, I.; Niedzwiecki, D.; Yoo, D.S.; Liu, J.-G.; Brizel, D.M.; Yin, F.-F. Intrinsic Radiomic Expression Patterns after 20 Gy Demonstrate Early Metabolic Response of Oropharyngeal Cancers. *Med. Phys.* 2021, 48, 3767–3777. [CrossRef]

47. Du, D.; Feng, H.; Lv, W.; Ashrafinia, S.; Yuan, Q.; Wang, Q.; Yang, W.; Feng, Q.; Chen, W.; Rahimim, A.; et al. Machine Learning Methods for Optimal Radiomics-Based Differentiation Between Recurrence and Inflammation: Application to Nasopharyngeal Carcinoma Post-Therapy PET/CT Images. *Mol. Imaging Biol.* 2020, 22, 730–738. [CrossRef]

48. Zhong, J.; Frood, R.; Brown, P.; Nelstrop, H.; Prestwich, R.; McDermott, G.; Currie, S.; Vaidyanathan, S.; Scarsbrook, A.F. Machine Learning-Based FDG PET-CT Radiomics for Outcome Prediction in Larynx and Hypopharynx Squamous Cell Carcinoma. *Clin. Radiol.* 2021, 76, 78.e9–78.e17. [CrossRef]

49. Lv, W.; Ashrafinia, S.; Ma, J.; Lu, L.; Rahimim, A. Multi-Level Multi-Modality Fusion Radiomics: Application to PET and CT Imaging for Prognostication of Head and Neck Cancer. *IEEE J. Biomed. Health Inform.* 2020, 24, 2268–2277. [CrossRef]

50. Haider, S.P.; Mahajan, A.; Zeevi, T.; Baumeister, P.; Reichel, C.; Sharaf, K.; Forghani, R.; Kucukkaya, A.S.; Kann, B.H.; Judson, B.L.; et al. PET/CT Radiomics Signature of Human Papilloma Virus Association in Oropharyngeal Squamous Cell Carcinoma. *Eur. J. Nucl. Med. Mol. Imaging* 2020, 47, 2978–2991. [CrossRef]

51. Bogowicz, M.; Leijenaar, R.T.H.; Tanadini-Lang, S.; Riesterer, O.; Pruschy, M.; Studer, G.; Unkelbach, J.; Guckenberger, M.; Konukoglu, E.; Lambin, P. Post-Radiochemotherapy PET Radiomics in Head and Neck Cancer—The Influence of Radiomics Implementation on the Reproducibility of Local Control Tumor Models. *Radiother. Oncol. J. Eur. Soc. Ther. Radiol.* Oncol. 2017, 125, 385–391. [CrossRef]

52. Haider, S.P.; Zeevi, T.; Baumeister, P.; Reichel, C.; Sharaf, K.; Forghani, R.; Kann, B.H.; Judson, B.L.; Prasad, M.L.; Burtness, B.; et al. Potential Added Value of PET/CT Radiomics for Survival Prognostication beyond AJCC 8th Edition Staging in Oropharyngeal Squamous Cell Carcinoma. *Cancers* 2020, 12, 1778. [CrossRef]

53. Crispin-Ortuzar, M.; Apte, A.; Grkovski, M.; Oh, J.H.; Lee, N.Y.; Schöder, H.; Humm, J.L.; Deasy, J.O. Predicting Hypoxia Status Using a Combination of Contrast-Enhanced Computed Tomography and [(18)F]-Fluorodeoxyglucose Positron Emission Tomography Radiomics Features. *Radiother. Oncol. J. Eur. Soc. Ther. Radiol.* Oncol. 2018, 127, 36–42. [CrossRef]

54. Peng, L.; Hong, X.; Yuan, Q.; Lu, L.; Wang, C.; Chen, W. Prediction of Local Recurrence and Distant Metastasis Using Radiomics Analysis of Pretreatment Nasopharyngeal [18F]FDG PET/CT Images. *Ann. Nucl. Med.* 2021, 35, 458–468. [CrossRef]

55. Haider, S.P.; Sharaf, K.; Zeevi, T.; Baumeister, P.; Reichel, C.; Forghani, R.; Kann, B.H.; Petukhova, A.; Judson, B.L.; Prasad, M.L.; et al. Prediction of Post-Radiotherapy Locoregional Progression in HPV-Associated Oropharyngeal Squamous Cell Carcinoma Using Machine-Learning Analysis of Baseline PET/CT Radiomics. *Transl. Oncol.* 2021, 14, 100906. [CrossRef]

56. Ghosh, S.; Maulik, S.; Chatterjee, S.; Mallick, I.; Chakravorty, N.; Homma, A.; et al. Prediction of Post-Radiotherapy Locoregional Progression in HPV-Associated Oropharyngeal Squamous Cell Carcinoma Using Machine-Learning Analysis of Baseline PET/CT Radiomics. *Transl. Oncol.* 2021, 76, 711.e1–711.e7. [CrossRef]

57. Folkert, M.R.; Setton, J.; Apte, A.P.; Grkovski, M.; Young, R.J.; Schöder, H.; Thorstad, W.L.; Lee, N.Y.; Deasy, J.O.; Oh, J.H. Predictive Modeling of Outcomes Following Definitive Chemoradiation for Oropharyngeal Cancer Based on FDG-PET Image-Based Multimetric Approach. In Patients with Oral Cavity Squamous Cell Carcinoma. *Clin. Radiol.* 2021, 76, 711.e1–711.e7. [CrossRef]

58. Martens, R.M.; Koopman, T.; Noij, D.P.; Paehleer, E.; Ubelhör, C.; Sharma, S.; Vergeer, M.R.; Leemans, C.R.; Hoekstra, O.S.; Yaqub, M.; et al. Predictive Value of Quantitative (18)F-FDG PET-Radiomics Analysis in Patients with Head and Neck Squamous Cell Carcinoma. *EJNMMI Res.* 2020, 10, 102. [CrossRef]

59. Lin, H.-C.; Chan, S.-C.; Cheng, N.-M.; Liao, C.-T.; Hsu, C.-L.; Wang, H.-M.; Lin, C.-Y.; Chang, J.T.-C.; Ng, S.-H.; Yang, L.-Y.; et al. Pretreatment (18)F-FDG PET/CT Texture Parameters Provide Complementary Information to Epstein-Barr Virus DNA Titers in Patients with Metastatic Nasopharyngeal Carcinoma. *Oral Oncol.* 2020, 104, 104628. [CrossRef]

60. Peng, H.; Dong, D.; Fang, M.-J.; Li, L.; Tang, L.-L.; Chen, L.; Li, W.-F.; Mao, Y.-P.; Fan, W.; Liu, L.-Z.; et al. Prognostic Value of Deep Learning PET/CT-Based Radiomics: Potential Role for Future Individual Induction Chemotherapy in Advanced Nasopharyngeal Carcinoma. *Clin. Cancer Res. Off. J. Am. Assoc. Cancer Res.* 2019, 25, 4271–4279. [CrossRef]
62. Guzennec, C.; Robin, P.; Orlhac, F.; Bourhis, J.; Delcroix, O.; Gobel, Y.; Roussel, J.; Schick, U.; Salatin, P.-Y.; Abgral, R. Prognostic Value of Textural Indices Extracted from Pretherapeutic 18-F FDG PET/CT in Head and Neck Squamous Cell Carcinoma. *Head Neck* 2019, 41, 495–502. [CrossRef] [PubMed]

63. Yoon, H.; Ha, S.; Kwon, S.J.; Park, S.Y.; Kim, J.; Yoo, I.R. Prognostic Value of Tumor Metabolic Imaging Phenotype by FDG PET Radiomics in HNSCC. *Ann. Nucl. Med.* 2021, 35, 370–377. [CrossRef] [PubMed]

64. Feliciani, G.; Fioroni, F.; Grassi, E.; Bertolini, M.; Rosca, A.; Timon, G.; Galaverni, M.; Iotti, C.; Versari, A.; Iori, M.; et al. Radiomic Profiling of Head and Neck Cancer: (18)F-FDG PET Texture Analysis as Predictor of Patient Survival. *Contrast Media Mol. Imaging* 2018, 2018, 3574310. [CrossRef] [PubMed]

65. Feng, Q.; Liang, J.; Wang, L.; Niu, J.; Ge, X.; Pang, P.; Ding, Z. Radiomics Analysis and Correlation With Metabolic Parameters in Nasopharyngeal Carcinoma Based on PET/CT Imaging. *Front. Oncol.* 2020, 10, 1619. [CrossRef] [PubMed]

66. Lv, W.; Yuan, Q.; Wang, Q.; Ma, J.; Feng, Q.; Chen, W.; Rahmim, A.; Lu, L. Radiomics Analysis of PET and CT Components of PET/CT Imaging Integrated with Clinical Parameters: Application to Prognosis for Nasopharyngeal Carcinoma. *Mol. Imaging Biol.* 2019, 21, 954–964. [CrossRef] [PubMed]

67. Liao, K.Y.-K.; Chiu, C.-C.; Chiang, W.-C.; Chiou, Y.-R.; Zhang, G.; Yang, S.-N.; Huang, T.-C. Radiomics Features Analysis of PET Images in Oropharyngeal and Hypopharyngeal Cancer. *Medicine* 2019, 98, e15446. [CrossRef] [PubMed]

68. Ger, R.B.; Zhou, S.; Elgohari, B.; Elhalawani, H.; Mackin, D.M.; Meier, J.G.; Nguyen, C.M.; Anderson, B.M.; Gay, C.; Ning, J.; et al. Radiomics Features of the Primary Tumor Fail to Improve Prediction of Overall Survival in Large Cohorts of CT- and PET-Imaged Head and Neck Cancer Patients. *PloS ONE* 2019, 14, e0222509. [CrossRef]

69. Vallières, M.; Kay-Rivest, E.; Perrin, L.J.; Liem, X.; Furstoss, C.; Aerts, H.J.W.L.; Khaouam, N.; Nguyen-Tan, P.F.; Wang, C.-S.; Sultanem, K.; et al. Radiomics Strategies for Risk Assessment of Tumour Failure in Head-and-Neck Cancer. *Sci. Rep.* 2017, 7, 10117. [CrossRef]

70. Liu, Z.; Cao, Y.; Diao, W.; Cheng, Y.; Jia, Z.; Peng, X. Radiomics-Based Prediction of Survival in Patients with Head and Neck Squamous Cell Carcinoma Based on Pre- and Post-Treatment (18)F-FDG PET/CT Imaging. *Aging* 2020, 12, 14593–14619. [CrossRef]

71. Lv, W.; Yuan, Q.; Wang, Q.; Ma, J.; Jiang, J.; Yang, W.; Feng, Q.; Chen, W.; Rahmim, A.; Lu, L. Robustness versus Disease Differentiation When Varying Parameter Settings in Radiomics Features: Application to Nasopharyngeal PET/CT. *Eur. Radiol.* 2018, 28, 3245–3254. [CrossRef]

72. Xu, H.; Lv, W.; Feng, H.; Du, D.; Yuan, Q.; Wang, Q.; Dai, Z.; Yang, W.; Feng, Q.; Ma, J.; et al. Subregional Radiomics Analysis of PET/CT Imaging with Intra-tumor Partitioning: Application to Prognosis for Nasopharyngeal Carcinoma. *Mol. Imaging Biol.* 2020, 22, 1414–1426. [CrossRef]

73. Chen, S.-W.; Shen, W.-C.; Hsieh, T.-C.; Liang, J.-A.; Hung, Y.-C.; Yeh, L.-S.; Chang, W.-C.; Lin, W.-C.; Yen, K.-Y.; Kao, C.-H. Textural Features of Cervical Cancers on FDG-PET/CT Associate with Survival and Local Relapse in Patients Treated with Definitive Chemoradiotherapy. *Sci. Rep.* 2018, 8, 11859. [CrossRef]

74. Cheng, N.-M.; Fang, Y.-H.D.; Chang, J.T.C.; Huang, C.-G.; Tsan, D.-L.; Ng, S.-H.; Wang, H.-M.; Lin, C.-Y.; Liao, C.-T.; Yen, T.-C. Textural Features of Pretreatment 18F-FDG PET/CT Images: Prognostic Significance in Patients with Advanced T-Stage Oropharyngeal Squamous Cell Carcinoma. *J. Nucl. Med. Off. Publ. Soc. Nucl. Med.* 2013, 54, 1703–1709. [CrossRef]

75. Wang, C.-K.; Chan, S.-C.; Ng, S.-H.; Hsieh, C.-H.; Cheng, N.-M.; Yen, T.-C.; Liao, C.-T. Textural Features on 18F-FDG PET/CT and Dynamic Contrast-Enhanced MRI for Predicting Treatment Response and Survival of Patients with Hypopharyngeal Carcinoma. *Medicine* 2019, 98, e16608. [CrossRef]

76. Kimura, M.; Kato, I.; Ishibashi, K.; Sone, Y.; Nagoa, T.; Umemura, M. Texture Analysis Using Preoperative Positron Emission Tomography Images May Predict the Prognosis of Patients With Resectable Oral Squamous Cell Carcinoma. *J. Oral Maxillofac. Surg. Off. J. Am. Assoc. Oral Maxillofac. Surg.* 2021, 79, 1168–1176. [CrossRef]

77. Tixier, F.; Cheze-le-Resle, C.; Schick, U.; Simon, B.; Dufour, X.; Key, S.; Pradier, O.; Aubry, M.; Hatt, M.; Corcos, L.; et al. Transcriptomics in Cancer Revealed by Positron Emission Tomography Radiomics. *Sci. Rep.* 2020, 10, 5660. [CrossRef]

78. Chan, S.-C.; Chang, K.-P.; Fang, Y.-H.D.; Tsang, N.-M.; Ng, S.-H.; Hsu, C.-L.; Liao, C.-T.; Yen, T.-C. Tumor Heterogeneity Measured on F-18 Fluorodeoxyglucose Positron Emission Tomography/Computed Tomography Combined with Plasma Epstein-Barr Virus Load Predicts Prognosis in Patients with Primary Nasopharyngeal Carcinoma. *Laryngoscope* 2017, 127, E22–E28. [CrossRef]

79. Cheng, N.-M.; Fang, Y.-H.D.; Lee, L.; Chang, J.T.C.; Tsan, D.-L.; Ng, S.-H.; Wang, H.-M.; Liao, C.-T.; Yang, L.-Y.; Hsu, C.-H.; et al. Zone-Size Nonuniformity of 18F-FDG PET Regional Textural Features Predicts Survival in Patients with Oropharyngeal Cancer. *Eur. J. Nucl. Med. Mol. Imaging* 2015, 42, 419–428. [CrossRef]

80. Cheng, N.-M.; Hsieh, C.-E.; Fang, Y.-H.D.; Liao, C.-T.; Ng, S.-H.; Wang, H.-M.; Chou, W.-C.; Lin, C.-Y.; Yen, T.-C. Development and Validation of a Prognostic Model Incorporating [(18)F]FDG PET/CT Radiomics for Patients with Minor Salivary Gland Carcinoma. *EJNMMI Res.* 2020, 10, 74. [CrossRef]

81. Cheng, N.-M.; Hsieh, C.-E.; Liao, C.-T.; Ng, S.-H.; Wang, H.-M.; Fang, Y.-H.D.; Chou, W.-C.; Lin, C.-Y.; Yen, T.-C. Prognostic Value of Tumor Heterogeneity and SUVmax of Pretreatment 18F-FDG PET/CT for Salivary Gland Carcinoma With High-Risk Histology. *Clin. Nucl. Med.* 2019, 44, 351–358. [CrossRef]

82. Wu, W.-J.; Li, Z.-Y.; Dong, S.; Liu, S.-M.; Zheng, L.; Huang, M.-W.; Zhang, J.-G. Texture Analysis of Pretreatment [(18)F]FDG PET/CT for the Prognostic Prediction of Locally Advanced Salivary Gland Carcinoma Treated with Interstitial Brachytherapy. *EJNMMI Res.* 2019, 9, 89. [CrossRef]
83. Polverari, G.; Ceci, F.; Bertaglia, V.; Reale, M.L.; Rampado, O.; Gallio, E.; Passera, R.; Liberini, V.; Scapoli, P.; Arena, V.; et al. (18)F-FDG Pet Parameters and Radiomics Features Analysis in Advanced Nsclc Treated with Immunotherapy as Predictors of Therapy Response and Survival. Cancers 2020, 12, 1163. [CrossRef]

84. Wang, L.; Li, T.; Hong, J.; Zhang, M.; Ouyang, M.; Zheng, X.; Tang, K. (18)F-FDG PET-Based Radiomics Model for Predicting Occult Lymph Node Metastasis in Clinical N0 Solid Lung Adenocarcinoma. Quant. Imaging Med. Surg. 2021, 11, 215–225. [CrossRef]

85. Yang, B.; Ji, H.-S.; Zhou, C.-S.; Dong, H.; Ma, L.; Ge, Y.-Q.; Zhu, C.-H.; Tian, J.-H.; Zhang, L.-J.; Zhu, H.; et al. (18)F-Fluorodeoxyglucose Positron Emission Tomography/Computed Tomography-Based Radiomic Features for Prediction of Epidermal Growth Factor Receptor Mutation Status and Prognosis in Patients with Lung Adenocarcinoma. Transl. Lung Cancer Res. 2020, 9, 563–574. [CrossRef]

86. Orlahc, F.; Soussan, M.; Chouahnia, K.; Martinod, E.; Buvat, I. 18F-FDG PET-Derived Textural Indices Reflect Tissue-Specific Uptake Pattern in Non-Small Cell Lung Cancer. PloS ONE 2015, 10, e0145063. [CrossRef]

87. Carvalho, S.; Leijenaar, R.T.H.; Troost, E.G.C.; van Timmeren, J.E.; Oberije, C.; van Elmtree, W.; de Geus-Oei, L.; F.; Bussink, J.; Lambin, D. 18F-Fluorodeoxyglucose Positron Emission Tomography (FDG-PET)-Radiomics of Metastatic Lymph Nodes and Primary Tumor in Non-Small Cell Lung Cancer (NSCLC)—A Prospective Externally Validated Study. PloS ONE 2018, 13, e0192859. [CrossRef]

88. Mattonen, S.A.; Davidzon, G.A.; Bakr, S.; Echegaray, S.; Leung, A.N.C.; Vasanawala, M.; Horng, G.; Napel, S.; Nair, V.S. [18F] FDG Positron Emission Tomography (PET) Tumor and Penumbra Imaging Features Predict Recurrence in Non-Small Cell Lung Cancer. Tomogr. Ann. Arbor. Mich. 2019, 5, 145–153. [CrossRef]

89. Valentinuzzi, D.; Vrankar, M.; Boc, N.; Ahac, V.; Zupancic, Z.; Unk, M.; Skalic, K.; Zagar, I.; Studen, A.; Simoncic, U.; et al. [18F]FDG PET Immunotherapy Radiomics Signature (IRADIOMICS) Predicts Response of Non-Small-Cell Lung Cancer Patients Treated with Pembrolizumab. Radiol. Oncol. 2020, 54, 285–294. [CrossRef]

90. Chang, C.; Zhou, S.; Yu, H.; Zhao, W.; Ge, Y.; Duan, S.; Wang, R.; Qian, X.; Lei, B.; Wang, L.; et al. A Clinically Practical Radiomics-Clinical Combined Model Based on PET/CT Data and Nomogram Predicts EGFR Mutation in Lung Adenocarcinoma. Eur. Radiol. 2021, 31, 6259–6268. [CrossRef]

91. Chang, C.; Sun, X.; Wang, G.; Yu, H.; Zhao, W.; Ge, Y.; Duan, S.; Qian, X.; Wang, R.; Lei, B.; et al. A Machine Learning Model Based on PET/CT Radiomics and Clinical Characteristics Predicts ALK Rearrangement Status in Lung Adenocarcinoma. Front. Oncol. 2021, 11, 603882. [CrossRef]

92. Hyun, S.H.; Ahn, M.S.; Koh, Y.W.; Lee, S.J. A Machine-Learning Approach Using PET-Based Radiomics to Predict the Histological Subtypes of Lung Cancer. Clin. Nucl. Med. 2019, 44, 956–960. [CrossRef] [PubMed]

93. Luo, Y.; McShan, D.L.; Matuszak, M.M.; Ray, D.; Lawrence, T.S.; Jolly, S.; Kong, F.-M.; Ten Haken, R.K.; El Naqa, I. A Multibjective Bayesian Networks Approach for Joint Prediction of Tumor Local Control and Radiation Pneumonitis in Nonsmall-Cell Lung Cancer (NSCLC) for Response-Adapated Radiotherapy. Med. Phys. 2018, 45, 3980–3995. [CrossRef] [PubMed]

94. Zhou, J.; Zou, S.; Kuang, D.; Yan, J.; Zhao, J.; Zhu, X. A Novel Approach Using FDG-FDG/CT-Based Radiomics to Assess Tumor Immune Phenotypes in Patients with Non-Small Cell Lung Cancer. Front. Oncol. 2021, 11, 769272. [CrossRef] [PubMed]

95. Nakajo, M.; Jingui, M.; Shinai, T.; Aoki, M.; Tani, A.; Nakabeppe, Y.; Nakajo, M.; Sato, M.; Yoshiura, T. A Pilot Study of Texture Analysis of Primary Tumor ([18F]FDG PET Uptake to Predict Recurrence in Surgically Treated Patients with Non-Small Cell Lung Cancer. Mol. Imaging Biol. 2019, 21, 771–780. [CrossRef]

96. Li, S.; Yang, N.; Li, B.; Zhou, Z.; Hao, H.; Folkert, M.R.; Iyengar, P.; Westover, K.; Choy, H.; Timmerman, R.; et al. A Pilot Study Using Kneled Support Tensor Machine for Distant Failure Prediction in Lung SBRT. Med. Image Anal. 2018, 50, 106–116. [CrossRef]

97. Shen, H.; Chen, L.; Liu, K.; Zhao, K.; Li, J.; Yu, L.; Ye, H.; Zhu, W. A Subregion-Based Positron Emission Tomography/Computed Tomography (PET/CT) Radiomics Model for the Classification of Non-Small Cell Lung Cancer Histopathological Subtypes. Quant. Imaging Med. Surg. 2021, 11, 2918–2932. [CrossRef]

98. Kirienko, M.; Cozz, L.; Rossi, A.; Voula, E.; Antunovic, L.; Fogliata, A.; Chiti, A.; Sollini, M. Ability of FDG PET and CT Radiometrics to Differentiate between Primary and Metastatic Lung Lesions. Eur. J. Nucl. Med. Mol. Imaging 2018, 45, 1649–1660. [CrossRef]

99. Nie, P.; Yang, G.; Wang, N.; Yan, L.; Miao, W.; Duan, Y.; Wang, Y.; Gong, A.; Zhao, Y.; Wu, J.; et al. Additional Value of Metabolic Parameters to PET/CT-Based Radiomics Nomogram in Predicting Lymphovascular Invasion and Outcome in Lung Adenocarcinoma. Eur. J. Nucl. Med. Mol. Imaging 2018, 45, 217–230. [CrossRef]

100. Cook, G.J.R.; Yip, C.; Siddique, M.; Goh, V.; Chicklore, S.; Roy, A.; Marsden, P.; Ahmad, S.; Landau, D. Are Pretreatment 18F-FDG PET Tumor Textural Features in Non-Small Cell Lung Cancer Associated with Response and Survival after Chemoradiotherapy? J. Nucl. Med. Off. Publ. Soc. Nucl. Med. 2013, 54, 19–26. [CrossRef]

101. Jiang, M.; Zhang, Y.; Xu, J.; Ji, M.; Guo, Y.; Guo, Y.; Xiao, J.; Yao, X.; Shi, H.; Zeng, M. Assessing EGFR Gene Mutation Status in Non-Small Cell Lung Cancer with Imaging Features from PET/CT. J. Nucl. Med. Commun. 2019, 40, 842–849. [CrossRef]

102. Kim, B.S.; Kang, J.; Jun, S.; Kim, H.; Pak, K.; Kim, G.H.; Heo, H.J.; Kim, Y.H. Association between Immunotherapy Biomarkers and Glucose Metabolism from F-18 FDG PET. Eur. Rev. Med. Pharmacol. Sci. 2020, 24, 8288–8295. [CrossRef]

103. Koh, Y.W.; Park, S.Y.; Hyun, S.H.; Lee, S.J. Associations Between PET Textural Features and GLUT1 Expression, and the Prognostic Significance of Textural Features in Lung Adenocarcinoma. Anticancer Res. 2018, 38, 1067–1071. [CrossRef]
104. Yip, S.S.E.; Kim, J.; Coroller, T.P.; Parmar, C.; Velazquez, E.R.; Huynh, E.; Mak, R.H.; Aerts, H.J.W.L. Associations Between Somatic Mutations and Metabolic Imaging Phenotypes in Non-Small Cell Lung Cancer. *J. Nucl. Med. Off. Publ. Soc. Nucl. Med.* 2017, 58, 569–576. [CrossRef]

105. Ha, S.; Choi, H.; Cheon, G.J.; Kang, K.W.; Chung, J.-K.; Kim, E.E.; Lee, D.S. Autoclustering of Non-Small Cell Lung Carcinoma Subtypes on (18)F-FDG PET Using Texture Analysis: A Preliminary Result. *Nucl. Med. Mol. Imaging* 2014, 48, 278–286. [CrossRef]

106. Mattonen, S.A.; Davidson, G.A.; Benson, J.; Leung, A.N.C.; Vasanawala, M.; Horng, G.; Shraga, J.B.; Napse, S.; Nair, V.S. Bone Marrow and Tumor Radiomics at (18)F-FDG PET/CT: Impact on Outcome Prediction in Non-Small Cell Lung Cancer. *Radiology* 2019, 293, 451–459. [CrossRef]

107. Karacavus, S.; Yilmaz, B.; Tasdemir, A.; Kayaalt, Ö.; Kaya, E.; İçer, S.; Ayyıldız, O. Can Laws Be a Potential PET Image Texture Analysis Approach for Evaluation of Tumor Heterogeneity and Histopathological Characteristics in NSCLC? *J. Digit. Imaging* 2018, 31, 210–223. [CrossRef]

108. Wolsztynski, E.; O’Sullivan, J.; Hughes, N.M.; Mou, T.; Murphy, P.; O’Sullivan, F.; O’Regan, K. Combining Structural and Textural Assessments of Volumetric FDG-PET Uptake in NSCLC. *IEEE Trans. Radiat. Plasma Med. Sci.* 2019, 3, 421–433. [CrossRef]

109. Moon, S.H.; Kim, J.; Joung, J.-G.; Park, W.-Y.; Ahn, J.S.; Ahn, M.-J.; Park, K.; Choi, J.Y.; Lee, K.-H.; et al. Correlations between Metabolic Texture Features, Genetic Heterogeneity, and Mutation Burden in Patients with Lung Cancer. *Eur. J. Nucl. Med. Mol. Imaging* 2019, 46, 446–454. [CrossRef]

110. Ouyang, M.-L.; Wang, Y.-R.; Deng, Q.-S.; Zhu, Y.-F.; Zhao, Z.-H.; Wang, L.; Wang, L.-X.; Tang, K. Development and Validation of a (18)F-FDG PET-Based Radiomic Model for Evaluating Hypermetabolic Mediastinal-Hilar Lymph Nodes in Non-Small-Cell Lung Cancer. *Front. Oncol.* 2021, 11, 710909. [CrossRef]

111. Yang, B.; Zhong, J.; Zhong, J.; Ma, L.; Li, A.; Ji, H.; Zhou, C.; Duan, S.; Wang, Q.; Zhu, C.; et al. Development and Validation of a Radiomics Nomogram Based on (18)F-Fluorodeoxyglucose Positron Emission Tomography/Commoned Tomography and Clinicopathological Factors to Predict the Survival Outcomes of Patients With Non-Small Cell Lung Cancer. *Front. Oncol.* 2020, 10, 1042. [CrossRef]

112. Desseroit, M.-C.; Visvikis, D.; Tixier, F.; Majdoub, M.; Perdrisot, R.; Guillevin, R.; Cheze Le Rest, C.; Hatt, M. Development of a Radiomic Prediction Model for Pre-Therapy 2-Deoxy-2-(18)F-Fuoro-D-Glucose Positron Emission Tomography Using Primary Tumor and Nodal Imaging Features to Predict Progression-Free Survival of Locally Advanced Non-Small Cell Lung Cancer. *Theranostics* 2020, 11, e1057836. [CrossRef]

113. Li, J.; Ge, S.; Li, Y.; Guo, M.; Zhu, H.; Yu, J.; Diehn, M.; Loo, B.W.J.; Li, R.; Wu, J. Early Response Evaluation Using Primary Tumor and Nodal Imaging Features to Predict Progression-Free Survival of Locally Advanced Non-Small Cell Lung Cancer. *Theranostics* 2020, 10, 11707–11718. [CrossRef]

114. Arshad, M.A.; Thornton, A.; Lu, H.; Tam, H.; Wallitt, K.; Rodgers, N.; Scarsbrook, A.; McDermott, G.; Cook, G.J.; Landau, D.; et al. Discovery of Pre-Therapy 2-Deoxy-2-(18)F-Fluro-D-Glucose Positron Emission Tomography-Based Radiomics Classifiers of Survival Outcome in Non-Small-Cell Lung Cancer Patients. *Eur. J. Nucl. Med. Mol. Imaging* 2019, 46, 455–466. [CrossRef]

115. Zhang, J.; Ma, G.; Cheng, J.; Song, S.; Zhang, Y.; Shi, L.Q. Diagnostic Classification of Solitary Pulmonary Nodules Using Support Vector Machine Model Based on 2-[18F] Fluorodeoxyglucose PET/Computed Tomography Texture Features. *Nucl. Med. Commun.* 2020, 41, 560–566. [CrossRef]

116. Zhang, N.; Liang, R.; Gensheimer, M.F.; Guo, M.; Zhu, H.; Yu, J.; Diehn, M.; Loo, B.W.J.; Li, R.; Wu, J. Early Response Evaluation Using Primary Tumor and Nodal Imaging Features to Predict Progression-Free Survival of Locally Advanced Non-Small Cell Lung Cancer. *Theranostics* 2020, 10, 11707–11718. [CrossRef]
125. Miwa, K.; Inubushi, M.; Wagatsuma, K.; Nagao, M.; Murata, T.; Koyama, M.; Koizumi, M.; Sasaki, M. FDG Uptake Heterogeneity Evaluated by Fractal Analysis Improves the Differential Diagnosis of Pulmonary Nodules. *Eur. J. Radiol.* **2021**, *130*, 11073. [CrossRef]

126. Carles, M.; Fechter, T.; Radicioni, G.; Schimek-Jasch, T.; Adebah, S.; Zamboglou, C.; Nicolay, N.H.; Marti-Bonmati, L.; Nestle, U.; Grosu, A.L.; et al. FDG-PET Radiomics for Response Monitoring in Non-Small-Cell Lung Cancer Treated with Radiation Therapy. *Cancers* **2021**, *13*, 814. [CrossRef]

127. Afshar, P.; Mohammadi, A.; Tyrrell, P.N.; Cheung, P.; Sigiuk, A.; Plataniotis, K.N.; Nguyen, E.T.; Oikonomou, A. [Formulas: See Text]: Deep Learning-Based Radiomics for the Time-to-Event Outcome Prediction in Lung Cancer. *Sci. Rep.* **2020**, *10*, 12366. [CrossRef]

128. Chen, L.; Liu, K.; Zhao, X.; Shen, H.; Zhao, K.; Zhu, W. Habitat Imaging-Based (18)F-FDG PET/CT Radiomics for the Preoperative Discrimination of Non-Small Cell Lung Cancer and Benign Inflammatory Diseases. *Front. Oncol.* **2021**, *11*, 759897. [CrossRef]

129. van Gómez López, O.; García Vicente, A.M.; Honguero Martínez, A.F.; Soriano Castrejón, A.M.; Jiménez Londoño, G.A.; Udías, J.M.; León Atance, P. Heterogeneity in [18F]Fluorodeoxyglucose Positron Emission Tomography/Computed Tomography of Non-Small Cell Lung Carcinoma and Its Relationship to Metabolic Parameters and Pathologic Staging. *Mol. Imaging* **2014**, *13*, 11073. [CrossRef]

130. Krarup, M.M.K.; Nygård, L.; Vogelius, I.R.; Andersen, F.L.; Cook, G.; Goh, V.; Fischer, B.M. Heterogeneity in Tumours: Validating the Use of Radiomic Features on (18)F-FDG PET/CT Scans of Lung Cancer Patients as a Prognostic Tool. *Radiother. Oncol.* *J. Eur. Soc. Ther. Radiol. Oncol.* **2020**, *144*, 72–78. [CrossRef]

131. Han, Y.; Ma, Y.; Wu, Z.; Zhang, F.; Zheng, D.; Liu, X.; Tao, L.; Liang, Z.; Yang, Z.; Li, X.; et al. Histologic Subtype Classification of Non-Small Cell Lung Cancer Using PET/CT Images. *Eur. J. Nucl. Med. Mol. Imaging* **2021**, *48*, 350–360. [CrossRef]

132. Ninomiya, K.; Arimura, H. Homological Radiomics Analysis for Prognostic Prediction in Lung Cancer Patients. *Phys. Med. Int. J. Devoted Appl. Phys. Med. Biol. Off. J. Ital. Assoc. Biomed. Phys. AIFB* **2020**, *69*, 90–100. [CrossRef]

133. Shao, D.; Du, D.; Liu, H.; Lv, J.; Cheng, Y.; Zhang, H.; Lv, W.; Wang, S.; Lu, L. Identification of Stage IIIIC/IV EGFR-Mutated Non-Small Cell Lung Cancer Populations Sensitive to Targeted Therapy Based on a PET/CT Radiomics Risk Model. *Front. Oncol.* **2021**, *11*, 721318. [CrossRef]

134. Sha, X.; Gong, G.; Qiu, Q.; Duan, J.; Li, D.; Yin, Y. Identifying Pathological Subtypes of Non-Small-Cell Lung Cancer by Using the Radiometric Features of (18)F-Fluorodeoxyglucose Positron Emission Computed Tomography. *Transl. Cancer Res.* **2019**, *8*, 1741–1749. [CrossRef]

135. Lv, J.; Chen, X.; Liu, X.; Du, D.; Lv, W.; Lu, L.; Wu, H. Imbalanced Data Correction Based PET/CT Radiomics Model for Predicting Lymph Node Metastasis in Clinical Stage T1 Lung Adenocarcinoma. *Front. Oncol.* **2022**, *12*, 788968. [CrossRef]

136. Chen, Y.-H.; Wang, T.-F.; Chu, S.-C.; Lin, C.-B.; Wang, L.-Y.; Lue, K.-H.; Liu, S.-H.; Chan, S.-C. Incorporating Radiomic Feature of Pretreatment 18F-FDG PET Improves Survival Stratification in Patients with EGFR-Mutated Lung Adenocarcinoma. *PloS ONE* **2020**, *15*, e0244502. [CrossRef]

137. Liu, W.; Sun, X.; Yi, Y.; Jia, X.; Huang, Y.; Liu, N.; Chen, J.; Yuan, S. Integrated Texture Parameter of 18F-FDG PET May Be a Stratification Factor for the Survival of Nonoperative Patients with Locally Advanced Non-Small-Cell Lung Cancer. *Nucl. Med. Commun.* **2018**, *39*, 732–740. [CrossRef]

138. Kang, F.; Mu, W.; Gong, J.; Wang, S.; Li, G.; Li, G.; Qin, W.; Tian, J.; Wang, J. Integrating Manual Diagnosis into Radiomics for Reducing the False Positive Rate of (18)F-FDG PET/CT Diagnosis in Patients with Suspected Lung Cancer. *Eur. J. Nucl. Med. Mol. Imaging* **2019**, *46*, 2770–2779. [CrossRef]

139. Cui, S.; Ten Haken, R.K.; El Naqa, I. Integrating Multimetic Information in Deep Learning Architectures for Joint Actuarial Outcome Prediction in Non-Small Cell Lung Cancer Patients After Radiation Therapy. *Int. J. Radiat. Oncol. Biol. Phys.* **2021**, *110*, 893–904. [CrossRef]

140. Du, D.; Gu, J.; Chen, X.; Lv, W.; Feng, Q.; Rahimn, A.; Wu, H.; Lu, L. Integration of PET/CT Radiomics and Semantic Features for Differentiation between Active Pulmonary Tuberculosis and Lung Cancer. *Mol. Imaging Biol.* **2020**, *23*, 287–298. [CrossRef]

141. Koh, Y.W.; Lee, D.; Lee, S.J. Intratumoral Heterogeneity as Measured Using the Tumor-Stroma Ratio and PET Texture Analyses in Pretreatment PET in Non-Small Cell Lung Cancer Patients Predicts Progression-Free Survival on EGFR Tyrosine Kinase Inhibitor. *Transl. Cancer Res.* **2019**, *8*, 4156–4165. [CrossRef] [PubMed]

142. Piñeiro-Fiel, M.; Moscoso, A.; Lado-Cacheiro, L.; Pombo-Pasín, M.; Rey-Bretal, D.; Gómez-Lado, N.; Mondelo-Garcia, C.; Silva-Rodriguez, J.; Pubul, V.; Sánchez, M.; et al. Is FDG-PET Texture Analysis Related to Intratumoral Biological Heterogeneity in Lung Cancer? *Eur. Radiol.* **2021**, *31*, 4156–4165. [CrossRef] [PubMed]

143. Ren, C.; Zhang, J.; Qi, M.; Zhang, J.; Zhang, Y.; Song, S.; Sun, Y.; Cheng, J. Machine Learning Based on Clinico-Biological Features Integrated (18)F-FDG PET/CT Radiomics for Distinguishing Squamous Cell Carcinoma from Adenocarcinoma of Lung. *Eur. J. Nucl. Med. Mol. Imaging* **2021**, *48*, 1538–1549. [CrossRef] [PubMed]
145. Lee, S.H.; Kao, G.D.; Feigenberg, S.J.; Dorsey, J.F.; Frick, M.A.; Jean-Baptiste, S.; Uche, C.Z.; Cengel, K.A.; Levin, W.P.; Berman, A.T.; et al. Multiblock Discriminant Analysis of Integrative (18)F-FDG-PET/CT Radiomics for Predicting Circulating Tumor Cells in Early-Stage Non-Small Cell Lung Cancer Treated With Stereotactic Body Radiation Therapy. *Int. J. Radiat. Oncol. Biol. Phys.* 2021, 110, 1451–1465. [CrossRef]

146. Shiri, I.; Maleki, H.; Hajianfar, G.; Abdollahi, H.; Ashrafinia, S.; Hatt, M.; Zaidi, H.; Oveis, M.; Rahimim, A. Next-Generation Radiogenomics Sequencing for Prediction of EGFR and KRAS Mutation Status in NSCLC Patients Using Multimodal Imaging and Machine Learning Algorithms. *Mol. Imaging Biol.* 2020, 22, 1132–1148. [CrossRef]

147. Mu, W.; Jiang, L.; Zhang, J.; Shi, Y.; Gray, J.E.; Tunali, I.; Gao, C.; Sun, Y.; Tian, J.; Zhao, X.; et al. Non-Invasive Decision Support for NSCLC Treatment Using PET/CT Radiomics. *Nat. Commun.* 2020, 11, 5228. [CrossRef]

148. Mu, W.; Jiang, L.; Shi, Y.; Tunali, I.; Gray, J.E.; Katsoulakis, E.; Tian, J.; Gillies, R.J.; Schabath, M.B. Non-Invasive Measurement of PD-L1 Status and Prediction of Immunotherapy Response Using Deep Learning of PET/CT Images. *J. Immunother. Cancer* 2021, 9. [CrossRef]

149. Cook, G.K.; O’Brien, M.E.; Siddique, M.; Chicklore, S.; Loi, H.Y.; Sharma, B.; Punwani, R.; Bassett, P.; Goh, V.; Chua, S. Non-Small Cell Lung Cancer Treated with Erlotinib: Heterogeneity of (18)F-FDG Uptake at PET-Association with Treatment Response and Prognosis. *Radiology* 2015, 276, 883–893. [CrossRef]

150. Amini, M.; Hajianfar, G.; Hadadi Avval, A.; Nazari, M.; Deevband, M.R.; Oveis, M.; Shiri, I.; Zaidi, H. Overall Survival Prognostic Modelling of Non-Small Cell Lung Cancer Patients Using Positron Emission Tomography/Computed Tomography Harmonised Radiomics Features: The Quest for the Optimal Machine Learning Algorithm. *Clin. Oncol. R. Coll. Radiol.* 2022, 34, 114–127. [CrossRef]

151. Zhang, M.; Bao, Y.; Rui, W.; Shangguan, C.; Liu, J.; Xu, J.; Lin, X.; Zhang, M.; Huang, X.; Zhou, Y.; et al. Performance of (18)F-FDG PET/CT Radiomics for Predicting EGFR Mutation Status in Patients With Non-Small Cell Lung Cancer. *Front. Oncol.* 2020, 10, 568857. [CrossRef]

152. Kim, C.; Cho, H.-H.; Choi, J.Y.; Franks, T.J.; Han, J.; Choi, Y.; Lee, S.-H.; Park, H.; Lee, K.S. Pleomorphic Carcinoma of the Lung: Prognostic Models of Semantic, Radiomics and Combined Features from CT and PET/CT in 85 Patients. *Eur. J. Radiol. Open* 2021, 8, 100351. [CrossRef]

153. Zhang, R.; Zhu, L.; Cai, Z.; Jiang, W.; Li, J.; Yang, C.; Yu, C.; Jiang, B.; Wang, W.; Xu, W.; et al. Potential Feature Exploration and Model Development Based on 18F-FDG PET/CT Images for Differentiating Benign and Malignant Lung Lesions. *Eur. J. Radiol.* 2019, 121, 108735. [CrossRef]

154. Zheng, K.; Wang, X.; Jiang, C.; Tang, Y.; Fang, Z.; Hou, J.; Zhu, Z.; Hu, S. Pre-Operative Prediction of Mediastinal Node Metastasis Using Radiomics Model Based on (18)F-FDG PET/CT of the Primary Tumor in Non-Small Cell Lung Cancer Patients. *Front. Med.* 2021, 8, 673876. [CrossRef]

155. Ahn, H.K.; Lee, H.; Kim, S.G.; Hyun, S.H. Pre-Treatment (18)F-FDG PET-Based Radiomics Predict Survival in Resected Non-Small Cell Lung Cancer. *Clin. Radiol.* 2019, 74, 467–473. [CrossRef]

156. Liu, Q.; Sun, D.; Li, N.; Kim, J.; Feng, D.; Huang, G.; Wang, L.; Song, S. Predicting EGFR Mutation Subtypes in Lung Adenocarcinoma Using (18)F-FDG PET/CT Radiomic Features. *Transl. Lung Cancer Res.* 2020, 9, 549–562. [CrossRef]

157. Kirienko, M.; Cozzi, L.; Antunovic, L.; Lozza, L.; Fogliata, A.; Voula, E.; Rossi, A.; Chiti, A.; Sollini, M. Prediction of Disease-Free Survival by the PET/CT Radiomic Signature in Non-Small-Cell Lung Cancer Patients Undergoing Surgery. *Eur. J. Nucl. Med. Mol. Imaging* 2018, 45, 207–217. [CrossRef]

158. Lyi, X.; Yin, G.; Zhang, Y.; Dai, D.; Liu, J.; Chen, P.; Zhu, L.; Ma, W.; Xu, W. Predictive Power of a Radiomic Signature Based on (18)F-FDG PET/CT Images for EGFR Mutational Status in NSCLC. *Front. Oncol.* 2019, 9, 1062. [CrossRef]

159. Dissaix, G.; Visvikis, D.; Da-Ano, R.; Pradier, O.; Chajon, E.; Barillot, I.; Duvergé, L.; Masson, I.; Abgral, R.; Santiago Ribeiro, M.-J.; et al. Pretreatment (18)F-FDG PET/CT Radiomics Predict Local Recurrence in Patients Treated with Stereotactic Body Radiotherapy for Early-Stage Non-Small Cell Lung Cancer: A Multicentric Study. *J. Nucl. Med. Off. Publ. Soc. Nucl. Med.* 2020, 61, 814–820. [CrossRef]

160. Ohri, N.; Duan, F.; Snyder, B.S.; Wei, B.; Machtay, M.; Alavi, A.; Siegel, B.A.; Johnson, D.W.; Bradley, J.D.; DeNittis, A.; et al. Pretreatment 18F-FDG PET Textural Features in Locally Advanced Non-Small Cell Lung Cancer: Secondary Analysis of ACRIN 6688/RT0G 0235. *J. Nucl. Med. Off. Publ. Soc. Nucl. Med.* 2016, 57, 842–848. [CrossRef]

161. Jensen, G.L.; Yost, C.M.; Mackin, D.S.; Fried, D.V.; Zhou, S.; Court, L.E.; Gomez, D.R. Prognostic Value of Combining a Quantitative Image Feature from Positron Emission Tomography with Clinical Factors in Oligometastatic Non-Small Cell Lung Cancer. *Radiother. Oncol. J. Eur. Soc. Ther. Radiol. Oncol.* 2018, 126, 362–367. [CrossRef]

162. Moran, A.; Wang, Y.; Dyer, B.A.; Yip, S.S.F.; Daly, M.E.; Yamamoto, T. Prognostic Value of Computed Tomography and/or (18)F-Fluorodeoxyglucose Positron Emission Tomography Radiomics Features in Locally Advanced Non-Small Cell Lung Cancer. *Clin. Lung Cancer* 2021, 22, 461–468. [CrossRef]

163. Sharma, A.; Pandey, A.K.; Sharma, A.; Arora, G.; Mohan, A.; Bhalla, A.S.; Gupta, L.; Biswal, S.K.; Kumar, R. Prognostication Based on Texture Analysis of Baseline (18)F Fluorodeoxyglucose Positron Emission Tomography/Computed Tomography in Nonsmall-Cell Lung Carcinoma Patients Who Underwent Platinum-Based Chemotherapy as First-Line Treatment. *Indian J. Nucl. Med. IJNM Off. J. Soc. Nucl. Med. India* 2021, 36, 252–260. [CrossRef]
164. Harmon, S.; Seder, C.W.; Chen, S.; Traynor, A.; Jeraj, R.; Blasberg, J.D. Quantitative FDG PET/CT May Help Risk-Stratify Early-Stage Non-Small Cell Lung Cancer Patients at Risk for Recurrence Following Anatomic Resection. J. Thorac. Dis. 2019, 11, 1106–1116. [CrossRef]

165. Nair, J.K.R.; Saeed, U.A.; McDougall, C.C.; Sabri, A.; Kovacina, B.; Raidu, B.V.S.; Khokhar, R.A.; Probst, S.; Hirsh, V.; Chankowsky, J.; et al. Radiogenomic Models Using Machine Learning Techniques to Predict EGFR Mutations in Non-Small Cell Lung Cancer. Can. Assoc. Radiol. J. J. Assoc. Can. Radiol. 2021, 72, 109–119. [CrossRef]

166. Oikonomou, A.; Khalvati, F.; Tyrrell, P.N.; Haider, M.A.; Tarique, U.; Jimenez-Juan, L.; Tjong, M.C.; Poon, I.; Eilaghi, A.; Ehrlich, L.; et al. Radiomics Analysis at PET/CT Contributes to Prognosis of Recurrence and Survival in Lung Cancer Treated with Stereotactic Body Radiotherapy. Sci. Rep. 2018, 8, 4003. [CrossRef]

167. Konert, T.; Everitt, S.; La Fontaine, M.D.; van de Kamer, J.B.; MacManus, M.P.; Vogel, W.V.; Callahan, J.; Sonke, J.-J. Robust, Independent and Relevant Prognostic 18F-Fluorodeoxyglucose Positron Emission Tomography Radiomics Features in Non-Small Cell Lung Cancer: Are There Any? PloS ONE 2020, 15, e0228793. [CrossRef] [PubMed]

168. Mu, W.; Tunali, I.; Qi, J.; Schabath, M.B.; Gillies, R.J. Radiomics of (18)F Fluorodeoxyglucose PET/CT Images Predicts Severe Immune-Related Adverse Events in Patients with NSCLC. Radiol. Artif. Intell. 2020, 2, e190063. [CrossRef]

169. Mu, W.; Tunali, I.; Gray, J.E.; Qi, J.; Schabath, M.B.; Gillies, R.J. Radiomics of (18)F FDG PET/CT Images Predicts Clinical Benefit of Advanced NSCLC Patients to Checkpoint Blockade Immunotherapy. Eur. J. Nucl. Med. Mol. Imaging 2020, 47, 1168–1182. [CrossRef]

170. Konert, T.; Everitt, S.; La Fontaine, M.D.; van de Kamer, J.B.; MacManus, M.P.; Vogel, W.V.; Callahan, J.; Sonke, J.-J. Robust, Independent and Relevant Prognostic 18F-Fluorodeoxyglucose Positron Emission Tomography Radiomics Features in Non-Small Cell Lung Cancer: Are There Any? PloS ONE 2020, 15, e0228793. [CrossRef] [PubMed]

171. Whi, W.; Ha, S.; Bae, S.; Choi, H.; Paeng, J.C.; Cheon, G.J.; Kang, K.W.; Lee, D.S. Relationship of EGFR Mutation to Glucose Metabolic Activity and Asphericity of Metabolic Tumor Volume in Lung Adenocarcinoma. Mol. Imaging. Nucl. Med. 2020, 54, 175–182. [CrossRef]

172. Bashir, U.; Azad, G.; Siddique, M.M.; Dhillon, S.; Patel, N.; Bassett, P.; Landau, D.; Goh, V.; Cook, G. The Effects of Segmentation Algorithms on the Measurement of (18)F-FDG PET Texture Parameters in Non-Small Cell Lung Cancer. Eur. J. Nucl. Med. Mol. Imaging 2019, 21, 1200–1209. [CrossRef]

173. Albano, D.; Gatta, R.; Marini, M.; Rodella, C.; Camoni, L.; Dondi, F.; Giubbini, R.; Bertagna, F. Role of (18)F-FDG PET/CT Radiomics Features in the Differential Diagnosis of Solitary Pulmonary Nodules: Diagnostic Accuracy and Comparison between Two Different PET/CT Scanners. J. Clin. Med. 2020, 10, 5064. [CrossRef] [PubMed]

174. Ji, Y.; Qiu, Q.; Fu, J.; Cui, K.; Chen, X.; Xing, L.; Sun, X. Stage-Specific PET Radiomic Prediction Model for the Histological Subtype Classification of Non-Small-Cell Lung Cancer. Cancer Manag. Res. 2021, 13, 307–317. [CrossRef] [PubMed]

175. Pyka, T.; Bundschuh, R.A.; Andratschke, N.; Mayer, B.; Specht, H.M.; Papp, L.; Zsoter, N.; Essler, M. Textural Features in Pre-Treatment [F18]-FDG-PET/CT Are Correlated with Risk of Local Recurrence and Disease-Specific Survival in Early Stage NSCLC Patients Receiving Primary Stereotactic Radiation Therapy. Radiat. Oncol. 2015, 10, 100. [CrossRef]

176. Bianconi, F.; Palumbo, I.; Fravolini, M.L.; Chiari, R.; Minestrini, M.; Brunese, L.; Palumbo, B. Texture Analysis on [(18)F]FDG PET/CT in Non-Small-Cell Lung Cancer: Correlations Between PET Features, CT Features, and Histological Types. Mol. Imaging Biol. 2019, 21, 1200–1209. [CrossRef]

177. Bashir, U.; Azad, G.; Siddique, M.M.; Dhillon, S.; Patel, N.; Bassett, P.; Landau, D.; Goh, V.; Cook, G. The Effects of Segmentation Algorithms on the Measurement of (18)F-FDG PET Texture Parameters in Non-Small Cell Lung Cancer. EJNMMI Res. 2017, 7, 60. [CrossRef]

178. Örner, H.; Coşkun, N.; Erol, M.; Eren Karanis, M.İ. The Role of Histogram-Based Textural Analysis of (18)F-FDG PET/CT in Evaluating Tumor Heterogeneity and Predicting the Prognosis of Invasive Lung Adenocarcinoma. Mol. Imaging Radionucl. Ther. 2021, 32, 33–41. [CrossRef]

179. Lue, K.-H.; Chu, S.-C.; Wang, L.-Y.; Chen, Y.-C.; Li, M.-H.; Chang, B.-S.; Chan, S.-C.; Chen, Y.-H.; Lin, C.-B.; Liu, S.-H. Tumor Glycolytic Heterogeneity Improves Detection of Regional Nodal Metastasis in Patients with Lung Adenocarcinoma. Ann. Nucl. Med. 2021, 36, 256–266. [CrossRef]

180. Li, H.; Galperin-Aizenberg, M.; Pryma, D.; Simone, C.B., II; Fan, Y. 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. J. Eur. Soc. Ther. Radiol. Oncol. 2018, 129, 218–226. [CrossRef]

181. Zhou, Y.; Ma, X.-L.; Zhang, T.; Wang, J.; Zhang, T.; Tian, R. Use of Radiomics Based on (18)F-FDG PET/CT and Machine Learning Methods to Aid Clinical Decision-Making in the Classification of Solitary Pulmonary Lesions: An Innovative Approach. Eur. J. Nucl. Med. Mol. Imaging 2021, 48, 2904–2913. [CrossRef]

182. Koyasu, S.; Nishio, M.; Isoda, H.; Nakamoto, Y.; Togashi, K. Usefulness of Gradient Tree Boosting for Predicting Histological Subtype and EGFR Mutation Status of Non-Small Cell Lung Cancer on (18)F FDG-PET/CT. Ann. Nucl. Med. 2020, 34, 49–57. [CrossRef]

183. Chen, S.; Harmon, S.; Perk, T.; Li, X.; Chen, M.; Li, Y.; Jeraj, R. Using Neighborhood Gray Tone Difference Matrix Texture Features on Dual Time Point PET/CT Images to Differentiate Malignant from Benign FDG-Avid Solitary Pulmonary Nodules. Cancer Imaging Off. Publ. Int. Cancer Imaging Soc. 2019, 19, 56. [CrossRef]

184. Hu, Y.; Zhao, X.; Zhang, J.; Han, J.; Dai, M. Value of (18)F-FDG PET/CT Radiomic Features to Distinguish Solitary Lung Adenocarcinoma from Tuberculosis. Eur. J. Nucl. Med. Mol. Imaging 2021, 48, 231–240. [CrossRef]
185. Shao, X.; Niu, R.; Shao, X.; Jiang, Z.; Wang, Y. Value of (18)F-FDG PET/CT-Based Radiomics Model to Distinguish the Growth Patterns of Early Invasive Lung Adenocarcinoma Manifesting as Ground-Glass Opacity Nodules. EJNMMI Res. 2020, 10, 80. [CrossRef]

186. Yang, B.; Ji, H.; Zhong, J.; Ma, L.; Zhong, J.; Dong, H.; Zhou, C.; Duan, S.; Zhu, C.; Tian, J.; et al. Value of (18)F-FDG PET/CT-Based Radiomics Nomogram to Predict Survival Outcomes and Guide Personalized Targeted Therapy in Lung Adenocarcinoma with EGFR Mutations. Front. Oncol. 2020, 10, 567160. [CrossRef]

187. Zhang, J.; Zhao, X.; Zhao, Y.; Zhang, J.; Zhang, Z.; Wang, J.; Wang, Y.; Dai, M.; Han, J. Value of Pre-Therapy (18)F-FDG PET/CT Radiomics in Predicting EGFR Mutation Status in Patients with Non-Small Cell Lung Cancer. Eur. J. Nucl. Med. Mol. Imaging 2020, 47, 1137–1146. [CrossRef]

188. Palumbo, B.; Bianconi, F.; Palumbo, I.; Fravolini, M.L.; Minestrini, M.; Nuvoli, S.; Stazzola, M.L.; Rondoni, M.; Spanu, A. Value of Shape and Texture Features from (18)F-FDG PET/CT to Discriminate between Benign and Malignant Solitary Pulmonary Nodules: An Experimental Evaluation. Diagnostics 2020, 10, 696. [CrossRef]

189. Tixier, F.; Hatt, M.; Valla, C.; Fleury, V.; Lamour, C.; Ezzouhri, S.; Ingrand, P.; Perdrisot, R.; Visvikis, D.; Le Rest, C.C. Visual versus Quantitative Assessment of Intratumor 18F-FDG PET Uptake Heterogeneity: Prognostic Value in Non-Small Cell Lung Cancer. J. Nucl. Med. Off. Publ. Soc. Nucl. Med. 2014, 55, 1235–1241. [CrossRef]

190. Li, P.; Wang, X.; Xu, C.; Liu, C.; Zheng, C.; Fulham, M.J.; Feng, D.; Wang, L.; Song, S.; Huang, G. (18)F-FDG PET/CT Radiomic Predictors of Pathologic Complete Response (PCR) to Neoadjuvant Chemotherapy in Breast Cancer Patients. Eur. J. Nucl. Med. Mol. Imaging 2020, 47, 1116–1126. [CrossRef]

191. Antunovic, L.; Gallivanone, F.; Sollini, M.; Sagona, A.; Invento, A.; Manfrinato, G.; Kirienko, M.; Tinterri, C.; Chiti, A.; Castiglioni, I. [(18)F]FDG PET/CT Features for the Molecular Characterization of Primary Breast Tumors. Eur. J. Nucl. Med. Imaging 2017, 44, 1945–1954. [CrossRef]

192. Groheux, D.; Martineau, A.; Teixeira, L.; Espié, M.; de Cremoux, P.; Bertheau, P.; Merlet, P.; Lemarignier, C. (18)FDG-PET/CT for Predicting the Outcome in ER+/HER2- Breast Cancer Patients: Comparison of Clinico pathological Parameters and PET Image-Derived Indices Including Tumor Texture Analysis. Breast Cancer Res. BCR 2017, 19, 3. [CrossRef]

193. Song, B.-I. A Machine Learning-Based Radiomics Model for the Prediction of Axillary Lymph-Node Metastasis in Breast Cancer. Breast Cancer 2021, 28, 664–671. [CrossRef]

194. Ou, X.; Wang, J.; Zhou, R.; Zhu, S.; Pang, F.; Zhou, Y.; Tian, R.; Ma, X. Ability of (18)F-FDG PET/CT Radiomic Features to Distinguish Breast Carcinoma from Breast Lymphoma. Contrast Media Mol. Imaging 2019, 2019, 4507694. [CrossRef]

195. Romeo, V.; Clauser, P.; Rasul, S.; Kapetas, P.; Gibbs, P.; Baltzer, P.A.T.; Hacker, M.; Woitek, R.; Helbich, T.H.; Pinker, K. Al-Enhanced Simultaneous Multiparametric (18)F-FDG PET/MRI for Accurate Breast Cancer Diagnosis. Eur. J. Nucl. Med. Mol. Imaging 2022, 49, 596–608. [CrossRef]

196. Payan, N.; Presles, B.; Brunotte, F.; Coutant, C.; Desmoulins, I.; Vrigneaud, J.-M.; Cochet, A. Biological Correlates of Tumor Perfusion and Its Heterogeneity in Newly Diagnosed Breast Cancer Using Dynamic First-Pass (18)F-FDG PET/CT. Eur. J. Nucl. Med. Mol. Imaging 2020, 47, 1103–1115. [CrossRef]

197. Krajnc, D.; Papp, L.; Nakuz, T.S.; Magometschnigg, H.F.; Grahovac, M.; Spielvogel, C.P.; Ecsedi, B.; Bago-Horvath, Z.; Haug, A.; Karanikas, G.; et al. Breast Tumor Characterization Using [(18)F]FDG-PET/CT Imaging Combined with Data Preprocessing and Radiomics. Cancers 2021, 13, 1249. [CrossRef]

198. Araz, M.; Soydal, Ç.; Gündüz, P.; Kirmizi, A.; Bakirarar, B.; Dizbay Sak, S.; Özkan, E. Can Radiomics Analyses in (18)F-FDG PET/CT Images of Primary Breast Carcinoma Predict Hormone Receptor Status? Mol. Imaging Radioucl. Ther. 2022, 31, 49–56. [CrossRef]

199. Lee, J.W.; Kim, S.Y.; Han, S.W.; Lee, J.E.; Hong, S.H.; Lee, S.M.; Jo, I.Y. Clinical Significance of Peritumoral Adipose Tissue PET/CT Imaging Features for Predicting Axillary Lymph Node Metastasis in Patients with Breast Cancer. J. Pers. Med. 2021, 11, 1029. [CrossRef]

200. Acell, E.; Turgut, B.; Yiğit, S.; Kaya, G. Comparison of the Volumetric and Radiomics Findings of 18F-FDG PET/CT Images with Immunohistochemical Prognostic Factors in Local/ Locally Advanced Breast Cancer. Nucl. Med. Commun. 2019, 40, 764–772. [CrossRef]

201. Lemarignier, C.; Martineau, A.; Teixeira, L.; Vercellino, L.; Espié, M.; Merlet, P.; Groheux, D. Correlation between Tumour Characteristics, SUV Measurements, Metabolic Tumour Volume, TLG and Textural Features Assessed with (18)F-FDG PET in a Large Cohort of Oestrogen Receptor-Positive Breast Cancer Patients. Eur. J. Nucl. Med. Mol. Imaging 2017, 44, 1145–1154. [CrossRef]

202. Groheux, D.; Majdoub, M.; Tixier, F.; Le Rest, C.C.; Martineau, A.; Merlet, P.; Espié, M.; de Roquancourt, A.; Hindié, E.; Hatt, M.; et al. Do Clinical, Histological or Immunohistochemical Primary Tumour Characteristics Translate into Different (18)F-FDG PET/CT Volumetric and Heterogeneity Features in Stage II/III Breast Cancer? Eur. J. Nucl. Med. Mol. Imaging 2015, 42, 1682–1691. [CrossRef] [PubMed]

203. Huang, S.-Y.; Franc, B.L.; Harnish, R.J.; Liu, G.; Mitra, D.; Copeland, T.P.; Arasu, V.A.; Kornak, J.; Jones, E.F.; Behr, S.C.; et al. Exploration of PET and MRI Radiomic Features for Decoding Breast Cancer Phenotypes and Prognosis. NPJ Breast Cancer 2018, 4, 24. [CrossRef] [PubMed]
204. Aide, N.; Elie, N.; Blanc-Fournier, C.; Levy, C.; Salomon, T.; Lasnon, C. Hormonal Receptor Immunochemistry Heterogeneity and (18)F-FDG Metabolic Heterogeneity: Preliminary Results of Their Relationship and Prognostic Value in Luminal Non-Metastatic Breast Cancers. *Front. Oncol.* **2020**, *10*, 599050. [CrossRef] [PubMed]

205. Schiano, C.; Franzese, M.; Pane, K.; Garbino, N.; Sorcielli, A.; Salvatore, M.; de Nigris, F.; Napoli, C. Hybrid (18)F-FDG-PET/MRI Measurement of Standardized Uptake Value Coupled with Yin Yang 1 Signature in Metastatic Breast Cancer. A Preliminary Study. *Cancers* **2019**, *11*, 1444. [CrossRef]

206. Boughdad, S.; Nieco, C.; Orliac, F.; Jehl, L.; Champion, L.; Buvat, I. Influence of Age on Radiomic Features in (18)F-FDG PET in Normal Breast Tissue and in Breast Cancer Tumors. *Oncotarget* **2018**, *9*, 30855–30868. [CrossRef]

207. Molina-Garcia, D.; Garcia-Vicente, A.M.; Pérez-Beteta, J.; Amo-Salas, M.; Martínez-González, A.; Tello-Galán, M.J.; Soriani-Castrojón, A.; Pérez-García, V.M. Intratumoral Heterogeneity in (18)F-FDG PET/CT by Textural Analysis in Breast Cancer as a Predictive and Prognostic Subrogate. *Ann. Nucl. Med.* **2018**, *32*, 379–386. [CrossRef]

208. Yoon, H.-J.; Kim, Y.; Kim, B.S. Intratumoral Metabolic Heterogeneity Predicts Invasive Components in Breast Ductal Carcinoma in Situ. *Eur. Radiol.* **2015**, *25*, 3648–3658. [CrossRef]

209. Ha, S.; Park, S.; Bang, J.-I.; Kim, E.-K.; Lee, H.-Y. 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*, 1556. [CrossRef]

210. Liu, J.; Bian, H.; Zhang, Y.; Gao, Y.; Yin, G.; Wang, Z.; Li, X.; Ma, W.; Xu, W. Molecular Subtype Classification of Breast Cancer Using Established Radiomic Signature Models Based on (18)F-FDG PET/CT Images. *Front. Biosci. Landmark Ed.* **2021**, *26*, 475–484. [CrossRef]

211. Umutlu, L.; Kirchner, L.; Bruckmann, N.M.; Morawitz, J.; Antoch, G.; Ingenwerth, M.; Bittner, A.-K.; Hoffmann, O.; Haubold, J.; Grueneisen, J.; et al. Multiparametric Integrated (18)F-FDG PET/MRI-Based Radiomics for Breast Cancer Phenotyping and Tumor Decoding. *Cancers* **2021**, *13*, 2928. [CrossRef]

212. Antunovic, L.; De Sanctis, R.; Cozzi, L.; Kirienko, M.; Sagona, A.; Torrisi, R.; Tinterri, C.; Santoro, A.; Chiti, A.; Zelic, R.; et al. PET/CT Radiomics in Breast Cancer: Promising Tool for Prediction of Pathological Response to Neoadjuvant Chemotherapy. *Eur. J. Nucl. Med. Mol. Imaging* **2019**, *46*, 1468–1477. [CrossRef]

213. Yoon, H.-J.; Kim, Y.; Chung, J.; Kim, B.S. Predicting Neo-Adjuvant Chemotherapy Response and Progression-Free Survival of Locally Advanced Breast Cancer Using Textural Features of Intratumoral Heterogeneity on F-18 FDG PET/CT and Diffusion-Weighted MR Imaging. *Breast J.* **2019**, *25*, 373–380. [CrossRef]

214. Lee, H.; Lee, D.-E.; Park, S.; Kim, T.S.; Jung, S.-Y.; Lee, S.; Kang, H.S.; Lee, E.S.; Sim, S.H.; Park, I.H.; et al. Predicting Response to Neoadjuvant Chemotherapy in Patients With Breast Cancer: Combined Statistical Modeling Using Clinicopathological Factors and FDG PET/CT Texture Parameters. *Clin. Nucl. Med.* **2019**, *44*, 21–29. [CrossRef]

215. Chen, Y.; Wang, Z.; Yin, G.; Sui, C.; Liu, Z.; Li, X.; Chen, W. Prediction of HER2 Expression in Breast Cancer by Combining PET/CT Radiomic Analysis and Machine Learning. *Ann. Nucl. Med.* **2022**, *36*, 172–182. [CrossRef]

216. Chang, C.-C.; Chen, C.-J.; Hsu, W.-L.; Chang, S.-M.; Huang, Y.-F.; Tyan, Y.-C. Prognostic Significance of Metabolic Parameters and Textural Features on (18)F-FDG PET/CT in Invasive Ductal Carcinoma of Breast. *Sci. Rep.* **2019**, *9*, 10946. [CrossRef]

217. Bouron, C.; Mathie, C.; Seegers, V.; Morel, O.; Jézéquel, P.; Lasla, H.; Guillermimenter, C.; Girault, S.; Lacombe, M.; Sher, A.; et al. Prognostic Value of Metabolic, Volumetric and Textural Parameters of Baseline ([18]F)FDG PET/CT in Early Triple-Negative Breast Cancer. *Cancers* **2022**, *14*, 637. [CrossRef]

218. Ou, X.; Zhang, J.; Wang, J.; Pang, F.; Wang, Y.; Wei, X.; Ma, X. Radiomics Based on (18)F-FDG PET/CT Could Differentiate Breast Carcinoma from Breast Lymphoma Using Machine-Learning Approach: A Preliminary Study. *Cancer Med.* **2020**, *9*, 496–506. [CrossRef]

219. Soussan, M.; Orliac, F.; Boubaya, M.; Zelek, L.; Ziol, M.; Eder, V.; Buvat, I. Relationship between Tumor Heterogeneity Measured on FDG-PET/CT and Pathological Prognostic Factors in Invasive Breast Cancer. *PLoS ONE* **2014**, *9*, e94017. [CrossRef]

220. Cheng, L.; Zhang, J.; Wang, Y.; Xu, X.; Zhang, Y.; Zhang, Y.; Liu, G.; Cheng, J. Textural Features of (18)F-FDG PET after Two Cycles of Neoadjuvant Chemotherapy Can Predict PCR in Patients with Locally Advanced Breast Cancer. *Ann. Nucl. Med.* **2017**, *31*, 544–552. [CrossRef]

221. Moscoso, A.; Ruibal, Á.; Domínguez-Prado, I.; Fernández-Ferreiro, A.; Herranz, M.; Albaina, L.; Argibay, S.; Silva-Rodríguez, J.; Pardo-Montero, J.; Aguilar, P. Texture Analysis of High-Resolution Dedicated Breast (18) F-FDG PET Images Correlates with Immunohistochemical Subtypes and Stage of Breast Cancer. *Eur. J. Nucl. Med. Mol. Imaging* **2018**, *45*, 196–206. [CrossRef]

222. Nakajo, M.; Jingui, M.; Shinaji, T.; Tani, A.; Nakabeppe, Y.; Nakajo, M.; Nakajo, A.; Natsugoe, S.; Yoshiura, T. (18)F-FDG-PET/CT Features of Primary Tumours for Predicting the Risk of Recurrence in Thyroid Cancer after Total Thyroidectomy: Potential Usefulness of Combination of the SUV-Related, Volumetric, and Heterogeneous Texture Parameters. *Br. J. Radiol.* **2019**, *92*, 20180620. [CrossRef]

223. Sollini, M.; Cozzi, L.; Pepe, G.; Antunovic, L.; Lania, A.; Di Tommaso, L.; Magnoni, P.; Erba, P.A.; Kirienko, M. ([18]F)FDG-PET/CT Texture Analysis in Thyroid Incidentalomas: Preliminary Results. *Eur. J. Hybrid Imaging* **2017**, *1*, 3. [CrossRef]

224. Aksu, A.; Karahan Şen, N.P.; Acar, E.; Çapa Kaya, G. Evaluating Focal (18)F-FDG Uptake in Thyroid Gland with Radiomics. *Nucl. Med. Mol. Imaging* **2020**, *54*, 241–248. [CrossRef]
225. de Koster, E.J.; Noortman, W.A.; Mostert, J.M.; Booij, J.; Brouwer, C.B.; de Keizer, B.; de Klerk, J.M.H.; Oyen, W.J.G.; van Velden, F.H.P.; de Geus-Oei, L.-F.; et al. Quantitative Classification and Radiomics of [(18)F]FDG-PET/CT in Indeterminate Thyroid Nodules. *Eur. J. Nucl. Med. Mol. Imaging* 2022, 49, 2174–2188. [CrossRef] [PubMed]

226. Giovanella, L.; Milan, L.; Piccardo, A.; Bottino, G.; Cuzzocrea, M.; Paone, G.; Ceriani, L. Radiomics Analysis Improves (18)FDG PET/CT-Based Risk Stratification of Cytologically Indeterminate Thyroid Nodules. *Endocrine* 2022, 75, 202–210. [CrossRef] [PubMed]

227. Ceriani, L.; Milan, L.; Virili, C.; Cascione, L.; Paone, G.; Trimboli, P.; Giovanella, L. Radiomics Analysis of [(18)F]-Fluorodeoxyglucose-Avid Thyroid Incidentalomas Improves Risk Stratification and Selection for Clinical Assessment. *Thyroid Off. J. Am. Thyroid Assoc.* 2021, 31, 88–95. [CrossRef] [PubMed]

228. Lee, H.S.; Oh, J.S.; Park, Y.S.; Jang, S.J.; Choi, I.S.; Ryu, J.-S. Differentiating the Grades of Thymic Epithelial Tumor Malignancy Using Textural Features of Intratumoral Heterogeneity via (18)F-FDG PET/CT. *Ann. Nucl. Med.* 2016, 30, 309–319. [CrossRef] [PubMed]

229. Nakajo, M.; Jinguji, M.; Shinaji, T.; Nakajo, M.; Aoki, M.; Tani, A.; Sato, M.; Yoshiura, T. Texture Analysis of (18)F-FDG PET/CT for Grading Thymic Epithelial Tumours: Usefulness of Combining SUV and Texture Parameters. *Br. J. Radiol.* 2018, 91, 20170546. [CrossRef]

230. Gillies, R.J.; Kinahan, P.E.; Hricak, H. Radiomics: Images Are More than Pictures, They Are Data. *Radiology* 2016, 278, 563–577. [CrossRef]

231. Zwanenburg, A.; Vallières, M.; Abdalah, M.A.; Aerts, H.J.W.L.; Andrearczyk, V.; Apte, A.; Ashrafinia, S.; Bakas, S.; Beukinga, R.J.; Boellaard, R.; et al. The Image Biomarker Standardization Initiative: Standardized Quantitative Radiomics for High-Throughput Image-Based Phenotyping. *Radiology* 2020, 295, 328–338. [CrossRef]

232. Lambin, P.; Leijenaar, R.T.H.; Deist, T.M.; Peerlings, J.; de Jong, E.E.C.; van Timmeren, J.; Sanduleanu, S.; Larue, R.T.H.M.; Even, A.J.G.; Jochems, A.; et al. Radiomics: The Bridge between Medical Imaging and Personalized Medicine. *Nat. Rev. Clin. Oncol.* 2017, 14, 749–762. [CrossRef]

233. Piñeiro-Fiel, M.; Moscoso, A.; Pubul, V.; Ruibal, Á.; Silva-Rodríguez, J.; Aguiar, P. A Systematic Review of PET Textural Analysis and Radiomics in Cancer. *Diagnostics* 2021, 11, 380. [CrossRef]