New advances in radiomics of gastrointestinal stromal tumors

Roberto Cannella, Ludovico La Grutta, Massimo Midiri, Tommaso Vincenzo Bartolotta

Abstract
Gastrointestinal stromal tumors (GISTs) are uncommon neoplasms of the gastrointestinal tract with peculiar clinical, genetic, and imaging characteristics. Preoperative knowledge of risk stratification and mutational status is crucial to guide the appropriate patients’ treatment. Predicting the clinical behavior and biological aggressiveness of GISTs based on conventional computed tomography (CT) and magnetic resonance imaging (MRI) evaluation is challenging, unless the lesions have already metastasized at the time of diagnosis. Radiomics is emerging as a promising tool for the quantification of lesion heterogeneity on radiological images, extracting additional data that cannot be assessed by visual analysis. Radiomics applications have been explored for the differential diagnosis of GISTs from other gastrointestinal neoplasms, risk stratification and prediction of prognosis after surgical resection, and evaluation of mutational status in GISTs. The published researches on GISTs radiomics have obtained excellent performance of derived radiomics models on CT and MRI. However, lack of standardization and differences in study methodology challenge the application of radiomics in clinical practice. The purpose of this review is to describe the new advances of radiomics applied to CT and MRI for the evaluation of gastrointestinal stromal tumors, discuss the potential clinical applications that may impact patients’ management, report limitations of current radiomics studies, and future directions.

Key words: Gastrointestinal stromal tumors; Radiomics; Texture analysis; Computed tomography; Magnetic resonance imaging; Clinical applications

©The Author(s) 2020. Published by Baishideng Publishing Group Inc. All rights reserved.
diagnosis of gastrointestinal stromal tumors (GISTs) with other gastrointestinal neoplasms in the stomach and duodenum. Excellent performances have been reported for the evaluation of risk status, the preoperative identification of high-risk tumors, and the prediction of prognosis after target therapies. Radiogenomics studies are still lacking, with only initial evidences describing the potential of radiomics for the diagnosis of GISTs without KIT mutations. In this work we review the new advances in radiomics applied to the computed tomography and magnetic resonance imaging of GISTs.

Citation: Cannella R, La Grutta L, Midiri M, Bartolotta TV. New advances in radiomics of gastrointestinal stromal tumors. World J Gastroenterol 2020; 26(32): 4729-4738
URL: https://www.wjgnet.com/1007-9327/full/v26/i32/4729.htm
DOI: https://dx.doi.org/10.3748/wjg.v26.i32.4729

INTRODUCTION

Gastrointestinal stromal tumors (GISTs) are uncommon mesenchymal neoplasms of the gastrointestinal tract, originating from the interstitial cells of Cajal[1]. GISTs may arise anywhere along all the gastrointestinal tract, being more commonly encountered in the stomach (50%-60% of cases) or small intestine (30%-40%), while they are rarely observed in the esophagus and colorectum[2,3]. All GISTs have malignant potential with varying degree of biological aggressiveness. Liver and peritoneum are the most common sites of metastatic disease or recurrence after curative resection, which occurs in about 40% of patients[3,4]. GISTs are also characterized by peculiar genetic alterations, with 85% of tumors presenting with activating mutations in the KIT proto-oncogene, while a minority of lesions show mutations of platelet-derived growth factor α (PDGFRα), or occasionally may lack of known mutations (wild type GISTs)[5]. The advent of imatinib mesylate, a selective tyrosine kinase inhibitor of the KIT and PDGFRα receptors, has revolutionized the treatment of GISTs, significantly improving the patients’ survival even in advanced stages.

Contrast-enhanced computed tomography (CT) is the imaging modality of choice for preoperative diagnosis, staging, as well as postoperative follow-up and assessment of treatment response in patients with GISTs[6,7]. On contrast-enhanced CT, GISTs usually present with peculiar imaging features, most often with large (> 5 cm) abdominal mass, heterogeneous enhancement, and variable amount of necrosis[8-12]. Other imaging findings include presence of calcifications, ulceration or cystic degeneration[10,13]. Magnetic resonance imaging (MRI) may provide additional information for the evaluation of primary tumors in peculiar location (i.e., rectum) and may be preferred for the differential diagnosis of liver metastasis from other benign hepatic lesions[8,10,12]. In clinical practice, predicting the behavior of GISTs is challenging, unless the lesions have already metastasized at the time of diagnosis. Although some imaging predictors of malignant potential have been identified (size, location, margins, enhancement pattern) and variably correlated with prognosis and survival of GISTs, small tumors lacking of concerning imaging features may still metastasize, making difficult to predict aggressive tumors.

Radiomics is emerging as a promising tool that allows to quantify lesion heterogeneity, extracting additional quantitative data from radiological imaging that cannot be evaluated by human eyes[13-15]. In recent years, multiple researches have explored the performance of radiomics models in abdominal oncologic applications, with significant results for lesions characterization, evaluation of therapeutic response and prediction of patients’ survival after surgical or systemic treatments[16-22]. The application of radiomics in GISTs could be used to further improve the patients’ management and provide new advances in quantitative lesion evaluation due to the unique clinical, genetic, and imaging characteristics of these tumors.

With this review, we aim to describe the new advances of radiomics applied to CT and MR imaging for the evaluation of gastrointestinal stromal tumors, discuss the potential clinical applications that may impact patients’ management, report limitations of current radiomics studies, and future directions.
WORKFLOW OF RADIOMICS ANALYSIS

Radiomics is based on the mathematical quantification of images heterogeneity, through the analysis of distribution and relationships of pixel intensities within a region of interest (ROI)\[18\]. Radiomics analysis requires a multistep process, starting from imaging acquisition, and including lesion segmentation, features extraction, features selection and reduction, predictive model building, and finally validation and clinical interpretation of the results\[18,20\].

Radiomics can be potentially applied to any type of radiological images, including ultrasound, CT, MRI and positron emission tomography/CT, but most of studies are nowadays based on CT or MRI examinations\[19\]. Image acquisition is one of the most critical steps for radiomics, since scanning and technical parameters may influence the reproducibility of radiomics features. Particularly, reconstruction algorithm and slice thickness had demonstrated to largely impact on the reproducibility of radiomics features on CT\[24,25\]. The heterogeneous imaging acquisition may be problematic for evaluation of retrospective data acquired with different CT or MRI scanners, while prospective study should ensure that all patients will be imaged using standardized parameters\[27\]. It is also important to select the optimal phase/sequence for image analysis. Pre-contrast images are not affected by the contrast administration, but lesion segmentation is more difficult, especially for smaller tumors that are difficult to distinguish on non-contrast CT. Contrast-enhanced images may provide better assessment of lesion heterogeneity, but type and non-standardized timing of contrast agent administration may represent additional confounding factors, especially for images acquired on arterial phase.

Lesion segmentation is the most critical step of radiomics process. Segmentation may be performed manually by expert radiologists, using semi-automatic, or automatic software\[21\]. Although manual segmentation is time consuming and it is subject to intra- and inter-reader variability, it is still considered as the gold standard for most of radiomics studies\[18,20\]. The segmentation is usually realized by drawing a ROI within the tumor margins (Figure 1), avoiding the inclusion of any extra-tumoral tissues such as bowel mucosa, intestinal content, or peritumoral vessels. The ROI can be placed on a single slide (2D ROI) on the largest tumor cross section or include the whole lesion (3D ROI). Although the latter may capture more tissue heterogeneity, its clinical advantage remains debated.

Several in-house build or commercially available radiomics research software are nowadays used for extract a large number of radiomics features. These features may be divided into semantic (qualitative features usually reported by radiologists such as size, margins, enhancement pattern) or agnostic (which are mathematical and quantitative descriptors of heterogeneity) features. Agnostic features are further classified in first, second and third order features\[19\]. The first order features are obtained from the analysis of the gray level histogram within a defined ROI, without considering spatial relations among pixels. Most common histogram-based features include mean (average of the pixels within the ROI), standard deviation (dispersion from the mean), skewness (asymmetric of the histogram), kurtosis (peakedness/flatness of the histogram), and entropy (image irregularity or complexity)\[24\]. The second order texture features consider the spatial relationship among pixels, and most commonly include grey level co-occurrence matrix (GLCM), that quantifies the arrangements of pairs of pixels with the same values in specific directions, and grey-level run length matrix (GLRLM), that quantifies consecutive pixels with the same intensity along specific directions. Third or higher order features evaluate spatial relationship among three or more pixels through statistical methods after applying filters or mathematical transforms. These features include fractal analysis, wavelet transform, and Laplacian transforms of Gaussian-filtered image. Due to the large number of extracted parameters, features reduction should be performed in order to excluded features that are not reproducible or with high similarity (i.e., redundant features). This is a significant step to avoid overfitting problems, especially in small cohorts\[18,21\].

Only uncorrelated features with significant diagnostic performance are selected for final radiomics models. The choice of statistical methods and models may depend on multiple factors such as evaluation of primary outcome, number of features, and number of analyzed lesions\[19\]. These models can be also combined with other patient clinical characteristics in order to increase their predictive power\[19\]. Finally, radiomics models should be tested and validated using independent internal validation cohort or external population\[19\]. To assess the quality of radiomics studies, scores have been proposed, such as the Radiomics Quality Score developed by Lambin et al\[29\], which evaluates 16 key components of radiomics workflow\[25,29\].
RADIOMICS METHODOLOGY IN GISTS

Existing articles of radiomics in GISTS (Table 1) have been performed with heterogeneous methodology regarding the imaging studies, type of radiomics features and analysis\(^{30-44}\). Up to May 2020, all the radiomics research studies on GISTs were performed in retrospective population, and only four studies were multicentric\(^{31,32,35,44}\). The number of included GISTs widely ranged from 15 to 440 lesions. All except one of radiomics GIST studies used CT imaging for features extraction, while only one study\(^{36}\) evaluated the MRI. On CT studies, radiomics analysis was most commonly carried out on venous phase (48%), followed by arterial phase (38%), and pre-contrast images (14%) (Figure 2). No study included the delayed phase in radiomics evaluation. First, second, and third order features were extracted in 80%, 67%, and 20% of studies, respectively. Volumetric analysis (3D ROI) was performed in 60% of cases, while 2D ROIs were placed in 47% cases. Only one study\(^{41}\) compared the accuracy of 2D vs 3D ROIs in GISTs, reporting an excellent agreement between the two segmentation methods.

Few studies have investigated the intra- and inter-reader variability of radiomics features in GISTS, with promising results for reproducibility of tumor segmentation and features extraction. A recent study\(^{41}\) described an almost perfect intra- and inter-reader reproducibility of radiomics features (reported ICC > 0.98) using both single-ROI and whole lesions-ROI manual segmentations. Other studies assessed the inter-reader variability for manual segmentation, all reporting an excellent inter-observer agreement for whole tumor radiomics parameters extracted by two abdominal radiologists (ICC ranging from 0.85 to 0.99)\(^{35,37-39}\).

Validation of radiomics models in independent cohorts was performed in 47% of studies. However only three of them\(^{31,32,44}\) included external validation cohorts.

RADIOMICS APPLICATIONS IN GISTS

Differential diagnosis between GIST and other tumors

Stomach is the most common organ affected by GISTs. The differential diagnosis should be carried with other gastric benign mesenchymal neoplasms (i.e., schwannomas and leiomyomas) or malignant tumors (i.e., gastric adenocarcinomas and lymphomas), and it may be difficult due to the overlap in imaging appearance\(^{45-47}\). Using a texture analysis approach, Ba-Ssalamah et al\(^{30}\) differentiated GISTs from gastric adenocarcinomas and lymphomas with a high successful rate on arterial and venous phase CT images.

Another challenging location for the differential diagnosis of GISTs from other gastrointestinal neoplasms is the duodenum\(^{48}\). GISTs occur rarely in the duodenum (less than 5% of cases) and the differentiation from more common duodenal adenocarcinomas (DACs), pancreatic ductal adenocarcinomas (PDACs), or pancreatic neuroendocrine tumors is significantly relevant for preoperative management and patient prognosis\(^{48,49}\). To improve the preoperative characterization of these lesions, a
Accurate evaluation of malignant risk and outcome in GISTs is mainly based on tumor size, location (gastric vs non-gastric tumors), and mitotic count obtained with resection specimens. These factors are combined in the National Institutes of Health 2008 criteria,

which classified GISTs four risk classes: very low, low, intermediate and high-risk tumors. However, in clinical practice risk stratification may be limited by the evaluation of mitotic count in patients treated with neoadjuvant therapies, or the assessment of biopsy specimens that could not be representative of the whole tumor. Therefore, several studies have tried to predict risk stratification based on preoperative imaging features. CT features like size, growth pattern, or enlarged feeding vessels have been used for preoperative risk stratification. 

### Risk stratification and prediction of prognosis of GISTs

Table 1 Summary of radiomics studies including gastrointestinal stromal tumors

| Ref. | Number of lesions | Imaging | Radiomics analysis | Key radiomics results |
|------|------------------|---------|--------------------|-----------------------|
| Ba-SSalamah et al\(^{[39]}\) | 15 GISTs, 27 gastric adenocarcinomas, 5 lymphomas | CT | Histogram-based, GLCM, GLRLM, absolute gradient, autoregressive model, Wavelet transform. | On AP texture features perfectly differentiated between GIST vs lymphoma. On PVP texture features differentiated GIST vs adenocarcinoma in 90% of cases and GIST vs lymphoma in 92% of cases. |
| Chen et al\(^{[31]}\) | 222 GISTs | CT | GLCM, GLRLM, GLSZM, NGTDM, Support Vector Machine for model building. | AUROC 0.848-0.86 of radiomics models for GIST risk stratification. |
| Chen et al\(^{[32]}\) | 147 GISTs | CT | Residual Neural Network for model building. | AUROC of 0.887-0.947 for ResNet nomogram and model for prediction of disease-free survival after surgical resection. |
| Choi et al\(^{[33]}\) | 145 GISTs | CT | Histogram-based. | AUROC of 0.782-0.779 for differentiation of high-risk GISTs. |
| Ekert et al\(^{[34]}\) | 25 GISTs | CT | Histogram-based, GLCM, GLDLM, GLRLM, GLSZM, NGGLDM. | Ten GLCM, GLRLM, NGLDM features significantly correlated with disease progression and progression free survival. |
| Feng et al\(^{[35]}\) | 90 GISTs | CT | Histogram-based. | AUROC of 0.823-0.830 of entropy for the differentiation of low from high-risk GISTs. |
| Fu et al\(^{[36]}\) | 51 GISTs | MRI | Fractal features, GLCM, GLRLM. | Texture features on DWI and ADC map correlated with overall survival in metastatic GISTs. |
| Liu et al\(^{[37]}\) | 78 GISTs | CT | Histogram-based. | AUROC of 0.637-0.811 for the identification of very low and low-risk GISTs. |
| Lu et al\(^{[38]}\) | 28 GISTs, 26 DACs, 20 PDACs | CT | Histogram-based. | AUROC of 0.809-0.936 of 90\(^{th}\) percentile for differentiation of GISTs from DACs and PDACs. |
| Ren et al\(^{[39]}\) | 440 GISTs | CT | Histogram-based, GLCM. | AUROC of 0.933-0.935 for the differentiation of low from high-risk GISTs. |
| Wang et al\(^{[40]}\) | 333 GISTs | CT | Histogram-based, GLCM, GLRLM. | AUROC of 0.882-0.920 for the differentiation of low from high-risk GISTs. AUROC of 0.769-0.820 for the differentiation of low from high mitotic count. |
| Xu et al\(^{[41]}\) | 86 GISTs | CT | Histogram-based, GLCM, GLRLM. | AUROC of 0.904-0.962 of standard deviation for diagnosis of GIST without KIT exon 11 mutations. |
| Yan et al\(^{[42]}\) | 213 GISTs | CT | Histogram-based, GLCM, GLRLM, absolute gradient, autoregressive model, Wavelet transform. | AUROC of 0.933 of texture analysis model for preoperative risk stratification. |
| Zhang et al\(^{[43]}\) | 140 GISTs | CT | Histogram-based, shape-based, GLCM, GLRLM, GLSZM. | AUROC of 0.809-0.935 for discrimination of advanced GISTs and four risk categories of GISTs. |
| Zhang et al\(^{[44]}\) | 339 GISTs | CT | GLCM, GLRLM, GLSZM, GLDM. | AUROC of 0.754-0.787 of radiomics features for prediction of high Ki67 expression. |

**AUROC:** Area under the receiver operating characteristics curve; **CT:** Computed tomography; **DACs:** Duodenal adenocarcinomas; **GIST:** Gastrointestinal stromal tumors; **GLCM:** Grey level co-occurrence matrix; **GLDM:** Grey-level dependence matrix; **GLRLM:** Grey-level run length matrix; **GLSZM:** Gray-level size zone matrix; **MRI:** Magnetic resonance imaging; **NGLDM:** Neighborhood grey-level different matrix; **NGTDM:** Neighbourhood gray-tone difference matrix; **PDACs:** Pancreatic ductal adenocarcinomas.

Study by Lu et al\(^{[38]}\) investigated the whole lesion histogram analysis on contrast-enhanced CT, reporting an excellent discrimination of GISTs from DACs and PDACs in the periampullary region.

**Risk stratification and prediction of prognosis of GISTs**
Figure 2  Chart shows the frequency of computed tomography imaging phases included in radiomics gastrointestinal stromal tumors studies. Corresponding computed tomography images shows an 8.6 cm gastric gastrointestinal stromal tumor in a 64-year-old woman.

been associated with high-risk tumors\textsuperscript{[51-53]}. Nevertheless, risk stratification using qualitative imaging evaluation is affected by the readers’ experience, heterogeneous definition of imaging features, and subjective assessment with suboptimal reproducibility of qualitative features\textsuperscript{[54]}.

Radiomics models have demonstrated to improve the preoperative prediction of high-risk GISTs compared to the conventional visual evaluation\textsuperscript{[33,42]}. The added value of radiomics and texture analysis on contrast-enhanced CT was firstly investigated by Yan et al\textsuperscript{[42]} in a retrospective cohort of 213 small bowel GISTs. In that study, texture analysis model achieved a similar diagnostic accuracy compared to that of clinical and subjective imaging features for preoperative risk prediction of GISTs\textsuperscript{[42]}. When combining the clinical and texture analysis features, the diagnostic performance (AUROC of 0.943) significantly improved compared to the model incorporating clinical and imaging features only\textsuperscript{[42]}. In a more recent study, Choi et al\textsuperscript{[33]} investigated the diagnostic performance of histogram-based texture parameters and qualitative analysis of CT imaging features for the differentiation of low-risk from high-risk GISTs. Their results confirmed that the radiomics features showed a higher diagnostic performance (AUROC of 0.782-0.779) compared to conventional qualitative evaluation (AUROC of 0.59-0.70) by two radiologists in the differential diagnosis of low-risk from high-risk GISTs\textsuperscript{[33]}.

The potential of radiomics for the risk stratification in GISTs have been further evaluated by other evidences with promising results and excellent diagnostic performance\textsuperscript{[35,37,39,40,43]}. Liu et al\textsuperscript{[37]} applied CT-based texture analysis for the identification of very low and low risk GISTs in a cohort of 78 patients, reporting a fair diagnostic performance (AUROC of 0.637-0.811) for the most discriminant features obtained on pre-contrast, arterial and venous phases CT images. Feng et al\textsuperscript{[35]} extracted histogram-based parameters from arterial and venous phase CT images of 90 small bowel GISTs. Among them, entropy showed the highest diagnostic accuracy on arterial and venous phases (AUROC of 0.823 and 0.830, respectively) for the identification of high-risk GISTs. Zhang et al\textsuperscript{[43]} analyzed 140 GISTs using arterial phase CT images, reporting an excellent diagnostic performance for preoperative prediction of advanced (i.e., high and intermediate risk) GISTs and four-class risk stratification (AUROC of 0.935 and 0.809, respectively).

In a large population of 440 pathologically proven GISTs, Ren et al\textsuperscript{[39]} reported an excellent performance of radiomics models for the differentiation of low-risk from high-risk GISTs (AUROC of 0.935 and 0.933 in training and validation cohort, respectively). In that study, the prediction nomogram (incorporating lesion size, cystic degeneration, and texture-based mean) demonstrated a sensitivity of 90.6% and a specificity of 75.7% for the diagnosis of high-risk GISTs\textsuperscript{[39]}. Similarly, Wang et al\textsuperscript{[40]} analyzed the contrast-enhanced CT images of 333 GISTs and reported an excellent
radiomics in the imaging evaluation of treatment response is currently underexplored. In two subsequent studies\(^\text{[15,25]}\), Chen et al.\(^\text{[20,25]}\) built support vector machine and residual neural network based models to predict malignant potential or 3-year and 5-year recurrence-free survival after complete surgical resection of localized GISTs, respectively. In those researches, the Authors enrolled an internal patients’ cohort for training the model, which was subsequently validated in internal and external cohorts, with a good-to almost perfect performance for GIST risk stratification and prediction of recurrence free survival at 3-year and 5-year, respectively\(^\text{[16,25]}\).

Survival analysis for disease progression according to texture features was carried out also by Ekert et al.\(^\text{[3]}\) on contrast-enhanced CT, while only one study\(^\text{[24]}\) has performed radiomics analysis on MRI. Fu et al.\(^\text{[31]}\) extracted texture features from T2-weighted, DWI and ADC map images to determine prognosis of metastatic GISTs, reporting that texture features on DWI and ADC map well-correlated with overall survival.

Finally, Ki67 index represents a marker of proliferation of tumor cells, which have also been associated with poor prognosis in GISTs\(^\text{[5]}\). In a study of 339 GISTs\(^\text{[44]}\), radiomics signature from contrast-enhanced CT have demonstrated a significant correlation with Ki67 expression, providing an added value for prognosis assessment.

\section*{Assessment of mutational status}

Genetic alterations and mutational status is crucial for GISTS optimal target therapy. About 80\%-85\% of GISTs have mutation in KIT genes, 10\% of GISTs have mutations in PDGFRα, while the remaining 10\%-15\% GISTs are wild type due to the lack of mutations in either of these genes\(^\text{[6]}\). Particularly, PDGFRα and wild type GISTs have a lower response rate or resistance to the target therapies with tyrosine kinase inhibitors, depending on the specific mutational status\(^\text{[15,25]}\).

Few data exist regarding the association between CT imaging features and mutations in GISTs\(^\text{[5,21]}\). The performance of radiomics features and radiologists visual analysis for the differentiation of GISTs with and without KIT exon 11 mutations have been explored by Xu et al.\(^\text{[31]}\) in a study cohort and validation group of 69 and 17 GISTs, respectively. In that investigation, the standard deviation was strongly correlated with absence of KIT exon 11 mutations, and achieved an AUROC of 0.904-0.962. Contrarily, there was no statistically significant differences in the visual ratings of lesions heterogeneity between GISTs with and without KIT exon 11 mutations. Further researches are needed to correlate the radiomics signature with the genomics patterns of mutational status (known as radiogenomics analysis\(^\text{[34]}\)) in order to provide reliable information to guide the most appropriate treatment, especially in advanced GISTs that are not suitable for surgical resection.

\section*{Limitations and Future Directions}

Although radiomics has an enormous research potential for the improvement of quantitative tumors evaluation, there are some limitations that challenges its application in everyday clinical practice. Standardization of methodology is the primary problem for radiomics analysis. Differences in imaging acquisition, features extraction, and radiomics software challenge the comparisons between studies and the repeatability or application of radiomics models in different populations. All the current published studies on radiomics of GISTs are retrospective and mostly performed in single centers. The lack of standardization in CT and MRI acquisition is another major problem for radiomics assessment of GISTs. This latter is strictly related to the rarity of GISTS compared to other neoplasms, which require collection of imaging studies obtained during a long period of time. Moreover, the peculiar histopathological characteristics of GISTS, such as mitotic count and mutational status, require pathological diagnosis through resections specimens as reference standard for radiomics studies.

The evaluation of treatment response after tyrosine kinase inhibitors therapy needs also the be further investigated. Indeed, the response to target therapy may occur even without reduction of tumor size\(^\text{[40]}\). As consequence, Choi criteria\(^\text{[40]}\), based on the measurements of CT attenuation values, have been adopted for the evaluation of treatment response in patients undergoing target therapies. The added values of radiomics in the imaging evaluation of treatment response is currently undereexplored.
and may be investigated in future studies.

Further prospective multicentric studies will be needed to validate the optimal diagnostic performance of radiomics models provided by retrospective analysis. Future works are also warranted for optimization and standardization of radiomics software, imaging acquisition, features extraction and models analysis.

CONCLUSION

Radiomics is emerging as a promising tool for quantitative evaluation of GISTs, with excellent diagnostic performance for the differential diagnosis with other gastrointestinal neoplasms, prediction of risk stratification, and evaluation of mutational status. Future implementation of radiomics models in clinical practice may provide additional information from radiological images that will be helpful to guide patients management and more tailored treatments.

REFERENCES

1 Parab TM, Delogatiss MJ, Boaz AM, Grasso SA, Issack PS, Duarte DA, Urayeneza O, Vahdat S, Qiao JH, Honika GS. Gastrointestinal stromal tumors: a comprehensive review. J Gastrointest Oncol 2019; 10: 144-154 [PMID: 30788170 DOI: 10.21017/jgo.2018.08.02]

2 Akahoshi K, Oya M, Koga T, Shirisuchis Y. Current clinical management of gastrointestinal stromal tumors. World J Gastroenterol 2018; 24: 2806-2817 [PMID: 30018476 DOI: 10.3748/wjg.v24.i26.2806]

3 Plumb AA, Kochhar R, Lehy M, Taylor MB. Patterns of recurrence of gastrointestinal stromal tumour (GIST) following complete resection: implications for follow-up. Clin Radiol 2013; 68: 770-775 [PMID: 23663875 DOI: 10.1016/j.crad.2013.03.002]

4 D’Ambrosio I, Paleandro E, Boccone F, Tolomeo F, Miano S, Galizia D, Manca A, Chiara G, Bertotto I, Russo F, Cannarella D, Venesio T, Sangiolo D, Pignochino Y, Statis D, De Simone M, Ferroero A, Pisacane A, De Tolfs AP, Alberti S, Aglietta M, Grigioni G. Impact of a risk-based follow-up patients affected by gastrointestinal stromal tumour. Eur J Cancer 2017; 78: 122-132 [PMID: 28484856 DOI: 10.1016/j.ejca.2017.03.025]

5 Burkill GJ, Badran M, Al-Muderis O, Meirion Thomas J, Judson IR, Fisher C, Moskvic EC. Malignant gastrointestinal tumours: distribution, imaging features, and pattern of metastatic spread. Radiology 2003; 226: 527-532 [PMID: 12563150 DOI: 10.1148/radiol.2262011880]

6 Oppelt PJ, Hirbe AC, Van Tine BA. Gastrointestinal stromal tumors (GISTs): point mutations matter in management, a review. J Gastrointest Oncol 2017; 8: 466-473 [PMID: 28736634 DOI: 10.21037/jgo.2016.09.15]

7 Vernuccio F, Taibbi A, Picone D, LA Grutta L, Midiri M, Lagalla R, Lo Re G, Bartolotta TV. Imaging of Gastrointestinal Stromal Tumors: From Diagnosis to Evaluation of Therapeutic Response. Anticancer Res 2016; 36: 2639-2648 [PMID: 27227772]

8 Inoue A, Ota S, Sato S, Nitta N, Shimizu T, Sonoda H, Tani M, Ban H, Inatomi O, Ando A, Kushira R, Murata K. Comparison of characteristic computed tomographic findings of gastrointestinal and non-gastrointestinal stromal tumors in the small intestine. Abdom Radiol (NY) 2019; 44: 1237-1245 [PMID: 30660331 DOI: 10.1007/s00261-018-1865-9]

9 Bartolotta TV, Taibbi A, Galia M, Cannella I, Lo Re G, Sparacig A, Midiri M, Lagalla R. Gastrointestinal stromal tumour: 40-row multislice computed tomography findings. Radiol Med 2006; 111: 651-660 [PMID: 16791466 DOI: 10.1007/s11547-006-0063-y]

10 Xing GS, Wang S, Sun YM, Yuan Z, Zhao XM, Zhou CW. Small Bowel Stromal Tumors: Different Clinicopathologic and Computed Tomographic Features in Various Anatomic Sites. PLoS One 2015; 10: e0144277 [PMID: 26646242 DOI: 10.1371/journal.pone.0144277]

11 Baheti AD, Shingare AH, O’Neill AC, Krajewski KM, Hornick JL, George S, Ramaiya NH, Tirunum SH. MDCT and clinicopathological features of small bowel gastrointestinal stromal tumours in 102 patients: a single institute experience. Br J Radiol 2015; 88: 20150085 [PMID: 26110609 DOI: 10.1259/bjr.20150085]

12 Scola D, Bahoura L, Copelan A, Shirhkoa A, Sokhandon F. Getting the GIST: a pictorial review of the various patterns of presentation of gastrointestinal stromal tumours on imaging. Abdom Radiol (NY) 2017; 42: 1350-1364 [PMID: 28070658 DOI: 10.1007/s00261-016-1025-z]

13 Yu MH, Lee JM, Baek JH, Han JK, Choi BI. MRI features of gastrointestinal stromal tumors. AJR Am J Roentgenol 2014; 203: 980-991 [PMID: 25341135 DOI: 10.2214/AJR.13.11667]

14 Kang TW, Kim SH, Jung KM, Choi D, Ha SY, Kim KM, Kang WK, Kim MJ. Gastrointestinal stromal tumours: correlation of modified NIH risk stratification with diffusion-weighted MR imaging as an imaging biomarker. Eur J Radiol 2015; 84: 33-40 [PMID: 25466773 DOI: 10.1016/j.ejrad.2014.10.020]

15 Gillies RJ, Kinahan PE, Hricak H. Radiomics: Images Are More than Pictures, They Are Data. Radiology 2016; 278: 563-577 [PMID: 26579733 DOI: 10.1148/radiol.2015151169]

16 Vernuccio F, Cannella R, Cornelli A, Salvaggio G, Lagalla R, Midiri M. [Radiomics and artificial intelligence: new frontiers in medicine.]. Recent Prog Med 2020; 110: 130-135 [PMID: 32157259 DOI: 10.1701/3315.32853]

17 Lubner MG, Smith AD, Sandrasegaran K, Sahani DV, Pickhardt PJ. CT Texture Analysis: Definitions, Applications, Biologic Correlates, and Challenges. Radiographics 2017; 37: 1483-1503 [PMID: 28891819 DOI: 10.1148/rg.2017170056]

18 Wakabayashi T, Ouhmich F, Gonzalez-Cabrera C, Feli E, Saviano A, Agnus V, Savadjiev P, Baumert TF,
Gastrointestinal Stromal Tumors: Radiomics-Based Models for Preoperatively Predicting Malignant Potential and Mitotic Count of Wang C

Texture analysis for preoperative prediction of the malignant potential in gastrointestinal stromal tumors. 2019;

Differentiation of periampullary neoplasms based on CT whole-lesion histogram analysis. Lu J

Texture analysis of CT images in predicting malignancy risk of gastrointestinal stromal tumours. Liu S

Evaluation of DWI texture as potential biomarker of overall survival. Fu J

Cancer Imaging 2019; 115: e537-e543

Texture-based classification of different gastric tumors at contrast-enhanced CT. Park JE

Parameters. Radiology 2018; 288: 407-415

Cannella R et al. Radiomics of gastrointestinal stromal tumors

Pessaux P, Marescaux J, Gallix B. Radiomics in hepatocellular carcinoma: a quantitative review. Hepatol Int 2019; 13: 546-559

Lewis S, Hectors S, Taouli B. Radiomics of hepatocellular carcinoma. Abdom Radiol (NY) 2020 [PMID: 31925592] DOI: 10.1007/s00261-019-02378-5

Miranda Magalhaes Santos JM, Clemente Oliveira B, Araujo-Filho JAB, Assuncao-Jr AN, de M Machado FA, Carlos Tavares Rocha C, Horvat JV, Menezes MR, Horvat N. State-of-the-art in radiomics of hepatocellular carcinoma: a review of basic principles, applications, and limitations. Abdom Radiol (NY) 2020; 45: 342-355

Kocak B, Durrmaez ES, Erdin C, Ates E, Kaya OK, Kilickesmez O. Radiomics of Renal Masses: Systematic Review of Reproducibility and Validation Strategies. AJR Am J Roentgenol 2020; 214: 129-136

Differentiation of periampullary neoplasms based on CT whole-lesion histogram analysis. Varghese BA, Cen SY, Hwang DH, Duddalwar VA. Texture Analysis of Imaging: What Radiologists Need to Know. AJR Am J Roentgenol 2019; 212: 520-528

Texture analysis: evidence for liver parenchyma, focal solid liver lesions, and renal cysts. Ahn SJ

Texture analysis: evidence for liver parenchyma, focal solid liver lesions, and renal cysts. Eur Radiol 2019; 29: 4008-4015

Meyer M, Ronald J, Vernuccio F, Nelson RC, Ramirez-Giraldo JC, Solomon J, Patel BN, Samei E, Marin D. Reproducibility of CT Radiomic Features within the Same Patient: Influence of Radiation Dose and CT Reconstruction Settings. Radiology 2019; 293: 583-591

Kocak B, Durrmaez ES, Ates E, Kilickesmez O. Radiomics with artificial intelligence: a practical guide for beginners. Diagn Interv Radiol 2019; 25: 485-495

Lambin P, Leijenaar RTH, Deist TM, Peelings J, de Jong EEC, van Timmeren J, Sanduleanu S, Larae RTHM, Even A, Jochems A, van Wijk Y, Woodruff H, van Soest LR, Lustberg T, Roelofs E, van Elswit E, Dekker A, Motaghy FM, Wildberger JE, Walsh S. Radiomics: the bridge between medical imaging and personalized medicine. Nat Rev Clin Oncol 2017; 14: 749-762

Park JE, Kim D, Kim HS, Park SY, Kim JY, Cho SJ, Shin JH, Kim JH. 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

Ya-Susalamah A, Muan D, Schertheraner R, Kalunsa-Coventini C, Bastati N, Sittl R, Gore R, Mayerhofer ME. Texture-based classification of different gastric tumors at contrast-enhanced CT. Eur Radiol 2013; 82: e537-e543

Chen T, Ning Z, Xu L, Feng X, Han S, Roth HR, Xiong W, Zhao X, Hu Y, Liu H, Yu J, Zhang Y, Li Y, Xu Y, Mori K, Li G. Radiomics nomogram for predicting the malignant potential of gastrointestinal stromal tumours preoperatively. Eur Radiol 2019; 29: 1074-1082

Chen T, Liu S, Li Y, Feng X, Xiong W, Zhao X, Yang Y, Zhang C, Hu Y, Chen H, Lin T, Zhao M, Liu H, Yu J, Xu Y, Zhang Y, Li G. Developed and validated a prognostic nomogram for recurrence-free survival after complete surgical resection of local primary gastrointestinal stromal tumors based on deep learning. ElBioMedicine 2019; 39: 272-279

Ekert K, Hinterlinzer C, Horger M. Prognosis assessment in metastatic gastrointestinal stromal tumors treated with tyrosine kinase inhibitors based on CT-texture analysis. Eur J Radiol 2019; 116: 98-105

Feng C, Lu F, Shen Y, Li A, Hu Y, Tang H, Li Z, Hu D. Tumor heterogeneity in gastrointestinal stromal tumors of the small bowel: volumetric CT texture analysis as a potential biomarker for risk stratification. Cancer Imaging 2018; 18: 46

Fu J, Fang MJ, Dong D, Li J, Sun YS, Tian J, Tang L. Heterogeneity of metastatic gastrointestinal stromal tumor on texture analysis: DWI texture as potential biomarker of overall survival. Eur J Radiol 2020; 125: 108825

Liu S, Pan X, Liu R, Zhang H, Chen L, Guan W, Wang H, Sun Y, Tang L, Guan Y, Ge Y, He J, Zhoa Z. Texture analysis of CT images in predicting malignancy risk of gastrointestinal stromal tumours. Clin Radiol 2018; 73: 266-274

Lu J, Hu D, Tang H, Hu X, Shen Y, Li Z, Peng Y, Kamil L. Assessment of tumor heterogeneity: Differentiation of periampullary neoplasms based on CT whole-lesion histogram analysis. Eur J Radiol 2019; 115: 1-9

Ren C, Wang S, Zhang S. Development and validation of a nomogram based on CT images and 3D texture analysis for preoperative prediction of the malignant potential in gastrointestinal stromal tumors. Cancer Imaging 2020; 20: 5

Wang C, Li H, Juarenk Y, Huang P, Sun L, Dong F, Huang Y, Dong D, Tian J, Zhang M. Building CT Radiomics-Based Models for Preoperatively Predicting Malignant Potential and Mitotic Count of Gastrointestinal Stromal Tumors. Transl Oncol 2019; 12: 1229-1236

Xu F, Ma X, Wang Y, Tian Y, Tang W, Wang M, Wei R, Zhao X. CT texture analysis can be a potential tool to differentiate gastrointestinal stromal tumors without KIT exon 11 mutation. Eur J Radiol 2018; 107: 90-97

DOI: 10.1016/j.ejrad.2017.09.003

DOI: 10.1016/j.ejrad.2018.03.021

DOI: 10.1016/j.ejrad.2019.03.021

DOI: 10.1016/j.ejrad.2019.07.025
Cannella R et al. Radiomics of gastrointestinal stromal tumors

42 Yan J, Zhao X, Han S, Wang T, Miao F. Evaluation of Clinical Plus Imaging Features and Multidetector Computed Tomography Texture Analysis in Preoperative Risk Grade Prediction of Small Bowel Gastrointestinal Stromal Tumors. J Comput Assist Tomogr 2018; 42: 714-720 [PMID: 30015796 DOI: 10.1097/RCT.0000000000000975]

43 Zhang L, Kang L, Li G, Zhang X, Ren J, Shi Z, Li J, Yu S. Computed tomography-based radiomics model for discriminating the risk stratification of gastrointestinal stromal tumors. Radiol Med 2020; 125: 465-473 [PMID: 32048155 DOI: 10.1007/s11547-020-01138-6]

44 Zhang QW, Gao YJ, Zhang RY, Zhou XX, Chen SL, Zhang Y, Liu Q, Xu JR, Ge ZZ. Personalized CT-based radiomics nomogram preoperative predicting Ki-67 expression in gastrointestinal stromal tumors: a multicenter development and validation cohort. Clin Transl Med 2020; 9: 12 [PMID: 32006208 DOI: 10.1186/s40169-020-0263-4]

45 Choi JW, Choi D, Kim KM, Sohn TS, Lee JH, Kim HJ, Lee SJ. Small submucosal tumors of the stomach: differentiation of gastric schwannoma from gastrointestinal stromal tumor with CT. Korean J Radiol 2012; 13: 425-433 [PMID: 22778564 DOI: 10.3348/kjr.2012.13.4.425]

46 Choi YR, Kim SH, Kim SA, Shin CI, Kim HJ, Kim SH, Choi BI. Differentiation of large (≥ 5 cm) gastrointestinal stromal tumors from benign subepithelial tumors in the stomach: radiologists’ performance using CT. Eur J Radiol 2014; 83: 250-260 [PMID: 24325848 DOI: 10.1016/j.ejrad.2013.10.028]

47 Huh CW, Jung DH, Kim JS, Shin YR, Choi SH, Kim BW. CT Versus Endoscopic Ultrasound for Differentiating Small (2-5 cm) Gastrointestinal Stromal Tumors From Leiomyomas. AJR Am J Roentgenol 2019; 213: 586-591 [PMID: 31063418 DOI: 10.2214/AJR.18.20877]

48 Cai PQ, Lv XF, Tian L, Luo ZP, Mitteer RA Jr, Fan Y, Wu YP. CT Characterization of Duodenal Gastrointestinal Stromal Tumors. AJR Am J Roentgenol 2015; 204: 988-993 [PMID: 25905932 DOI: 10.2214/AJR.14.12870]

49 Ren S, Chen X, Wang J, Zhao R, Song L, Li H, Wang Z. Differentiation of duodenal gastrointestinal stromal tumors from hypervascular pancreatic neuroendocrine tumors in the pancreatic head using contrast-enhanced computed tomography. Abdom Radiol (NY) 2019; 44: 867-876 [PMID: 30291109 DOI: 10.1007/s00261-018-1803-x]

50 Joensuu H. Risk stratification of patients diagnosed with gastrointestinal stromal tumor. Hum Pathol 2008; 39: 1411-1419 [PMID: 18774375 DOI: 10.1016/j.humpath.2008.06.025]

51 Zhou C, Daan X, Zhang X, Hu H, Wang D, Shen J. Predictive features of CT for risk stratifications in patients with primary gastrointestinal stromal tumour. Eur Radiol 2016; 26: 3086-3093 [PMID: 26699371 DOI: 10.1007/s00330-015-4172-7]

52 O’Neill AC, Shinagare AB, Kurra Y, Tiumani SH, Jagannathan JP, Baheti AD, Hornick JL, George S, Ramayya NH. Assessment of metastatic risk of gastric GIST based on treatment-naive CT features. Eur J Surg Oncol 2016; 42: 1222-1228 [PMID: 27178777 DOI: 10.1016/j.ejso.2016.03.032]

53 Li H, Ren G, Cai R, Chen J, Wu X, Zhao J. A correlation research of Ki67 index, CT features, and risk stratification in gastrointestinal stromal tumor. Cancer Med 2018; 7: 4467-4474 [PMID: 30123969 DOI: 10.1002/cam4.1737]

54 Maldonado FJ, Sheedy SP, Iyer VR, Hansel SL, Bruining DH, McCollough CH, Harmsen WS, Barlow JM, Fletcher JG. Reproducible imaging features of biologically aggressive gastrointestinal stromal tumors of the small bowel. Abdom Radiol (NY) 2018; 43: 1567-1574 [PMID: 29110055 DOI: 10.1007/s00261-017-1370-6]

55 Basilio-de-Oliveira RP, Pannain VL. Prognostic angiogenic markers (endoglin, VEGF, CD31) and tumor cell proliferation (Ki67) for gastrointestinal stromal tumors. World J Gastroenterol 2015; 21: 6924-6930 [PMID: 26078569 DOI: 10.3748/wjg.v21.i22.6924]

56 Tateishi U, Miyake M, Maeda T, Azai Y, Seki K, Hasegawa T. CT and MRI findings in KIT-weak or KIT-negative atypical gastrointestinal stromal tumors. Eur Radiol 2006; 16: 1537-1543 [PMID: 16397744 DOI: 10.1007/s00330-005-0091-3]

57 Yin YQ, Liu CJ, Zhang B, Wen Y, Yin Y. Association between CT imaging features and KIT mutations in small intestinal gastrointestinal stromal tumors. Sci Rep 2019; 9: 7257 [PMID: 31076599 DOI: 10.1038/s41598-019-43659-9]

58 Apfaltrer P, Meyer M, Meier C, Hienzler T, Barraza JM Jr, Dinter DJ, Hohenberger P, Schoepf UJ, Schoenenberg SO, Fink C. Contrast-enhanced dual-energy CT of gastrointestinal stromal tumors: is iodine-related attenuation a potential indicator of tumor response? Invest Radiol 2012; 47: 65-70 [PMID: 21934517 DOI: 10.1097/RLI.0b013e3182300322]

59 Choi H, Chamsangavage C, Faria SC, Macapinlac HA, Burgess MA, Patel SR, Chen LL, Podoloff DA, Benjamin RS. Correlation of computed tomography and positron emission tomography in patients with metastatic gastrointestinal stromal tumor treated at a single institution with imatinib mesylate: protocol of new computed tomography response criteria. J Clin Oncol 2007; 25: 1753-1759 [PMID: 17470865 DOI: 10.1200/JCO.2006.07.3049]
