Cellular Therapy and Transplantation (CTT). Vol. 11, No. 3-4, 2022
doi: 10.18620/ctt-1866-8836-2022-11-3-4-93-98
Submitted: 18 July 2022, accepted: 28 October 2022

Application of radiomics in the differential diagnosis in ameloblastomas and dentigerous cysts. Part 2

Anna V. Lysenko [1], Andrey I. Yaremenko [2], Anna A. Zubareva [3], Alexander V. Shirshin [4], Aleksandr I. Lyubimov [5], Elizaveta A. Ivanova [1]

[1] Department of Maxillofacial Surgery, Research Institute of Dentistry and Maxillofacial Surgery, St. Petersburg, Russia
[2] Department of Maxillofacial Surgery, Pavlov University, St. Petersburg, Russia
[3] Department of Otorhinolaryngology, Pavlov University, St. Petersburg, Russia
[4] Clinic of X-ray Radiology and Ultrasound Diagnostics, Kirov's Military Medical Academy, Faculty of control Systems and Robotics, ITMO University, St. Petersburg, Russia
[5] 1st Department for Surgeons' Advanced Training, Kirov's Military Medical Academy, St. Petersburg, Russia

Dr. Anna V. Lysenko, Department of Maxillofacial Surgery, Research Institute of Dentistry and Maxillofacial Surgery, Pavlov University, 44 Petrogradskaya Emb., 197101, St. Petersburg, Russia

Phone: +7 (812) 429-03-33
E-mail: lysenko.anna@mail.ru

Citation: Lysenko AV, Yaremenko AI, Zubareva AA, et al. Application of radiomics in the differential diagnosis in ameloblastomas and dentigerous cysts. Part 2. Cell Ther Transplant 2022; 11(3-4): 93-98.

Summary

Ameloblastomas and dentigerous cysts have an identical clinical and radiographic appearance. In our study we demonstrate the importance of radiological features careful consideration that can help in non-invasive differential diagnosis and ensuring appropriate management of these lesions.

Methods

This was a retrospective study including 18 CT images of patients with jaw neoplasm (8 ameloblastomas and 10 dentigerous cysts with histopathological verification). Each lesion was manually segmented using 3D Slicer software [1] on CT images, and textural features were extracted using 3D Slicer Radiomics extension [2]. Statistical analysis was performed.

Results

After texture analysis we found no (statistically significant) differences in the shape-based features and the first-order statistics values of these lesions. We found statistically significant differences in 13 second-order features of dentigerous cysts and ameloblastomas, most of them were closely correlated. Multiple logistic regression analysis was performed to rank features and to determine most significant predictors. The final model included 2 features (Cluster shade and IMC 1) and provided high predictive value (the area under a ROC=0.93).

Conclusions

Our pilot study demonstrates a new technique for non-invasive differential diagnosis of jaw neoplasms based on texture features extracted from CT-data.

Keywords

Radiomics, jaw neoplasms, ameloblastoma, dentigerous cysts, CT scan.

Introduction

Ameloblastoma (AB) and dentigerous cyst (DC) are both clinically common benign odontogenic lesions. Due to the significant differences in biological behaviors these two diseases have different treatment strategies. Surgical management is the only effective method in the treatment for odontogenic tumors, but the choice of effective surgical method is controversial. The treatment plan for AB mainly includes the radical operation of partial resection of the jawbone, for DC – the preservation surgery of decompression combined with curettage. Because of the different treatment principles of the two lesions, it is very important to find a more accurate preoperative differential diagnosis method. Differential diagnosis of these two lesions is difficult because they share many clinical and radiographic features. Therefore, it is difficult to differentiate these lesions radiographically, and definitive diagnosis is based only on histopathologic examination. Thus, differences in radiographic findings of these two lesions may play an important role in making the diagnosis.

The conversion of digital medical images into mineable high-dimensional data is motivated by the concept that biomedical images contain information that reflects underlying pathophysiology and that these relationships can be revealed *via* quantitative image analyses. Radiomics is a process that allows the extraction and analysis of quantitative data from medical images. Radiomics is designed to develop decision support tools; therefore, it involves combining radiomic data with other patient characteristics, as available, to increase the power of the decision support models.

In the past few years, radiomics has been used for diagnosis Nasopharyngeal carcinoma [3]; prediction of treatment response in non-small-cell lung cancer [4]; for preoperative prediction of microvascular invasion in hepatocellular carcinoma [5]; for the Non-Invasive Assessment of Coronary Inflammation [6]; in precision diagnosis, prognostication and treatment planning of head and neck squamous cell carcinomas [7]. Textural analysis of images in the studies was aimed at identifying prognostic biomarkers of disease imaging. Such objective biomarkers are readily available and have the potential to improve personalized treatment and precision medicine.

We hypothesized that CT texture analysis can detect subtle differences of the jaw neoplasm. This information is required to determine the correct treatment tactics.

The purpose of this study was to evaluate the utility of CT texture features in distinguishing common jaw neoplasms, i.e., ameloblastoma (AB) from dentigerous cysts (DC).

Materials and methods

1. Patient selection

A total of 35 records of patients with jaw neoplasm attended at the department of maxilla-facial surgery of the First Pavlov state medical university of Saint-Petersburg were analyzed. The inclusion criteria for the selection of the medical records were:

- The cases should present a report of the histipathological examination of AB or DC. Samples were fixated in 10% buffered formalin, later they were bathed in paraffin and histological cuts of X microns were performed, after hematoxylin and eosine stain, cuts examined under a light microscope Leica.
- There should be CBCT of the jaw before surgical treatment.

The exclusion criteria were:

- no histological conclusion,
- presence of recurrent lesion and with odontogenic keratocyst,
- imaging slices with severe artifact.

We excluded 17 cases according to the exclusion criteria. The remaining 18 patients: 10 patients with DC (9 men, 1 woman; median age 45 years) and 8 patients with AB (2 men, 6 women; median age, 58 years) were enrolled in this study.

2. CT imaging protocol

CT examinations were performed on 64-slice CT scanners (Toshiba Aquilion 64) with 120 kV, 225 mA and 1 s/rotation, and 0.5 mm thick images were reconstructed using per our institutional clinical protocol. Axial 0.5-mm images in reconstruction were used for this analysis.

3. Image Interpretation

Characteristics of the lesions were qualitatively assessed by radiologist with 7-year experience in oral and maxillofacial radiology.

3.1. Image segmentation and texture analysis

Segmentation is an essential step of the radiomics workflow, as highly distinctive features will be obtained from the segmented region of interest that can be traced in a volume, the accuracy of the segmentation will determine the radiomics features that will be extracted. The lesion was manually contoured by an oral and maxillofacial radiologist with 7-year professional experience. Segmentation of the lesion was performed using 3D Slicer on each axial image which includes the lesion, septum and peripheral bone up to 2 mm from visible edge of the formation.

Feature extraction is the next step after the region of interest is segmented. It is the selection of useful information to assist in the characterization of normal and abnormal radiological images. This step is the heart of radiomics. To extract radiomics features from the manually-segmented volumes, the Radiomics extension of 3D Slicer was used.

The extracted characteristics were shape-based features (e.g., maximum diameter, surface area, volume), first-order features (based on histogram statistics), second-order and higher-order statistics (based on spatial dependence matrices).

4. Statistical analysis

Due to relatively small number of cases, we chose nonparametric methods for statistical analysis: description of quantitative variables was performed with median and interquartile range, Mann-Whitney U test was used to compare them. Fisher's exact test with Freeman-Halton extension was used in the analysis of contingency tables.

Results

5. Characteristics of lesions

The characteristics of lesions and segmented volumes included in the study are shown in Table 1.

The anterior maxillary region was the most frequently encountered location in dentigerous cyst and posterior mandibular region has been most often observed in ameloblastomas.

6. Texture features and statistical analysis

The examples of segmented volumes are shown on Fig. 1.

The shape-based features are descriptors of the region of interest 3D size and shape. They are independent from the region of interest gray level intensity distribution and give a quantitative description of the region of interest geometrical characteristics.

First-order statistics features consider the distribution of values of individual voxels disregarding the spatial relationships. Second-order features, are based on the joint probability distribution of pairs of voxels, describing the spatial arrangement of patterns, sometimes imperceptible to the human eye. We used Gray Level Cooccurrence Matrix (GLCM), Gray Level Run Length Matrix (GLRLM), Gray Level Size Zone Matrix (GLSZM), Neighboring Gray Tone Difference Matrix (NGTDM), Gray Level Dependence Matrix (GLDM).

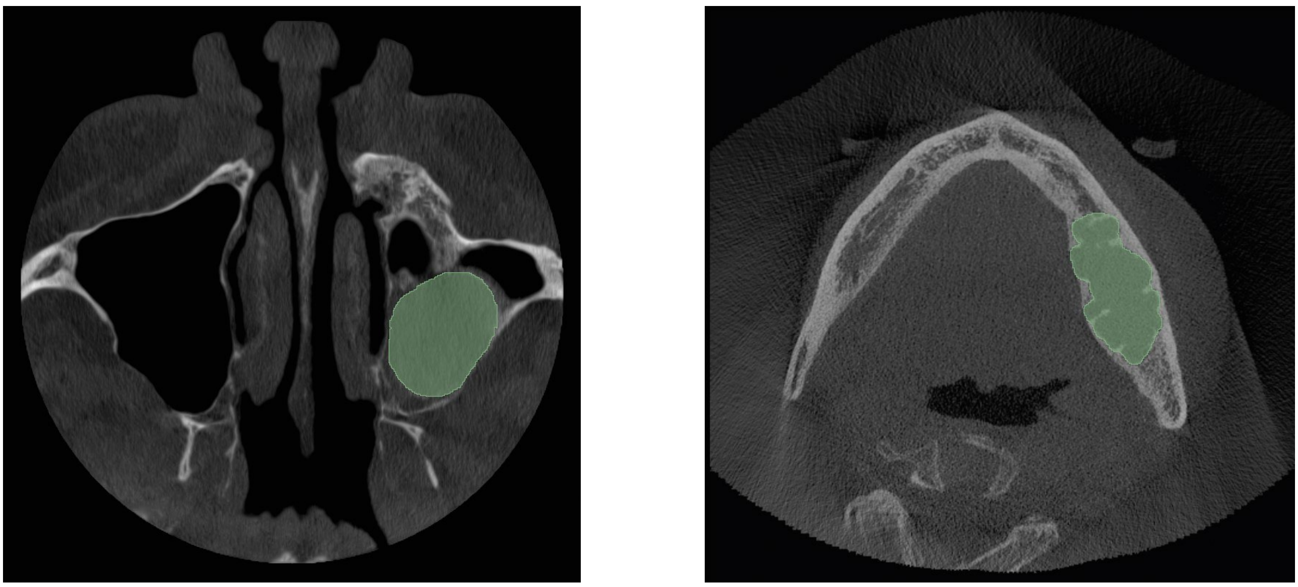
In our study, we evaluated the CT image texture features of DC and AB. After texture analysis we didn't found difference in the shape-based features and the first-order statistics values in two groups. In our opinion, this was expected, since both formations have similar radiographic features that can be superficially assessed during routine image analysis.

We found statistically significant differences in 13 second-order features of DC and AB (Fig. 2).

Cluster shade is a measure of the skewness and uniformity of the GLCM. Cluster prominence is a measure of the skewness and asymmetry of the GLCM. Contrast is a measure of the local intensity variation, favoring values away from the diagonal. Difference variance is a measure of heterogeneity that places higher weights on differing intensity level pairs that show more deviation from the mean. Informational Measure of Correlation is a quantification of the complexity of the texture. Dependence variance is the variance in dependence size in the image. Large dependence emphasis is the joint distribution of large dependence with lower gray level values. Long run emphasis – a measure of the distribution of long run lengths, with a greater value indicative of longer run lengths and more coarse structural textures.

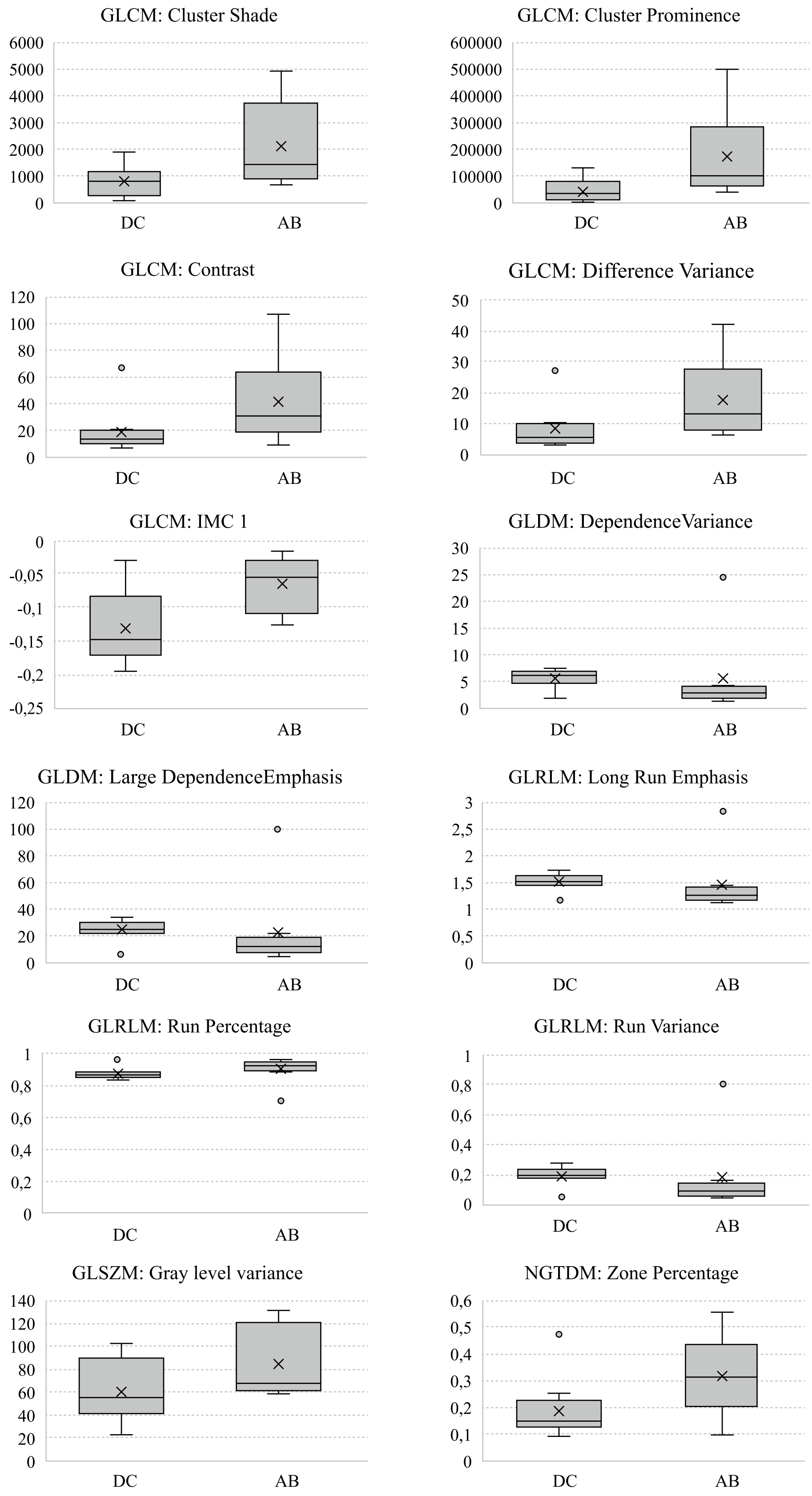
Table 1. Characteristics of lesions and segmented volume

	Dentigerous cyst, n=10	Ameloblastoma, n=8	p
Region			
Maxillary anterior	4 (40 %)	–	0.39
Maxillary posterior	2 (20 %)	1 (25 %)	
Mandibular anterior	1 (10 %)	–	
Mandibular posterior	3 (30 %)	3 (75 %)	
Segmented Volume			
Maximum 3D diameter, mm	34.9 [27.4, 42.1]	40.3 [29.4, 51.3]	0.46
Sphericity	0.63 [0.55, 0.67]	0.50 [0.50, 0.54]	0.12
Surface volume ratio	0.56 [0.46, 0.58]	0.47 [0.42, 0.62]	0.57



A B

Figure 1. Segmented CT images: A, ameloblastoma; B, dentigerous cyst



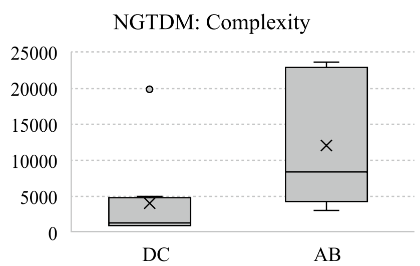


Figure 2. Differences in 13 second-order features of DC and AB

Run percentage is a measure of the coarseness of the texture by taking the ratio of number of runs and number of voxels in the region of interest. Run variance is the variance in runs for the run lengths. Gray level variance (GLSZM) is the variance in gray level intensities for the zones. Zone percentage is a measure of the coarseness of the texture by taking the ratio of number of zones and number of voxels in the region of interest. Complexity is a measure of non-uniformity and rapid changes in gray levels.

Multiple logistic regression analysis with direct stepwise inclusion of factors (forward LR) was performed to rank features and to determine most significant predictors. The final model included Cluster shade and IMC 1. Combined use of these indicators significantly increased the predictive value of the model (the area under a ROC=0.93).

Discussion

Jaws are the only site in the body where epithelium may normally be found within bone. The epithelium of the dental lamina is involved in the formation of enamel and maps out the shape of the tooth. On completion of tooth formation, epithelial remnants remain in the jaws. These give rise to a range of lesions, including neoplasms, which should pose no problem with diagnosis when seen to be associated with teeth, but can cause difficulty in other situations.

Two different types of lesions were the sample of this study: ameloblastoma, and dentigerous cyst. This selection was based on 2 factors: the frequency and the similarity of the radiographic image among these lesions.

As the components of the various lesions are inherently different pathologically, the texture features should also be different.

Ameloblastomas are composed of epithelium and do not show induction of dental hard tissues. In the conventional type, the epithelium may show a follicular or a plexiform pattern, but a mixture of patterns is often seen within a single tumor. The most common pattern is follicular, characterized by islands of epithelium with peripheral palisading of elongated columnar cells with reversed polarity, in that the nuclei are orientated away from the basement membrane. These cells resemble the preameloblasts of normal tooth development. Centrally the follicles contain loosely arranged stellate cells, showing a resemblance to the stellate reticulum of the tooth germ.

Dentigerous cyst consist of epithelial lining and wall. Epithelial lining – typically, 2-4 cells thick. Flattened non-keratinsing cells with a regular flat interface with the underlying wall. Inflammation results in features identical to radicular cyst. Metaplastic changes with mucous cells and cilia occur more commonly in dentigerous cysts than other types. Inflamed specimens may also show hyperplasia, occasionally with keratinization. Hyaline bodies and even sebaceous cells can be included. Wall – typically, uninflamed fibromyxoid connective tissue (similar to dental follicle) with plentiful glycosaminoglycan-rich ground substance. Odontogenic epithelial rests present in variable numbers and may undergo calcification. Increased fibrosis along with cholesterol clefts and haemosiderin deposition seen in longstanding and inflamed cysts.

We suppose the differences between radiomic features reflected the differences in X-ray density of lesions components.

Conclusion

Our pilot study demonstrates a new technique for non-invasive differential diagnosis of jaw neoplasms based on texture features. This research may contribute to actual implementation of these radiomics-based techniques into clinical practice, contributing the effective support of clinical decision-making and the fostering of precision medicine.

Funding sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest

None declared.

References

1. Fedorov A, Beichel R, Kalpathy-Cramer J, Finet J, Fillion-Robin JC, Pujol S, et al. 3D Slicer as an image computing platform for the quantitative imaging network. Magn Reson Imaging. 2012 ;30(9):1323-1341. doi: 10.1016/j.mri.2012.05.001

2. van Griethuysen JJM, Fedorov A, Parmar C, Hosny A, Aucoin N, Narayan V, et al. Computational radiomics system to decode the radiographic phenotype. Cancer Res. 2017; 77(21):e104-e107. doi: 10.1158/0008-5472.CAN-17-0339

3. Duan W, Xiong B, Tian T, Zou X, He Z, Zhang L. Radiomics in nasopharyngeal carcinoma. Clin Med Insights Oncol. 2022; 16:11795549221079186. doi: 10.1177/11795549221079186

4. Chetan MR, Gleeson FV. Radiomics in predicting treatment response in non-small-cell lung cancer: current status, challenges and future perspectives. Eur Radiol. 2021;31(2):1049-1058. doi: 10.1007/s00330-020-07141-9

5. Yang L, Gu D, Wei J, Yang C, Rao S, Wang W, et al. A radiomics nomogram for preoperative prediction of microvascular invasion in hepatocellular carcinoma. Liver Cancer. 2019;8(5):373-386. doi: 10.1159/000494099

6. Cheng K, Lin A, Yuvaraj J, Nicholls SJ, Wong DTL. Cardiac computed tomography radiomics for the non-invasive assessment of coronary inflammation. Cells. 2021; 10(4):879. doi: 10.3390/cells10040879

7. Haider SP, Burtness B, Yarbrough WG, Payabvash S. Applications of radiomics in precision diagnosis, prognostication and treatment planning of head and neck squamous cell carcinomas. Cancers Head Neck. 2020; 5:6. doi: 10.1186/s41199-020-00053-7

Применение радиомики в дифференциальной диагностике амелобластом и одонтогенных кист челюстей: часть 2

Анна В. Лысенко [1], Андрей И. Яременко [2], Анна А. Зубарева [3], Александр В. Ширшин [4], Александр И. Любимов [5], Елизавета А. Иванова [1]

[1] Отдел челюстно-лицевой хирургии НИИ стоматологии и челюстно-лицевой хирургии, Санкт-Петербург, Россия
[2] Кафедра челюстно-лицевой хирургии, Первый Санкт-Петербургский государственный медицинский университет им. И. П. Павлова, Санкт-Петербург, Россия
[3] Кафедра оториноларингологии, Первый Санкт-Петербургский государственный медицинский университет им. И. П. Павлова, Санкт-Петербург, Россия
[4] Клиника рентгенорадиологии и ультразвуковой диагностики Военно-медицинской академии имени Кирова, факультет систем управления и робототехники, Университет ИТМО, Санкт-Петербург, Россия
[5] 1-е отделение усовершенствования хирургов, Военно-медицинская академия им. С.М. Кирова, Санкт-Петербург, Россия

Резюме

Амелобластомы и одонтогенные кисты имеют идентичный клинический и рентгенологический вид. В нашем исследовании мы демонстрируем важность тщательного рассмотрения радиологических особенностей, которые могут помочь в неинвазивной дифференциальной диагностике и обеспечении надлежащего лечения этих поражений.

Методы

Было проведено ретроспективное исследование, включавшее 18 КТ-изображений пациентов с новообразованиями челюсти (8 амелобластом и 10 зубочелюстных кист с гистопатологической верификацией). Каждое поражение было вручную сегментировано с помощью программного обеспечения 3D Slicer на КТ-изображениях, а текстурные особенности были извлечены с использованием расширения 3D Slicer Radiomics. Был проведен статистический анализ.

Результаты

После анализа текстуры мы не обнаружили (статистически значимых) различий в характеристиках формы и статистических значениях первого порядка этих поражений. Мы обнаружили статистически значимые различия по 13 признакам второго порядка зубочелюстных кист и амелобластом, большинство из которых тесно коррелировали. Был проведен множественный логистический регрессионный анализ для ранжирования признаков и определения наиболее значимых предикторов. Окончательная модель включала 2 признака (кластерный оттенок и IMC 1) и обеспечивала высокую прогностическую ценность (площадь под ROC=0,93).

Выводы

В нашем пилотном исследовании мы продемонстрирован новый метод неинвазивной дифференциальной диагностики новообразований челюстей на основе особенностей текстуры, извлеченных из данных КТ.

Ключевые слова

Радиомика, новообразования челюстей, амелобластома, одонтогенные кисты, компьютерная томография.