



## REVIEW ARTICLE

## From Pixels to Prognosis: Radiomics and AI Applications in Maxillofacial Radiology

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## ABSTRACT

Recently, the beneficial impacts of digitalization in healthcare have facilitated the advancement of innovative methodologies in diagnosis and treatment planning through the integration of medical data with artificial intelligence algorithms. Radiomics, a pioneering field, underlies image-based decision support systems, which use statistics and artificial intelligence to extract quantitative data from medical pictures. Quality and accuracy are required throughout the radiomics workflow, including image acquisition, model construction, and clinical application. Due to the complexity of maxillofacial anatomy, radiomics and artificial intelligence using cross-sectional three-dimensional imaging techniques like CT and CBCT have gained popularity in dentistry. Clinical models must meet accuracy, repeatability, and generalizability standards. Future research expects radiomics to improve dentistry diagnosis, treatment planning, and disease prognosis.

**Keywords:** Artificial intelligence; Dentistry; Maxillofacial radiology; Radiomics

### 1 INTRODUCTION

For two decades, digitalization has penetrated many aspects of life, especially in health through clinical data digitization. Digitizing medical data has enhanced data analysis. Clinicians employ engineering-designed programs. Clinical software solutions accelerate solution manufacturing and boost 'big data' by extending data repositories. The Federal Big Data Commission of the TechAmerica Foundation defined big data as "extensive volumes of rapid, intricate, and variable data necessitating sophisticated techniques and technologies for the capture, storage, distribution, management, and analysis of information" in 2012<sup>(1)</sup>. In dentomaxillofacial radiology, diagnostic and therapeutic imaging techniques utilize various forms of energy, such as X-rays, magnetic fields, and ultrasound waves, which are applied in a generally non-invasive and safe manner to visualize anatomical structures and pathologies. Medical imaging assesses tissue morphology, function, and metabolism. Computed Tomography (CT), Cone Beam Computed Tomography (CBCT), Magnetic Resonance Imaging (MRI), Positron

Emission Tomography (PET), and Ultrasonography (US) have transformed diagnosis and treatment. Experience, competence, and personal traits (e.g., fatigue, psychological state) can influence physician observation of anatomical pictures, requiring more objective and quantitative analytic methods. Radiomics, a new medical imaging method, quantifies biological processes. Medical images are analyzed for tissue structure, shape, intensity, and signal change using statistical methods and Artificial Intelligence (AI)/ Machine Learning (ML) algorithms. Thus, clinical conclusions about diagnosis, prognosis, and therapy response can be made<sup>(2)</sup>. Grossmann led a 2017 study that used 'radiomics' to improve diagnostic imaging for tailored treatment. Digital medical images are more than just 'pictures'—they contain complex data that may be analyzed mathematically or quantitatively<sup>(3)</sup>. Radiomics, a quantitative imaging domain related to machine learning, is a relatively new field. By statistically inferring signal intensity distribution and pixel/voxel correlations that the human eye cannot see, it may measure the textural information of selected regions and volumes of interest (ROI and VOI) in digital diagnostic

images<sup>(4)</sup>. Radiomics improves tissue understanding by analyzing imaging properties to predict disease development, treatment response, and recurrence<sup>(5)</sup>. The radiomics workflow begins with digital radiography data collection. Many imaging systems with different characteristics can give quantitative radiomics data<sup>(6,7)</sup>. Radiomics converts images into quantifiable data with high precision and efficiency, involving many stages with different inputs and outputs, each with its own challenges. Inaccuracies in any of these processes might cause disparities in results (Figure 1)<sup>(8)</sup>.

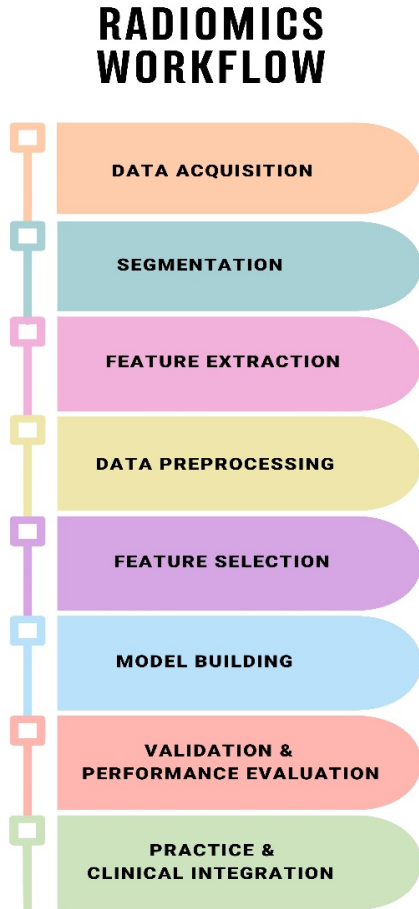


Fig. 1: Radiomics Workflow

## 1.1 Radiomics Procedure

### 1.1.1. Image Acquisition

The initiation of radiologic analysis involves the selection of a high-quality and suitable imaging protocol. Imaging modalities including CBCT, CT, MRI, nuclear medicine, PET, and US<sup>(9)</sup>. The quality of the image is crucial, as substandard or artifact-laden photographs might negatively impact the entire process.

### 1.1.2. Segmentation

After collecting image data, segmentation can be done manually, semi-automatically, or automatically. Image ROIs and VOIs are segregated. At this point, the target lesion, tumor, tissue, or anatomical structure is properly defined<sup>(10)</sup>. Each segmentation approach has pros and cons. Most photo segmentation methods are manual or semi-automatic, including manual correction, although they have many limitations. Initially, manual segmentation is laborious. Manual segmentation time depends on target area size and data amount. Second, manual and semi-automated segmentation may have user-specific faults<sup>(11)</sup>. Human mistake reduction is best with automatic segmentation. However, machine learning-based segmentation algorithms may fail if the training data lacks diversity. Clinical staff may be skeptical of automatic segmentation algorithms due to a lack of understanding of their operational mechanisms (the “black box” issue), requiring a post-procedure user verification. However, further study is needed to develop robust and generalizable automatic segmentation systems<sup>(12)</sup>.

### 1.1.3. Feature Extraction

The quantitative analysis of segmented data calculates radiomics properties. Theory allows infinite probability computation of shape-based first, second, and higher order features<sup>(13)</sup>. Shape-based examination includes ROI morphology, size, placement, vascularization, and spiculation. First-order statistics directly examine pixel or voxel intensity<sup>(14)</sup>. Instead of intensity values, second-order features focus on spatial relationships between pixels or voxels. Understanding texture patterns and features is the goal<sup>(15)</sup>. Wavelet, LoG, and LBP filters and transformations are used to extract higher-order features from the image, followed by image preprocessing. Re-extraction of first- or second-order characteristics reveals hidden patterns and complicated relationships<sup>(8)</sup>.

### 1.1.4. Data Preprocessing

Normalization and standardization are used to prepare the photos and extracted attributes for analysis, which ensures accuracy and reproducibility<sup>(2)</sup>. In high-dimensional data sets, model correctness, consistency, and generalizability must be improved. Thus, photo noise and artifacts are identified. Radiological feature values at various scales greatly affect AI algorithm parameter stability. By synchronizing photos from different devices or protocols, findings are guaranteed to be comparable<sup>(16)</sup>.

### 1.1.5. Features Selection

This large dataset should be augmented by a model that includes genomic profiles, histological characteristics, serum biomarkers, patient history, and diagnostic procedures to ensure data repeatability and accuracy. Only important elements are kept, while redundant, repetitive, or noise-

inducing ones are removed. This level uses statistics and machine learning<sup>(17,18)</sup>.

### 1.1.6. Development of the Model

Model development algorithms abound. The categorizing process requires a good model. Logistic regression, Support Vector Machine (SVM), random forests, and Extreme Gradient Boosting (XGBoost) distinguish benign and malignant tumors. Survival time is predicted using linear regression and survival trees. Convolutional neural networks (CNN) can handle large datasets. The literature seems to randomly select algorithms, while optimal practice involves substantial trial<sup>(16,18–20)</sup>.

### 1.1.7. Training and Validation

Data is split into training and test sets before validation. The test set (20-30%) is smaller than the training set (70-80%). Validation is performed on clustered data at a given rate. For clinical approval, results must be validated using independent datasets, preferably from another institution<sup>(10,20)</sup>. Thus, independent external validation is the best model validation method. Small-scale pilot or early studies may not have independent validation data. These situations may require internal validation. In the literature, k-fold and leave one-out cross-validation (LOOCV) are the main internal validation methods<sup>(20)</sup>.

### 1.1.8. Assessment of Performance

The assessment of categorization performance is typically conducted using the area under the curve (AUC)<sup>(21)</sup>. In datasets with class imbalance, AUC may not be a reliable performance indicator. A complete evaluation must include accuracy, sensitivity, specificity, Receiver Operating Characteristic (ROC) curve, and Matthews correlation coefficient<sup>(16)</sup>. Following the assessment of classifications, regression and clinical validation analyses are performed and tested on real patient data for inclusion in the clinical decision support system<sup>(14)</sup>.

### 1.1.9. Readyng the Model for Clinical Utilization

The models must be tested using independent datasets from many centers or devices, regardless of previous procedures. The model must be generalizable on the training dataset and in clinical applications<sup>(22)</sup>. Standardize the imaging parameters, segmentation methodologies, and feature extraction criteria<sup>(23)</sup>. Before clinical use, the model's diagnostic precision, treatment efficacy, and prognosis prediction are evaluated. Finally, we must prospectively test the model in new patient cohorts and real-time clinical scenarios<sup>(24)</sup>.

## 1.2 Radiomics and Artificial Intelligence

Radiomics and artificial intelligence are vast fields with many methods. This heterogeneity leads to disagreements on several phases, which may hinder standardization and lead

to inconsistent results<sup>(20)</sup>. Effective integration, processing capacity, and the availability of large data sets make human-machine collaboration in future therapeutic applications inevitable.

## 1.3 Applications in Dentistry

Since most dento-maxillofacial illnesses need radiography, many hospitals and clinics archive and store digital radiography images. For successful diagnosis and therapeutic planning, maxillofacial 3D imaging is critical to digital workflows in patient care due to its anatomical complexity and proximity to vital vascular and brain structures. Many maxillofacial illnesses are diagnosed, treated, and prognosed using deep learning and radiomics applications using CT images<sup>(25)</sup>. Artificial intelligence research is promising, yet the field is young. It must be practical and provide accurate results for clinical use. Radiomics was barely recognized in dentistry till 2019. After this, this field has seen more research. The clinical usage of three-dimensional imaging technologies like CBCT and artificial intelligence/machine learning algorithms in healthcare have also contributed to this increase (Figure 2). In dentistry, radiologists and artificial intelligence professionals should collaborate to construct radiomics models for strong and therapeutic application.

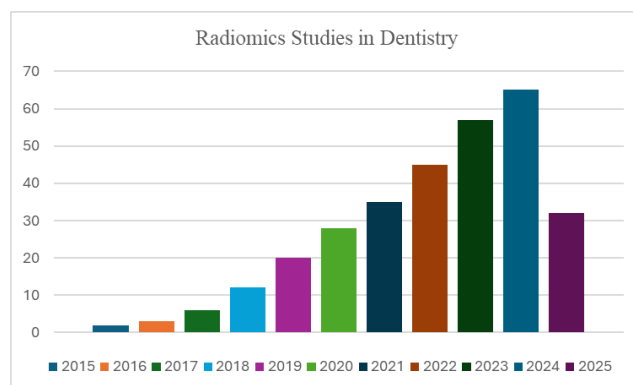


Fig. 2: Radiomics-based studies in dentistry to date

### 1.3.1. Assessment of Cysts and Neoplasms in the Mandibular Bones

Panoramic radiographs usually detect jaw cysts and cancers. CBCT is the most common imaging modality in dentistry for thorough examination, however radiographic images alone cannot diagnose certain diseases due to their different clinical, radiographic, and histopathologic features. Indeed, CBCT is difficult for discriminating benign from malignant tumors. Numerous studies have developed deep learning models using 2D or 3D radiographic images to automatically identify various jaw cysts and malignancies in response to the need for accurate diagnosis<sup>(26–29)</sup>. Xu et al.<sup>(30)</sup> developed

artificial intelligence models to differentiate between odontogenic cysts and ameloblastomas by utilizing particular characteristics from CBCT images, achieving remarkably high accuracy rates. Sha et al.<sup>(31)</sup> developed a precise CBCT-based radiomics model to differentiate odontogenic cysts, keratocysts, and ameloblastomas. Additional imaging in this region may help maxillofacial radiologists identify jaw cysts and malignancies, improving early diagnosis and prognosis<sup>(25)</sup>.

### 1.3.2. *Assessment of Salivary Gland Pathologies*

Salivary gland diseases are inflammatory, infectious, or neoplastic ailments that affect the parotid, submandibular-sublingual, and minor salivary glands. Salivary gland diseases are difficult to diagnose in dentistry and otolaryngology because they require clinical competence and diagnostic imaging (MRI, CT, US)<sup>(25)</sup>. Radiomics analysis enables the automatic and objective differentiation of benign and malignant tumors by assessing lesion features, including tissue heterogeneity, form, and margins<sup>(32)</sup>. Because MRI scans better depict soft tissues than other imaging modalities, deep learning models for salivary gland diseases have mostly used them<sup>(33)</sup>. Since MRI is rarely used in dentistry and radiomics ultrasound research is limited, the models were mostly based on CT images<sup>(25)</sup>. Yuan et al.<sup>(34)</sup> created a CNN model utilizing CT images to differentiate between pleomorphic adenoma and malignant parotid gland tumors; Zhang et al.<sup>(35)</sup> established a CNN model on CT images to distinguish between benign and malignant parotid gland tumors; Kise et al.<sup>(36)</sup> used a CNN model on CT scans to autonomously identify salivary gland fatty degeneration, a key indication of Sjögren's syndrome, with great accuracy.

### 1.3.3. *Assessment of Pulpal and Periapical Pathologies*

Pulpal tissue is usually healthy but can be damaged by inflammation or trauma. This injury may migrate from the pulpal tissue to the periapical region, causing bone inflammation. Inflammatory periapical lesions alter alveolar bone internal imaging, indicating bone structure decrease, augmentation, or a combination. CBCT is often used in endodontics to investigate root canal blockages, dilations, contractions, perforations, canal morphology, and alveolar bone changes. Rosa et al.<sup>(37)</sup> used textural radiomic parameters from CBCT images to detect periapical granulomas and cysts with more accuracy than radiologic assessment. Gonzalez et al.<sup>(38)</sup> found textural and first-order radiomic differences in CBCT images for diagnosing periapical lesions based on volumetric size, cortical expansion, resorption, and shape.

### 1.3.4. *Assessment of Maxillary Sinus Pathologies*

The maxillary sinus, the biggest face sinus, is often involved in posterior tooth and dental implant procedures. A satisfactory treatment outcome requires accurate diagnosis

and categorization of maxillary sinus disorders before sinus surgery. CT, CBCT, or MRI are used to detect mucocoeles, sinusitis, mucus retention cysts, maxillary sinus cysts, and tumors and analyze their association with neighboring anatomical structures. Precise identification of maxillary sinus diseases on conventional imaging modalities can occasionally be challenging. Ito et al.<sup>(39)</sup> used CT to compare the tissue characteristics of maxillary sinus mucosal thickening in odontogenic and non-odontogenic maxillary sinusitis, finding significant differences. Shaujan et al.<sup>(40)</sup> employed CT scans to differentiate inverted papilloma from chronic rhinosinusitis polyps, and their radiomic models demonstrated high accuracy in this classification. Moreover, literature also presents CNN-based sinus segmentation<sup>(41)</sup> and morphological alterations in sinus mucosa<sup>(42)</sup>.

### 1.3.5. *Assessment of Temporomandibular Joint (TMJ) Disorders*

TMJ disorders include issues with the joint itself (such as disc displacement, partial dislocation, and stiffness), conditions impacting the joint (like arthritis and specific cancers), fractures, developmental anomalies, and complications involving the masticatory muscles (including pain and tension). Inflammatory changes in the synovial membrane of the joints or masticatory muscles lead to variations in the joint complex caused by inflammatory mediators. This leads to degenerative and deformative changes in the cartilage matrix, subchondral bone, and related joint tissues. The diagnosis and treatment of TMJ disorders depend significantly on comprehensive clinical expertise, resulting in diverse viewpoints among doctors concerning diagnostic and therapeutic approaches. Recent research indicate that radiomics algorithms, especially those utilizing MRI and CBCT data, provide substantial insights in evaluating TMJ issues. Orhan et al.<sup>(43)</sup> categorized alterations in the condyle and disc dislocations using radiomicing with MRI data and saw a significant concordance in their results. Ogawa et al.<sup>(44)</sup> found significant tissue changes linked with condylar flatness and erosion in CT and MRI images. The findings suggest that tissue analysis may help detect TMJ degeneration early.

### 1.3.6. *Differentiation Between Benign and Malignant*

Many clinical and radiographic indications are used to identify benign from malignant craniofacial diseases. However, some benign forms may mislead the doctor during the first diagnosis by seeming malignant on radiographs. Early-stage tumors may not show radiographic abnormalities. Therefore, radiomics can distinguish benign from malignant lesions by examining microscopic textural variations (heterogeneity, edge patterns, density distributions) that are imperceptible to the naked eye and converting them into mathematical data for artificial intelligence algorithms to analyze. Iqbal et al.<sup>(45)</sup> found that combining clinical exams, imaging modalities, and histopathologic tests improves oral lesion diagnoses

and reduces misdiagnosis rates. Yuan et al.<sup>(46)</sup> developed an MRI-based radiomics algorithm and nomogram to predict preoperative outcomes in head and neck squamous cell carcinoma (SCC) patients. Research and technology predict that radiomics will reduce the need for intrusive therapies to distinguish benign from malignant illnesses, improve prognosis, and make diagnosis easier for physicians.

### 1.3.7. Assessment of Dental Implants

Although dental implants are a reliable treatment method for toothless areas, they can involve certain complications, as with any surgical procedure<sup>(47)</sup>. These complications may occur during the surgical procedure or in the subsequent period. Failure may occur due to reasons such as incorrect application of the surgical intervention, insufficient bone quality, infection, or incorrect application of prosthetic rehabilitation<sup>(48)</sup>. While monitoring success radiographically, physicians mostly use conventional radiographs (periapical and panoramic radiography) and CBCT images. However, this may not always provide sufficient results. The evaluation of dental implants using the radiomics method is an innovative approach that goes beyond traditional radiographic examinations and is based on obtaining quantitative data from medical images that cannot be distinguished by the human eye. This approach entails the examination of data acquired from three-dimensional imaging modalities, such as CBCT, with sophisticated mathematical algorithms<sup>(49)</sup>. Radiomics analysis seeks to forecast the efficacy and enduring stability of the implant by delivering comprehensive insights into the tissue, density, and microarchitecture of the bone at the implant site. The integration of radiomics and machine learning techniques is regarded as a potential strategy for forecasting phenomena such as physiological bone remodeling (PBR) that may transpire shortly after implant implantation<sup>(50)</sup>. This technology enables the prior identification of risk variables that may influence the effectiveness of implant treatment, allowing for the formulation of more precise tailored treatment programs.

## 2 CONCLUSION

Radiomics is new to dentistry and associated studies, thus it needs more work. However, this field has shown encouraging outcomes. Future research and AI models incorporating radiomics data should improve disease diagnosis, tailored treatment planning, and outcome prediction.

## 3 DISCLOSURE

**Funding:** None

**Conflict of Interest:** Nil

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