REVIEW PAPER

THE ROLE OF RADIOMICS IN DENTISTRY AND ORAL RADIOLOGY

Tannishtha, Shruthi Hegde, G. Subhas Babu, Vidya Ajila, B.S. Shama

Department of Oral Medicine and Radiology, Nitte (Deemed to be University), AB Shetty Memorial Institute of Dental Sciences (ABSMIDS), Mangalore, India

ABSTRACT

Technological advances in healthcare sector have led to an increasing use of new digital techniques for diagnosis and therapeutics in medical and dental professions. Artificial intelligence (AI) is one of the most commonly discussed innovations of the present era that present the capability to transform clinical practice and research. Radiomics is an emerging field in quantitative imaging related to AI. Radiomics technology is produced as a result of combining genomic data, imaging, and pathology results. This new technology can quantify textural information through mathematical analysis from the region of interest in medical images, which the human eye cannot perceive. In oral and maxillofacial imaging, the use of cone beam computed tomography (CBCT) has been increasing that in turn encourages AI and radiomics research to assist clinicians in early diagnosis and effective treatment planning. The advent of radiomics in dentistry made it possible to improve diagnostic, prognostic, and predictive accuracy, by combining radiographic data, biological data, and clinical outcomes. Radiomics technology in dentistry is still in early phases of development. The present narrative review aimed to provide an up-to-date overview of the workflow and potential applications of radiomics in diagnosing and managing oral maxillofacial diseases.

Key words: oral radiology, radiomics, artificial intelligence.

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INTRODUCTION

Artificial intelligence (AI) research has advanced, and is used outside of a computer science department. As a result, there was a steady rise in the use of AI applications in healthcare. AI technology is intended to help clinical practitioners in clinical decision-making, and to reduce repetitive tasks performed in their daily work [1]. Radiomics is a quantitative approach to medical imaging that aims to enhance the available radiographic data through sophisticated mathematical analysis. The main idea of radiomics is based on the concept that biomedical imaging comprises data reflecting disease-specific processes and is accessible by quantitative image analyses [2]. Radiomics technology is produced as a result of combining genomic data, imaging, and pathology results [3]. The application of artificial intelligence-aided programs in maxillofacial radiology is increasing [4, 5].

Vast availability and an increased use of digital imagining techniques, such as computed tomography (CT) and cone beam computed tomography (CBCT), enabled the introduction of AI and radiomics in oral and maxillofacial imaging. The advent of radiomics in dentistry made it possible to improve diagnostic, prognostic, and predictive accuracy, by combining radiographic, biological, and clinical data. Qualitative data extracted from the radiographs using data-characterization algorithms in radiomics allow specialists to obtain additional diagnostic information for personalized care [6, 7]. Research in radiomics and AI have advanced in the field of dentistry, demonstrating these

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Address for correspondence: Dr. Shruthi Hegde, Nitte (Deemed to be University), AB Shetty Memorial Institute of Dental Sciences (ABSMIDS), Department of Oral Medicine and Radiology, Mangalore, India,
e-mail: drshruthihegde@yahoo.co.in

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technologies' potential to significantly enhance clinical treatment [6-9]. This article highlighted the potential role of radiomics in dentistry and oral radiology.

CONCEPT OF ARTIFICIAL INTELLIGENCE

Intelligence is referred to as the capacity to learn and use information and skills. Artificial intelligence (AI) can be defined as the non-biological potential to perform complicated tasks [10]. Currently, AI become one of the most sought-after domains in terms of research, and has a vital role in many people's daily activities [11].

Artificial intelligence in dentistry mainly depends on the output of a number of schemes based on pre-determined programming models and computer analysis, using complicated mathematical models and formulas [12]. Machine learning (ML) is a sub-set of AI. Computer-aided detection and diagnosis are two important areas of medical applications in machine learning [13]. Algorithms for image processing are often used in radiology, especially for in-depth evaluation of multi-planar medical images. These techniques start from extracting the features of a given image before conducting target detection or classifying the image into pre-defined groups, to achieve image detection or classification. Out of all the existing ML models, convolutional neural networks (CNNs) are the most utilized technology in medical imaging due to their exceptional effectiveness in enhancing image diagnostic characteristics [14]. Despite their role as promising adjunctive tools in radiology, the applications of ML algorithms in dental and maxillofacial radiology are still in early phases of development [15].

AI-ENABLED MAXILLOFACIAL IMAGING

Artificial intelligence is gradually influencing every part of our lives with various conveniences, such as speakers with built-in AI, content recommendation systems, etc. The development of deep learning also opens exciting opportunities for the automation of picture analysis in the fields of dentistry and medicine. Significant developments have been made in every subject of artificial intelligence, including robotics, data mining, medical image analysis, and processing [16]. Studies on artificial intelligence for diagnosing dental caries, periodontal disease, odontogenic cysts and tumors, diseases of the maxillary sinus, temporomandibular joints, and osteosclerosis, have shown promising results in the field of oral radiology [4]. AI-enabled programs are used in maxillofacial radiology for cephalometric tracing, detection of caries, alveolar bone loss, periapical pathosis, detection and tracing of the inferior alveolar nerve canal, and other similar functions [17].

A deep learning hybrid approach was recently developed by Chang *et al.* [18] for the automated staging of periodontitis on dental panoramic radiographs. The basis of their AI system was a combination of deep learning architecture and traditional computer-assisted diagnosis approach. Their system demonstrated greater accuracy and reliability in staging periodontitis based on the amount of alveolar bone loss.

Image analysis of a maxillofacial radiograph using artificial intelligence has been employed for a variety of tasks, including segmentation or localization of teeth, evaluation of bone quantity and quality, estimation of age using hand-wrist radiographs based on analysis of the pattern of ossifications, and localization of cephalometric landmarks [17, 19].

Panoramic radiographs are considered an important modality for identifying osteopenia and osteoporosis. In post-menopausal females, osteoporosis can be diagnosed using the reduction in mandibular cortical width and severity of erosion of the mandibular lower cortex. There are artificial intelligence models in panoramic radiography available to diagnose osteopenia and osteoporosis [17]. Lee *et al.* [20] analyzed the efficacy of a deep convolutional neural network (DCNN)-based CAD system in assessing diagnostic performance for the detection of osteoporosis on panoramic radiographs, and reported satisfactory results. Promising findings from AI-enabled technologies have led to a sharp rise in the innovation of new deep learning techniques for oral and cranio-facial radiology, including head and neck oncology [11, 15].

RADIOMICS

The "-omics" ideology has emerged in the recent decade due to the improvements in high-throughput computing and machine learning methods. It refers to the collective characterization and quantification of biological information pools, including genomics, proteomics, and metabolomics. Radiomics consists of the automatic extraction of numerical descriptors with mathematical definitions, referred to as "radiomics features", from 2-dimensional and 3-dimensional radiographic image series [21].

Physical characteristics of the imaged region, such as tissue cellularity, heterogeneity, and necrosis, are represented by radiomics features. According to the literature evidence on radiomics research, radiomics traits usually correlate with diagnostic and outcome variables [22, 23]. Moreover, radiomics comprises algorithms that divide input images into basic properties, such as edges, gradients, form, signal intensity, wavelength, and textures, which can be further used to categorize or analyze the radiographic image. Therefore, a straightforward definition of radiomic analysis is the extraction of quantitative data in a radiograph to measure and extract specific parameters. As a result, radiomics' software can define or find numerous abstract mathematical properties on images based on variations in the spatial patterns of grey levels and signal intensity, which are typically not visible to human sight in images and cannot be assessed visually [7].

The workflow of radiomics involves image acquisition, image segmentation, image processing, feature extraction, feature selection, dimension reduction, and analysis. Acquisition of high-quality and standardized imaging is necessary [1, 24]. The source of data for radiomics are retrospective medical images. Different techniques for imaging may lead to changes in image signals and image textures due to various parameters used for acquisition and reconstruction in medical imaging. Standardization is essential for radiomics image analysis, and segmentation also must be reproducible and reliable. Automated segmentation is preferred over manual and semi-automatic. The automated professional software usually performs the extraction of features in radiomics, and shape and texture features are mined [1, 24]. The workflow of radiomics is shown in Figure 1 [1, 24].

Valid and quantitative features from medical images extracted in radiomics can be combined with other characteristics, such as clinical staging, pathological features, and tissue molecular markers [1, 24].

Various clinical decision-making systems have been developed in recent years based on radiomics, which may aid in the correlation of radiographic data with biological and clinical endpoints, and could increase the accuracy of diagnosis and prediction of possible prognosis. Investigation of correlations between quantitative bio-imaging features and disease properties resulted in a sub-specialty known as radio-genomics [25, 26].

APPLICATIONS OF RADIOMICS IN ORAL AND MAXILLOFACIAL RADIOLOGY

The potential of radiomics in the diagnosis and treatment planning of oral and maxillofacial lesions is increasing. Hung *et al.* [27] have recently reported that the performance of radiomics models on CT/CBCT images showed promising features for maxillofacial diseases. The roles of radiomics in odontogenic and non-odontogenic cysts and tumors of the jaws, developmental deformities of the dentomaxillofacial region, oral cancer, cervical lymph node metastasis, diseases of salivary glands, temporomandibular (TMJ) disorders, paranasal sinus pathologies, oro-maxillofacial fractures, age estimation, and endodontic therapy, are described in Table 1 [8, 9, 27-29].

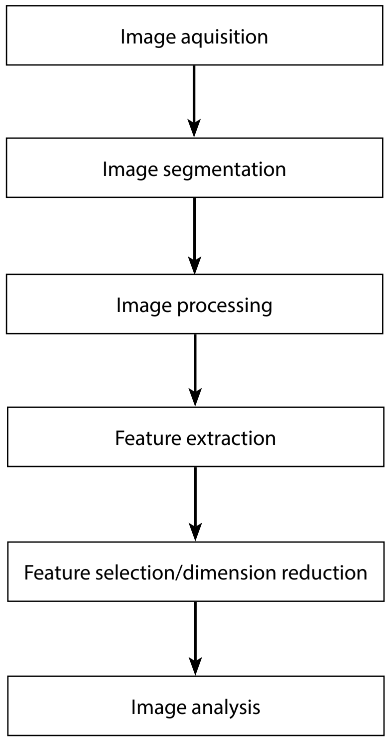

FIGURE 1. Workflow of radiomics

TABLE 1. Applications of radiomics in oral and maxillofacial radiology

Conditions	Applications
Metastasis of lymph node	Non-invasive method for determining the nature of occult cervical lymph nodes in oral squamous cell carcinoma patients
Diseases of salivary gland	To help distinguish between benign and malignant salivary gland tumors
Disorders of temporomandibular joint (TMJ)	Individuals with early TMJ osteoarthritis can be screened
Maxillary sinus pathologies	To help doctors recognize lesions in the maxillary sinus, assess the degree of opacification in the area, and plan surgical procedures
Mandibular fractures	Helpful for finding hidden condylar fractures
Dentofacial deformities and malocclusion	Identification of those who require surgical skeletal malocclusion correction during an orthognathic evaluation To determine how orthognathic surgery can affect the skeletal and soft tissue profile
Cysts and tumors	To distinguish between different odontogenic cysts For identifying both odontogenic cysts and tumors
Dental implant	Helpful for early prediction of physiological bone re-modeling
Age estimation	Radiomics of the condyles using CBCT showed potential for use in age classification
Endodontic treatment	To predict obturation outcomes and sub-optimal endodontic treatment

RADIOMICS AND ORAL ONCO-DIAGNOSIS

Head and neck cancer has a variety of challenges, which are hard to diagnose and treat. The role of imaging is inevitable in cancer, especially in head and neck carcinoma (HNC), both pre and post-operatively, for treatment planning and determination of prognosis. Contrast-enhanced computed tomography (CECT), magnetic resonance imaging (MRI), and positron emission tomography (PET) imaging, are the most widely used modalities in head and neck cancer (HNC) cases for the evaluation of anatomic extent, nodal involvement, perineural invasion, skull base and intra-cranial involvement, cartilaginous involvement, calcifications, infiltrations, and associated inflammations related to HNC [30].

However, the diagnosis is challenging due to complex regional anatomy, presence of numerous small-sized vital structures, pathways of primary and recurrent tumors, and high intra-tumoral heterogeneity that changes depending on the site and biological character of the tumor. Radiomics is considered an emerging solution for the potential diagnostic challenges associated with HNC imaging [31].

By applying radiomics in head and neck oncology, the radiographic data obtained from various imaging modalities facilitate the exploration of relevant diagnostic data by radiomic analysis. Additionally, it is possible to non-invasively capture the diverse structure and biological behavior of head and neck malignancies, which might be crucial for clinical decision-making [31]. Radiomics' data must be extracted in a way that can be repeated and the same each time for clinical applications to be possible. In onco-diagnosis, the radiomics workflow starts with a standardized protocol for obtaining high-quality images. Next step is the segmentation of tumor, followed by details of the tumor area. Then, the extracted features that show the best performance, stability, or other similar defining metrics, are selected for using in clinical applications [32].

Previous research demonstrated that textural features taken from CT and MR images can be used to learn more about the tumors' heterogeneity that is linked to necrosis, angiogenesis, and hypoxia [3, 33]. However, a study by Ger *et al.* [34] reported radiomics to be inconsistent with regard to the estimation of survival in CT or PET images of head and neck patients. Although discrepancies exist in the validation of radiomics-aided onco-diagnosis, active research is being undertaken worldwide for AI-aided clinical decisions feasible in oncology [35].

RADIOMICS AND DENTAL IMPLANTS

The long-term success of implant therapy is based on peri-implant marginal bone stability. Within one year of functional loading, physiological re-modelling of the peri-implant crestal bone can occur [36]. Inadequate crestal width, traumatic surgery, supra-cranial tissue height establishment, microbial colonization of implant-abutment interface, implant crest module characteristics, number of abutment connections/disconnections, height of prosthetic abutment, mechanical stability of implant/abutment connection, and adaptability, are just a few of surgical and restorative factors, which can affect physiological bone re-modelling (PBR), a complex process with multi-factorial etiology. It is still debatable whether the quality of the bone at the time of implant placement influences the development of peri-implantitis and/or late implant failure [37]. In contrast, radiomics takes a quantitative approach to medical imaging with the goal of enhancing data that doctors have access to through sophisticated mathematical calculations [38]. Radiomics develops prediction models with sufficient accuracy to help clinical decisions by extracting and analyzing "features" or "quantitative characteristics" from medical pictures. In a recent study by Troiano *et al.* [39], it was determined that radiomic analysis could reveal subtle bone characteristics helpful in the early prediction of PBR. The study's results revealed that after three months of unsubmerged healing, specific radiomic features were associated with higher PBR around tissue-level implants, and the researchers came to the conclusion that using radiomics in conjunction with machine learning techniques appears to be a promising strategy.

FUTURE PERSPECTIVES

Incorporating deep learning models in radiology has improved the efficiency of diagnostic data by reducing the time required for data interpretation without compromising diagnostic accuracy. It enabled bone age determination with accuracy comparable to that of a trained radiologist [40-42]. However, AI-enabled radio-diagnosis and fully automated image interpretation are evolving concepts, which will be soon available, the European Society of Radiology emphasized the inevitable role of human intervention by trained radiologists in radio-diagnosis because radiologists play a vital in both developing and validating AI applications in medical imaging [43].

Limitations of radiomics include lack of standardization in image acquisition, multiple software usage, and different statistical approaches, which restricts the comparison between studies and data reproduction. It is of utmost importance to use standardized imaging protocols with open-source software to eliminate the confounding variability with respect to radiomics. Variations with scanner manufacturer, model, calibrations, and differences in algorithms and software may lead to different results [44].

CONCLUSIONS

Radiomics is an advanced application of artificial intelligence in diagnostic radiology combining clinical and radiographic data, to establish diagnostic and prognostic accuracy. Although radiomics in the field of oral and maxillofacial radiology is still in the growing phase, it has a considerable potential to be applied in day-to-day radiology practice.

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