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Radiomics in Dentistry: A Paradigm Shift in Diagnostic Imaging and Treatment Planning in Oral Cancer

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ABSTRACT
Oral cancer is a substantial worldwide health burden. Improving results requires early diagnosis, precise staging, and well-thought-out treatment planning. Conventional imaging techniques and human radiologic interpretation, however, have limits in sensitivity, quantification, objectivity, and prognostic prediction. For dentistry and oral oncology, the developing area of radiomics—quantitative analysis of medical images using computational techniques and machine learning—offers a revolutionary paradigm. Radiomics can improve oral cancer detection, classification, prognosis, and individualized treatment planning by extracting high-dimensional, sub-visual information from imaging (CT, CBCT, MRI, optical coherence tomography). This review addresses the principles and workflow of radiomics, its current and potential uses in dentistry and oral cancer, highlights recent evidence (diagnostic and prognostic), identifies problems and limitations, and recommends options for future research and clinical translation.

Key words- *oral radiology, radiomics, artificial intelligence. cancer, squamous cell carcinoma*.

INTRODUCTION
Research on artificial intelligence (AI) has progressed and is being applied outside of computer science departments. The use of AI applications in healthcare has increased steadily. AI technology is meant to support clinical practitioners in clinical decision-making, and to eliminate repetitive tasks performed in their everyday work [1]. Radiomics is a quantitative approach to medical imaging that uses advanced mathematical analysis to improve the radiographic data that is already available. The core premise of radiomics is founded on the concept that biomedical imaging incorporates data representing disease-specific processes and is accessible via quantitative image analyses [1]. Radiomics technology is generated as a result of merging genomic data, imaging, and pathology results [1].

The goal of AI technology is to make it easier for medical professionals to make clinical decisions and to reduce the amount of repetitive work they do every day. [1]. Similar to many other areas of human endeavour, the medical field has witnessed a steady increase in the digitization of data generated during clinical procedures over the past few decades. To analyse the newly digitized medical data, more advanced software was developed. [2]. The many AI techniques—primarily machine learning and deep learning algorithms—are particularly helpful in the developing field of "big data." Big data is defined as “a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information.”[2]. Techniques from the field of artificial intelligence are required to extract the desired information from the large amount of multi-dimensional data.[2].

Radiomics is a quantitative approach to medical imaging that uses advanced mathematical analysis to enhance the data currently available to clinicians. To date, radiomics has been shown to improve clinical decision-making in several imaging-related studies. However, the many technical factors affecting the extracted radiomic features are the main cause of the many important challenges in the field. [2]

UNDERSTANDING RADIOMICS

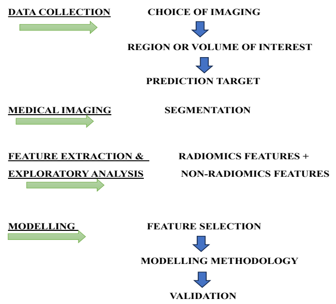
Despite the lack of a clear definition, the overall objective of radiomics is to extract quantitative, ideally repeatable information from diagnostic images, including complex patterns that are difficult for the human eye to measure or detect. Radiomic features taken from metabolic imaging methods such as PET and SPECT may be helpful in several situations.[3]. Radiomics, which uses quantitative analysis of medical images to extract a set of high-dimensional data, is revolutionizing prognostic and diagnostic techniques.

The concept behind radiomics is that complex details of disease-related phenomena are captured in biomedical images.[4]. Radiomics, using quantitative analysis on medical images, extracts a set of high-dimensional data driving a substantial change in diagnostic and prognosis procedures. Radiomics is based on the notion that complex features of disease-related processes are captured in biomedical images [4]. These nuances often bypass human awareness and are not accessible through normal visual inspection of the photos. Radiomics seeks to quantify the textural characteristics by analyzing patterns in signal intensities and pixel interactions using mathematical techniques.[4]. Radiomic biomarkers (textural characteristics) are developed using data, whereas traditional biomarker development usually starts with biology-based theories. Methods such as genomes, transcriptomics, proteomics, and radiomics are applied to investigate enormous databases in search of sensitive indicators for predicting outcomes, often leading to the formation of post hoc hypotheses [4]. Nowadays, the combination of radiomics with artificial intelligence has garnered substantial attention among physicians, signaling a new way to approach diagnostics and research methodologies.[4].

Radiomics measures the textural features by analyzing patterns in signal intensities and pixel relationships using mathematical algorithms. Radiomic biomarkers (textural features) are developed based on data, whereas traditional biomarker development usually starts with biology-based hypotheses. Large datasets are analyzed using techniques like genomics, transcriptomics, proteomics, and radiomics to find sensitive markers for outcome prediction, which frequently results in the creation of post hoc hypotheses.[4]. Because radiomic features are so sensitive to changes in reconstruction parameters, protocol, and imaging modality, the biological aspects may be obscured [4]. The National Institute for Biomedical Imaging and Bioengineering and the Radiological Society of North America have launched programs like the European Imaging Biomarkers Alliance subcommittee (EIBALL) and the Quantitative Imaging Biomarkers Alliance (QIBA) to address this issue [4]. These groups developed a consensus on the measurement accuracy of quantitative imaging biomarkers and explain essential processes for reaching desirable accuracy levels.[4].

WORK FLOW OF RADIOMICS:

The workflow for a radiomics analysis provides an illustration of the steps required for a radiomics study. [5].



Advances in diagnostic imaging modalities have increased in terms of complexity and volume of generated digital data. [5].These characteristics lead to the establishment of a new technique to imaging diagnosis termed radiomics. It contains of algorithms that breakdown input images into basic properties that may be utilized to identify or interpret the image, such as edges, gradients, form, signal intensity, wavelength, and textures.[5]. From 2D or 3D images, a variety of radiomic features can be extracted, including textures extracted from filtered images, complex fractal features, descriptors of the relationship between image pixels or voxels, gray-level occurrence matrix, run-length matrix, and histograms of image intensity. Malignant or many bone disorders may be detected early with the help of these imaging findings.[5]. They can also be used to predict treatment response to therapies, including oncotherapy, and to measure functional characteristics. 18–37, 39–41 The ability to identify and forecast diagnosis and results may be enhanced by combining these imaging characteristics with additional clinical and genetic information. Integrated data processing in oral healthcare may allow offering more patient-specific diagnostics and individualized treatment planning.[5].

Thus, radiomic analysis may be simply defined as an extraction of quantitative features or parameters, quantifiable and mineable from radiological pictures. Therefore, hundreds of abstract mathematical properties, often not extractable by the human sight, can be defined or recognized on imaging modalities by applying software.[5].

RADIOMICS IN ORAL CANCER DIAGNOSIS

Radiomics offers additional insights beyond what can be seen visually by gathering data pertaining to tumour shape, texture, morphology, and intensity. These radiomic characteristics act as useful imaging biomarkers that can help distinguish between benign and malignant lesions, predict treatment outcomes, and track the development of diseases [6]. Radiomics and deep learning approaches give clinicians the tools they need to make accurate cancer diagnosis decisions by providing them with objective and quantitative data.[6].One measure of tissue differentiation is tumour grade. Heterogeneous tumours are typically associated with higher tumour grades and more aggressive biologic behaviour. This heterogeneity and other tumour characteristics can be detected using radiomic features. [7]. Radiomics features reflect biological properties of the tissue, including cellularity, heterogeneity, and necrosis, and often show correlation with diagnostic and outcome variables [8].

Radiomics aspects often describe shape, intensity (histogram) and textural qualities. These features can be derived from numerous imaging modalities, such as CT, MRI, or metabolic imaging like 18- fludeoxyglucose positron emission tomography (FDG-PET). The notion that certain properties of medical pictures – which are not reliably judged by human visual inspection – can provide medically meaningful information for diagnostic and prognosis purposes as well as therapy recommendations is the basic hypothesis in the burgeoning discipline of radiomics[8] Additionally, some traits may be indicative of the genetic and molecular makeup of cancerous tissue. The main goal of the radio genomics subfield is to identify and scientifically exploit correlations between the tumour's genomic features and quantitative bioimaging features. [8] The diagnostic validity of localized methods, such as tissue sampling, may be compromised in heterogeneous tumours, but radiomics analysis, which gathers data from the entire volume of interest (VOI), may serve as a quantitative descriptor of tumour spatial heterogeneity. [8].

CLINICAL IMPLEMENTATION AND CHALLENGES

During the conversion and preprocessing phases, one of these worries is the potential for errors to be introduced or for processed data and features to be rendered useless. [9]. However, there are unique challenges when applying them to quantitative analysis with radiomics features, such as inadequate documentation, complex preprocessing, non-uniform data formats, poor visibility, and data inhomogeneity. [9]. Inadequate documentation and mislabeling of datasets can lead to misinterpretation and unintentional bias, whereas limited visibility results from datasets being hosted across numerous platforms. System interoperability is hampered by the lack of centralized data repositories with established formats, which also restricts prospects for cooperation and mutual advancement in the sector. [9]. There are potential hazards and challenges related with RadiomicsHub. One such risk is the possibility of adding errors or generating non-meaningful processed data and features during the conversion and preparation procedures. We have put in place strong quality control procedures, such as error recording and consistent, repeatable processing instructions, to allay this worry. Volumes have been tested for numerous claims, including accurate dimensionality, shape, label presence, and appropriate ROI placement. But even with our best efforts, there is still a chance that the data's accuracy and integrity could be compromised.[9].

Furthermore, changes in acquisition techniques, scanners, and settings across studies might induce bias and impair the robustness of radiomics models.[9] Depending on the clinical application, datasets can require unique, time-consuming preparation to handle different modalities (e.g., CT and PET), sequences, ROIs, or readers and to validate data quality before their usage in a radiomics study.[9]. Another significant issue with radiomics models is their lack of generalizability and reproducibility. Insufficient transparency in reporting radiomics investigations further limits the application of the developed radiomics signatures into clinical practice.[9].

One of the most frequent reasons for overfitting, in which the model learns statistical regularity specific to the training data, is a lack of training data. [10]. The use of multiple software programs, inconsistent statistical approaches, and a lack of standardization in image acquisition are some of the disadvantages of radiomics that make it challenging to compare studies and replicate data. The elimination of radiomics variability requires the use of open-source software and standard imaging protocols. Results, software and algorithm variations, calibrations, the manufacturer, and the model could all be influencing factors. [11].

FUTURE PERSPECTIVES

In oncology, tumor subtypes are generally evaluated through repeated intrusive biopsies, which are tiring for the patient and are expense and labour intensive. Tumor heterogeneity can be captured non-invasively, economically, and widely by quantitative analysis of routine clinical imaging. [12]. Radiological images are currently qualitatively analyzed in clinical practice by skilled radiologists, whose interpretation is known to suffer from inter- and intra-operator variability. Radiomics, the high-throughput extraction of image features from medical pictures, provides a quantitative and robust way to quantify tumor heterogeneity, and radiomics-based signatures provide a significant tool for precision medicine in cancer treatment.[12].

The method can be used in clinical settings to reduce workload because it can be done automatically. Future studies looking at different tumor types and locations might show how generalizable the approach is, which would establish radiomics as a clinical standard practice. Larger amounts of data will eventually be accessible for use in radiomics research thanks to distributed learning and centralized, publicly accessible datasets. Combining radiomics with other parameters can result in high-quality decision support systems. To improve these models' predictive accuracy, radiomics analyses can be combined with deep learning and semantic feature approaches. Radiomics has a long way to go before it can be fully applied in clinical settings, but it might be crucial to the application of precision medicine in cancer treatment. [12].

Assessment of prognosis in oral cancer is a complicated and crucial element of clinical care [13]. The use of imaging examination plays a key impact in predicting disease progression, lymph node metastases, and tissue infiltration [13]. Although the TNM staging method based on imaging characteristics aids in assessing patient prognosis, its prognostic accuracy is restricted AI technologies can analyze multidimensional data from patient evaluations, offering more accurate information for prognosis assessment, patient survival rates, and illness progression.It greatly minimizes patient discom-fort and saves a substantial amount of economic costs.[13].

CONCLUSION

In conclusion, radiomics represents a promising non-invasive precision medicine approach. [14]. It may be possible to increase the accuracy of prognostication estimation for these patients by providing accurate information prior to surgery by incorporating radiomics into conventional clinical models. Furthermore, regardless of the type of surgery or common clinical factors, radiomics models can independently predict prognosis. Future developments in precision medicine for patients with oral cancer are anticipated to be facilitated by the integration of radiomics into clinical practice. [14].

The integration of radiomics to established clinical models has the potential to boost the accuracy in evaluating the prognosis of these patients, providing reliable information before surgery. Our findings further demonstrate that radiomics models are independent predictors of prognosis, independent of traditional clinical variables and surgical therapy type. In the future, patients with OTSCC will probably benefit from improved precision medicine thanks to the integration of radiomics into clinical practice. To attain these objectives, external validation of our data and further prospective studies of adequate numbers will be needed in the future.[14].

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