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Review Article

Delineating the grey areas in radiodiagnosis-Radiomics a new way forward Radiomics- A virtual biopsy

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ABSTRACT

Omics are the branches of science which constitute the various affiliates of biology. It determines the structure, function and dynamics of organisms through collective characterization and quantification of biological molecules. The diagnostic imaging modalities have peaked in their advancements, leading to escalated complexity and volume of database. This has ushered the foundation of a novel approach to imaging diagnosis called radiomics. Radiomics refers to the accentuation and procurement of ambiguous data from medical imaging and has been applied within oncology to enhance diagnosis and prognostication, aiding in clinical decision, with the aim of delivering precision medicine. The chief application of radiomics is in oncology to augment diagnosis and prognosis, thereby improving clinical decision. Consequently, the success rates for delivering precision medicine is higher as it facilitates the procurement and accentuation of ambiguous data from rradiographs. Radiologists as well as data and imaging scientists represent an integral part of the interdisciplinary workflow of radiomics. It involves a comprehensive process of step by step tumour segmentation, image pre-processing, feature extraction, analysis, model development, and validation. By this paramount potentiality, it serves as a definitive solution for both clinical and research purposes. This paper highlights the role of radiomics in defining, standardization, and cultivating vast databases accessible to clinicians. This will empower them to tap into every particular case, eventually creating a link among patients having comparable profiles for treatments or clinical trials all over the world.

1. Introduction

Radiomic analysis can be construed as the extraction of quantifiable, measurably based traits or parameters from radiological images. As a consequence, the software can define or characterize numerous abstract mathematical properties on imaging modalities that are typically not discernible to the human sight.[1]

The sophistication and volume of created digital data have expanded their horizon due to the breakthrough in diagnostic imaging techniques. These elements stimulated the development of radiomics, a novel technique for imaging diagnosis.[2] It contains algorithms that fractionate incoming images based on elementary features like edges, gradients, form, signal intensity, wavelength, and textures that can be deployed to interpret the image. In a nutshell, thousands of abstract mathematical traits that are typically improbable for the naked eye to distinguish can be specified and delineated utilizing imaging modalities and software.[3]

The enhancement of diagnostic, prognostic, and predictive accuracy may derive from the association of radiomics-based data with clinical and biological end results. Intensity, shape, and texture are examples

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of radiomics properties that have been retrieved from both imaging modalities and have shown to be more accurate.[4,5] This article confers a bird eye view to project the role and future prospective of radiomics in the field of radiodiagnosis.

2. Radiomics- A Fragment of AI

In contrast to being a subjective perceptual talent, radiology is increasingly becoming an objective science. Several scientists agree that the "mathematical imaging phenotype" of disease manifestation may be conveyed by radiomic characteristics. They combine numerous aspects of medical imaging for a tailored treatment in this way.[6]

New image acquisition techniques might be implemented or developed as a result of the potential for AI technologies to optimize photographs by minimizing radiation exposure and reducing scatter and artefacts.[7,8]

By pre-analyzing and prioritizing cases, AI-driven management and processing of vast imaging databases may potentially have an effect on daily workflow. The association of words, visuals, and quantitative characteristics, as well as the reduction of errors, can strengthen the radiologist's reports.[9] Hence, AI will boost clinical decision-making processes such as precise illness and outcome prediction, surgical and therapeutic planning, and diagnosis. Additionally, automated recommendations for processing complex cases and the foretelling of surgical complications may result in a more fruitful workflow for radiologists.[10]

3. Working Principle

Image acquisition, reconstruction, pre-processing, segmentation, features extraction, and analysis constitute a few stages in the radiomics workflow. The need for an integrated radiomics database is vital. The data must be exported and exchanged among different clinics. If not used properly, this could infringe the patient's privacy policy. Consolidating clinical and molecular information is essential, and a site is needed for the storage of a sizable database.[11] In order to extrapolate information from the data base material to the input data, the algorithm in the database has to correlate the photos and the features.

3.1. Image acquisition

The first component is the acquisition of biomedical pictures, during which a number of parameters must be configured depending on the imaging modality and the tissue that needs to be identified. Radiological modalities like CT, MRI, PET/CT, or even PET/MR offer the picture data. Through the use of extraction techniques, the generated raw data volumes are used to cover multiple pixel/voxel characteristics.[12] To facilitate widespread collaborative and cumulative work in which all can gain from escalating volumes of data and, ideally, offer a more precise workflow, the derived features are saved in substantial databases to which clinics have access.

3.2. Image segmentation

The second phase entails pre-processing photos in order to set them up for the subsequent processes.

Following pre-processing of the obtained pictures, the region of interest—which, according to the intended use, may either be a lesion or normal tissue—is segregated. The photos must initially be reduced to their core parts, in this case the tumours, which are known as "volumes of interest," prior to getting saved in the database.[13,14]

Experts in diagnostic imaging can section data manually, or segmentation tools can classify data automatically. An automated approach must be employed in place of manual segmentation. Automatic and semiautomatic segmentation algorithms might serve as a solution. An algorithm must score well in all four of the following tests prior to being employed on a broader scale:

First, it needs to be repeatable, which means the results won't change when it's applied to the same data.

Consistency is also another crucial element. As opposed to doing something irrelevant, the algorithm should tackle the current issue. In this scenario, it's critical that the algorithm is able to spot the diseased part across all scan types.

To accurately diagnose the diseased part, the algorithm must also be precise, which can only be done with reliable data. The time efficiency is a tiny element that's nevertheless significant. In a bid to accelerate the entire radiomics process, the findings should be produced as quickly as feasible.

3.3. Feature extraction and quantification

The penultimate phase implicates extracting radiomic features from the target area. A high-dimensional feature space is created by the massive number of features that are produced as a result of statistical, filtering, and morphological analysis.[15]

Subsequently, a review of the relationships between the different features is conducted, followed by a preliminary evaluation to find the features that are "highly" informative and their choice according to user-provided norms.

3.4. Analysis

Eventually, in order to create predictive and prognostic models, this data is correlated with clinical data.

The chosen data must be analyzed only after features that are of the essence for the given purpose have been defined. The clinical, molecular, and perhaps even genetic data must be amalgamated prior to the actual analysis, because they have an immense impact on the implications that may be drawn. The data may be further analyzed using a multitude of methods. To establish whether the various features share any information and to clarify their implication when they all occur at once, the features are first compared between themselves.[16]

The various methods that have been outfitted are illustrated below.

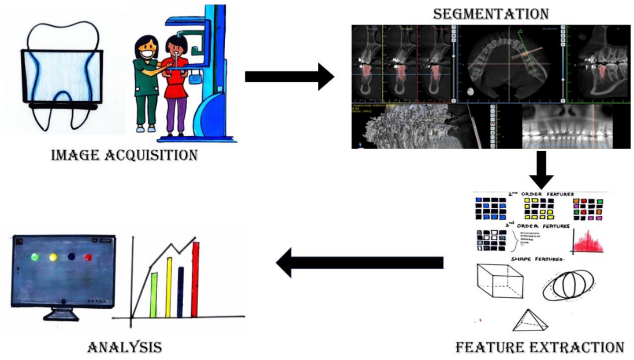

Fig. 1:

4. Applications

Radiomics is an emerging field in quantitative imaging that uses advanced imaging features to help clinical decision-making, improving diagnostic, prognostic, tumor staging for predictive accuracy.[17]

When data derived from radiomic features is associated with biological and clinical knowledge categorization of molecular profiling is enabled.

The process of classification refers to the segregation of a population into various groups. This can be executed by organization of these groups into parameters like benign versus malignant, genomic status, tumor stage, and presence of metastases, among many others. The stratification of patients into distinct risk groups effected by predictive models that utilize clinical outcomes. It works on the principle of clinical end-points to determine the risk of occurrence of disease, affecting the survival rate by using a time-to-event analysis.[18]

These applications are guided by the notion that radiomic data convey information about tumor biology. Spatial heterogeneity is an essential determinant of tumour behaviour and resistance to therapy. Radiomic features have been successful in revealing the spatial heterogeneity of tumours.

Although biopsy is considered as the gold standard for the diagnosis of any tumour, its invasiveness has made it unpopular among a vast number of patients. Biopsy samples are always procured from the site that has the most clinically malignant features. Unlike radiomics which expedites the analysis of the whole area, standard biopsies are limited to a particular part of the tumour. Often this drawback of the standard biopsy may cause misdiagnosis leading to delivery of an ineffective treatment to the patient. Thus, radiomics operates as a biopsy in a virtual sense by virtue of its non-invasive nature.[19]

Most of the tumours require biopsies at various intervals of therapy to check for the progress of the disease. During the course of any disease, radiomics can be assuredly equipped for monitoring the disease, in order to provide invaluable diagnostic information about the evolution and progression.

This has led to considerable interest of many due to its significant applications in personalized medicine.[20]

There are innumerable ways in which radiomics can fortify the diagnostic and therapeutic aspects in various specialities of dentistry. This is enlisted in Table 1.

Table 1: Applications of radiomics in dentistry

Field of Dentistry	Applications
Oral and Maxillofacial Surgery	1. Virtual biopsy of various tumours and oral cancer
	2. Differentiation of different jaw tumors
	3. assessment of the impact of orthognathic treatment on facial attractiveness and estimated age
Periodontics	4. Segmentation and classification of gingival diseases
	5. Diagnosis and prediction of periodontally compromised teeth
Orthodontics	1. Prediction of growth and mandibular morphology in class I, II and III patients
	2. Understanding of aetiopathogenesis of craniofacial diseases
	3. Automated identification of craniofacial syndromes
	4. Analysis of mandibular condyles and temporomandibular joint disorder
	5. Prediction of treatment and outcomes models
Restorative Dentistry	1. Evaluation of lifespan of dental restorations
	2. Improving accuracy of caries diagnosis
Endodontics	1. Evaluation of periapical lesions and healing after treatment
	2. Assessment of root morphology on radiographs
Forensic Odontology	1. Automated determination of skeletal and dental ages

4.1. Advantages

Radiomics objectively and quantitatively describes tumour phenotypes. Essential phenotypic information, such as intra-tumour heterogeneity that provides information which is invaluable to customize therapy, can be encapsulated by radiomics.

It has been proven by numerous studies that intensity histogram-based radiomic features are potentially beneficial for predicting cancer response to treatment.[21]

Several radiomic features have the capability to significantly differentiate early and advanced stage diseases.

It is also favorable in distinguishing malignant tissues in many diseases.

It improves the accuracy and timeliness of the diagnosis. Due to its non-invasiveness, it causes less trauma to the patients. It can also predict the risk of distant metastasis thereby reflecting on the malignant potential of a tumour.[22]

The means to monitor the progress of a disease can be initiated by virtue of radiomics.

4.2. Disadvantages

It is technique sensitive and requires delineation of images. The algorithm may contain human bias. It also necessitates significant number of samples. The larger the database, more will be the efficiency of the software.[23]

Radiomic feature quantification may be hindered by factors such as metal artifacts in CT images, CT x-ray tube peak voltage and current.[24]

Nevertheless, the intrinsic impediments can be vanquished by promoting precision diagnostics and personalized treatment for head and neck cancer. Although the application of imaging biomarkers still lies in its infancy, the development of radiomics and radiogenomics may revolutionize the field of oncology.[25] The key objective is to entitle the oncologist with the foundation to arrive at the apposite treatment plan for an efficient clinical practice.[26]

5. Conclusion

The next few decades will be a witness to the emancipation of radiologists from the mundane and methodical tasks; instead they will lavishly validate AI generated reports, with modern tools for brainstorming intensive 'radiomic' data.[27] Radiologists will be empowered like never before, due to enhanced productivity upgrading the communication among clinicians and patients, reinforcing the bond between them.[28] That day is not too far where radiologists will be data communicators, invigorating the community of experts.[29,30]

The profession at the moment is tainted by the obscurity of the dark rooms and, if anything, artificial intelligence is competent enough to rekindle these dampened spirits. Thus, proper utilization of its true potential is awaited.

Doctors can never be replaced with AI, they will aid them to practice precision medicine with enhanced accuracy and fortify their efficiency. It isn't an intruder in our lives but is a multi talented assistant that will improve our lifestyle, if used righteously.

6. Source of Funding

None.

7. Conflict of Interest

None.

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