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# In a Patient-specific Model: The Role of Deep Learning and Radiomic Features

**Vishnu Swarup[1], Yashbir Singh[2] and Himanshu Narayan Singh[3]***

*[1]Neurology, All India Institute of Medical Sciences, New Delhi, India*

*[2]Radiology, Mayo Clinic, Rochester, MN, USA*

*[3]Systems Biology, Columbia University Irving Medical Center, New York, USA*

***Corresponding Author:** Himanshu Narayan Singh, Systems Biology, Columbia University Irving Medical Center, New York, USA.

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Radiomic applications are rapidly expanding, ranging from diagnostics, prognosis to response of the prediction. Image processing techniques developed decades ago like adjusting the image's brightness and contrast, reducing image noise, and removing imaging artifacts, gave rise to a new way to understand disease etiology. Linking imaging phenotypes to tumor genetic profiles is known as "radiogenomics". In recent years, imaging markers obtained from routine clinical images that may provide deep insights into non-invasive tumours. Imaging highlights can be subjective, or semantic [1-3], in which a pursuer, ordinarily an radiologist, relegates a score to certain factors based on expertise-based perception, or quantitative, in which the values are inferred specifically from the image, such as tumour measurements, attenuation, or radiomics. Using specialized computer algorithms, features are mathematically extracted in radiomics. Radiomic landscapes reveal a wide range of image specifications and also capture distinctive imaging phenotypes beyond what the bare eye can see [3]. However, numerous technical and clinical insights need to be explored. Nonetheless, precise models are developed with huge future possibilities. Convolutional neural networks (CNNs) are commonly used to combine imaging filters with artificial neural networks by utilizing a series of linear and nonlinear layers [4]. CNN's use local weights and connections to demonstrate the input images, accompanied via pooling operations to accomplish spatially invariant features. Furthermore, the final two-dimensional layers could be converted into a one-dimensional feature vector which leads to a fully connected network upon completion of the CNN. The CNN based deep learning algorithms can determine the best from the feature-set and relative importance after gathering enough training data. Subsequently, they use feature combinations to classify images [5-7].

Because of their independence from humans in feature design, CNNs is leading the field of medical image analysis. CNN is able to extract multitudes of quantitative features than previously used feature extraction algorithms used in traditional radiomics. Another significant benefit is that feature extraction, selection, and classification occur at different layers within the same CNN. A combination of tumor profiles may provide comprehensive information for the diagnosis by increasing the classification accuracy.

Several human diseases involve pathogenic mutations and inheritable genomic instability leading to altered genetic signatures [8]. These deregulated gene profiles are of prime interest of clinicians these days [9]. The radiogenomics has the capability to integrate these genetic profiles with precise detection and diagnosis of such variations, potential treatments and their responses, and even the survival probabilities. However, more complicated models combining a couple of information resources ought to conquer the various challenges that stand between radiogenomics and its scientific implementation. The artificial intelligence in medicine, particularly deep learning can enlighten the path of such successful integration and can be proven as landmark in future clinical aspects.

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