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Transfer Learning for Deep Learning Radiotherapy Planning

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(a) Muscle Window $(35, 55)$ [1] (b) Cancellous Bone Window $(300, 400)$ [2] (c) Fat Window $(-120, -90)$ [1]

Figure 2.1: Coronal view the same image slice of a CT image, with different window cropping (Patient id: 49, slice 251, axis 1)

The CT scan is a popular imaging modality in clinical environments because of its non-invasive ability to provide detailed images of the internal structures of the body. A series of X-ray devices are rotated around a specified body part, and computer-generated cross-sectional images are produced [3]. Whilst the scanner rotates, the table the patient lies on slowly moves up and down inside the tube to produce different cross-section images.

The granularity or image slice thickness is decided by the operator or physician and ranges from 1mm to 10mm. Therefore, the precision along each axis creates a cube, or voxel which represents the value on a grid in three-dimensional space. The voxel values are measured in Hounsfield Units (HU) [4].

Contrary to natural images, where pixel values vary from 0 to 255 in 3 channels representing Red, Blue and Green, the Hounsfield scale is a quantitative scale for describing radiodensity where the image intensity reflects tissue type; each voxel intensity refers to specific tissue composition. The positive values are a consequence of more dense tissue with greater X-ray beam absorption, and negative values are less dense tissue with less X-ray beam absorption [5].

Therefore, becuase the HU scale is relative, different windows may be taken of a CT scan to highlight different tissues. Those voxels that lie within the window, are likely to be tissues of a specific classification. For example, disaplyed in Figure 2.1 we display 3 such windows, muscle, cancellous bone and fat.

2.2 Technical Context

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Ethics

The lack of effort to protect the identities and confidentiality of patients during research projects may result in “stigma, embarrassment, and discrimination” [6] if the data is misused. This project involves very intimate and personal information of many female patients whose privacy must be established concretely before research is to take place.

7.1 Patient disclosures

Reserachers may collaborate with third-parties such as Imperial College London by providing anonymized data which may not be reverse engineered back to the patient. The collaborating hospital, The Royal Marsden Hospital, doesn’t require “explicit consent” for sharing collected clinical data with outside entities as long as the patient is made aware of the ways their “de-identified/anonymized” data may be used. [7]. Formalities are also arranged with Imperial Collage’s Medical Imaging team such as acting as “ethical data stewards” [8]. Without such disclosure and anonymisation of data, patients may be reluctant to provide candid and complete disclosures of their sensitive information, even to physicians, which may prevent a full diagnosis if their data isn’t maintained in an anonymous fashion.

The MIRA team acts as responsible data stewards by storing anonymized data within a folder on the college network. All provided data was anonymized by the Royal Marsden Hospital and sent to team MIRA in the `NIfTI` file format which discloses no personal identifiable information, as defined by GOV website [9]. This folder contains security measures which limit the availability of data only to those with specific access rights. Furthermore, operating on the preamble of de-identified data further reduces individual patient risk in the event that data is ever brought outside the confines of this folder.

7.2 Using the tool

The applications of this tool bode well in the healthcare ecosystem as the community slowly accepts the involvement of AI-powered medical tools. Radiology has been one application that has been most welcoming of the new advances in technology as there is potential for substantial aid by reducing manual labor, increasing precision and freeing up the primary care physician’s time [10].

Yet, it is too early to take result the medical tool as gospel. For current cervical radiotherapy delineation tools, only 90% of the output is considered as acceptable for clinical use [11]. The remainder therefore has the potential to cause more harm than good if not checked properly. For example, overlap of a PTV onto an organ-at-risk may invoke a cascade of negative effects for the patient. A physician may base their final judgement subject to a multivariate analysis, which is contrary to the single image modality that this tool is based on. Therefore, the tool should be used as a second opinion rather than a primary source of information.

Clinicians can fall into the trap of automation-bias as AI becomes more common place in clinical environments [12]. However, many models of this age codify the existing bias in common cases, which often will fail those patients who do not fit the expectations of the majority. Therefore, a degree of supervision required from physicians has to be established if this tool is to be used in practice. Oncologists will be required to reverse-engineer results of the 'black-box' to verify why a decision has been made. Secondly, the responsible party for incorrect decisions made by DL tools should also be determined [13].

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