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Transfer Learning for Deep Learning Radiotherapy Planning

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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” [1] 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. [2]. Formalities are also arranged with Imperial Collage’s Medical Imaging team such as acting as “ethical data stewards” [3]. 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 [4]. 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 realizes the importance of AI-powered tools for the next generation of medical technology. 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 [5].

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 [6]. 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 potential cause may be the lack of multivariate analysis, where an oncologist would need to consider a variety of data, whereas this model only considers a single point of evidence (results of an imaging modality).

Clinicians can fall into the trap of automation-bias as AI becomes more common place in clinical environments [7]. 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 [8].

Bibliography

[1] Nass SJ, Levit LA, and Gostin LO. Beyond the hipaa privacy rule: Enhancing privacy, improving health through research. page 18, 2009. doi: 10.17226/12458. pages 8

[2] The Royal Marsden NHS Foundation Trust. Privacy note. URL `https://rm-d8-live.s3.eu-west-1.amazonaws.com/d8live.royalmarsden.nhs.uk/s3fs-public/2023-10/T22020ac_Revisedprivacypolicy_V1_AW_WEB.pdf`. pages 8

[3] David B Larson, David C Magnus, Matthew P Lungren, Nigam H Shah, and Curtis P Langlotz. Ethics of using and sharing clinical imaging data for artificial intelligence: A proposed framework. *Radiology*, 295(3):675–682, March 2020. doi: 10.1148/radiol.2020192536. pages 8

[4] *Data Protection Act 2018*. URL `https://www.legislation.gov.uk/ukpga/2018/12/contents/enacted`. pages 8

[5] Amisha, Paras Malik, Monika Pathania, and Vyas Kumar Rathaur. Overview of artificial intelligence in medicine. *J Family Med Prim Care*, 8(7):2328–2331, July 2019. doi: 10.4103/jfmpc.jfmpc_440_19. pages 8

[6] Zhikai Liu, Xia Liu, Hui Guan, Hongan Zhen, Yuliang Sun, Qi Chen, Yu Chen, Shaobin Wang, and Jie Qiu. Development and validation of a deep learning algorithm for auto-delineation of clinical target volume and organs at risk in cervical cancer radiotherapy. *Radiotherapy and Oncology*, 153:172–179, 2020. ISSN 0167-8140. doi: https://doi.org/10.1016/j.radonc.2020.09.060. pages 8

[7] Isabel Straw. The automation of bias in medical artificial intelligence (ai): Decoding the past to create a better future. *Artificial Intelligence in Medicine*, 110:101965, 2020. ISSN 0933-3657. doi: 10.1016/j.artmed.2020.101965. pages 9

[8] Zi-Hang Chen, Li Lin, Chen-Fei Wu, Chao-Feng Li, Rui-Hua Xu, and Ying Sun. Artificial intelligence for assisting cancer diagnosis and treatment in the era of precision medicine. *Cancer Communications*, 41(11), 2021. doi: 10.1002/cac2.12215. pages 9