Advancing Healthcare Through Open Science: StudierFenster and MedShapeNet

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Abstract

In the dynamic landscape of digitized healthcare, open science principles are instrumental in driving transformative changes. This contribution describes two open science initiatives: StudierFenster, a cloud-based framework for (bio-)medical image analysis, and MedShapeNet, a comprehensive and open-access dataset of medical shapes. StudierFenster offers seamless access to medical image analysis tools through common web browsers, facilitating widespread utilization. MedShapeNet bridges the gap between medical imaging and 3D deep learning by providing a repository of anatomical shapes extracted from real patient data. With over 100,000 shapes spanning various datasets, MedShapeNet enables diverse applications in medical image analysis, mixed reality, and 3D printing.

1 Introduction

In the modern, ever-evolving landscape of digitized healthcare, the integration of open science principles is instrumental to driving transformative changes. Open science refers to the practice of sharing and exchanging research outputs, such as data, code, and publications. The goal is to make these resources freely available and accessible to the public, which encourages transparency, reproducibility, and knowledge sharing, thereby accelerating innovation.

In this contribution, we describe two open science initiatives from our group: StudierFenster [1] (`http://studierfenster.icg.tugraz.at`, Fig. 1), an open, browser-based framework for biomedical image analysis, and MedShapeNet [2] (`https://medshapenet.ikim.nrw`, Fig. 2), a comprehensive and open-access repository of medical shapes.

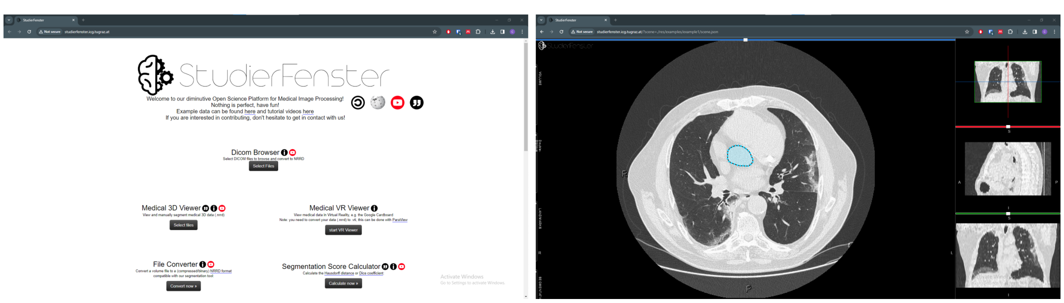

Figure 1: StudierFenster, a browser-based framework for biomedical image analysis. Left: StudierFenster landing page. Right: Manual outlining using StudierFenster.

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2 StudierFenster

(Bio-)medical image analysis is vital for accurate diagnosis, treatment planning, and research in modern healthcare. Advanced imaging technologies, such as computed tomography (CT) and magnetic resonance imaging (MRI) produce an ever-increasing amount of clinical data every day, and computerized analysis methods and algorithms are essential to interpret them. Recently, machine and deep learning (DL) have greatly transformed the landscape of medical image analysis tools [3]. However, accessing these algorithms remains a challenge for healthcare professionals or the general public, as they are often confined to proprietary platforms with limited accessibility or require programming skills and capable hardware environments to set up.

To address this challenge, we propose StudierFenster, a free, online, cloud-based environment for medical image analysis applications. Accessible through common web browsers such as Google Chrome, Mozilla Firefox, Safari, or Microsoft Edge, StudierFenster eliminates the need for manual software updates and maintenance, providing users with seamless access across various devices, regardless of hardware constraints. The StudierFenster backend is based on the common open-source Insight Segmentation and Registration Toolkit (ITK; https://itk.org) and the Visualization Toolkit (VTK; https://www.vtk.org), which ensures support for a wide variety of use cases. To this date, various algorithms and applications have been integrated into StudierFenster, such as a DICOM browser and conversion tool [4], a medical 2D and 3D viewer with an integrated manual slice-by-slice outlining (segmentation, seen in Fig. 1) and landmarking tool [5], an automatic landmarking algorithm for the aorta [6], a module for inpainting medical images [7], centerline computation for vessels from CT or CT-Angiography (CTA) scans [8], automatic reconstruction of skull defects [9], 3D face reconstruction and registration [10] as well as the computation of common similarity metrics used in medical image segmentation, such as the Dice similarity coefficient and the Hausdorff distance [11].

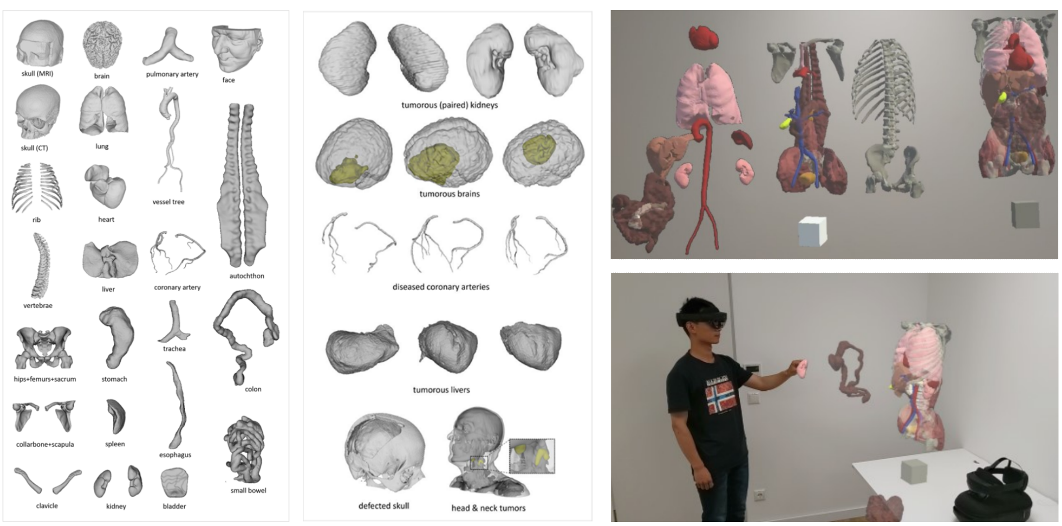

Figure 2: MedShapeNet, a data repository of medical shapes. Left: Samples of anatomies and pathologies included in MedShapeNet. Right: MedShapeNet data used in mixed reality.

3 MedShapeNet

The recent success of DL across various domains, including vision, language, and medicine, can largely be attributed to the availability of high-quality, extensive datasets. Medical data is unique in the sense that it is mostly supplied in the form of 3D volumetric images, as obtained from CT or MRI scans. In contrast, within the broader DL community, 3D data is commonly represented as *shapes*, namely voxel grids, point clouds, meshes, or implicit surface models, such as signed distance functions. These representations can be readily converted into one another, facilitating knowledge transfer across different domains. To leverage the latest advancements in 3D DL within the medical domain, the establishment of a large repository of medical shapes is needed.

In this context, we present MedShapeNet, a dataset for medical imaging shapes extracted from real patients, which aims to close the gap between medical imaging and general 3D DL. The shapes within MedShapeNet originate from segmentation masks of anatomical structures, such as organs, bones, vessels, and muscles, as well as 3D scanned medical instruments [12]. These segmentation masks were largely obtained from existing repositories; generated either manually from domain experts [13]–[15] or semi-automatically using DL-based segmentation algorithms, such as TotalSegmentator [16] or AbdomenAtlas [17]. To this date, over 100.000 shapes from 23 datasets and more than 100 contributors are included in MedShapeNet, and the repository is constantly growing. The dataset is freely available via a simple and user-friendly web interface or an open-source Python API for expert users (`https://github.com/Jianningli/medshapenet-feedback`). The applications of this data span a wide spectrum, encompassing discriminative tasks like classification, reconstructive tasks such as shape completion [18], and variational tasks such as imposing morphological changes on existing data. Furthermore, the data can be used for applications in mixed and virtual reality, as well as 3D printing.

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