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AI Driven IoT Web-Based Application for Automatic Segmentation and Reconstruction of Abdominal Organs from Medical Images

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***Abstract*—Medical imaging technology has rapidly advanced in the last few decades, providing detailed images of the human body. The accurate analysis of these images and the segmentation of anatomical structures can produce significant morphological information, provide additional guidance toward subject stratification after diagnosis or before a clinical trial, and help predict a medical condition. Usually, medical scans are manually segmented by expert operators, such as radiologists and radiographers, which is complex, time-consuming and prone to inter-observer variability. A system that generates automatic, accurate quantitative organ segmentation on a large scale could deliver a clinical impact, supporting current investigations in subjects with medical conditions and aiding early diagnosis and treatment planning. This paper proposes a web-based application that automatically segments multiple abdominal organs and muscle, produces respective 3D reconstructions and extracts valuable biomarkers using a deep learning backend engine. Furthermore, it is possible to upload image data and access the medical image segmentation tool without installation using any device connected to the Internet. The final aim is to deliver a web-based image-processing service that clinical experts, researchers and users can seamlessly access through IoT devices without requiring knowledge of the underpinning technology.**

***Index Terms*—IoT Web Application, Deep Learning, 3D Reconstruction, Web Technology, Medical Image Computing, Organ Segmentation**

I. Introduction

The accurate, computer-aided quantitative segmentation and classification of organs can provide significant information about medical conditions and produce additional guidance towards stratifying subjects after diagnosis or before clinical trials. For example, recent research studies show that automatic segmentation and computer-aided investigation of organ volume variations in patients with conditions such as polycystic liver disease (PLD) [1], renal (kidney) disease [2], and type 1 and 2 diabetes mellitus [3] have contributed to raising the quality of biomedical research [4]. Computer-aided diagnosis systems can provide a "second opinion" and, therefore, support interpretations of medical scans, reducing possible misdiagnosis and providing a valuable guidance for therapy planning [5].

State-of-the-art works show high segmentation accuracy scores of 90% or above for the automatic segmentation of organs such as kidneys [6], liver [7] and spleen [8]. However, other anatomical structures, such as the pancreas and iliopsoas muscles, present significant challenges due to size, high structural variability and location, and a full inspection from a scan is often very problematic.

In the last decade, the use of convolutional neural networks (CNNs) has increased the performance of several imaging tasks using large-scale data, particularly semantic segmentation [9]. It has been successfully integrated into medical image segmentation tasks, especially for abdominal organs that are highly deformable and possess vague edge boundaries.

This work aims to provide the scientific community with a web-based framework for the automatic feature extraction and segmentation of abdominal organs in medical scans, using newly developed CNNs algorithms. Medical Internet of Things (IoT) can vastly improve the standards of care. As healthcare systems increasingly use cloud technologies, software applications for medical image computing are evolving to benefit from these services [10]. The application is easy-to-use without requiring an expert operator's interaction. The broader research community could use the proposed framework since the developed algorithms are open-source and easily accessible; this will help accurately reconstruct a patient's anatomical structure and improve the disease detection and treatment planning performed by radiologists and clinicians in medical health services. The proposed framework will also support the stratification of subjects according to organ morphology.

This paper is structured as follows: Section II explains the web-based application's backend methodology, the automated segmentation approach, 3D visualisation, and the extraction of morphological features following segmentation. Section III presents the developed web-based application. Section IV discusses its evaluation and usage. Finally, section IV provides a conclusion, including references to future work.

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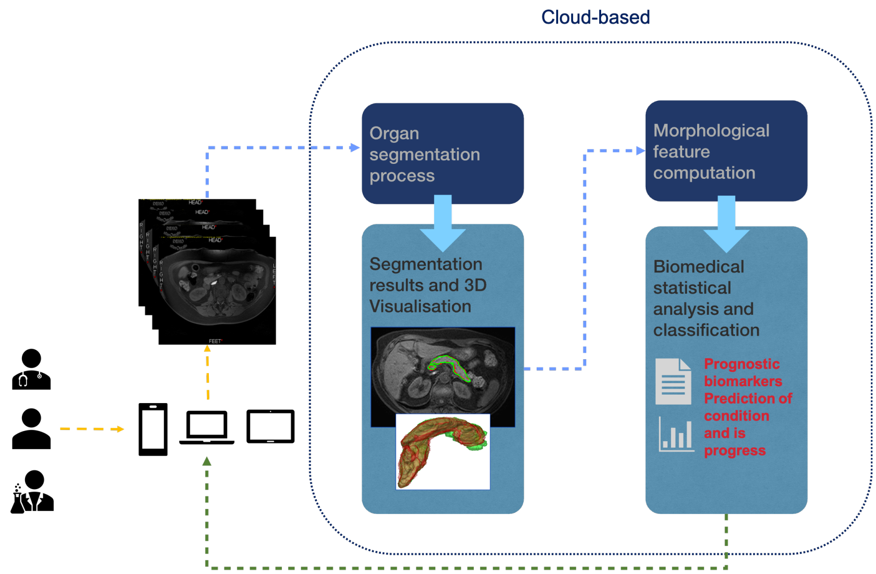

Fig. 1. Overview of the proposed framework. The initial input is a 3D medical volume that runs through a segmentation process, achieving a 3D accurate reconstruction of the organ (or muscle) of interest. Next, the segmentation result processes through a biomedical model, which computes morphological features to enable the final prediction of a medical condition or evaluate that condition's progression.

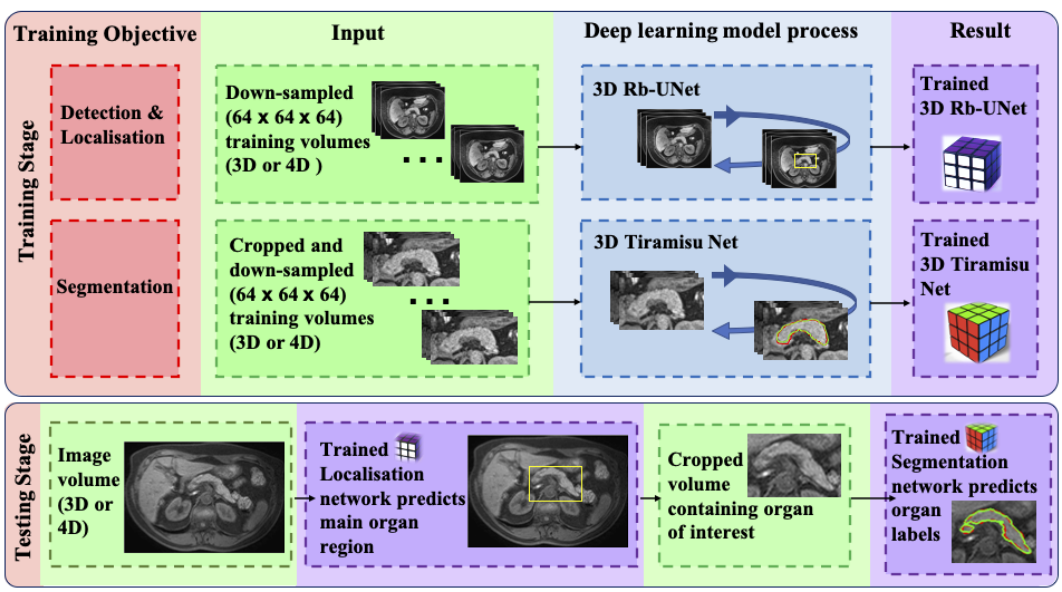

Fig. 2. Overview of the proposed automated organ segmentation approach [11]. The figure shows two different stages. In the training stage, the 3D Rb-UNet localises the organ of interest and the 3D Tiramisu predicts the labels that correspond to that organ. In the testing stage, an original scan (e.g., a 3D or 4D volume) is processed to predict the bounding box capturing the organ of interest and then the cropped image volume is processed to predict the labels of that organ.

II. Methodology

The proposed web-based application aims to automatically obtain, from medical scans, relevant morphological features that can be used to predict a medical condition or evaluate the progression of a condition. The initial input is a 3D medical scan as a volume that can be uploaded from any smart device connected to the Internet: it is processed through a segmentation stage driven by Artificial Intelligence (AI) using deep learning modelling to obtain an accurate 3D reconstruction of the anatomical structure of interest (e.g. the pancreas). The segmentation result is then processed through a computational biomedical model that calculates relevant morphological features or biomarkers and enables the final prediction of a condition or evaluates the progression of a pre-diagnosed condition. The overview of the proposed approach is shown in Fig. 1.

A. AI Driven Models for Automatic Segmentation of Abdominal Organs

The algorithms used to perform automatic organ segmentation in medical volumes are based on 3D deep learning techniques that employ volumetric information instead of 2D pixel information, presented and evaluated in [11]. The developed framework has a two-part process: the first part develops a localisation model known as 3D Rb-UNet to "capture" the target organ of interest, and the second part performs detailed organ segmentation through a 3D Tiramisu network. The testing stage processes an original medical volume to predict the minimal bounding box surrounding the organ, and then the cropped image volume is processed to predict that organ's labels. The training stage and testing stage for each part are shown in Fig. 2.

The first part of the training stage implements a model, defined as Rb-UNet, which aims to identify the region of interest where the organ is localised. Residual connections are added at each block of a baseline 3D U-Net architecture, connecting the input of convolutional layers at each scale to the outputs of the corresponding layer. The main aim is to improve convergence through this bypass with identity connections for convolutional blocks at each scale. Empirically tested, the 3D Rb-UNet model performed significantly better than the standard 3D U-Net for organ localisation [11].

The second part of the training stage develops a 3D Tiramisu model [12] using the cropped region obtained in the previous stage, where the organ of interest is fully present, discarding background information unrelated to the organ. While the 3D Rb-UNet model employs the full spatial context of an image volume, the 3D Tiramisu model only utilises the main region surrounding the organ. Therefore, the main aim of the 3D Tiramisu model is to perform voxel-wise predictions: does a voxel belong to the organ of interest or otherwise? The Tiramisu model builds upon DenseNet to work as Fully Convolutional Networks by adding an upsampling path to compensate for the full resolution of the input. In this architecture, a standard skip connections is used to pass the higher resolution information between the downsampling and the upsampling paths. Empirically tested, this upsampling path built from dense blocks performs better than an upsampling path with conventional operations in DenseNet or U-Net. Further details about the network architecture can be found in [11].

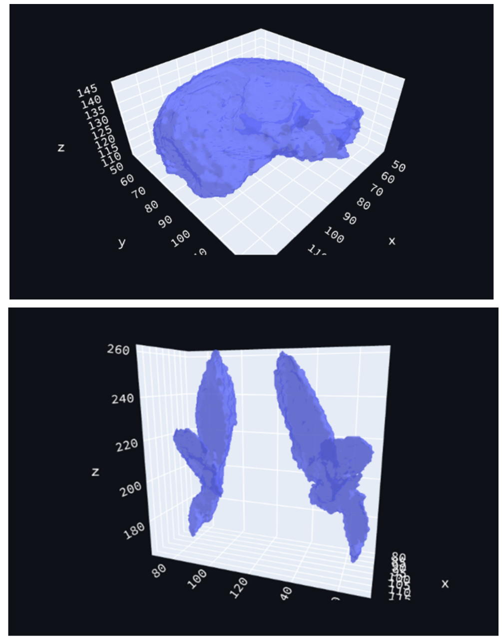

Fig. 3. Example of automatic 3D organ visualisation from the proposed web-based application after performing automatic liver segmentation (top) and segmentation of the iliopsoas muscles (bottom).

B. 3D Organ Visualisation

The automatic segmentation framework produces a 3D binary volume of a target organ. The reconstruction process employs a Gaussian smoothing algorithm applied to a 3D interpolation for noise removal. This technique is often used as a pre-processing stage in computer vision tasks to enhance image structures at varying scales of visualisation [13]. Following the Gaussian process, the smoothed data is represented as an isosurface, which can be described as a set of points where the function represented by the data takes on a common value called isovalue. The marching cube [14] algorithm is used to reconstruct the isosurface as a polygonal mesh. Finally, Laplacian smoothing is used to refine the polygonal mesh, after which the 3D organ model is visualised against a single 2D slice in the original medical image volume. The 3D representation of the organ is interactive, with the option to load the 3D binary mask from the segmentation process and display the 3D mesh. Also, functionalities such as zoom-in, zoom-out and rotation are enabled. Examples of 3D interactive representations are provided in Fig. 3.

Organ visualisation is also an important aspect of the web-based application's functionalities. The medical image volume, once loaded, can be visualised in three main views: axial, sagittal and coronal. The segmented organ appears overimposed on the original medical slice (2D) as shown in Fig. 4.

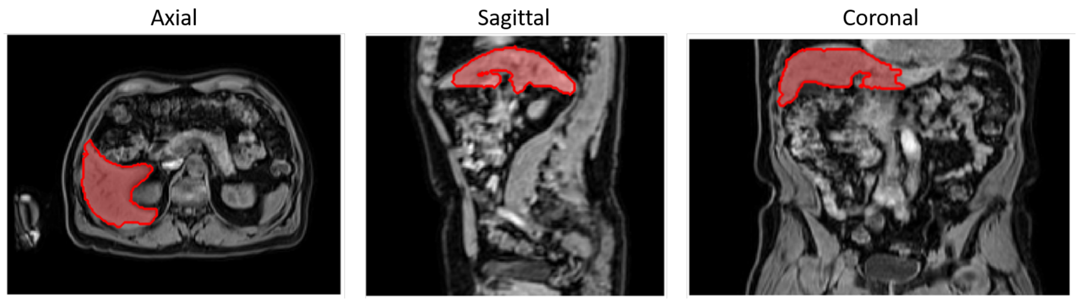

Fig. 4. Overview of the proposed automated organ segmentation approach [11]. A single 2D slice in a medical volume is displayed in three different views (axial, sagittal and coronal) with over-imposed segmentation results. The web-based application delivers these different views after performing automatic liver segmentation.

C. Morphological Features Extraction

An important aspect of this framework is the automatic computation of medically valuable morphological features of the target organ, enabling early diagnosis or stratification of subjects according to organ morphology.

Two values have been calculated as a descriptor of the organ's morphological structure: volume and curvature. Details of the algorithms implemented to compute these values are described in [15]. The volume provides a measure of the organ's dimensions, while the curvature describes the organ's surface and its level of "smoothness" or "raggedness", indicating the potential deformity of the organ.

D. Open-source Imaging Framework

Development of commercial systems driven by medical imaging manufacturers suffer of some limitations [16]. They usually follow research and clinical validation and require several years before releasing new products on the market despite the increasing and urgent demand for advanced processing tools. For these reasons, open-source and free software is more widely adopted in the medical community. It is cost effective and it can be customised to match the needs and specific usage in clinical setups. Furthermore, it is a quick way of providing new innovative and challenging analysis tools that respond to users' demands, even before industry and commercial vendors identify these new trends as a potential source of revenue.

All source code and the files produced in this work are openly available on GitHub by accessing the link: `https://github.com/medicimage/AI_med_seg_app`. In addition, guidelines and details on how to run the application locally are also provided.

III. Web-Based Application and Results

There are numerous limitations to local medical imaging processing applications. Firstly, operating system and processing power constraints prevent the application from running in any workstation. Furthermore, the application would need to be accessible from one specific machine where the software is installed and not available from other workstations. Addressing this limitation, a web-based application has been developed to enable users to access a medical image processing and visualisation platform from any machine without installing any software or knowing the underpinning technology.

All the source code is written in Python 3.8 and uses Streamlit (https://www.streamlit.io) and Plotly (https://plotly.com) for a graphical user interface (GUI) and interactive data visualisation. Streamlit.io is a new open-source framework for developing web applications and allows the implementation of graphical interfaces to Python backend code.

Streamlit Cloud handles all the Python dependencies, container orchestration, server provisioning, scaling and data security. Also, it continuously deploys the app from GitHub, providing version-controlled code development and facilitating collaborations and tools maintainability (Fig. 5).

The developed prototype integrates the AI-driven algorithms developed for organ segmentation in medical image volumes as described in Section II.

The user can perform the following actions:

- upload a medical image volume (DICOM or NIfTI files);
- load a sample image volume: the user can use an image volume stored in the server (without uploading their own) to run the main functionalities available in the web-app;
- visualise each slice in the medical image volume in three different views (axial, sagittal, coronal). The slice can be selected using a sliding bar on each image;
- select which organ is to be segmented by clicking the appropriate radio-button. Afterwards, segmentation will be performed, and the final segmentation results will be displayed on each visualised slice. In addition, the segmentation contouring will be updated by changing the slice;
- visualise the 3D reconstructed organ volume;
- zoom-in, zoom-out, rotate and save the 3D reconstructed volume;
- compute morphological features such as organ volume and curvature;
- visualise metadata from the uploaded DICOM and NIfTI file.

In Fig. 6 the web interface has been shown performing the main functionalities. A short demo is available at this link: https://share.streamlit.io/medicimage/ai_med_seg_app/main/mainProgram.py.

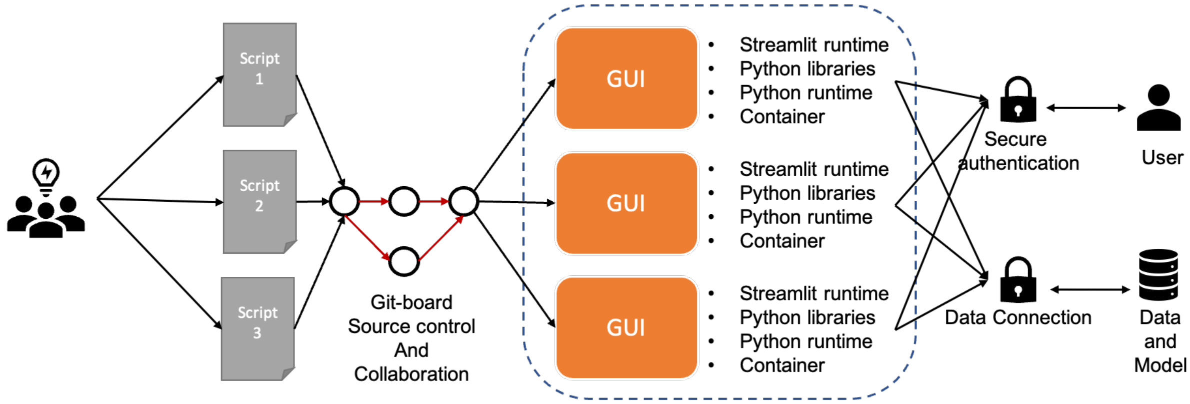

Fig. 5. Secure application sharing and collaborating architecture in Streamlit.

IV. Tests and Discussion

The system has been tested using the available datasets. In addition, users not familiar with the project have been involved in running some usability tests. Taking into consideration their feedback and comments, the interface will be improved by adding exception handling and extra functionalities, including loading medical images as .png or .jpeg; an icon with loading bars while the model is performing automatic segmentation; a text box where the user can type the slice number to visualise; and the segmentation contouring of multiple organs on the same slice.

Furthermore, there are a number of limitations when running the application in the cloud-host browser. In particular, due to some server power limitations, it is not possible to load image volumes with a high resolution (maximum is around 150 slices). Also, the pre-processing and model computation requires high-memory allocation, currently not supported by the Streamlit server. These factors impacted the accuracy of organ identification as some of the algorithms were fine-tuned to perform on less memory and disk space. These limitations will be addressed, and the web application prototype will be further improved. Finally, the plan is to migrate into a high-performance server available at the University of Westminster, where the data and the deep learning models will be stored. Furthermore, the functionalities will be extended with possibilities to train the deep learning models on a user dataset, potentially enabling higher accurate segmentation results for extensive medical data types and different types of target anatomical structures.

V. Conclusion

This paper proposes a web-based application for the automatic segmentation of anatomical structures in medical image volumes using an AI-driven approach. The main goal is to elaborate the concept of publicly available cloud-based image-processing services that clinical experts and researchers in Life Sciences can seamlessly access through web pages from any IoT device without requiring knowledge of the underpinning technology. Furthermore, given that the developed algorithms are open-source and easily accessible, the broader research community could employ the proposed framework and deliver 3D reconstructions of patient-specific anatomical structures, helping to improve disease detection and treatment planning performed by radiologists and clinicians throughout the medical health service industry.

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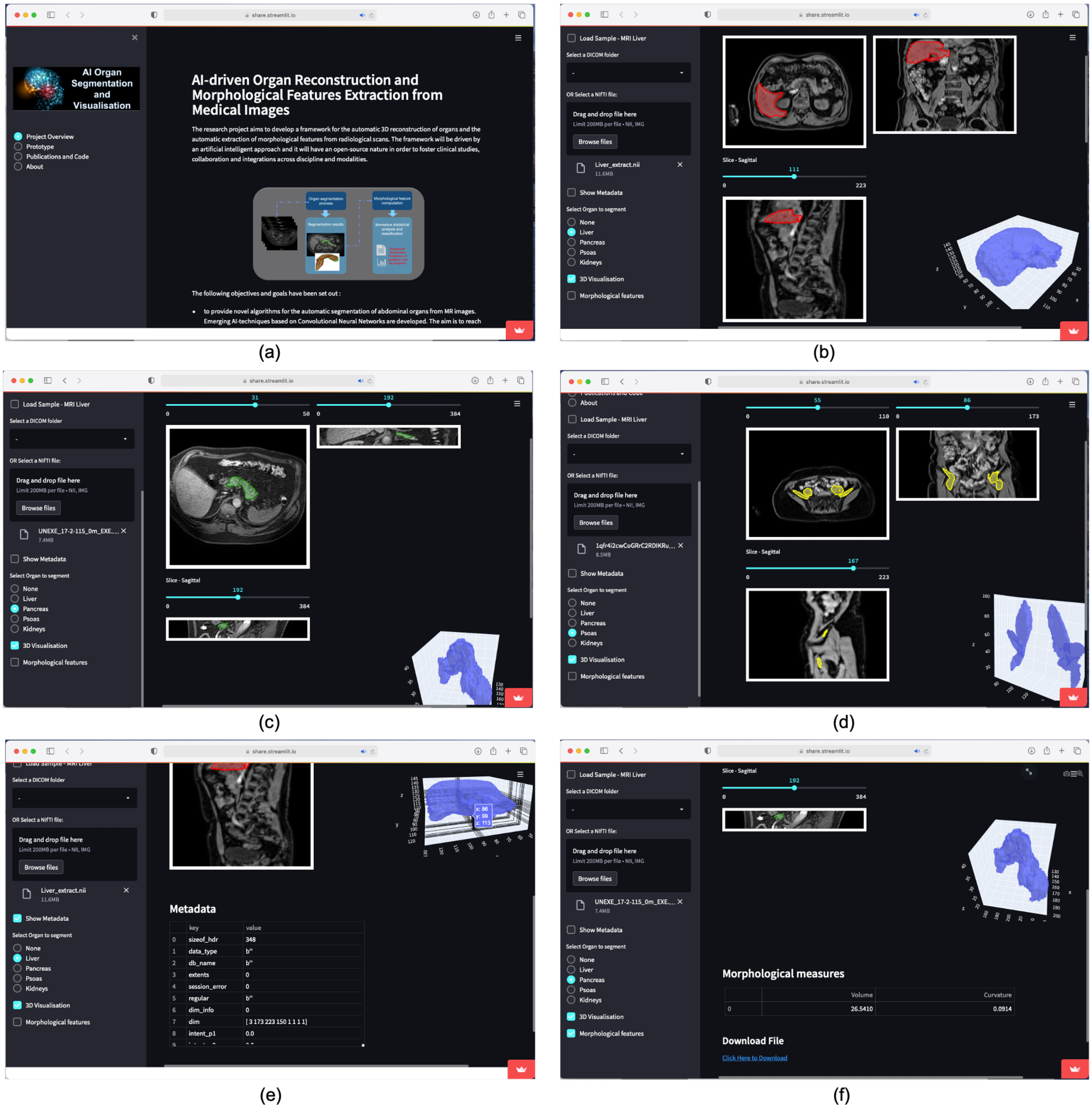

Fig. 6. Web-based application screenshots: (a) landing page with research project information; (b) liver segmentation results in a magnetic resonance imaging (MRI) volume; (c) pancreas segmentation results in an MRI volume; (d) iliopsoas muscles segmentation results in an MRI volume; (e) example of metadata in an MRI volume; (f) example of morphological features computed in a reconstructed organ according to the physical dimensions stored in the metadata.

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