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Seadra : a fully customizable and user-friendly application for image annotation and segmentation

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Abstract—With new technologies and advances in biology, practitioners are faced with an ever-growing amount of data. Among this data, images are of particular interest thanks to the ability to segment and annotate directly on the image. These annotations are time-consuming, but indispensable for machine learning methods. In this paper, for the sake of a project on oral cancer detection, we developed an application that aims to enable easy-to-use and customizable annotation of data. It also has the advantage to consider multimodal annotation, to be able to read complex formats which are useful in the medical field such as MIRAX for example and to be compatible with graphic tablets. This software is completely free to use and the whole implementation, along with the ready-to-use executables are available on Github. It can be useful for many others data-driven projects that need accurate annotation on images especially while having time constraints for the annotator.

Index Terms—Image annotation, segmentation, user-friendly application.

I. INTRODUCTION

Nowadays, Artificial Intelligence (AI) is becoming a central tool in medicine to help practitioners to better understand the huge and growing amount of data they are facing. Recent approaches are mainly based on Machine Learning and Deep Learning to automatically extract patterns from annotated data [1], [6]. However, building datasets, the basis of any Machine Learning algorithms, is a necessary preliminary task that takes a tremendous amount of time from medical experts, who could instead use this time to take care of patients. In this paper, a new efficient and flexible software, called Seadra¹ is presented. It is dedicated to annotating medical data with a wide range of options, going from the textual tag to the image segmentation.

Its use in the field of oral cancer detection is illustrated which is one of the cases for which Seadra was developed and which is presented below.

Oral cancer kills around 180,000 people each year in the world for approximately 380,000 new cases in 2020 for example [8], even though survival rates are between 75% and 90% if diagnosed early. As with many diseases, the lack of specialists and their poor geographical distribution reduces the survival rates of patients because they are often diagnosed too late [10]. In this case, as in many others, AI-based methods could be beneficial to propose a first diagnosis for the patients with the objectives to save pathologists' time and help them to better schedule their appointments by prioritizing patients with higher risks of cancer [9].

Developing such an AI-based solution requires the automatic analysis of photos of the oral cavity and more particularly the tongue, which, thanks to the mucous membranes, is highly informative about cancer risk. This is however a challenging task as only few pathologists are able to perform this type of diagnosis accurately. At this time, specialists have constituted a dataset of thousands of unannotated images. Annotating them not only requires to segment specific features in the image but also to add textual clinical information about the patient, for the moment only the diagnosis is added but further information such as gender, age, history, etc. could also be useful in the future. Having both the lesions and the diagnosis appeared mandatory for us because the oral cavity is too rich in terms of visual information and so a single classification process didn't provide satisfying results, that's why a 2 steps process is opted with first identifying the lesions and then using them to classify the image. This process matches the way pathologists produce a diagnosis by

¹Seadra Github: <https://github.com/KevinCortacero/Seadra>

themselves. This information is crucial to improve multimodal machine learning models. However, most existing software cannot annotate both images and medical cases. This implies that the specialist has to switch between different softwares (often an image annotation software such as QuPath [2], [3], LabelBox [7] or V7 [4], [5] and a spreadsheet) to build the dataset, resulting in a significant loss of time.

In the following of the paper, our proposed application is presented for image annotation and segmentation called Seadra in section II. Then as numerical experiments, Seadra is compared with Qupath, state-of-the art annotation software on oral lesions by a pathologist in section III and a conclusion is given in section IV.

II. PROPOSED SOLUTION: SEADRA

To overcome these limitations, we propose a new open-source application, named Seadra, specifically developed for medical case annotation both with graphical and textual labeling.

A. Setup

The application is designed to be flexible and adaptive, so it can be used on any type of medical use case. To this end, a first graphical interface allows to configure the annotation tools according to the specific need of the problem. As shown in Figure 1, users can set up the classes to be segmented on the image, single and multiple-choice labels with a list of possibilities and an open text for additional comments. All this is completely customizable and the configuration is then stored in a file that can later be exported to other computers so their users can load the same annotation profile without having to set it up once again.

For example, in Figure 1, we have designed a dummy annotation setup that allows to segment 4 different types of objects on the image, named Label A, B, C, and D but also to add 2 sets of mutually exclusive tags Healthy/Malignant for the diagnosis and Man/Woman/Other for the gender of the patient. In addition to these, we can also use a tag with different options that can be selected simultaneously to explain the history of the patient with the values Alcohol/Tobacco/Cancer.

B. Annotation and Segmentation

Once set up, Seadra produces a graphical interface specifically designed for the dataset annotation task. It presents the list of images to be segmented and, for each image, the different information to be annotated. Each annotation can be validated to move to the next one. Images can be annotated with different geometric shapes: either with ellipsis, rectangles or polygons.

As presented in Figure 2, one can find on the left panel the different textual annotations, which have been filled for this fictive example. So the patient is a male, diagnosed with a malignant disorder, and who smoked and drank during his life but did not previously have another cancer. We also added a comment, which is always possible, indicating that the mother of the patient has also been diagnosed with cancer. On the right

panel, one can see the graphical annotation tools to segment the image by drawing on it, there are also counters of the number of objects of each label that have been annotated on the current image. And on the central part of the app, we have the image to annotate, with some annotations that have been made only for display purposes, they don't have any medical meaning, we have 1 polygon of class Label A, 2 ellipses of class Label C and 1 ellipsis of class Label D.

C. Export

For each annotated patient (image segmentation and textual labels), Seadra generates a *json* file that contains all necessary information: segmentations on the images, choices, and text. These files are organized as described during the application setup stage and can be easily read in standard programming languages (Python, Java, Matlab, etc.) for further analysis, cleaning, and training of Machine Learning algorithms.

For example, in Figure 3, one can see the different annotations described above:

- the 4 drawn annotations with a polygon defined by all its corners and 3 ellipses defined by its center, both radiuses, and a rotation angle
- the textual tags, being, as described earlier, "Malignant", "Male", "Alcohol" and Tobacco", and also the comment.

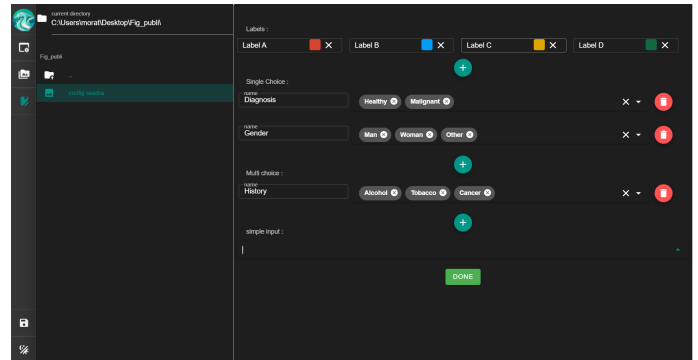


Fig. 1. Menu for defining the way in which you wish to annotate your data; the user fills in the labels to be used on this interface.



Fig. 2. Dummy example using the previous setup.

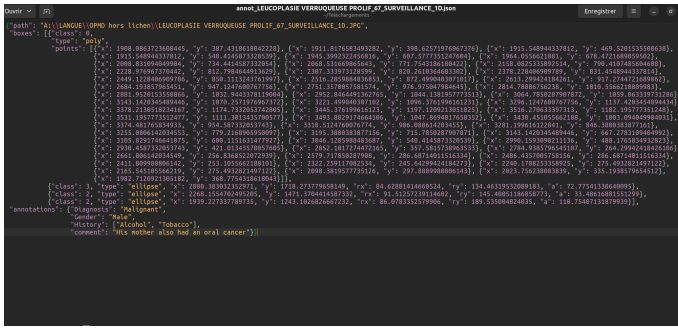


Fig. 3. Example of the annotation file produced by Seadra for the dummy example.

In figure 4, we can see a real example of annotation which has been made for our use case. The interface displays the list of images to be annotated with different coloring indicating whether the image has already been annotated or not, in order to save time for the annotator. Each annotation can be validated to move to the next one. At the time of this publication, Seadra is compatible with *png*, *jpeg*, and *mrzs* image file format. More compatibility will be added in the future.

This interface has been designed to be both user-friendly and minimizing the number of clicks the specialists have to make for each annotation, the aim being to be as efficient as possible. To improve user experience, Seadra is compatible with graphical tablets, strongly simplifying and accelerating the drawing on the images while keeping annotation simple with mouse and keyboard. This compatibility was a key feature in our development, which isn't guaranteed in most of the annotation software we have explored, and as we will show later in that paper, it has proven to be a real improvement in the annotation process.

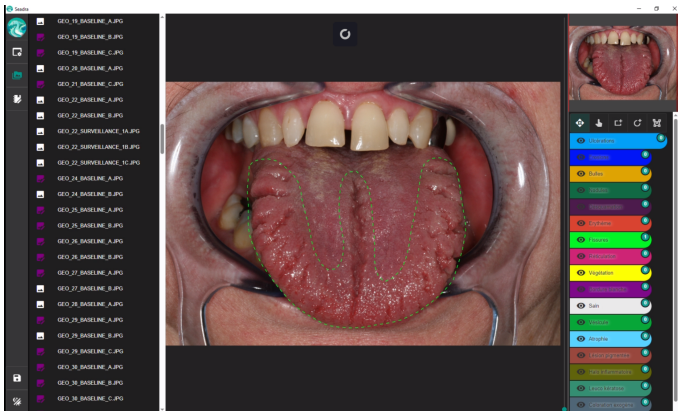


Fig. 4. Main window of the application with an example of labeling a patient's tongue.

III. EXPERIMENTAL RESULTS

Seadra has been designed to improve user experience and productivity to annotate medical cases, a preliminary task necessary to train any supervised machine learning algorithms.

To measure the potential gain obtained using Seadra, we compared the annotation speed in 3 different cases:

- using QuPath, an existing and widespread open-source annotation tool,
- Seadra with a standard computer (mouse and keyboard), and
- Seadra with a graphic tablet.

In this study, we evaluate Seadra on the specific case of oral lesion annotations due to the availability of both a pathologist and a data set. As mentioned above, Seadra is fully customizable to handle many medical cases such as cell segmentation, tumor detection, etc. We have used a laptop computer with a 1.8GHz i7 processor, 8GB of memory, and a Wacom Cintiq 16 graphic tablet.

The measurements were done by annotating a total of thirty images extracted from the dataset, split into ten for each of the three different setups. They have been selected to be equivalent in quality and not yet annotated by the pathologist to avoid any bias. For this study, we limited the annotation to four types of lesions. While the pathologist was annotating the cases with the different setups, we measured the time needed to annotate each case and the total duration to annotate the ten images. The reason why we distinguished these 2 measurements is that we observed that the transition time from an image to another is significantly higher in Seadra, but this is not something linked to our design choices, it may more likely come from the implementation of the app and how optimized it is. There is room for improvement there. However, even though Seadra has this drawback, we will see that it still outperforms QuPath. We also computed the average time by feature as it appeared that each method led to really different number of features. Table I provides the obtained results and Figure 5 presents them in a more visual way.

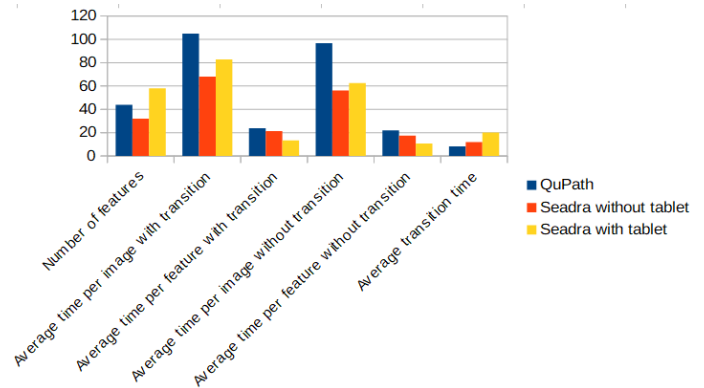


Fig. 5. Histogram of the measured durations

Compared to QuPath, Seadra allows a faster annotation of medical cases both with and without graphic tablet. The gain with the tablet is undeniable, accelerating the processing time of each feature by 60% on average. Additionally, while the images were selected to be as identical as possible, it appears that the expert pathologist is able to identify more features with the tablet than on the computer screen only. This is mainly

	Number of features	Total time (s)	Average time by feature	Average time by image	Average time by feature on a case	Average time of transition per case
QuPath	44	1050 s	23.86 s	96.8 s	22 s	8.2s
Seadra without tablet	32	680 s	21.45 s	56.1 s	17.53 s	11.9s
Seadra with tablet	58	827 s	13.45 s	62.5 s	10.76 s	20.2s

TABLE I
ANNOTATION'S TIME COMPARISONS BETWEEN QUPATH AND SEADRA

possible because of the screen quality of the tablet and the precision gain provided by the use of the numeric pen.

Notably, the gain on the annotation of the 10 cases is still noticeable even though Seadra has a longer loading duration for each case. This loading issue needs to be addressed in Seadra which will, ultimately, improve even more the user experience when using this annotation solution.

Finally, even if it is not quantified in this study, the adaptation to Seadra was easy for the pathologists, easier than to QuPath. This has been possible because Seadra has been designed with annotation efficiency in mind, leading to a simple and click-limited graphical interface.

IV. CONCLUSION

Having access to a large and well-annotated dataset is the cornerstone of most AI projects. However building these datasets is a hard task, in particular in the medical domain in which expert pathologists have a limited amount of time to dedicate to this task. Providing most efficient tools can increase the capacity of pathologists to annotate large datasets. We have proposed a new easy to use and customizable application, called Seadra, that enables accurate annotation on images via different geometric shapes. This software can be used via a computer or a graphic tablet. It allows to consider multimodal annotations (images, medical information, ...) and can support different complex image formats. A study was conducted to estimate the improvements that Seadra can bring in terms of time spent for image annotation. In particular, it revealed that the ease of use significantly increases the number of possible annotations for the same amount of time.

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