SUPERVISED SEGMENTATION FOR 3D SLICER

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Abstract: The purpose of this work is to introduce an extendable framework for training and usage of machine learning algorithms. This framework is bundled in an extension for 3D Slicer that is to be used for medical images segmentation. An example usage of the extension is also provided.

Keywords: 3D Slicer, C++, extension, machine learning, optimization, segmentation, tomography

1 INTRODUCTION

3D Slicer[1] is an extendable platform used to process and visualize medical images. Extendability is achieved with Slicer Extensions, which provide a way to develop new functionality for the Slicer Community and third-party developers. One way to create such an extension is by means of compiling a dynamically linked library to be loaded through the interface of 3D Slicer. This library then has full access to 3D Slicer core utilities and does not sacrifice any performance due to being developed in the C++ language. This method is used to develop the Supervised Segmentation Extension. Other methods include a separate command line interfacable application or an extension written in the Python scripting language.

Although the Slicer Extension Library is already impressive in size and covers a vast range of topics, at the time of writing, none of them uses machine learning for segmentation.

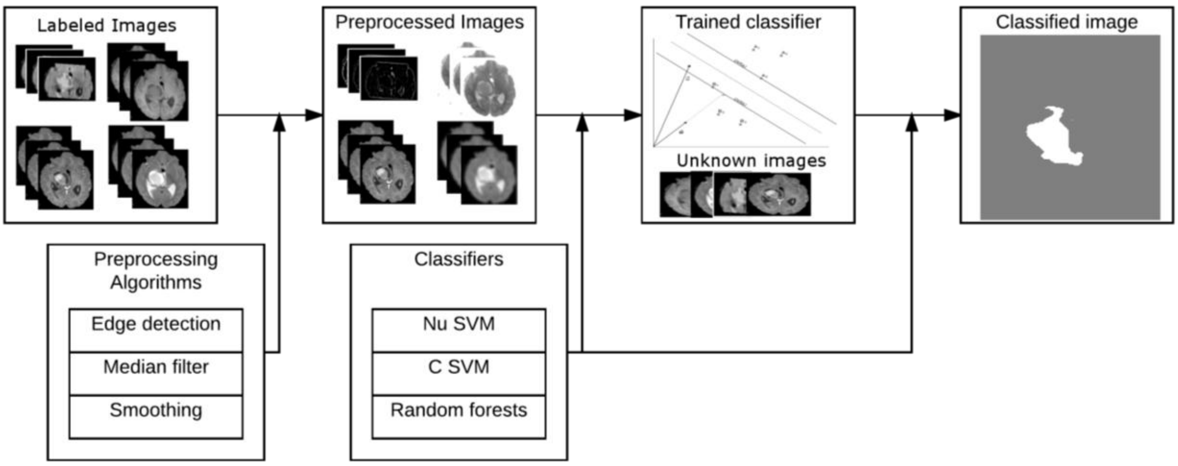

Figure 1: Simplified Supervised Segmentation Extension's operation

2 FEATURES

The Supervised Segmentation Extension will provide the means to preprocess images, train a classifier and then use the classifier to segment an unknown image following the diagram in **Figure 1**. To achieve this, a variety of third-party libraries, such as dlib[2] and Shark[3] will be included.

Libraries that provide equivalent functionality will be examined for the accuracy and performance of each will be recorded and presented in the graphical user interface (GUI).

An extendable list of preprocessing algorithms is included in the extension. At minimal this list will provide a median filter and a variety of spatial filters. At the time of writing, the 3D median filter and the Sobel operator are implemented.

Currently, an extendable list of classifiers includes dlib's C Support Vector Machine (SVM), Nu SVM and the online Pegasos SVM. C and Nu SVMs use radial basis kernel and provide the means to find and use the optimal parameters for training. In theory, the user is not limited by the modality, through which the data was obtained. All planned classifiers and preprocessing algorithms are general-purpose. SVMs were implemented first, because of their clear mathematical properties[4] and fast convergence in comparison with other techniques, such as neural networks.

Serialization and deserialization of trained classifier, together with metadata about the learning datasets are provided. This allows the user to train a classifier once and then use it multiple times across multiple sessions or projects.

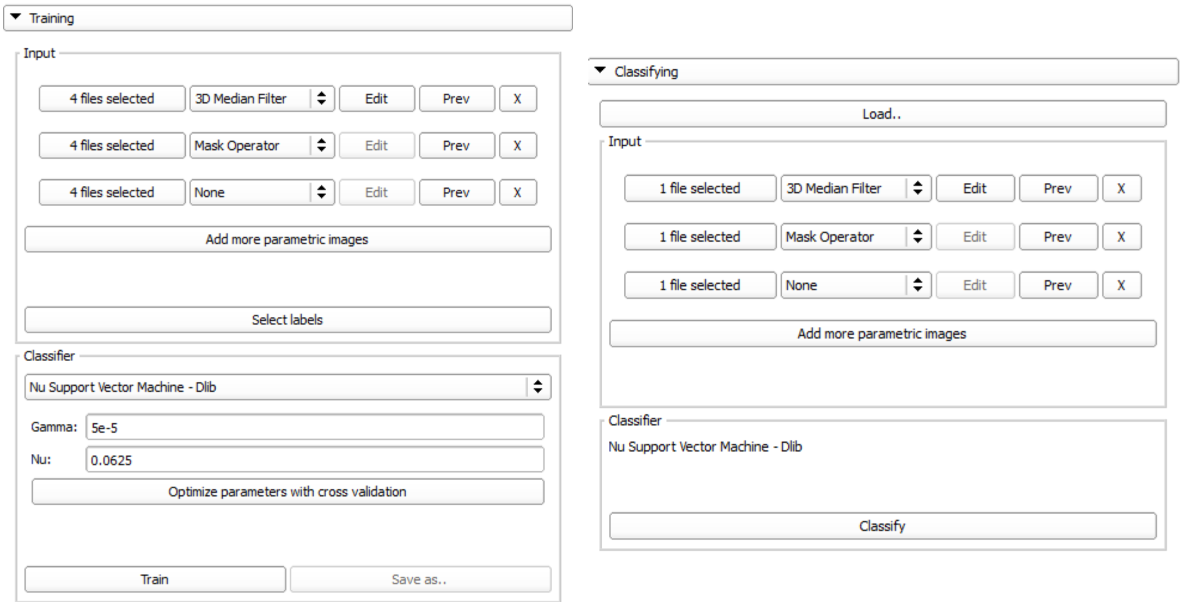

Figure 2: Separate Graphical User Interfaces for training and classifying

All used image volumes are included directly in 3D Slicer's own interface as vtkMRMLNode. This makes them readily available to be used in other extensions, or exported.

To train a classifier the user selects one or multiple images for each feature (e.g. 6 images of T1-weighted MRI image as one feature dimension and the same number of T2-weighted images). These images could be any image in data format that 3D Slicer can decode and use as a volume node. Then, the user provides 3D Slicer-readable labels for the data, picks a classifier and, if needed, modifies provided training parameters. The GUIs presenting this are shown in **Figure 2**.

To classify an image set, loading of a previously trained classifier is required. The user is then prompted to select unlabeled data with the same number of feature dimensions. Following the previous example, the user should select one or multiple T1-weighted images as one feature dimension and the same number of T2-weighted images as the second dimension.

3 RESULTS AND DISCUSSION

Using single unprocessed T2-weighted and FLAIR image from the BRATS database as two feature dimensions and dlib's Nu SVM classifier, the extension was able to optimize ν parameter and radial basis kernel's γ parameter in under a half an hour on a quad-core Intel i7-6700HQ. To achieve that, the extension used 6-fold cross-validation and the resulting sensitivity and specificity as a metric. The extension was able to achieve 99.33% sensitivity and 97.74% specificity using image set BRATS_LG0001, the extension found the optimal parameters as 2.5e-4 for ν and 1.0e-05 for γ. A more robustly trained classifier remains to be tested. The probable cause for these high values is the small sample size and lack of testing on untrained samples.

A more thorough research of the SVM-based classification of MRI images using various feature vectors conclude an accuracy of 87.5%[5], 92.71%[6] and over 90% with specificty over 70% and sensitivity around 85%[7]. The last paper also includes a quantitative comparison of SVM and other machine learning algorithms with the result being in favor of SVM.

4 CONCLUSION

Even though the extension is still a work-in-progress, the user is already able to train and classify images using the tools provided. All volume data formats supported by the 3D Slicer are also supported by the extension.

The ultimate goal is to provide an easy to use and extendable supervised classification platform that utilizes machine learning to users and third-party developers. Features remaining to be added include a multi-classifier classification, where two or more classification results may be combined using a specified function. Additional machine learning libraries and image preprocessing algorithms will also be included. The whole source code will be publicly avalable on GitHub for anyone to add features to or enhance performance.

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