INFO8010: Project Proposal

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I. PROBLEM STATEMENT

Identifying cell's nuclei in microscopy images is the starting point of many treatments development for major diseases. Indeed, the identification of nuclei allows the researchers to identify the different cells of a human tissue and to track their response to different stimuli, especially exposition to new drugs molecules.

Identification of nuclei is made difficult by their various shape and the fact that the boundary between several nuclei is not obvious in some microscopy images. In addition, there are a lot of different possibilities to capture microscopy images, and so is the appearance of nuclei in the images. For those reasons, classical computer vision techniques often fail at detecting nuclei and the biologists usually have to look at thousand of images by eyes.

Building a robust computer program that would be able to spot cell's nuclei accurately in various type of microscopy images would save a tremendous amount of hours to researchers, enabling faster development of drugs and treatments for serious diseases. It is in the hope of building such a program that the kaggle challenge 2018 Data Science Bowl: Find the nuclei in divergent images to advance medical discovery was launched last year.

II. PROJECT PROPOSAL

Our project proposition is to take part to the above mentioned kaggle challenge. Although that challenge ended a year ago, we can still use "late submission" to see how well our solution performs. The goal of this project is therefore to determine if a pixel in a microscopy image belong to a nucleus or not, and to separate the different nuclei from each other, i.e. perform instance segmentation.

III. IMPLEMENTATION STRATEGIES

The dataset provided by the challenge is not so huge ($\approx 350MB$, comprising training set, testing set and compressed segmentation masks). We may therefore use data augmentation. Elastic deformation as in [1] could be a good option. In addition, external data usage was permitted by the challenge under the condition that it was mentioned in a specific thread. In consequence, we will be able to find related datasets if needed (and if we have the computational capabilities to process more data).

There are 2 different ways of doing instance segmentation. The first one is based on bounding-boxes, for example Mask R-CNN[2]. The second one is to first do semantic segmentation and then to predict the instances from the output of the semantic segmentation, for example by using Watershed transform. In a first time, we want to try the second approach in our project. In fact, this kind of techniques seem really interesting to us. They look also promising since the winning team used them for their implementation.

Semantic segmentation can be carried out by convolutional neural networks. They were first used in semantic segmentation by [3]. Later, [1] greatly improved the state of the art by introducing the "U-net Architecture". Since then, several modifications of U-net were created, among which [4] based on DenseNets[5] and [6] based on Resnet[7]. Ultimately, we would want to experiment with both of these architectures and maybe try an ensemble of them. We also plan to experiment with different types of loss functions. Some examples are to weight more importantly the border pixels as in [1] or to use soft dice loss as in [8].

Deep Watershed transform [9] can be used to get the instance labels from the semantic segmentation masks. The idea behind deep Watershed transform is to improve the classical Watershed transform by using deep learning to learn the topology structure rather than using the intensity of the input image. Since we already have semantic segmentation to handle, we plan to use the code the authors released on github, although it doesn't seem to be very well maintained. Additionally, the winning team of this challenge on kaggle proposed to predict the border between different instances in addition to whether the pixel is a nuclei or not during semantic segmentation, stating that it significantly increased their results (see here). The train set labels corresponding to the borders were found by using dilation. We would like to investigate that approach as well.

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