Medical image segmentation and feature detection is arguably the most cutting-edge and important area in computerized image analysis. In fact, the first use of computerized image analysis was implemented to analyze cell microscopy images (Madabhushi, 2016). There is constant innovation in the field of medical imaging, whether it be in imaging for research, pathology, diagnosis, or one of many other possibilities. However, unlike many other image feature detection tasks, medical image data very rarely is labelled. In other tasks, such as identifying faces or animals in images, the manual labelling can be outsourced to the general population. However, in medical imaging, manual labelling must be done be a field expert, all of which have very valuable time and, often, better things to do with it.

This brings medical image segmentation in general to a predicament at this moment: there exists a massive amount of data, whose size and complexity increases more and more every day. Therefore, there is a large amount of room for automated segmentation and feature detection in medical images, on a large scale. Clearly, the algorithms used would be on a case-by-case basis, but techniques exist in the 2-dimensional plane and 3-dimensional plane to intelligently segment medical images with non-negligible results. Research in automatic image analysis has the potential to bridge the gap between professional fields, unlock insights about diseases (Madabhushi, 2016), and save lives (Zhou, 2014).

This paper outlines experiments performed on a dataset acquired by **(TODO: insert method and acquisition here)**. Experiments will be carried out in the following order: 2-dimensional automated image segmentation, 3-dimensional automated image segmentation, 2-dimensional CNN segmentation, 3-dimensional CNN segmentation. The 2-dimensional CNN architecture will be U-Net (Ronneberger, 2016) and the 3-dimensional CNN architecture will be DeepMedic.

Initially, automated image segmentation techniques will be implemented in the 2D and 3D plane. Techniques including gaussian blur, mean-shift filtering, histogram thresholding, connected component analysis, shape analysis, and region growing will be experimented with in both the 2D and 3D space. These techniques are among the leading choices in automatic medical image segmentation (Sharma, 2010) and combinations of them have had success in medical image segmentation in the past (Zhou, 2014).To benchmark, a small dataset of expert generated ground truth data will be compared with the output of the various algorithm combination strategies. Based on the results of these tests, the CNNs will ideally be trained using training data generated with these algorithms.

Because these medical images lack labelling, if the automatic labelling of the 2D and 3D algorithms is sufficiently close to human ground truth labelling, (because even experts have labelling variance), theoretically, the algorithms could be used to create training sets for deep learning. This paper proposes a bold idea: automated training set generation. Further experiments will be conducted, using the aforementioned human ground-truth data as a test set, and a massive automatically labelled dataset as a training set. Ideally, these CNN models can bring the segmentation performance from slightly/moderately below human ground truth labelling up to comparable/indistinguishable from human ground truth labelling.

**TODO: Insert results and model structure later**

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