Project name: FIND THE NUCLEI IN DIVERGENT IMAGES TO ADVANCE MEDICAL DISCOVERY

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Description: The idea of this project is to spot nuclei to speed up curing process for every disease. The aim is to create an algorithm to automate nucleus detection. The detection of nucleus is the first stage for most analyses as most of the human body's 30 trillion cells contain a nucleus full of DNA, the genetic code that programs each cell. Identifying nuclei allows researchers to identify each individual cell in a sample, and by measuring how cells react to various treatments, the researcher can understand the underlying biological processes at work.

Data source: https://www.kaggle.com/c/data-science-bowl-2018/data

The dataset contains many segmented nuclei images. Images were acquired under a variety of conditions and vary in the cell type, magnification and imaging modality.

Algorithms:

U-Net: CNN - for faster image segmentation

U-Net implementation is proposed by Ronneberger et al. developed along with tensorflow. The code has been developed and used for Radio Frequency Interference mitigation using deep convolutional neural networks. The network can be trained to perform image segmentation on arbitrary imaging data.

R-CNN

R-CNN is a state-of-the-art visual object detection system that combines bottom-up region proposals with rich features computed by a convolutional neural network. At the time of its release, R-CNN improved the previous best detection performance on PASCAL VOC 2012 by 30% relative, going from 40.9% to 53.3% mean average precision. Unlike the previous best results, R-CNN achieves this performance without using contextual rescoring or an ensemble of feature types.

RESNET – 101

Deeper neural networks are more difficult to train. A residual learning framework to ease the training of networks that are substantially deeper than those used previously. The layers are reformulated as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. On the ImageNet dataset evaluate residual nets with a depth of up to 152 layers---8x deeper than VGG nets but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test. The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 28% relative improvement on the COCO object detection dataset.

References:

1. https://github.com/rbgirshick/py-faster-rcnn
2. https://github.com/jakeret/tf_unet