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ABSTRACT

We discuss the current state of research, the best practices and the challenges in the field of Deep Learning for Histopatholgy. We also explore the approaches used prior to Deep Learning which involved classical image processing techniques and machine learning models.

Classical Methods

- Combination of Second-Order Edge Detection:OLGA (Optimum Laplacian of Gaussian Assimilator) and Principle Component Analysis for Counting of Cancer Cell Nuclei in Tissue Sections. LoG that provides greater smoothing due to the Gaussian. This combination helped to enhance the nuclear boundaries and suppress the unwanted effect of responding to image discontinuities that corresponded to noise rather than real edges simultaneously. (Loukas et al,2003)
- Conversion of RGB colorspace to HSV colorspace using color thresholding algorithm and generation of cell-web and cell-map using positional values for automated classification of inflamation in colon. (Ficsor et al, 2008)
- Automated segmentation of tissue images through variable color intensities and superposition. Edge based and region based segmentation performed on the stained tissues to obtain desired results.(Cataldo et al, 2010)
- Automated classification of breast cancer morphology using SVM classifiers. One-versus-rest SVM classifiers is deployed with a radial basis function kernel (RBF) combined with chi-square distance metric. The final class was chosen by selecting the largest of the scores produced by the individual SVM classifiers.(Ojansivu et al, 2013)
- Tumor type prediction using image tiling, PCA clustering and deep feature extraction. (Barker et al, 2015)

Challenges

Unlike the majority of computer vision tasks, dealing with whole slide digital pathology images poses a unique set of difficulties.

Size of the images

- The slides captured are gigabytes in size and thus pose a computation bottleneck both in terms of storage, processing and compatibility with deep learning algorithms.
- A large percentage of literature dealing with deep learning approaches to solve this problem using patch extraction/ tiling method.
- The patches are generated using sliding window approach, and the patches are sent further for processing.
- Another approach would be to downsample the whole slide images to a tractable size but this leads to loss of information which hampers the performance of the Deep Learning models.

There are various flaws with patch extraction approach too:

- In order to avoid information loss, significant attention needs to be given to ensure maximum overlap among the patches generated by the sliding window, by carefully adjusting the stride size.
- In order to perform classification at the whole slide image level, all the generated patches need to be processed, hence making the training and prediction process a tedious and computationally expensive.
- Patches are a very small region compared to the slide size, hence a lot of global contextual information is lost which limits the ceiling performance.

Solutions

A number of solutions to overcome these limitations are proposed:

- One of the significant viable solutions proposed is to use Sparse Coding of pathology slides for learning features and inferring representations of Cancer histology slides.
- LSTMs and Conditional Random Fields are increasingly being used in combination with CNNs to model the correlation between neighboring patches in order to capture larger contextual information. Cascaded CNNs and Visual Attention-based methods are being utilized to enforce a region selection method so that only the most relevant, diagnostically useful areas of the whole slide image is used for prediction and training.
- A highly ingenious solution called slide graph proposed in a work presented very recently in CVPR'20 addresses the issue of size using a Graph Convolution neural network-based model.

Discussion

Having an understanding of the classical approaches along with the state of the art research in the field of deep learning for histopathology, we can move forward to reproduce the SOTA results using the code base of the research paper and start experimenting the learnt techniques to improve the ceiling performance.