(Jurrus et al., 2010)

Jurrus, E., Paiva, A. R. C., Watanabe, S., Anderson, J. R., Jones, B. W., Whitaker, R. T., … Tasdizen, T. (2010). Detection of neuron membranes in electron microscopy images using a serial neural network architecture. *Medical Image Analysis*, *14*(6), 770–783. https://doi.org/10.1016/J.MEDIA.2010.06.002

The method described in this paper uses a series of artificial neural networks (ANNs) in a framework combined with a feature vector that is composed of image intensities sampled over a stencil neighborhood. Several ANNs are applied in series allowing each ANN to use the classification context provided by the previous network to improve detection accuracy. We develop the method of serial ANNs and show that the learned context does improve detection over traditional ANNs.

Bejnordi, B. E., Veta, M., Van Diest, P. J., Van Ginneken, B., Karssemeijer, N., Litjens, G., van der Laak, J. A. W. M. ,the CAMELYON16 Consortium, 2017. Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. JAMA, 318.

In dit artikel worden de resultaten van deelnemers van de challenge besproken en vergeleken met de resultaten van pathologen. In de Appendix van dit artikel staan de methodes die de verschillende deelnemers hebben gebruikt wat uitgebreider uitgelegd. Het waren dertig methodes dus hier een samenvatting.

* Method 1: This method is based on deep convolutional neural networks (CNNs). Key aspects include: two separate CNNs for different scanner types and two iterations of hard-negative mining.
* Method 2: This method is based on deep convolutional neural networks (CNNs). Key aspects include: augmentation with Gaussian blurring and mapping of the tumor probability maps to slide level scores with a second-stage CNN model.
* Method 3&4: Two methods were submitted. Both methods are based on deep convolutional neural networks (CNNs). Key aspects include: feature-based post-processing to compute lesion and slide scores and a separately trained model with hard-negative samples. The main difference between the first and second methods are the use of a whole-slide image stain standardization algorithm21 and more comprehensive data augmentation strategy in the second method.
* Method 5: This method is based on deep convolutional neural networks (CNNs). Key aspects include: use of the ResNet4 architecture and varying class balance during training.
* Method 6: This method is based on deep convolutional neural networks (CNNs). Key aspects include: use of a conditional random field as recurrent neural network11 on top of a fully convolutional network25 and the use of a pre-trained network for initialization of weights.
* Method 7: This method is based on deep convolutional neural networks (CNNs). Key aspects include: use of ADAM optimization18, computation of lesion and slide scores with second-stage random forest classifiers12 and use of GrabCut27 and watershed transform28 for lesion segmentation
* Method 8: This method is based on deep convolutional neural networks (CNNs). Key aspects include: use of SegNet8 architecture (encoder-decoder network) pre-trained with weights from VGG-166 and good results with only very limited additional training data.
* Method 9: This method is based on deep convolutional neural networks (CNNs). Key aspects include: use of the GoogLeNet3 architecture and use of an averaging filter in the post-processing stage.
* Method 10: This method is based on deep convolutional neural networks (CNNs). Key aspects include: use of a custom CNN architecture with relatively few layers yet good performance, and custom confidence filtering for post-processing
* Method 11: This method is based on deep convolutional neural networks (CNNs). Key aspects include: use of a CNN model in the preprocessing stage to segment the tissue regions and use of a U-NET-like7 architecture for lesion segmentation
* Method 12&13: This method is based on deep convolutional neural networks (CNNs). Two submissions were made based on two different network architectures. Key aspects of the method with better performance include: use of the GoogLeNet3 architecture, hard-negative mining and postprocessing with a random forest classifier12 trained with region-level features.
* Method 14: This method is based on deep convolutional neural networks (CNNs). A key aspect of this method is the use of a VGG-like6 CNN model.
* Method 15&16: This method is based on a random forest classifier12 using texture features. The authors performed a comparative analysis with a CNN-based method (method II).
* Method 17&18: This method is based on deep convolutional neural networks (CNNs). Key aspects include: use of multiple CNN models trained at different magnification levels and use of learned deconvolutional layers for upsampling. Two different approaches for merging the results from multiple CNNs were investigated, which resulted in two submissions.
* Method 19: This method is based on a random forest classifier12 using color and texture features. A key aspect of this method is the use of a lymphocyte probability map in the preprocessing step to exclude non-tumor regions.
* Method 20: This method is based on a random forest classifier12 using texture features. A key aspect of this method is the use of nuclei density features.
* Method 21&22: This team submitted two methods for evaluation. The first method uses a conventional machine learning approach, while the second method is based on a combination of deep learning and conventional machine learning using handcrafted features. Key aspects include: multiscale analysis, use of nuclei density features and use of the GoogLeNet3 architecture. The proposed solution is available on the Simagis Live platform (<http://web-pathology.net>).
* Method 23,24&25: This method is based on deep convolutional neural networks (CNNs). There are three submissions by this team, each employing a different CNN architecture. A key aspect of the best performing method is the use of a fully convolutional architecture for dense predictions.
* Method 26: This method is based on deep convolutional neural networks (CNNs). Key aspects include: the use of the pre-trained GoogLeNet3 architecture and a second-stage SVM classifier for computing slide scores.
* Method 27: This method is based on a SVM9 classifier using color and texture features for automated detection of metastatic cancer from whole-slide images of sentinel lymph nodes.
* Method 28,29,30: Three methods were submitted. The first two submissions are similar to the methods of the Harvard & MIT team, based on patch-wise classification using GoogLeNet3 and ResNet-1014, respectively. The third submission is based on dense prediction using fully convolutional ResNet-101 architecture with atrous convolution and atrous spatial pyramid pooling43