Breast cancer histology classification using Deep Residual Networks

Kamalakkannan Ravi[1], Sakthivel Selvaraj[1], Poorneshwaran J M[1], Keerthi Ram[1] and Mohanasankar Sivaprakasam[1,2,*]

***Abstract*— In this work, in order to improve the computer aided diagnosis systems' performance on histopathological image analysis, we have proposed an approach with image pre-processing followed by a deep learning method to classify the breast cancer histology images into four classes; (i) normal tissue, (ii) benign lesion, (iii) in-situ carcinoma, and (iv) invasive carcinoma. The images are preprocessed for intensity and stain normalization using histogram equalization method. The Fine-tuning ConvNet transfer learning method is used with ResNet152 to train and classify the images. This proposed approach yields an average fivefold cross validation accuracy of 83%, a substantial improvement over the state-of-the-art.**

I. Introduction

Breast cancer is the most common type of cancer among women. Teresa [1] designed a convolutional neural network (CNN) for breast cancer image classification into four classes where the features extracted by the CNN are used to train a support vector machine and the overall accuracy is 77.8%. Our method achieves a substantial progress over this state-of-the-art result. Moreover our approach earned 11th position by achieving 80% accuracy on 100 test images in ICIAR 2018 Grand Challenge on Breast Cancer Histology Images [2].

II. Methods

The dataset [1] contains 400 high resolution, uncompressed Hematoxylin and Eosin stained labeled images with size of 2048 x 1536 pixels and pixel scale of 0.42 µm. We normalize the intensity range to 0 – 1 and apply histogram equalization before training and testing to match the stain distribution of source image to that of target image. The training and validation set ratio is 4:1. While training, a 224 x 224 image patch is randomly sampled from an image or its horizontal flip and normalized to have the same mean and standard deviation as the ImageNet Dataset. We adopt 152 layer Residual Network architecture [3] and initialize with the weights of ResNet152 and reset the final fully connected layer to 4-d fc (number of classes) as shown in Table 1. We use stochastic gradient descent with batch size of 4, momentum of 0.9, and the learning rate is set to 0.001 and reduced by a factor of 0.1 for every 7 epochs. The model is trained with 10 epochs. While testing, the input image is scaled to 256 x 256 and then a 224 x 224 image patch is center cropped which is then normalized to match the ImageNet Dataset.

[1]Healthcare Technology Innovation Centre, IITM Research Park, Chennai, India. [2]Dept. of Electrical Engineering, Indian Institute of Technology Madras, Chennai, India. *Corresponding author: +91-44-2257-4454; fax: +91-44-2257-4401; e-mail: mohan@ee.iitm.ac.in).

TABLE I. Architecture of 152-layer residual network with final fully connected layer reset to 4 classes. Building blocks are shown in brackets, with numbers of blocks stacked.

Layer name	Output Size	152 – layer
conv1	112 x 112	7 x 7, 64 stride 2
conv2_x	56 x 56	3 x3 max pool, stride 2 [1x1, 64; 3x 3, 64; 1x1, 256] x 3
conv3_x	28 x 28	[1x1, 128; 3x 3, 128; 1x1, 512] x 8
conv4_x	14 x 14	[1x1, 256; 3x 3, 256; 1x1, 1024] x 36
conv5_x	7 x 7	[1x1, 512; 3x 3, 512; 1x1, 2048] x 3
	1 x 1	Average pool, 4-d fc, softmax

III. Results

A fivefold cross validation is carried out and the results are shown in Fig. 1.

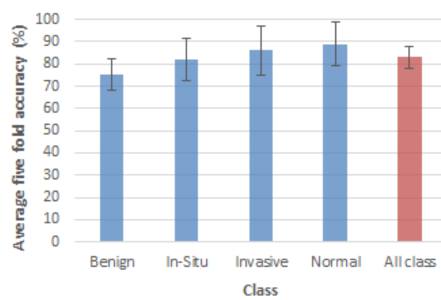

Figure. 1: Average accuracy and standard deviation plot for fivefold cross validation.

The image-wise classification accuracy is the percentage of the number of images correctly predicted from the given images. The overall average fivefold cross validation accuracy is 83% with standard deviation of ± 4.8 %.

IV. Discussion & Conclusion

The overall accuracy of this image level classification method is 83%. The deviation in accuracy is due to the random crop patches which can contain irrelevant regions (white spaces) and also similar characteristics (texture, color) between images of different classes.

References

[1] Teresa Araújo et al., "Classification of breast cancer histology images using Convolutional Neural Networks," in *PLoS ONE*, 2017, 12(6): e0177544.

[2] Leader Board of ICIAR 2018 Grand Challenge on Breast Cancer Histology Images, Team 412.

[3] K. He et al, "Deep residual learning for image recognition," in *Proc. IEEE CVPR*, Jun. 2016, pp. 770–778.

Preprint submitted to 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Received April 20, 2018.