MEDICAL UNIVERSITY OF VIENNA

# Prediction of Neoadjuvant Chemotherapy Response of Breast Cancer using Deep Learning based on Ultrasound Images

Christoph Fürböck[1], Georg Langs[1], Pascal A. T. Baltzer[1], Paola Clauser[1], Thomas H. Helbich[1], Panagiotis Kapetas[1]

[1] Department of Biomedical Imaging and Image-guided Therapy, Medical University of Vienna, Austria

## Objective

The cancer type with the highest incidence in females worldwide is breast cancer [1]. Among the 10 most common cancers in females breast cancer has the highest mortality [1]. The standard treatment for breast cancer is Neoadjuvant Chemotherapy (NAC) which comprises the application of chemotherapy prior to other therapies or surgery. The goal of NAC is decreasing the tumor volume to potentially enable resection for previously unoperable tumors or increase the prospect of breast conserving surgery. The treatment response varies dependent on the tumor subtype: the optimal result is the complete eradication of the tumor, the pathological complete response (pCR); while a delay of effective treatment and additional side-effects ensue poor response. In consequence it is advantageous to identify patients who will not respond to NAC in advance.

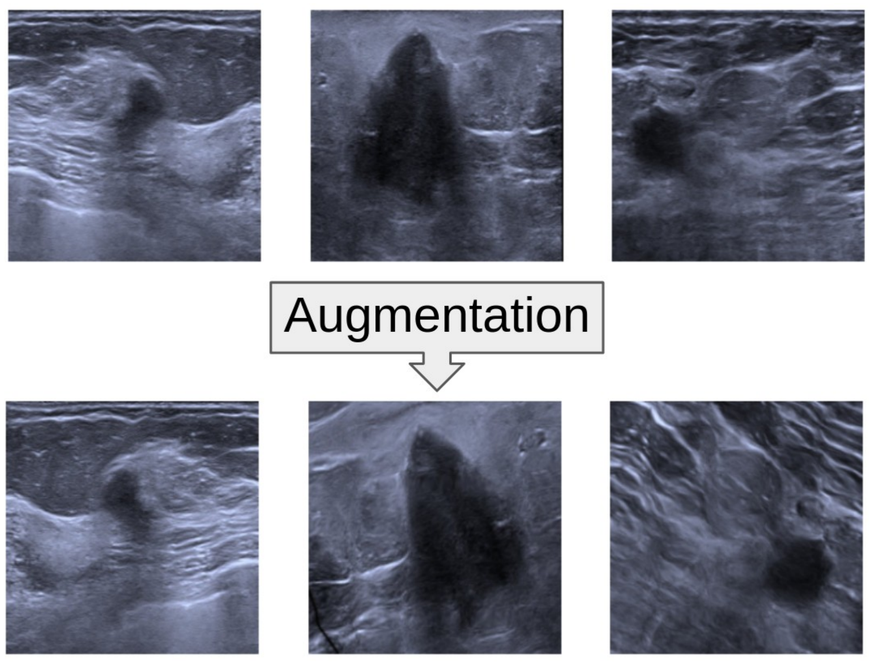
A deep learning (DL) model is trained on pre-treatment Ultrasound (US) images to predict the treatment response. In contrast to most NAC response prediction studies, which are based on magnetic resonance imaging [2-4], this study focuses on Ultrasonography as it is one of the most widespread imaging modalities for breast cancer imaging and does not require ionizing radiation or contrast media. The objective of this study is the prediction of the NAC response of breast cancer patients using deep learning based on pre-treatment US images of the breast.

## Patients and Methods

The dataset for this study includes 203 patients with histologically confirmed invasive breast cancer. Each patient underwent NAC and postoperative histology is used as the reference standard. Pathological complete response (pCR) is defined as the lack of invasive tumor in the breast or metastases in the axillary lymph-nodes. 120 patients have not achieved pCR after NAC (59.1% of all patients). For each tumor a representative B-mode US image has been selected from the baseline examination.

A DL model is trained to predict the treatment outcomes of complete response (CR) and non-complete response (non-CR). The model is based on the Resnet18 architecture [5] with Dropout layers instead of the Batch-Normalisation layers. This adaption decreases the amount of overfitting on the small dataset. To initialize the model weights the He method [6] is used for all convolutional layers except for the first one. To improve the model convergence transfer learning is used to initalize the weights of the first layer with the weights of the Resnet18 pre-trained on the ImageNet dataset [7]. Cross-Entropy loss and the Adam optimizer [8] are used for model training. The model is trained and validated using a 10-fold cross-validation.

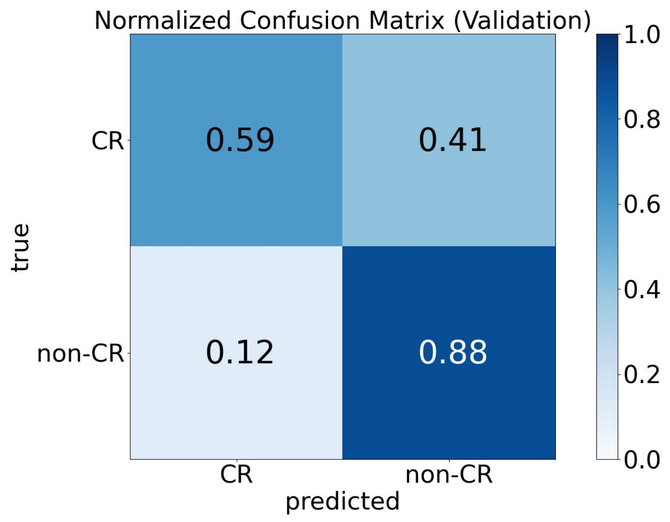
The images are pre-processed by rescaling to the same dimension and intensity normalization. During training the input images are randomly augmented by flipping, noise-addition as well as affine and elastic deformation using MONAI [9].




## Results

The overall accuracy of the model is 76%. Concerning the prediction of non-responders in the validation set the model demonstrates a sensitivity of 88% with a specificity of 59% and has a positive and negative predictive value of 76% and 78%.

| Measure | Value |
|---|---|
| Accuracy | 76% |
| Sensitivity | 88% |
| Specificity | 59% |
| PPV | 76% |
| NPV | 78% |







## Conclusion

This DL model based on baseline, pre-treatment breast ultrasound images has the potential to aid in the prediction of breast cancer, who do not respond to NAC. It demonstrates a high sensitivity for non-responders and approximately 90% of the non-CR tumors are correctly classified. While the accuracy of the model is comparable to other state of the art methods, the sensitivity is increased. The specificity of the model is 59% and has to be improved, as 41% of the CR samples are incorrectly predicted as non-CR tumors.

An improvement of the model may be achieved by including multiparametric ultrasound data as this study has the limitation of using B-mode US images exclusively. Additionally, while robust using cross-validation, an external validation is required before clinical implementation as a decision support tool.

## References

1 Sung, H, Ferlay, J, Siegel, RL, Laversanne, M, Soerjomataram, I, Jemal, A, Bray, F. Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J Clin. 2021: 71: 209- 249.

2 De Los Santos JF, Cantor A, Amos KD, Forero A, Golshan M, Horton JK, Hudis CA, Hylton NM, McGuire K, Meric-Bernstam F, Meszoely IM, Nanda R, Hwang ES. Magnetic resonance imaging as a predictor of pathologic response in patients treated with neoadjuvant systemic treatment for operable breast cancer. Translational Breast Cancer Research Consortium trial 017. Cancer. 2013;119(10):1776-83.

3 Comes MC, Fanizzi A, Bove S, Didonna V, Diotaiuti S, La Forgia D, Latorre A, Martinelli E, Mencattini A, Nardone A, Paradiso AV, Ressa CM, Tamborra P, Lorusso V, Massafra R. Early prediction of neoadjuvant chemotherapy response by exploiting a transfer learning approach on breast DCE-MRIs. Sci Rep. 2021;11(1):14123.

4 Kim, J., Han, BK., Ko, E.Y. et al. Prediction of pathologic complete response on MRI in patients with breast cancer receiving neoadjuvant chemotherapy according to molecular subtypes. Eur Radiol. 2022.

5 He K, Zhang X, Ren S and Sun J. Deep Residual Learning for Image Recognition, IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2016). 2016; 770-778.

6 He K, Zhang X, Ren S, Sun J. Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification. IEEE International Conference on Computer Vision (ICCV 2015). 2015; 1502.

7 Deng J, Dong W, Socher R, Li L-J, Li K, Fei-Fei L. Imagenet: A large-scale hierarchical image database. IEEE conference on computer vision and pattern recognition. 2009; 248–55.

8 Kingma D, Ba J. Adam: A Method for Stochastic Optimization. International Conference on Learning Representations. 2014.

9 MONAI Consortium. MONAI: Medical Open Network for AI. 2020.