Breast Cancer classification via Deep Learning approaches

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Abstract:
Breast cancer is the most common type of cancer in women worldwide. In 2023, there were 2.296.840 (23,8% of all women with cancer) new diagnoses. Early diagnosis is a key factor in reducing the mortality rate of breast cancer. One of the screening methods used to prevent breast cancer is breast ultrasound. In this paper, a new model is proposed that starts from a resnet101 and increases the classification capacity of a normal resnet101. Experimental studies show how deep learning models can successfully classify breast ultrasound images. The proposed model achieves 91% accuracy with convergence in less than 30 epochs. This study shows that deep learning models are effective in classifying ultrasound images and could be used by a radiologist to increase the accuracy of diagnoses.
Keywords Deep learning; Breast cancer; Classification; Convolutional Neural Network.

Introduction

Breast cancer is the most diagnosed cancer in women every year, with one in 5 women developing it in their lifetime. The 5-year mortality rate after diagnosis is now estimated at 10%. To reduce this estimate, it is important to increase prevention in women and improve screening techniques. Despite technological advances in recent years, these techniques still make mistakes that lead to unnecessary surgical interventions or missed detections [1]. In recent years, interest in deep learning techniques for image classification has increased [2]. These techniques require a large amount of input images to perform a good classification. The main structure of a deep learning algorithm is the Convolutional Neural Network (CNN) [3]. The CNN consists of convolutional layers, dense layers and pooling layers that are interconnected to extract information from the data and finally perform a good classification. The use of multiple convolutional layers allows the network to learn information in greater depth and thus achieve better classification [4]. Every year, more and more models are presented that achieve good classifications; this shows the great interest in this topic. The goal of these algorithms is not to replace radiologists, but to support them in improving the efficiency and accuracy of diagnoses in order to reduce the mortality rate and detect the tumor quickly. In this work, a new model is proposed that starts from a resnet101 and increases its performance.

In the literature, the most used dataset is the Breast Ultrasound Images (BUSI) [5], which contains only 780 images divided into benign tumors, malignant tumors, and images without tumors. Other studies use private datasets, but always with a number of images that is not sufficient for a good training of a deep learning algorithm. In this work, in addition to the Busi dataset, the Mendeley dataset [6] is used, which contains another 250 images divided into benign and malignant tumors, resulting in a total of 1030 images that are subjected to a data augmentation phase. The decision to use the second dataset is based on the goal of increasing the generalization of the model, even at the expense of lower accuracy. Although both datasets are breast ultrasound images, they appear to be very different in terms of both resolution and measurement angle.

The goal of this work is to obtain a good classification model that is able to automatically detect tumors from breast ultrasound images to help radiologists in diagnosis.

Related work

In the past few years, there has been a growing focus on researching models capable of accurately classifying breast tumors. Much of this research relies on deep learning techniques, introducing novel and high-performing models. Researchers typically utilize publicly available datasets like the BUSI dataset or leverage private datasets developed in collaboration with hospital facilities.

Ragab et al. [7] introduced an ensemble consisting of three models: VGG-16, VGG-19, and SqueezeNet, which were trained using the BUSI dataset. This set demonstrates good performance; however, this performance requires a very high number of training epochs.

Elham Yousef Kalafi et al. [8] explored the efficacy of three distinct loss functions: Cross-Entropy, Logcosh, and a hybrid variant that blends the former two with customizable parameters. Their findings underscored the pivotal role of parameter tuning, particularly evident in enhancing the performance of the VGG16 architecture. Furthermore, they leveraged attention gates as an additional measure to augment the model's overall efficacy.

Ishak PACAL et al [9] uses the BUSI dataset to compare popular deep learning models such as VGG16, ResNet, EfficientNet and GoogleNet with Transformer models that use attention mechanisms. The results show that Transformer models perform better performance compared to evaluated deep learning models.

Jiang Xie et al. [10] conducted a comparative study between radiologists and automated classification methods, employing metrics like accuracy, precision, and specificity. Their dataset comprised 1153 images sourced from 253 individuals at Renji Hospital. They employed models like SVM and DSCNN for analysis. Notably, the findings revealed a trend where automated classification models demonstrated superior accuracy and specificity compared to radiologists. However, it was observed that these models tended to exhibit lower sensitivity in comparison.

In this study, we initially tested pre-trained networks such as ResNet, accuracy and recall and has been modified to increase performance.

The model proposed in this study is a ResNet101 to which layers have been added at the end of its architecture. The following table shows the performance of our model compared to other ultrasound image classification models in the literature. As you can see, the performance is comparable to the best models.

Table 1 Comparison whit state of art

Model	**Dataset**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Attention-VGG16 [8]	private dataset (439 images)	93%	91%	96%	94%
Vision transformer [9]	BUSI (780 images)	88%	90%	87%	88%
DSCNN [10]	private dataset (1163 images)	91%	94%	89%	-
Proposed Model	BUSI+Mendelev (1030 images)	91%	90%	91%	90%

The Attention-VGG16 model proposed by Elham Yousef Kalafi et al. shows better performance than the model proposed in this work. However, the limitation of this model lies in the small number of images used for training (330 images) and the limited number of images used to evaluate its performance (45 images).

In addition to the models mentioned above, there are many other models that achieve similar or better performance than our model, but unlike our model, which only needs 27 epochs, other models need more than 100 epochs to converge. One limitation of our model is the small number of input images it was trained with compared to other studies that use private datasets with many more images.

Key Contribution

In this work we propose a new model for the classification of ultrasound images of the breast. The basis of the proposed model is a ResNet101[11] to which layers have been added to increase its performance. After the pre-trained ResNet model, a flatten layer was added in a first step, which converts the output of the pre-trained model into a flat vector. As further A dropout layer with a dropout rate of 50% was then used to prevent overfitting, Second-to-last dense layer with 256 neurons and a ReLu activation function was, and finally a batch normalization layer was added to improve the convergence of the model.

The addition of these layers involves an increase in computational terms of the model, but which is justified by an increase in performance and in the speed of convergence of the model.

After seeing the increase in performance of this model with the addition of these layers, we also tried adding these layers to other pre-trained models such as Xception net [12], DenseNet [13] and EfficientNet [14], also in these models' performance increase, but not reach those of the proposed model.

Method, Experiments and Results

n this work, two different data sets were used for a total of 1030 images, which were categorized into 3 classes: benign, malignant, and normal. The preprocessing phase is divided into several parts. The first part is the denoising phase, in which very dark images are lightened and small white dots that could affect the representation of the model are removed. Since the available images are not sufficient to run a deep learning model, a data augmentation phase is performed in which new images are created by zooming, translation and rotation and in the last phase the images are normalized to improve the stability of the model. A very important moment before running the model is the selection of the hyperparameters to be used. For this purpose, a grid search was performed to see which parameters would give the model the best performance. The hyperparameters identified are:

Table 2 Hyperparameters

Hyperparameter	Values Given
Batch size	32
Learning Rate	0.0005
Optimizer	Adam
Activation Function	ReLu
Shuffle	Every epoch

The classification model is based on a ResNet101 architecture [15], to which additional layers were added at the end of the model. To determine the best model, they were compared using the following metrics: Accuracy, Precision, Recall, and F1-score. The proposed model achieved an accuracy of 91%, a precision of 90%, a recall of 91%, and an F1 score of 90%. These values were achieved in the 27th epoch, demonstrating the rapid convergence of the proposed model.

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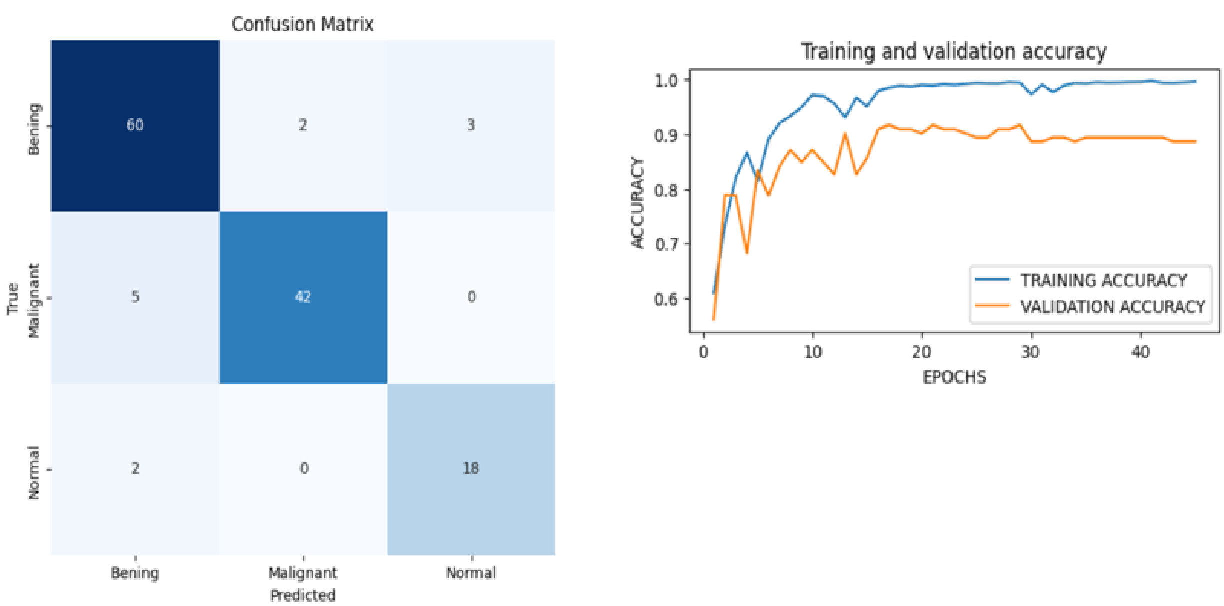

Figure 1. Confusion Matrix and Validation accuracy trend

The figure shows the confusion matrix obtained whit the test data and the trend of the validation accuracy during the training process, we can see how the model has a rapid convergence, in fact, despite the best epoch, it turns out to be the 27th, already at the 20th epoch it arrives with similar performance.

Conclusions

In this work, we propose a new model for the classification of breast ultrasound images that can be used by radiologists to improve the efficiency and accuracy of diagnosis. The use of deep learning models can be a great help for radiologists to be able to identify tumors that are difficult-to-detect tumors at an early stage and thus reduce tumor mortality. Although these models have already found their way into people's everyday lives, the introduction of these models is seen by many people as a threat that could replace humans. Many doctors are skeptical about the use of these methods as they are seen as “black boxes” that provide solution without knowing all the steps that have been taken. The scientific community is focusing on developing hybrid systems that combine the great performance of deep learning models and the adoption of manually created features, to reduce doctors' skepticism about these models [16]. Image classification is just one of the tasks that can be solved with these models. In the future, the volume of affected lesions involved, and the staging of pathologies could be studied to offer treatment in response, rather than the classification of the tumor [17].

The proposed model is derived from a ResNet101 to which layers were added in the last part of the model. The model was performed to classify the ultrasound images into benign tumor, malignant tumor and absence of tumor, the model achieves 91% accuracy on test data after only 27 epochs. There are many studies in the literature that show that different algorithms used for the same task also show better performance, but with a very high convergence time or a very low number of training images. The strength of this model lies in the speed of convergence with which it achieves excellent performance. The main limitations of this model are the limited number of input images used. In the future, we plan to apply this model to datasets with a larger number of images to increase generalization, reduce dependence on the training data, and improve the performance of the model. The final goal is to combine this model with a segmentation model that can detect the positions of the tumor within an image and integrate them into an ultrasound device to enable real-time classification.

References

1. Ullah, N., Raza, A., Khan, J. A., & Khan, A. A. (2022). An Effective Approach for Automatic COVID-19 Detection from Multiple Image Sources Using Shuffle Net Convolutional Neural Network (CNN) https://doi.org/10.21203/rs.3.rs-1668838/v1
2. Vocaturo, E., & Zumpano, E. (2021, December). Artificial intelligence approaches on ultrasound for breast cancer diagnosis. In 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 3116-3121). IEEE. DOI: 10.1109/BIBM52615.2021.9669690
3. LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278-2324. DOI: 10.1109/5.726791
4. Ting, F. F., Tan, Y. J., \& Sim, K. S. (2019). Convolutional neural network improvement for breast cancer classification. Expert Systems with Applications, 120, 103-115. https://doi.org/10.1016/j.eswa.2018.11.008
5. Al-Dhabyani, W., et al. (2020). Dataset of breast ultrasound images. Data in brief, 28, 104863. https://doi.org/10.1016/j.dib.2019.104863
6. Rodrigues, P.S. (2017), “Breast Ultrasound Image”, Mendeley Data, V1, https://doi.org/10.17632/wmy84gzngw.1
7. Ragab, M. et al. (2022). Ensemble deep-learning-enabled clinical decision support system for breast cancer diagnosis and classification on ultrasound images. Biology, 11(3), 439. **https://doi.org/10.3390/biology11030439**
8. Kalafi et al.(2021). Classification of breast cancer lesions in ultrasound images by using attention layer and loss ensemble in deep convolutional neural networks. Diagnostics, 11(10). **https://doi.org/10.3390/diagnostics11101859**

9. PACAL, İ. (2022). Deep learning approaches for classification of breast cancer in ultrasound (US) images. Journal of the Institute of Science and Technology, 12(4), 1917-1927. https://doi.org/10.21597/jist.1183679
10. Xie et al.(2020). A novel approach with dual-sampling convolutional neural network for ultrasound image classification of breast tumors. Physics in Medicine & Biology, 65(24), 245001. https://doi.org/10.1088/1361-6560/abc5c7
11. He, K., Zhang, X., Ren, S., & Sun, J. (2015). Deep Residual Learning for Image Recognition. *arXiv preprint arXiv:1512.03385*. https://doi.org/10.48550/arXiv.1512.03385
12. Kaiser, L., Gomez, A. N.,& Chollet, F. (2017). Depthwise separable convolutions for neural machine translation. arXiv preprint arXiv:1706.03059. https://doi.org/10.48550/arXiv.1706.03059
13. Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4700-4708). DOI**:** 10.1109/CVPR.2017.243
14. Wang, J., Liu, Q., Xie, H., Yang, Z., \& Zhou, H. (2021). Boosted efficientnet: Detection of lymph node metastases in breast cancer using convolutional neural networks. Cancers, 13(4), 661. https://doi.org/10.3390/cancers13040661
15. Zhuang F. et al.(2020). A comprehensive survey on transfer learning. Proceedings IEEE, 109(1), 43-76. DOI: 10.1109/JPROC.2020.3004555
16. Luciano Caroprese and Eugenio Vocaturo and Ester Zumpano. Argumentation approaches for explanaible AI in medical informatics, Intelligent Systems with Applications, v(16), pg 200109, 2022, 2667-3053, https://doi.org/10.1016/j.iswa.2022.200109
17. Pradhan, N and Dhaka, V. S and Rani, G and Pradhan, V and Vocaturo, E and Zumpano, E. Conditional Generative Adversarial Network Model for Conversion of 2 Dimensional Radiographs Into 3 Dimensional Views, IEEE Access, 2023, v(11), pg={96283-96296} DOI: 10.1109/ACCESS.2023.3307198