Brain-Inspired Deep Learning Classifier for Breast Tumor Identification

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Introduction

According to the American Cancer Society, "screening mammograms miss about 1 in 8 breast cancers." [1] It is apparent that, with over 260,000 people diagnosed with breast cancer each year in the United States [2], accurate imaging and detection for breast cancer diagnoses is crucial to introduce early and effective treatment for patients. The leveraging of deep learning (DL) and in particular convolutional neural networks (CNNs) points to optimistic improvements in the detection and accurate classification of malignant tumors in slides of histopathological imaging of breast tumor tissue. As digital storage and computational capabilities increase every year, it can be said that these improvements in detection also provide a sense of hope for scalability, potentially vastly increasing access to reliable and more accurate breast cancer detection for a greater number of at-risk communities in the short future.

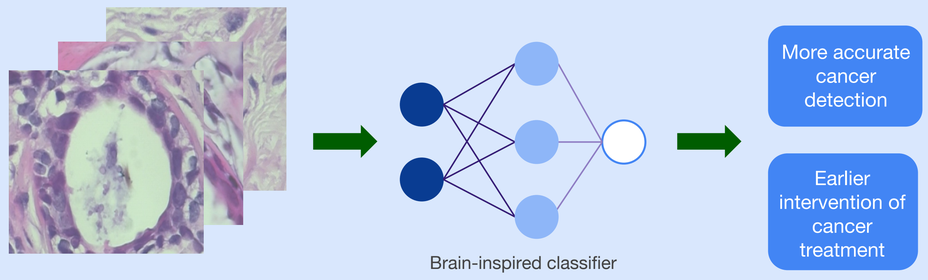

Figure 1 | **General approach for slide analysis using deep learning**

<u>Objective</u>: Assess the performance of brain-inspired classification models to distinguish between malignant and benign breast cancer tumors.

Materials and Methods

<u>Data:</u>

The data analyzed in this project was sourced from the Breast Cancer Histopathological Image Classification dataset (BreaKHis)[3]. This dataset comprised images of breast tumor tissue from four different magnifications, with a total of 9,109 microscopic images. For the scope of these experiments, only the images of 400x magnification were studied, as this magnification is the most commonly employed one for diagnosis. Thus, 868 malignant and 588 benign images were used as input to the models.

<u>Methods:</u>

In this work, we evaluated the performance of a brain-inspired approach that used a novel gaussian weighted divisive normalization combined with four different architectures taken as a basis: VGG19, ResNet-18, ResNet-50, and ResNet-101.

- The gaussian weighted divisive normalization mimics the brain's surrounding suppression from nearby neurons to the input being processed by the visual cortex [4]. We emulate this suppression from nearby neurons via a 2D gaussian distribution, where the distance to the center of the gaussian dictates the weight of the influence. We tested two functions to create a gaussian distribution: isotropic and square.
- We employed binary cross-entropy (BCE) loss.
- We tested different learning rates (0.001 and 0.00001), kernel sizes (3, 5, and 7), optimizers (Adam and RMSprop), and gaussian functions (isotropic and square) to study how these affect accuracy across the four proposed models.
- We used stratified 5-fold cross-validation in order to ensure accurate estimation and reduce overfitting [5].

<u>Metrics:</u>

- Confusion matrix
- Accuracy in distinguishing between malignant vs benign tumors
- F1-score
- Area under the receiver operating characteristic curve (AUROC)

Results

The best results achieved are presented in Figures 2 and 3. The results shown below correspond to proposed approach's assessment employing the averaged cross-validation scores.

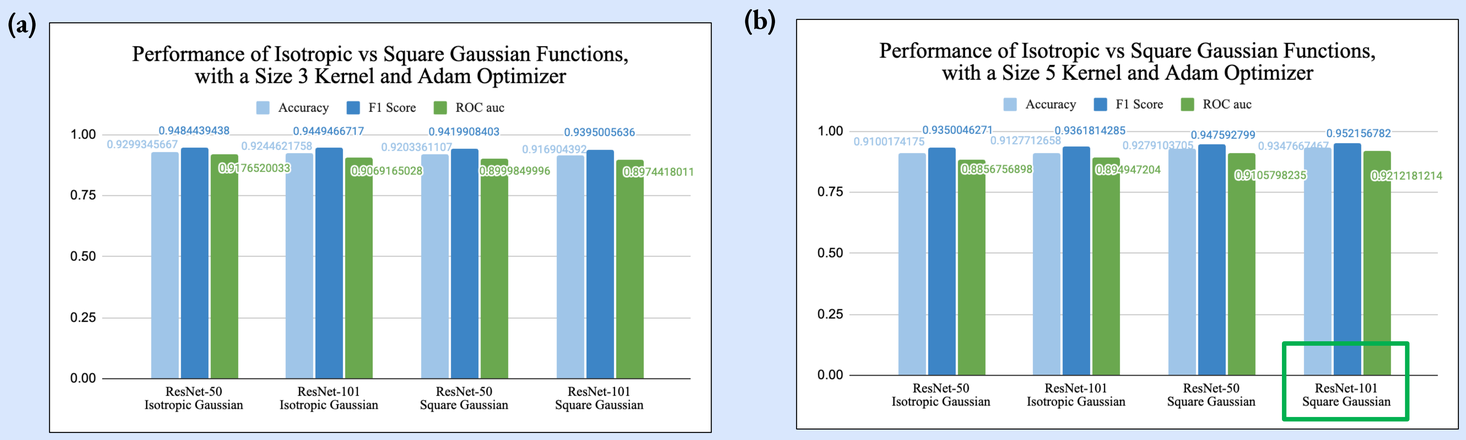

Figure 2 | **Results of applying the strongest-performing models for the 400x magnification.** Results of ResNet-50 and ResNet-101 models with kernel sizes 3 **(a)** and 5 **(b)**, learning rate of 0.001, optimizer Adam, and comparing two types of gaussian functions (isotropic and square).

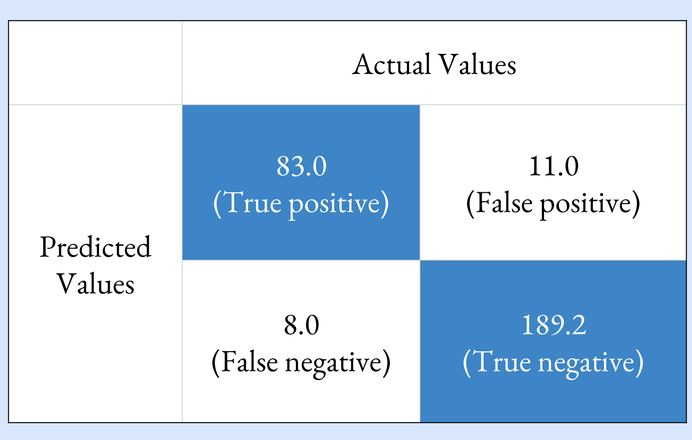

Figure 3 | **Confusion matrix of highest-performing combination of parameters.** The best results were achieved with Resnet-101, Adam optimizer, learning rate of 0.001, square gaussian function and kernel size of 5.

Conclusions

- We tested 96 combinations of possible configurations, to optimize the following parameters: optimizer, learning rate, deep learning model used as a basis, kernel size, and gaussian type.
- We achieved the best results employing the following configuration: ResNet-101 model with an Adam optimizer, at a learning rate of 0.001, a kernel size of 5, with a square gaussian function.
- For the dataset at 400x magnification, the best model reached an average accuracy of 93.48% and an F1-score of 95.22%. These scores are comparable to the state-of-the-art.
- The results obtained in this work suggest that the proposed model could be suitable for medical image analysis.

Future Work

Given the promising results obtained in this work, next steps could include:

- Integrating the gaussian weighted normalization within the deep learning blocks and comparing the models' performance.
- Test additional gaussian functions and perform more comprehensive experiments.
- Assess the proposed approach's performance on different medical image datasets and compare with state-of-the-art methods.

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References

1. "Limitations of Mammograms: How Accurate Are Mammograms?" *How Accurate Are Mammograms? | American Cancer Society*, www.cancer.org/cancer/types/breast-cancer/screening-tests-and-early-detection/mammograms/limitations-of-mammograms.html.
2. "Basic Information about Breast Cancer." *Centers for Disease Control and Prevention*, 26 Sept. 2022, www.cdc.gov/cancer/breast/basic_info/index.htm#:~:text=Each%20year%20in%20the%20United,What%20Is%20Breast%20Cancer%3F.
3. "Papers with Code - Breakhis Dataset." *BreakHis Dataset | Papers With Code*, paperswithcode.com/dataset/breakhis.
4. X Pan, E Kartal, L G Sanchez Giraldo, O Schwartz. Brain-inspired weighted normalization for CNN Image Classification, ICLR 2021, Brain2AI workshop, 2021.
5. Jung, Yoonsuh, and Jianhua Hu. "A *K*-fold Averaging Cross-validation Procedure." *Journal of nonparametric statistics* vol. 27,2 (2015): 167-179. doi:10.1080/10485252.2015.1010532