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ORIGINAL PAPER

Adaptive resizer-based transfer learning framework for the diagnosis of breast cancer using histopathology images

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Abstract

Breast cancer is a major global health concern, and early and accurate diagnosis is crucial for effective treatment. Recent advancements in computer-assisted prediction models have facilitated diagnosis and prognosis using high-resolution histopathology images, which provide detailed information on cancerous tissue. However, these high-resolution images often require resizing, leading to potential data loss. In this study, we demonstrate the effect of a learnable adaptive resizer for breast cancer classification using the BreakHis dataset. Our approach incorporates the adaptive resizer with various convolutional neural network models, including VGG16, VGG19, MobileNetV2, InceptionResnetV2, DenseNet121, DenseNet201, and EfficientNetB0. Despite producing visually less appealing images, the learnable resizer effectively improves classification performance. DenseNet201, when jointly trained with the adaptive resizer, achieves the highest accuracy of 98.96% for input images of 448×448 resolution. Our experimental results demonstrate that the adaptive resizer performs better at a magnification factor of $40\times$ compared to higher magnifications. While its effectiveness becomes less pronounced as image resolution increases to $100\times$, $200\times$, and $400\times$, the adaptive resizer still outperforms bilinear interpolation. In conclusion, this study highlights the potential of adaptive resizers in enhancing performance for medical image classification. By outperforming traditional image resizing methods, our work contributes to the advancement of deep neural networks in the field of breast cancer diagnostics.

Keywords Breast cancer · Histopathology images · Computer-assisted prediction · Deep neural networks · Adaptive resizer

1 Introduction

Cancer is the world's second leading cause of death, with an estimated 9.6 million deaths in 2018 [1]. There are many different types of cancer, but the most common are lung cancer, breast cancer, and skin cancer [2]. Breast cancer stands as the predominant form of cancer among women and represents the primary contributor to cancer-related mortality globally. Early diagnosis of breast cancer is crucial for the treatment process, as it is typically curable when detected early but often becomes incurable once it spreads to other body parts [3, 4]. Various techniques are available for breast cancer detection, including X-ray [5], ultrasound [6], magnetic resonance (MR) [7], and computed tomography (CT) [8]. In addition to these noninvasive methods, cancerous tissue samples can also be used for diagnosis. Histopathological images, obtained from hematoxylin and eosin (H&E) stained tissue sections, provide vital information for pathologists in diagnosing and determining prognosis [9]. Recently computer-aided classification methods have enhanced diagnostic accuracy, achieving high classification rates in automatically categorizing breast tissues. These methods can support pathologists and help reduce misdiagnosis [11].

For this purpose, studies have been conducted on classification algorithms with high accuracy and rapid processing capabilities. Han et al. proposed a class structure-based deep convolutional neural network (CSDCNN) method for multiclass classification applications. They compared CSDCNN with several popular convolutional neural netwroks (CNN) and achieved an accuracy between 92.8 and 94.7% for different magnification factors in multiclass classification. They also got an accuracy for binary classification of 94.8 and 97.1% [12]. Vo et al. proposed a method for the multiclass and binary classification of breast cancer using an incre-

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mental boosting convolutional network. They evaluated their approach by comparing it with several popular methods using two distinct datasets. In the Bioimaging 2015 breast histology classification challenge, they achieved a classification accuracy of 96.4% and 99.5% for four and two classes, respectively, and 96.9% accuracy for the 200× magnification factor on the BreakHis dataset [13]. Ahmad et al. introduced a novel hybrid model for breast cancer classification, called AlexNet-GRU, which combines the AlexNet CNN with gated recurrent units. This model was compared to two other models, CNN-GRU and CNN long short-term memory (CNN-LSTM), using the PCam dataset. The proposed method achieved an accuracy of 99.50%, outperforming the other two methods [2]. Srinidhi et al. reviewed more than 130 articles using different types of deep learning methods, such as supervised, poorly supervised, unsupervised, and cancer-based transfer learning. These studies focus on various tasks, such as cell or nucleus segmentation, tissue classification, tumor detection, disease prediction, and prognosis, and have been applied to multiple cancer types, including breast cancer [9]. These works show that computer-assisted methods improve classification, detection, and prognosis accuracy [2, 15–17]. Furthermore, it can assist the pathologist and decrease the misdiagnosis rate.

Histopathology images contain a significant amount of valuable information, but their large spatial size can pose a challenge for many computer-assisted models. Due to memory constraints, training CNN models at high resolutions may not be feasible, necessitating the resizing of images to a uniform size to accommodate deep learning training tools [18]. Therefore, spatial resizing is often necessary for the successful implementation of the computer-assisted models in histopathology [19]. However, conventional resizing methods like nearest neighbor, bilinear, and bicubic may result in data loss despite their speed, as they do not preserve the fine details of the original image. As a result, alternative resizing methods have been proposed to address these issues in artificial intelligence applications [18–22].

Talebi et al. introduced a new image resizer that is jointly trained with classification models to improve their performance. Their proposed resizer can be used in place of conventional resizers, and although it does not improve visual quality, it has been shown to enhance model accuracy. The researchers evaluated their learned resizer using four different models for classification with the ImageNet dataset and compared its performance to that of a bilinear resizer. The proposed resizer outperformed the bilinear resizer for all models tested [19]. Han et al. applied the learnable resizer proposed by Talebi et al. to COVID-19 lung CT image classification, jointly training the MobileNet model with the learnable resizer. The researchers compared their results with those of five different models, namely VGG19, Resnet50_v2, MobileNet, Inception_v3, and Densenet169. The jointly trained MobileNet model with the learnable resizer achieved an accuracy of 96.9%, sensitivity of 98.3%, and specificity of 95.3%, outperforming the other models. Notably, the jointly trained MobileNet model with the learnable resizer only had 30,000 more parameters than the MobileNet model [21]. Zhang et al. also applied a similar learnable resizer that maps the features to a high-dimensional space through convolution for image geolocation with the Pittsburgh30k dataset. The researchers compared their method with the resizer proposed by Talebi et al. and a model without a resizer. Their proposed method is simpler than existing methods and achieved better performance [18].

Table 1 The BreakHis dataset consists of 9109 microscopic images of breast tumor tissues, which were collected from 82 different patients with different magnification factors (40×, 100×, 200×, and 400×)

Magnification factor	Benign	Malignant	Total
40×	625	1370	1995
100×	644	1437	2081
200×	623	1390	2013
400×	588	1232	1820
Total image	2480	5429	7909

In this paper, we present a comprehensive evaluation of transfer learning models for classifying the BreakHis dataset using a hybrid approach with an adaptive resizer. We experimented with seven prominent models and assessed their performance using bilinear interpolation and various resolutions with the adaptive resizer. Additionally, we conducted further experiments to classify different magnifications of the dataset separately, employing both hold-out and five-fold cross-validation methods. Our findings provide valuable insights into the performance of transfer learning models on this dataset and emphasize the importance of utilizing an adaptive resizer for enhancing model performance.

2 Methods

2.1 Dataset

BreakHis dataset is a publicly available database of histopathological images of breast cancer tissues. It was developed by the Laboratory of Applied Mathematics in the Department of Statistics at the Federal University of Pernambuco, Brazil [23]. The general information about the BreakHis dataset is given in Table 1. The breast cancer dataset is composed of two main categories: benign and malignant, each of which has four different subtypes.

The normal and cancerous histopathology images samples from the dataset are shown in Fig. 1. The dataset stands out for its high-quality images of breast cancer tissues, which

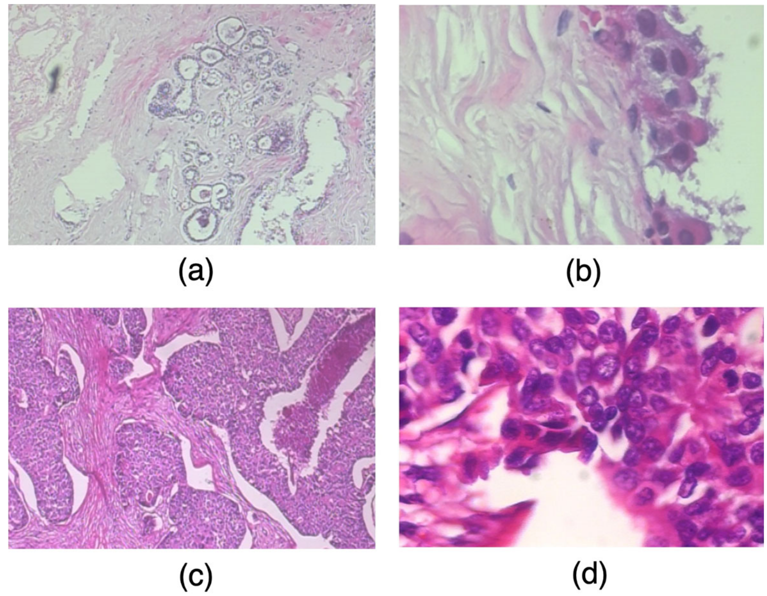

Fig. 1 Sample histopathology images from the dataset: **(a)** and **(b)** show benign samples, while **(c)** and **(d)** display malignant samples. **(a)** and **(c)** are at 40× magnification, and **(b)** and **(d)** are at 400× magnification

are crucial for the development of accurate computer-aided diagnosis systems.

2.2 Data augmentation

Data augmentation is a widely used machine learning technique that helps to expand the amount of training data without requiring additional data collection. This technique involves applying various transformations to the original data, such as image augmentation, rotation, flipping, or adding noise, to generate new data samples that are comparative to the initial data [24]. The augmented data is then used to train machine learning models, which can enhance the generalization performance, particularly when the amount of original data is limited [25].

In this study, classical augmentation techniques like zoom and vertical–horizontal flips from Keras libraries were used.

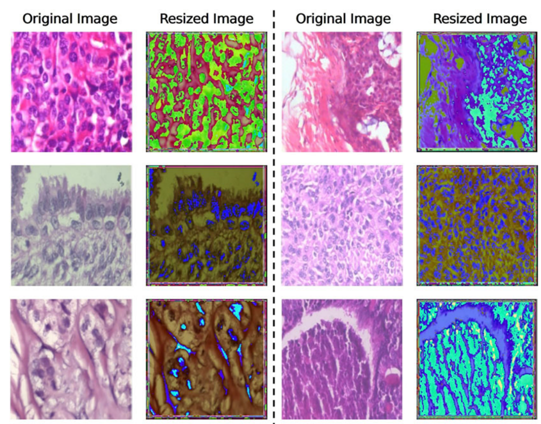

Fig. 2 Sample images of resizer input and output which are taken from various experiments, input images on the 1st, 3rd, and 5th columns, and resized images on the right side of them

2.3 Adaptive learnable resizer

Adaptive resizer model is designed to address the challenge of resizing images while preserving their content and maintaining visual quality [19]. The examples demonstrate how the model can be trained on a dataset of images and used to resize new images to a target size in Fig. 2. The learnable resizer model is based on a CNN architecture, which is a type of deep learning model commonly utilized for image analysis tasks [26]. The model is trained on a dataset of images using a supervised learning approach, where the goal is to predict the best resizing operation for the input image.

The detailed architecture of the adaptive resizer is shown in Fig. 3. The adaptive resizer model was designed by Talebi et al. [19] which was made up of convolutional layers that extract features from the input image, followed by dense layers that forecast the appropriate resizing action. The model predicts the best resizing operation for each pixel in the input image, with the resizing operation being a linear combination of predefined resizing functions. These functions are learned by the model along the training process. The model is trained using a mean squared error loss function, which measures the difference between the predicted and actual resizing operations. Adaptive resizer is jointly trained with classification models during the training and learns to adjust the weights of the resizing functions to minimize the loss and improve its ability to predict the best resizing operation over the baseline image classifiers to improve classification performance.

2.4 Adaptive resizer-based transfer learning framework

Transfer learning is a machine learning technique where a model trained on one task is leveraged to solve a different task. It has become increasingly popular in recent years, especially in deep learning, where pre-trained models can be used to speed up the training process, improve generalization, and achieve higher accuracy on the target task [27]. Transfer learning models can be broadly categorized into two types: feature-based transfer learning and fine-tuning transfer learning. Feature-based transfer learning entails extracting features from input data using pre-trained models, which are then used as an input to a new model trained on the target task. Fine-tuning transfer learning, on the other hand, involves taking a pre-trained model to a new task by slightly modifying its parameters during additional training. Utilizing pre-trained models as a foundation, transfer learning expedites the learning process, enhances accuracy for new tasks, and reduces the need for large amounts of labeled data. Transfer learning is also useful for tasks where acquiring labeled data is costly or time-intensive, as it can decrease the total amount of data required for training.

However, a significant challenge with transfer learning models is that their input resolution value is usually relatively small, ranging between 200 × 200 and 224 × 224 pixels. This down sampling is done through mathematical methods such as scaling, bilinear, and bicubic interpolation, which leads to a data loss for detailed images regardless of the original dataset's resolution [29]. To address this issue, Talebi et al. [19] developed an adaptive learnable resizer that mitigates the problem by convolution from the original size to 224 × 224. During the training phase, this technique also trains itself alongside the model, making it a jointly trainable model. As a result of these operations, the output is smaller than the original image, but it contains less information loss. This trade-off results in images that may appear degraded to the human eye, but since they contain more information, they significantly improve the performance of the model. The effectiveness of this technique relies on various factors, such as the quality of the pre-trained model, the interpolation method used, and the complexity of the target task. Therefore, it is crucial to carefully evaluate the performance of the adaptive learnable resizer and other similar techniques in different application scenarios and datasets to ensure their suitability and effectiveness.

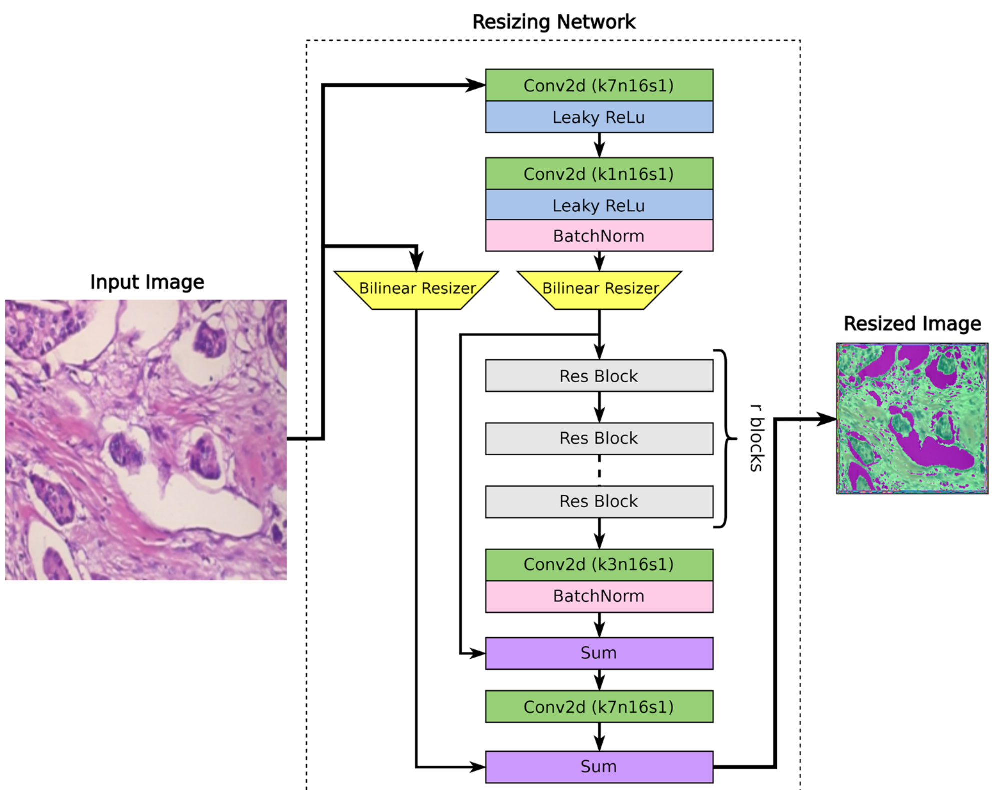

Fig. 3 Detailed architecture of the adaptive resizer. The input image, after undergoing two convolution layers and batch normalization, is bilinearly resized and processed through predefined residual blocks. Following an additional convolution and batch normalization, the image combines with its bilinearly resized form. The final output is the sum of this result and the input image resized to the target resolution

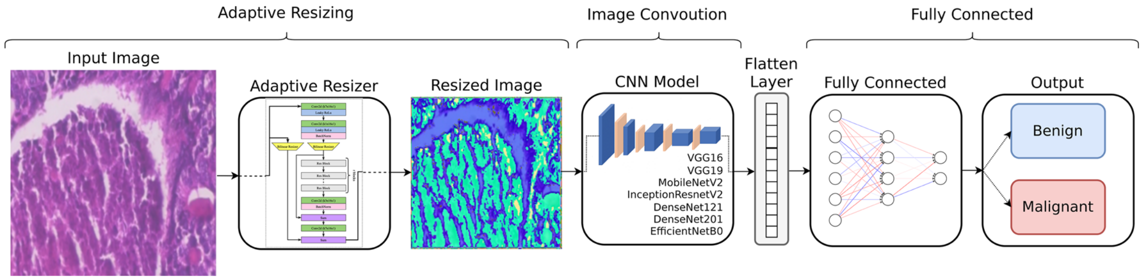

Fig. 4 Architecture of the adaptive resizer-based transfer learning framework for image classification. The input image is processed through the adaptive resizer, resulting in a detailed, 224 × 224 image that retains significant attributes for classification. This image is subsequently processed by the convolutional layers of the selected transfer learning models (VGG16, VGG19, MobileNetV2, InceptionResnetV2, Resnet, DenseNet121, DenseNet201, or EfficientNetB0) to extract salient features that are directly passed through fully connected layers for final classification as either benign or malignant

The model, which is shown in Fig. 4, takes an image as an input, passes it through to the adaptive learnable resizer to convert it into a 224 × 224 image, and then applies transfer learning using the CNN part of seven different transfer learning architectures. After obtaining the output from the CNN, the model passes it through a fully connected (FC) network consisting of five layers with ReLU activation. The first layer of the FC network has 200 neurons, followed by two more layers with 200 neurons each. Then, there are two additional layers with 50 and 40 neurons, respectively, and a final layer with 30 neurons. The output layer of the model has two neurons with softmax activation function, which is used for binary classification. Overall, the model appears to be a deep neural network with multiple hidden layers that allow it to learn complex features and patterns in the input image.

In this study, several experiments were conducted with different CNN models, including VGG16, VGG19, MobileNetV2, InceptionResnetV2, DenseNet121, DenseNet201, and EfficientNetB0.

2.5 Performance evaluation

Accuracy, precision, specificity, recall, F1-score, and MCC are commonly used metrics for evaluating the performance of machine learning models. These metrics provide a comprehensive view of the model's ability to correctly identify positive and negative cases. Precision indicates the proportion of correctly detected positive cases among all cases identified as positive, whereas accuracy measures the percentage of true predictions generated by a model. Sensitivity, also known as recall or true positive rate, measures the proportion of actual positive cases correctly identified by the model. Specificity, on the other hand, measures the proportion of actual negative cases correctly identified by the model. The F1-Score combines both precision and recall, where a score of 1 represents perfect precision and recall. MCC is a correlation coefficient that considers true and false positives and negatives, and produces a value between − 1 and 1, where a value of 1 represents a perfect prediction, 0 represents a random prediction, and − 1 represents a completely wrong prediction. These metrics are valuable tools for choosing the best model for a given task and guiding model performance improvements.

3 Results and discussions

It is important to preserve as much detail as possible when processing medical images, especially for datasets like BreakHis, which contain important microscopic details. Bilinear rescaling or downscaling of images may lead to the loss of fine details, which can be particularly problematic when working with lower magnification images, such as those in the 40× class. Adaptive resizing addresses this issue by considering each image's unique characteristics, such as size, shape, and content, ensuring critical details are preserved during the resizing process. Jointly trained with classification models, the adaptive resizer improves classification performance by adjusting the weights of resizing functions, providing better quality resized images that assist downstream CNNs in more effective learning [19]. This results in improved accuracy and generalization, making it a versatile component for various computer vision tasks, such as object detection, image segmentation, and classification.

In the first experiment, the use of an adaptive resizer had a positive effect on the training of the VGG19 model. As shown in Fig. 5, the model trained with the adaptive resizer was able to learn faster in the first 20 epochs compared to the model trained with bilinear rescaling. This indicates that the adaptive resizer was able to better preserve important details in the images, allowing the model to learn more efficiently. In addition, the fluctuating effect on the curves was reduced with the use of the adaptive resizer. This suggests

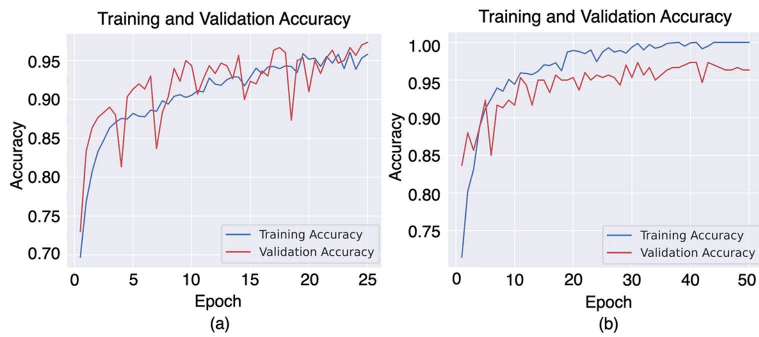

Fig. 5 Adaptive resizer effect on VGG19, **a** without resizer, **b** with resizer. The model trained with the adaptive resizer was able to learn faster in the first 20 epochs compared to the model trained with bilinear rescaling. The training difference is very evident in the first 10 epochs. The model without the adaptive resizer was able to learn between 85–90%, while the model using the adaptive resizer was able to learn up to 95%. The fluctuating effect on the curves was also reduced with the use of the adaptive resizer

that the model trained with the adaptive resizer was more stable during training, which can lead to better overall performance. These results suggest that the use of an adaptive resizer is beneficial for training deep learning models on medical image datasets like BreakHis. By preserving important details in the images, the adaptive resizer can help to improve the efficiency and stability of the training, ultimately leading to better performance of the model.

Selecting an appropriate model architecture for a given dataset is crucial since the model performance can vary depending on the dataset's unique characteristics. Furthermore, various factors, such as the input resolution of the adaptive resizer, the specific model used, and the system's hyperparameters, can all influence the model's performance. Thus, thorough consideration and experimentation are necessary to find the optimal configuration of these factors. In this study, multiple transfer learning models were assessed on the dataset without modifying any hyperparameters, with the goal of finding the best-suited structure for the dataset's unique characteristics. The adaptive resizer for image processing necessitates a square input image. However, the initial resolution of the examined image was 700×460, violating this prerequisite. To address this, a series of experiments were conducted to determine the optimal input size, assessing four different input dimensions: 224×224, 300×300, 448×448, and 600×600.

For the 224×224 size, the images were directly resized using the bilinear method without using an adaptive resizer. For the remaining sizes, the images were first resized from 700×460 to the target size using bilinear method before being fed into the adaptive resizer. These specific input sizes and resizing methods were selected based on their proportional relationship to each other. Seven different models were evaluated and their performances were compared using hold-out validation, as presented in Table 2. The winning model's training and validation accuracy-loss graphs are shown in Fig. 6. While this analysis is valuable for determining the most suitable model for a given dataset, it is essential to consider other factors such as the availability of pre-trained models, computational resources needed for training, and specific application requirements. However, it should be noted that the performance of the adaptive resizer might vary depending on the dataset and the issue being addressed. Therefore, we recommend experimenting with different transfer learning models and hyperparameters when using the adaptive resizer to identify the optimal configuration for a given task.

In deep learning, selecting the appropriate number of training epochs is crucial, as it significantly affects the resulting model's performance. To evaluate this factor, a comparative analysis was conducted on seven different transfer learning models using the BreakHis dataset's 40× class. The findings revealed that using an adaptive resizer with DenseNet201 resulted in the best performance when the input resolution was set to 448×448. The models were trained for 25 epochs with a batch size of 16, and a small number of epochs were chosen to identify the highest performing model while avoiding overfitting. The results emphasize the importance of selecting the right number of training epochs for optimal performance for a given task and dataset. Additionally, the study underscores the significance of choosing a suitable pretrained model and input resolution, which can considerably influence the model's overall performance.

After identifying the most optimal transfer learning model and hyperparameters for the BreakHis dataset, experiments were conducted to evaluate the model's performance using two different validation techniques: hold-out and fivefold cross-validation. In the hold-out method, the dataset is divided into training 70%, validation 15%, and testing sets 15%. The model is trained on the remaining data, and its performance is evaluated on the test set. The fivefold cross-validation splits the dataset into five equal parts, with each part serving as the validation set once, and the rest of it used for training. The process is repeated five times, with each

Table 2 Comparison of model performances with respect to resolutions, resizing type, training time, and accuracy. The experiments were performed on all transfer learning models to determine the best performance results regarding resolution for the adaptive resizer. The winning results were bolded for each model

Model name	Input resolution	Output resolution	Resizing type	Total parameters	Total training time (s)	Test acc
VGG16	700 × 460	224 × 224	Bilinear	15,972,470	175	0.8961
VGG16	300 × 300	224 × 224	A.Resizer	15,984,633	250	0.9515
VGG16	448 × 448	224 × 224	A.Resizer	15,984,633	300	0.9515
VGG16	**600 × 600**	**224 × 224**	**A.Resizer**	**15,984,633**	**350**	**0.9653**
VGG19	700 × 460	224 × 224	Bilinear	21,282,166	200	0.9446
VGG19	300 × 300	224 × 224	A.Resizer	21,294,329	275	0.9515
VGG19	448 × 448	224 × 224	A.Resizer	21,294,329	300	0.9377
VGG19	**600 × 600**	**224 × 224**	**A.Resizer**	**21,294,329**	**375**	**0.9653**
MobileNetV2	700 × 460	224 × 224	Bilinear	5,397,366	125	0.9169
MobileNetV2	300 × 300	224 × 224	A.Resizer	5,409,529	175	0.9342
MobileNetV2	448 × 448	224 × 224	A.Resizer	5,409,529	225	0.9307
MobileNetV2	**600 × 600**	**224 × 224**	**A.Resizer**	**5,409,529**	**275**	**0.9480**
InceptionResnetV2	700 × 460	224 × 224	Bilinear	56,240,118	475	0.9584
InceptionResnetV2	**300 × 300**	**224 × 224**	**A.Resizer**	**56,272,281**	**525**	**0.9723**
InceptionResnetV2	448 × 448	224 × 224	A.Resizer	56,272,281	525	0.9688
InceptionResnetV2	600 × 600	224 × 224	A.Resizer	56,272,281	625	0.9584
DenseNet121	700 × 460	224 × 224	Bilinear	9,549,686	275	0.9792
DenseNet121	**300 × 300**	**224 × 224**	**A.Resizer**	**9,561,849**	**350**	**0.9861**
DenseNet121	448 × 448	224 × 224	A.Resizer	9,561,849	375	0.9826
DenseNet121	600 × 600	224 × 224	A.Resizer	9,561,849	425	0.9688
DenseNet201	700 × 460	224 × 224	Bilinear	23,029,366	475	0.9757
DenseNet201	300 × 300	224 × 224	A.Resizer	23,041,529	525	0.9867
DenseNet201	**448 × 448**	**224 × 224**	**A.Resizer**	**23,041,529**	**550**	**0.9896**
DenseNet201	600 × 600	224 × 224	A.Resizer	23,041,529	625	0.9792
EfficientNetB0	700 × 460	224 × 224	Bilinear	16,687,553	225	0.9342
EfficientNetB0	300 × 300	224 × 224	A.Resizer	16,699,716	275	0.9433
EfficientNetB0	448 × 448	224 × 224	A.Resizer	16,699,716	325	0.9480
EfficientNetB0	**600 × 600**	**224 × 224**	**A.Resizer**	**16,699,716**	**350**	**0.9515**

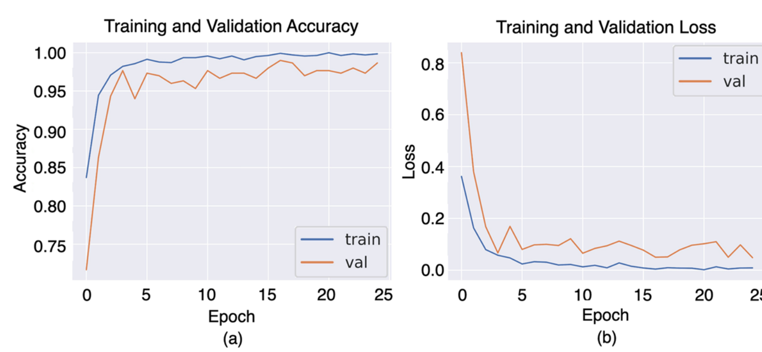

Fig. 6 Performance results of the winning model, DenseNet201, with adaptive resizer, on the 40× magnification class with hold-out validation method. The 40× class contains highly detailed images, and when resized with bilinear or bicubic methods, crucial features may be lost. The adaptive resizer excels in preserving these features, resulting in optimal performance

part used as the validation set once, and the performance of the model is evaluated by averaging the results across the five runs. These validation techniques assess the model's robustness and generalization ability, which is important in medical image analysis, where the model must perform well on unseen data. The training performance results of the models are shown in Fig. 7, while metric results are given in Table 3.

Table 3 shows that the model's performance in 40× images is superior compared to other image resolutions. This can be attributed to the fact that 40× images are captured from a farther distance, resulting in a loss of finer details when

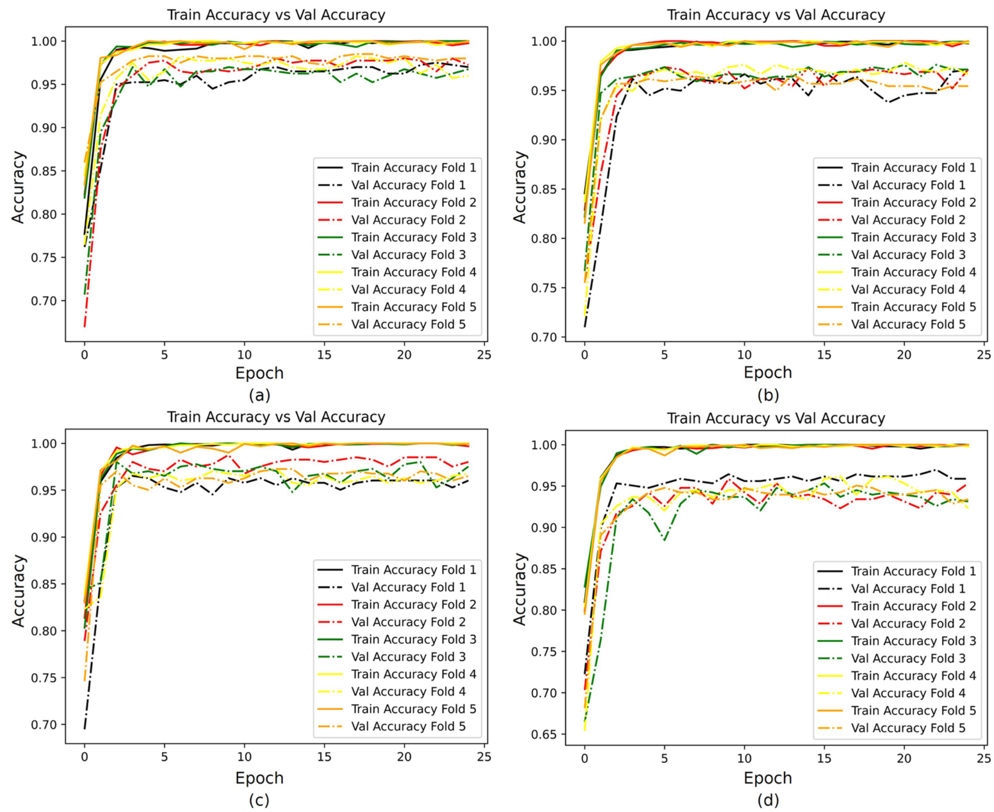

Fig. 7 Performance results of DenseNet201 with adaptive resizer for magnification classes: **a** 40×, **b** 100×, **c** 200×, **d** 400×, assessed through fivefold cross-validation. The beneficial effects of the adaptive resizer are evident across all classes, particularly in those containing highly detailed images, leading to improved performance outcomes

Table 3 Experiments results with DenseNet201

Model name	Validation method	Mag. factor	Acc.	MCC	Specificity	Precision	Recall	F1-score
DenseNet201	Hold-out	40×	0.9896	0.9684	0.9747	0.9815	0.9870	0.9841
DenseNet201	Cross val	40×	0.9779	0.9487	0.9850	0.9753	0.9735	0.9744
DenseNet201	Hold-out	100×	0.9833	0.9621	0.9850	0.9798	0.9823	0.9810
DenseNet201	Cross val	100×	0.9730	0.9233	0.9756	0.9643	0.9683	0.9663
DenseNet201	Hold-out	200×	0.9759	0.9457	0.9746	0.9691	0.9767	0.9727
DenseNet201	Cross val	200×	0.9587	0.9117	0.9785	0.9591	0.9527	0.9558
DenseNet201	Hold-Out	400×	0.9505	0.9074	0.9732	0.9537	0.9537	0.9537
DenseNet201	Cross val	400×	0.95	0.9151	0.9763	0.9588	0.9564	0.9575

rescaled using bilinear interpolation. However, the adaptive resizer preserves these details, allowing efficient learning by the downstream CNN models. As the image resolution increases to 100×, 200×, and 400×, the effectiveness of the adaptive resizer declines, although it still outperforms bilinear interpolation. Table 2 further demonstrates the observed performance advantages of the adaptive resizer over the bilinear method.

Moreover, our study also highlights that the adaptive resizer's structural characteristics make it a more effective method for image resizing. Unlike bilinear interpolation, which applies a uniform approach to all images, the adaptive resizer is designed to resize images based on their specific features. This flexibility enables the adaptive resizer to effectively capture and preserve fine details, leading to improved model performance. Furthermore, the findings also emphasize the importance of selecting appropriate image resolutions for specific tasks. While higher resolution images may provide more detail, they can also be more challenging to process and may require more sophisticated resizing methods. In contrast, lower resolution images may be easier to process, but they may lack sufficient detail for certain applications. Thus, selecting the right resolution and resizing method is crucial to achieve optimal performance in image-based tasks.

The study's results emphasize the advantages of using adaptive resizer over bilinear interpolation for image resizing, particularly in the context of machine learning applications. Furthermore, the findings highlight the importance of selecting appropriate image resolutions and resizing methods based on the specific requirements of the task being performed. It is possible that the adaptive resizer can quickly learn the images in the dataset after the first few epochs, as its adaptive nature allows it to adjust to the characteristics of the images. However, the exact performance of the adaptive resizer will depend on various factors, such as the size and complexity of the dataset, the chosen transfer learning model, and the specific hyperparameters used during training. It is also possible that the adaptive resizer may show different training performances when used with different transfer learning models. This is because the transfer learning models may have different architectures, and therefore may require different adaptations in order to effectively process the images.

4 Conclusion

Breast cancer is a prevalent disease affecting millions of women worldwide and ranking as the second most frequent cancer in humans. Early and accurate diagnosis is crucial for effective treatment, leading to a surge in computer-assisted prediction studies using histopathology images. These images, rich in detail and information about cancerous tissue, have high resolution and large spatial sizes, necessitating spatial resizing for most computer-assisted models. Our study demonstrates the effectiveness of an adaptive learning image resizer to improve the performance of deep learning models in medical image analysis, especially breast cancer classification using histopathological images with different magnifications. By preserving critical details during the resizing process, the adaptive resizer enables more efficient and stable learning in the underlying CNN models, outperforming traditional resizing methods like bilinear interpolation. Our experiments using the BreakHis dataset and seven transfer learning models have shown that DenseNet201, when jointly trained with an adaptive resizer, achieves the best performance with an accuracy of 98.96% for 40× magnification images. Our findings emphasize the potential of the adaptive resizer as a powerful tool for enhancing image classification. The adaptive resizer's ability to preserve important details and adapt to the unique characteristics of images resulted in better performance across all magnification factors, especially in 40× magnification images, where it significantly outperformed bilinear interpolation. The study also highlights the importance of selecting the appropriate image resolution, transfer learning model, and hyperparameters for optimal performance. The adaptive resizer's potential to generalize across various image classification tasks and its compatibility with different CNN models highlights its versatility as a powerful tool for medical image analysis and other computer vision applications. Future research can extend this study to include multiclass breast cancer classification, evaluate the adaptive resizer's performance with other transfer learning models, and explore its application in different datasets and diverse computer vision tasks. By offering an effective and flexible solution for image resizing, the adaptive resizer presents a valuable contribution to the ongoing advancements in the field of machine learning and computer vision.

Author Contributions Conceptualization, methodology, implementation, experiments, results analysis, and manuscript writing were performed by OD, MSC, and AG. CEK and AS contributed to the conceptualization of the study and manuscript review.

Data availability and access The Breast Cancer Histopathological Database (BreakHis), used in this study, is publicly available at https://web.inf.ufpr.br/vri/databases/breast-cancer-histopathological-database-breakhis/.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to participate Not applicable.

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