Breast Cancer Histopathology Image Classification Using Frequency Attention Convolution Network

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Abstract. The existing deep learning works mainly capture breast cancer histopathology image features in the spatial domain, and they rarely consider the frequency domain feature representation of histopathology images. According to the classical digital signal processing theory, frequency domain features may outperform spatial domain features in analyzing texture images. Motivated by this, we attempt to mine frequency domain features for the breast cancer histopathology image classification application, and further propose a novel frequency-attention convolutional network called SeFFT-Net by combining the Fourier transform with the channel attention mechanism. The core of SeFFT-Net consists of a newly constructed frequency-based squeeze and excitation (SeFFT) module, which first performs Fourier transform with residual construction to capture deep features in the frequency domain of histopathology images, followed by a squeeze-and-excitation attention operator to further enhance important frequency features. We extensively evaluate the proposed SeFFT-Net model on the public BreakHis breast cancer histopathology dataset, and it achieves the optimal image-level and patient-level classification accuracy of 98.67% and 98.16%, respectively. Meanwhile, ablation studies also well demonstrate the effectiveness of introducing frequency transforms for this medical image application.

Keywords: Breast cancer · Histopathology image classification · Convolutional neural network · Frequency domain · Channel attention

1 Introduction

Globally, breast cancer is the most common malignancy in women and the cancer with the highest mortality rate [1]. Early diagnosis and treatment of breast cancer is essential in augmenting the survival rate of patients, while pathological

X. Yang et al. (Eds.): ADMA 2023, LNAI 14177, pp. 217–229, 2023.
https://doi.org/10.1007/978-3-031-46664-9_15

diagnosis is still seen as the definitive method for breast cancer diagnosis [2]. Since the traditional pathological diagnosis mainly relies on the experience of pathologists, which is time-consuming and laborious, with the rapid growth of the demand for pathological diagnosis, computer-aided diagnosis of breast cancer histopathology images is becoming more and more important.

Recently, breast cancer histopathology image classification methods related to deep learning have achieved great success and gradually become the mainstream. Among them, some works employ typical convolutional neural networks (CNN), such as AlexNet, VGGNet, and ResNet, to pre-train on large-scale natural image datasets as feature extractors, and then use machine learning classifiers to distinguish the extracted deep feature image [3,8]. Deniz et al. utilize pre-trained AlexNet and VGG16 models to capture deep features of breast cancer histopathology images, and then employ support vector machine to distinguish the deep features [8]. As a counterpart, Gupta and Bhavsar employ residuals and dense networks to capture deep features of histopathology images, followed by XGBoost as a feature classifier, and they achieve the best patient-level classification result of 96.76% [3]. In order to narrow the gap between the extracted image features and the classifiers, researchers further leverage learnable CNNs for breast cancer histopathology image classification. Considering that the histopathological images used for model training are limited, transfer learning is usually used to improve performance. For example, Shalu and Mehra explored the effect of transfer learning on breast cancer histopathology images compared with fully trained networks using VGG16, VGG19 and ResNet50 models [5]. Subsequently, Chukwu et al. utilize pre-trained DenseNet and transfer learning technology to obtain the best accuracy rate of 97.42% on the public breast cancer histopathology image dataset [6]. Meanwhile, considering the characteristics of breast cancer histopathology images, some works attempt to build novel CNN models for this medical task. Spanhol et al. [7] construct a simple plain CNN model with five trainable layers, and experimental results demonstrate that it outperforms conventional methods. Likewise, Budak et al. [8] propose a learnable model combining fully convolutional networks and bidirectional long-short-term memory, and they achieve average results of 94.98% on the breast cancer histopathology image database. Moreover, to focus on important discriminative deep features, attention mechanisms are also widely introduced to classify histopathology images with excellent performance [9]. In general, deep learning-related models have recently greatly promoted the development of computer-aided histopathology diagnosis of breast cancer, showing obvious advantages in classification accuracy compared with traditional work [10–12].

However, current deep learning-related breast cancer histopathology image classification methods are mainly implemented in spatial domain, while rarely consider the frequency domain features of histopathological images. According to the theory of digital signal processing, frequency domain is more suitable for analyzing texture images than spatial domain. Actually, some researchers have recently attempted to explore frequency-domain deep learning methods for computer vision applications [13–15]. Gueguen et al. learn CNNs directly on the

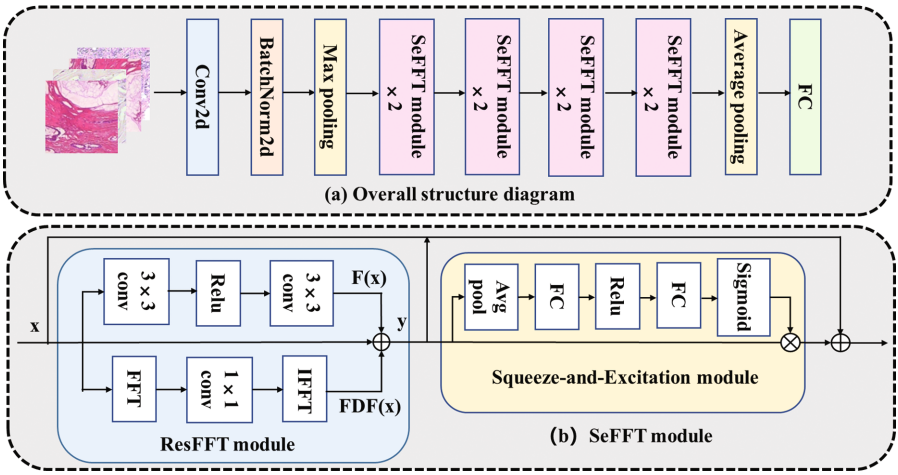

Fig. 1. Overall architecture of SeFFT-Net for breast cancer histopathology image classification. SeFFT-Net leverages ResNet18 as the backbone and embeds SeFFT modules at multiple layers that integrate residual Fourier transform (ResFFT) with channel attention to compute important frequency-domain features.

discrete cosine transform (DCT) of deep features for effective image classification [13], while Ehrlich et al. [14] propose a new method using frequency-domain compressed the image is used as input to the residual network. Additionally, Zhong et al. [15] explore frequency domain features as additional cues to better solve camouflaged object detection task.

Inspired by these works, we try to study breast cancer histopathology image classification task by introducing frequency domain deep features. In this work, we propose a novel frequency-domain attention convolutional network, namely SeFFT-Net, which firstly utilizes Fourier transform to capture the frequency-domain deep features of histopathology images, followed by an attention module [16] is used to further enhance important frequency features. The overall architecture of the given SeFFT-Net model is shown in Fig. 1. The main contributions of this paper can be encapsulated in three facets.

(1) This work attempts to explore frequency-domain deep features for breast cancer histopathology image classification applications, and further utilizes Fourier transform and channel attention mechanism to propose a novel frequency-domain attention convolution network called SeFFT-Net.
(2) SeFFT-Net first performs a Fast Fourier transform operator combined with residual construction (ResFFT) to compute deep features in the frequency domain of histopathology images, and then further enhances high-valued frequency feature impact with a squeeze and excite attention module to obtain more promising classification results.
(3) We extensively evaluate SeFFT-Net on the public BreakHis dataset. Ablation studies demonstrate the effectiveness of introducing frequency-domain

features for the classification of breast cancer histopathology image. Furthermore, comparing the experimental results with state-of-the-art spatial domain models further demonstrates its competitive performance in this task.

2 Method

In this section, we first introduce the overall structure of the proposed SeFFT-Net for breast cancer histopathology image classification. Then, the Fourier transform is briefly described, followed by the introduction of the frequency residual module as well as frequency attention module.

2.1 Overall Structure

As shown in Fig. 1, SeFFT-Net is composed mainly of two components, i.e., a backbone model and a SeFFT module. ResNet18 [17] is used as the backbone model owing to its superiority in the breast cancer histopathology image classification task. Actually, breast cancer pathological images have complex frequency distributions, and the essential information of such images is mainly concentrated in the low-frequency area. Therefore, capturing frequency domain features becomes critical, how to interact with convolutional features should be deeply considered.

We achieve that by proposed SeFFT module. We endeavor to replace the residual module of the backbone model with the newly constructed SeFFT module, which well integrates Fourier transform and channel attention mechanism, thereby capturing the frequency domain depth features of histopathological images and interacting with convolutional features. Specifically, the frequency domain is applied by the ResFFT module in SeFFT module, which can simultaneously process the images in the space domain and the frequency domain. Frequency domain features are captured by Fast Fourier Transform (FFT) and Inverse Fast Fourier Transform (IFFT). Initial interaction $\mathbf{Y}$ between frequency domain features and convolutional features is obtained here by element-wise addition. In addition, in order to enhance high-value information consequences and neglect low-value information consequences, we present a channel attention module, i.e., Squeeze-and-Excitation module, on the result of the ResFFT module. This will further interaction between the two types of features. It is noteworthy that our SeFFT-Net network structure is very flexible and can insert any convolutional neural networks applied to other medical image classification tasks.

2.2 Fourier Transform

The Fourier transform is the most basic and widely used frequency transform operator in image processing and analysis. During image processing and analysis, the Fourier transform decomposes the image into sine component and cosine

component. The frequency feature of the digital image after Fourier transform is a complex numbers. The frequency domain network [13–15,18] can perform various operations on real and imaginary images on the basis of the original network architecture, such as complex number operations, so as to learn more robust frequency domain features. In addition, we can transform the image from the spatial domain to the frequency domain using the Fourier transform, and processing the image in the frequency domain. Afterwards, the frequency domain image is restored to the space domain image by inverse Fourier transform. Given an input image patch m, of size $M \times N$, denoted as f_m(x, y), the following is the calculation expression of the discrete Fourier transform [18]:

$$f_m(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f_m(x,y) e^{-j2\pi(\frac{ux}{M} + \frac{vy}{N})} \tag{1}$$

The Fast Fourier Transform (FFT) is a fast algorithm for the discrete Fourier transform. It is obtained by improving the original algorithm according to the characteristics of discrete Fourier transform, which greatly reduces the calculation amount of the computer. Efficient fast Fourier transforms can model interactions between spatial locations with log-linear complexity. By using Fast Fourier Transform (FFT), the image is divided into real image and imaginary image, so that a series of feature extraction operations such as convolution, batch normalization, and activation can be performed on the image in the frequency domain. This enables the network to extract richer frequency feature information. Afterwards, the real and imaginary images are mixed. Finally, the Inverse Fast Fourier Transform (IFFT) can effectively aggregate local information and improve the learning ability of non-local information.

2.3 SeFFT Module

In this section, we mainly present the specific structure of SeFFT module. The SeFFT contains a ResFFT module and a channel attention module. The main purpose of ResFFT module is to capture frequency domain features. In ResFFT module, the Fourier transform is responsible for this purpose. The channel attention module aims to highlight important features from the ResFFT module or submitting for a classifier.

In Fig. 1, the SeFFT module integrates Fast Fourier Transform with the channel attention mechanism, which outputs meaningful frequency domain information by processing images in both spatial and frequency domains simultaneously. As shown in the blue box in the Fig. 1, to obtain more detailed frequency domain features, we add the Fourier Transform operation to the residual block of ResNet18 backbone [17], which can assist the network to concentrate on critical local features and enhance recognition accuracy. We first give the formulation of the classical residual block in the ResNet architecture. The conventional residual block is expressed as:

$$\mathbf{Y} = \mathbf{X} + F(\mathbf{X}). \tag{2}$$

Here, $\mathbf{X} \in R^{C\times H\times W}$ and $\mathbf{Y} \in R^{C\times H\times W}$ are input and output tensors, where C, H, W are channel number, height and width, respectively. Besides, F is a residual learning block. Then, ResFFT module improves the above residual block by adding a frequency domain branch that captures representative frequency domain features of breast cancer histopathological images. It is formulated as:

$$\mathbf{Y} = \mathbf{X} + F(\mathbf{X}) + FDF(\mathbf{X}) \tag{3}$$

$$FDF(\mathbf{X}) = IFFT(conv(FFT(\mathbf{X}))) \tag{4}$$

From above equation, ResFFT module fuses the input $\mathbf{X}$, convolution learning block F and frequency domain features learning block FDF, also providing interaction between convolution features and frequency domain features. For capturing frequency domain features, ResFFT module first performs fast Fourier transform FFT to convert images from the space domain to the frequency domain, then applies efficient 1×1 convolution (conv.) to compress the number of channels and add network nonlinearity, and finally utilises inverse fast Fourier transform $IFFT$ to convert the information in frequency domain to space domain. By doing so, the operation done in the frequency domain is presented on the image after inverse fast Fourier transform.

Next, after the ResFFT module, we introduce a classic Squeeze-and-Excitation module [16] to further enhance deep features. Specifically, the squeeze operation compresses image features from outputs of the ResFFT module by average pooling, followed by two FC layers and Relu layers for interaction between channel responses and increasing nonlinearity respectively. The excitation operation generates weights via sigmoid function for each feature channel, which fully captures the dependency between channels and outputs the same number of weights as the input characteristics. Thus, it automatically obtains the importance spatial and frequency information of each channel through learning, and suppresses the characteristics that are useless for the current task according to this. And then, in the weighting operation before output, we establish the connection of input, ResFFT module and SeFFT module, which is helpful for the reverse propagation of gradient in the training process and the realization of feature reuse through the connection of features.

3 Experimental Results and Discussion

First, we describe the public breast cancer histopathology image dataset used to evaluate the SeFFT-Net model. Then, the parameter settings and evaluation metrics are briefly introduced. Finally, we report and analyze the experimental results in detail, including ablation experiment results, Comparison with advanced spatial domain methods, as well as visualization results.

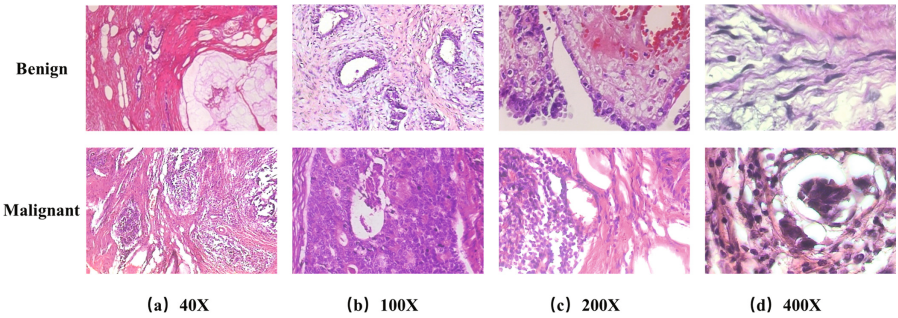

Fig. 2. Typical breast cancer histopathology images at four magnification factors in the BreakHis dataset.

3.1 Dataset

A commonly used breast cancer histopathological image dataset, namely BreakHis, is adopted to evaluate SeFFT-Net in this work. The BreakKHis dataset is a publicly available large-scale non-global breast cancer histopathology image dataset (http://web.inf.ufpr.br/vri/databases/breast-cancer-histopathological-database-breakhis), which provides a good benchmark for this medical application. The BreakHis dataset contains 7909 histopathological images from 82 patients, each of which is labeled with benign tumors (fibroadenoma, adenoma, tubular adenoma and trichoma) or malignant tumors (lobular carcinoma, ductal carcinoma, papillary carcinoma and mucinous carcinoma). In addition, 2480 samples belong to benign images, and the remaining 5429 samples are malignant images. Each sample image has an RGB channel mode with the size of 700×460 pixels in size, and the color depth of each channel is 8 bits. According to the different magnification, the samples of each patient can be divided into four groups of 40 times (40×), 100 times (100×), 200 times (200×) and 400 times (400×). Figure 2 shows some typical breast cancer histopathology images at different magnification factors in the BreakHis dataset.

3.2 Experimental Settings

The original data set of BreakHis is randomly divided into a training set and a test set at each magnification factor. The training set consists of 70% images, and the rest 30% images constitute the test set. In addition, 25% of the training set images are retained for cross validation to select model parameters. All experiments utilize the same training data set and test data set. In the image preprocessing stage, to reduce the impact of possible over fitting problems, we perform simple crop and flip operations to increase the sample size of the training set. For network training, the initial learning rate is set to LR = 0.001, and the learning rate decays to half of the current learning rate after every five iterations. The data set is randomly scrambled to avoid any negative impact on learning by using orderly training data. Besides, the loss function is optimized

using a stochastic gradient descent (SGD) algorithm with a batch size of 8. The momentum factor is set to 0.9 to prevent the loss function from falling into a local optimal solution, and control the loss function to reach the global minimum. All models are trained for cosine annealing learning rate attenuation in 100 cycles. All experiments are carried out on the server configured with NVIDIA GeForce RTX 2080Ti using the Python deep learning framework. Additionally, we adopt two commonly used classification accuracy indicators of image-level recognition rate and patient-level recognition rate to evaluate the model performance.

Table 1. Ablation experiment results at image level.

Method	40× (%)	100× (%)	200× (%)	400× (%)
ResNet18	95.99	95.68	97.35	93.77
ResFFT-Net	96.49	96.80	98.01	94.87
SENet	96.49	96.96	98.01	94.87
SeFFT-Net	96.99	98.08	98.67	95.24

Table 2. Ablation experiment results at the patient level.

Method	40× (%)	100× (%)	200× (%)	400× (%)
ResNet18	95.62	96.06	97.57	94.52
ResFFT-Net	96.77	96.94	97.10	95.53
SENet	96.04	96.61	98.01	95.47
SeFFT-Net	96.44	98.16	98.14	95.57

3.3 Experimental Results

Ablation Experiment Results. To prove the effectiveness of SeFFT-Net as well as the frequency domain features for this medical task, we first conduct image-level and patient-level ablation experiments on the BreakHis dataset, whose results are reported in Table 1 and Table 2, respectively. In the two tables, we first employ the typical ResNet18 model as the baseline. Then, we embed the Fourier transform module into the model to construct ResFFT-Net, and further integrate the ResFFT module with squeeze-and-excitation channel attention to construct SeFFT-Net. In addition, we also introduce SE-Net as a counterpart to better show the effectiveness of frequency domain features.

As shown in Table 1, the baseline of ResNet18 achieves the image-level recognition rates of 95.99%, 95.68%, 97.35% and 93.77% on 40X, 100X, 200X and 400X data sets, respectively. After introducing the frequency domain features, the ResFFT model gains the corresponding accuracy results of 96.49%, 96.80%, 98.01% and 94.87%, which outperforms ResNet18 on the four data sets, thus showing the effectiveness of introducing frequency domain features. By simultaneously integrating frequency transform and attention mechanism, SeFFT-Net

Table 3. Comparisons with advanced spatial domain methods at both image-level and patient-level.

Reference	Year	Image-Level (%)				Patient-Level (%)			
		40×	100×	200×	400×	40×	100×	200×	400×
Spanhol et al. [7]	2017	84.60	84.80	84.20	81.60	84.00	83.90	86.30	82.10
Han et al. [23]	2017	95.80	96.90	96.70	94.90	97.10	95.70	96.50	95.70
Gupta et al. [3]	2018	–	–	–	–	94.71	95.90	96.76	89.11
Lichtblau et al. [20]	2019	85.60	87.40	89.80	87.00	83.90	86.00	89.10	86.60
Alom et al. [24]	2019	97.95	97.57	97.32	**97.36**	**97.60**	97.65	97.56	**97.62**
Zhang et al. [19]	2020	95.03	90.41	88.48	85.00	95.50	91.57	89.20	89.20
Hou [21]	2020	90.89	90.99	91.00	90.97	91.00	91.00	91.00	91.00
Man et al. [28]	2020	**99.13**	96.39	86.38	85.20	96.32	95.89	86.91	85.16
Li et al. [27]	2021	87.85	86.68	87.75	85.30	87.93	87.41	88.76	85.55
Chukwu et al. [6]	2021	93.64	97.42	95.87	94.67	94.23	97.86	96.35	95.24
Sharma and Kumar [29]	2021	96.25	96.25	95.74	94.11	–	–	–	–
Boumaraf et al. [26]	2021	98.13	97.39	96.63	94.05	–	–	–	–
Saxena et al. [22]	2021	88.36	87.14	90.02	84.16	92.88	83.61	89.98	81.63
Xu et al. [30]	2022	94.94	94.18	95.38	92.64	–	–	–	–
Hao et al. [25]	2022	96.75	95.21	96.57	93.15	96.33	95.26	96.09	92.99
Chhipa et al. [4]	2022	93.00	93.26	92.28	88.74	93.26	93.45	92.45	89.57
SeFFT-Net (Ours)	–	96.99	**98.08**	**98.67**	95.24	96.44	**98.16**	**98.14**	95.57

further improves the classification performance to 96.99%, 98.08%, 98.67% and 95.24%, which is also better than the Squeeze-and-Excitation network (SENet) [16]. Compared with the baseline, SeFFT-Net can gain classification accuracy improvement of 1.00%, 2.40%, 1.32% and 1.47%, respectively. Thereby, the image-level ablation experimental results well demonstrate the effects of the frequency domain features as well as the proposed SeFFT-Net for breast cancer histopathology image classification.

When it comes to the patient-level ablation results listed in Table 2, SeFFT-Net respectively gains the accuracy values of 96.44%, 98.16%, 98.14% and 95.57% on the 40X, 100X, 200X and 400X datasets, which also shows the best performance among the four models. SeFFT-Net outperforms the baseline by 0.82%, 2.10%, 0.57% and 1.05% gains on the four data sets, respectively. Meanwhile, it is superior to SENet with average accuracy improvement of 0.55%. Additionally, ResFFT-Net averagely outperforms the baseline ResNet18 model by 0.64% classification accuracy. The above results again well prove the effectiveness of SeFFT-Net and the frequency domain features.

Comparison with Typical Spatial Domain Methods. To further show the performance of SeFFT-Net on breast cancer pathological image classification task, we compare it with a variety of advanced spatial domain methods proposed

in recent years. The detailed results at both image-level and patient-level are demonstrated in Table 3.

As shown in Table 3, SeFFT-Net has a notable competitive performance compared to the previously representative spatial domain methods. Specifically, it is worth noting that the given model achieves the image-level classification accuracy of 96.99%, 98.08%, 98.67% and 95.24% on 40×, 100×, 200× and 400× data sets, which are significantly better than results in literature [7,8,19–22]. Besides, SeFFT-Net gains the best accuracy values on both 100× and 200× data sets among all the works. Despite not achieving optimal results on the 40× and 400× data bases, it ranks fourth and second on the two data sets at the image level, respectively. Moreover, when it comes to the patient-level evaluation results, SeFFT-Net achieves recognition rates of 96.44%, 98.16%, 98.14% and 95.57% on four multiples, and it is also superior to other methods on 100× and 200× data sets. Meanwhile, SeFFT-Net ranks the third place on both 40× and 400× data bases. Among these spatial CNN-based methods, CSDCNN, IRRCNN+Aug., VGG 19 and DenseNet in literature [6,23,24,26] obtain the most promising results with the average recognition rate around 96%. However, SeFFT-Net overall shows very competitive or better performance over the three works. According to the above results, we can see that the SeFFT-Net model is effective for breast cancer pathological image classification task, which can be attributed to the frequency domain feature to some extent.

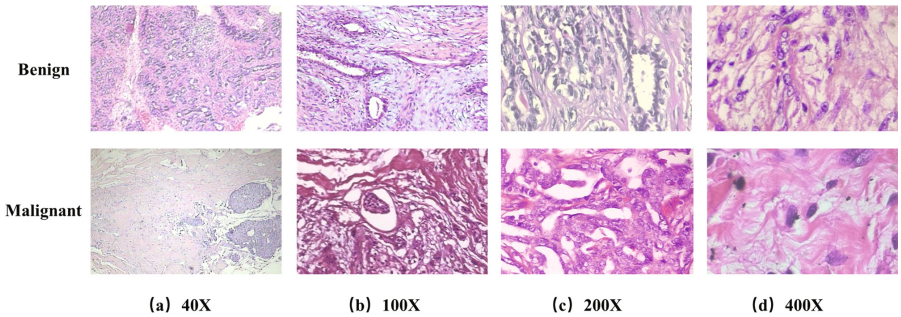

Fig. 3. Histopathological images that are incorrectly classified by ResNet18 but can be correctly classified by SeFFT-Net.

Visualization Results. In this section, we manage these breast cancer pathology tissue slices that are misclassified by the baseline but can be rightly distinguished by SeFFT-Net, and show eight typical images at four magnifications in Fig. 3. In the figure, images in the first row are labeled as benign tumors, while images in the second row belong to malignant tumors. Due to the complexity and irregularity of breast cancer histopathology images, the baseline model can not well distinguish some histopathology images, specially for those containing blank areas. After introducing frequency transform and channel attention modules, the SeFFT-Net model can well classify these breast cancer pathology tissue

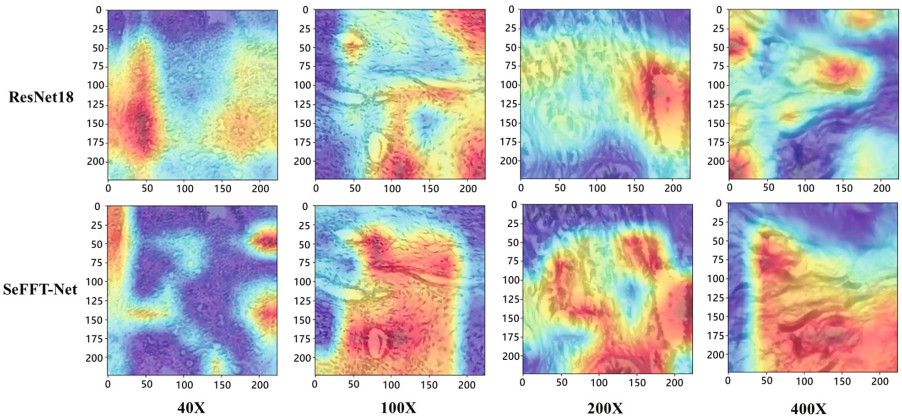

Fig. 4. Visualized heatmap results of ResNet18 and SeFFT-Net deep feature activations at four magnifications.

slices, and the classification accuracy is significantly improved compared to the baseline. Then, we also visualize heatmaps of deep features in Fig. 4, aiming to further display the regions of interest of different networks and hope to provide a valuable reference for classification results.

4 Conclusion

This paper attempts to explore the application of frequency domain related deep learning methods in breast cancer histopathology image classification tasks, and further propose a novel frequency attention network called SeFFT-Net by combining the advantages of frequency transformation and channel attention mechanism. SeFFT-Net adds Fourier transform on the spatial residual structure to extract the frequency-domain features of histopathology images, and then enhances the feature representation with an attention operator to obtain more promising classification performance. Experimental results on the public dataset BreakHis demonstrate the effectiveness of SeFFT-Net in this medical image application, while ablation studies on two landmark spatial counterparts provide a good demonstration of the effect of introducing frequency-domain features. In the future, we will attempt to capture more discriminant frequency features for breast cancer histopathology image classification. Besides, it is also interesting to explore the combination of frequency features with transformer models.

Acknowledgements. This work was supported in part by the National Natural Science Foundation of China under Grant 61972062, the Applied Basic Research Project of Liaoning Province under Grant 2023JH2/101300191 and 2023JH2/101300193.

References

1. Bray, F., Ferlay, J., Soerjomataram, I., Siegel, R.L., Torre, L.A., Jemal, A.: Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: Cancer J. Clin. **68**(6), 394–424 (2018)
2. Joy, J.E., Penhoet, E.E., Petitti, D.B., Ebrary, I.: Saving women's lives: strategies for improving breast cancer detection and diagnosis. J. Laryngol. Otol. **86**(2), 105–19 (2005)
3. Gupta, V., Bhavsar, A.: Sequential modeling of deep features for breast cancer histopathological image classification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops(CVPRW), Salt Lake City, UT, USA, pp. 2254–2261 (2018). https://doi.org/10.1109/CVPRW.2018.00302
4. Chhipa, P.C., Upadhyay, R., Pihlgren, G.G., Saini, R., Uchida, S., Liwicki, M.: Magnification prior: a self-supervised method for learning representations on breast cancer histopathological images. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 2717–2727 (2023). https://doi.org/10.48550/arXiv.2203.07707
5. Shallu, M.R.: Breast cancer histology images classification: training from scratch or transfer learning? ICT Exp. **4**(4), 247–254 (2018)
6. Chukwu, J.K., Sani, F.B., Nuhu, A.S.: Breast cancer classification using deep convolutional neural networks. FUOYE J. Eng. Technol. **6**(2), 35–38 (2021)
7. Spanhol, F.A., Oliveira, L.S., Cavalin, P.R., Petitjean, C., Heutte, L.: Deep features for breast cancer histopathological image classification. In 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Banff, AB, Canada, pp. 1868–1873 (2017). https://doi.org/10.1109/SMC.2017.8122889
8. Deniz, E., Şengür, A., Kadiroğlu, Z., Guo, Y., Bajaj, V., Budak, Ü.: Transfer learning based histopathologic image classification for breast cancer detection. Health Inf. Sci. Syst. **6**(1), 1–7 (2018)
9. Jiang, Y., Chen, L., Zhang, H., Xiao, X.: Breast cancer histopathological image classification using convolutional neural networks with small SE-ResNet module. PloS One **14**(3), e0214587 (2019)
10. Sohail, A., Khan, A., Wahab, N., Zameer, A., Khan, S.: A multi-phase deep CNN based mitosis detection framework for breast cancer histopathological images. Sci. Rep. **11**(1), 1–18 (2021)
11. Juppet, Q., De Martino, F., Marcandalli, E., Weigert, M., Burri, O., Unser, M.: Deep learning enables individual xenograft cell classification in histological images by analysis of contextual features. J. Mammary Gland Biol. Neoplasia **26**(2), 101–112 (2021)
12. Hirra, I., Ahmad, M., Hussain, A., Ashraf, M.U., Saeed, I.A., Qadri, S.F.: Breast cancer classification from histopathological images using patch-based deep learning modeling. IEEE Access **9**, 24273–24287 (2021)
13. Gueguen, L., Sergeev, A., Kadlec, B., Liu, R., Yosinski, J.: Faster neural networks straight from JPEG. In: 32nd Conference on Neural Information Processing Systems, pp. 1–13 (2018)
14. Ehrlich, M., Davis, L. S.: Deep residual learning in the JPEG transform domain. In: Proceedings of the IEEE/CVF International Conference on Computer Vision, Seoul, Korea, pp. 3484–3493 (2019). https://doi.org/10.1109/ICCV.2019.00358
15. Zhong, Y., Li, B., Tang, L., Kuang, S., Wu, S., Ding, S.: Detecting camouflaged object in frequency domain. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, New Orleans, LA, USA, pp. 4504–4513 (2022). https://doi.org/10.1109/CVPR52688.2022.00446

16. Hu, J., Shen, L., Sun, G.J., Albanie, S., Wu, E.H., Sun, G.: Squeeze-and-excitation networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 7132–7141. (2018). https://doi.org/10.48550/arXiv.1709.01507
17. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778 (2015). 10.48550/arXiv.1512.03385
18. Wang, K.N., He, Y., Zhuang, S., Miao, J., He, X., Zhou, P.: FFCNet: fourier transform-based frequency learning and complex convolutional network for colon disease classification. In: Proceedings of the 25th International Conference of Medical Image Computing and Computer Assisted Intervention-MICCAI 2022: 25th International Conference, Singapore, 18–22 September 2022, Proceedings, Part III, pp. 78–87 (2022). https://doi.org/10.1007/978-3-031-16437-8_8
19. Zhang, J., Wei, X., Dong, J., Liu, B.: Aggregated deep global feature representation for breast cancer histopathology image classification. J. Med. Imaging Health Inf. **10**(11), 2778–2783 (2020)
20. Lichtblau, D., Stoean, C., Magalhaes, M.: Cancer diagnosis through a tandem of classifiers for digitized histopathological slides. PLoS ONE **14**(1), e0209274 (2019)
21. Hou, Y.: Breast cancer pathological image classification based on deep learning. J. Xray Sci. Technol. **28**(4), 727–738 (2020)
22. Saxena, S., Shukla, S., Gyanchandani, M.: Breast cancer histopathology image classification using kernelized weighted extreme learning machine. Int. J. Imaging Syst. Technol. **31**(1), 168–179 (2021)
23. Han, Z., Wei, B., Zheng, Y., Yin, Y., Li, K., Li, S.: Breast cancer multi-classification from histopathological images with structured deep learning model. Sci. Rep. **7**(1), 4172 (2017)
24. Alom, M.Z., Yakopcic, C., Nasrin, M.S., Taha, T.M., Asari, V.K.: Breast cancer classification from histopathological images with inception recurrent residual convolutional neural network. J. Digit. Imaging **32**(5), 605–617 (2019)
25. Hao, Y., Zhang, L., Qiao, S., Bai, Y., Cheng, R., Xue, H.: Breast cancer histopathological images classification based on deep semantic features and gray level co-occurrence matrix. Plos One **17**(5), e0267955 (2022)
26. Boumaraf, S., Liu, X., Wan, Y., Zheng, Z., Ferkous, C., Ma, X.: Conventional machine learning versus deep learning for magnification dependent histopathological breast cancer image classification: a comparative study with visual explanation. Diagnostics **11**(3), 528 (2021)
27. Li, X., Li, H., Cui, W., Cai, Z., Jia, M.: Classification on digital pathological images of breast cancer based on deep features of different levels. Math. Prob. Eng. **2021**, 1–13 (2021)
28. Man, R., Yang, P., Xu, B.: Classification of breast cancer histopathological images using discriminative patches screened by generative adversarial networks. IEEE Access **8**, 155362–155377 (2020)
29. Sharma, S., Kumar, S.: The Xception model: a potential feature extractor in breast cancer histology images classification. ICT Exp. **8**(1), 101–108 (2022)
30. Xu, Y., dos Santos, M.A., Souza, L.F.F., Marques, A.G., Zhang, L., da Costa Nascimento, J.J.: New fully automatic approach for tissue identification in histopathological examinations using transfer learning. IET Image Process. **16**(11), 2875–2889 (2022)