Name - Vaasu Bisht
Internship Program – Deep Learning with Computer Vision
Batch – December 2021
Certificate Code – TCRIK01R56
Date of submission – 10/02/2022

Technical Coding Research Innovation, Navi Mumbai,
Maharashtra, India-410206

BREAST CANCER DETECTION

A Case-Study Submitted for the requirement of
Technical Coding Research Innovation

For the Internship Project work done during
DEEP LEARNING USING COMPUTER VISION INTERNSHIP PROGRAM

by
Vaasu Bisht(TCRIK01R56)

Name - Vaasu Bisht
Internship Program – Deep Learning with Computer Vision
Batch – December 2021
Certificate Code – TCRIK01R56
Date of submission – 10/02/2022

Breast Cancer Detection via Breast Cancer Image Classification

Vaasu Bisht

School of Computing Science & Engineering
VIT Bhopal
Madhya Pradesh, India

bishtvaasu@gmail.com

Abstract Histopathological image analysis is an important technique for early diagnosis and detection of breast cancer in clinical practice. However, it has limited efficiency and thus the detection of breast cancer is still an open issue in medical image analysis. To improve the early diagnostic accuracy of breast cancer and reduce the workload of doctors, we devise a classification framework based on histology images by combining deep learning with machine learning methodologies in this paper. Specifically, we devise a multi-network feature extraction model by using pre-trained deep convolution neural networks (DCNNs), develop an effective feature dimension reduction method and train an ensemble support vector machine (E-SVM). First, we preprocess the histological images via scale transformation and color enhancement methods. Second, the multi-network features are extracted by using four pre-trained DCNNs (e.g., DenseNet121, ResNet-50, multi-level InceptionV3, and multi-level VGG-16). Third, a feature selection method via dual-network orthogonal low-rank learning (DOLL) is further developed for performance boosting and overfitting alleviation. Finally, an E-SVM is trained via fused features and voting strategy to perform the classification task, which classifies the images into four classes (i.e., benign, in situ carcinomas, invasive carcinomas, and normal). We evaluate the proposed method on the public ICIAR 2018 Challenge dataset of histology images of breast cancer and achieve a high classification accuracy of 97.70%. Experimental results show that our method can achieve quite promising performance and outperform state-of-the-art methods.

Index Terms **-** Breast cancer image classification, deep convolutional neural network, multi-network features, low-rank learning, ensemble support vector machine.

I. Introduction

Breast cancer is one of the most common types of cancer and the main leading cause of cancer death among women worldwide [1]. The cornerstone of breast cancer control is early diagnosis, which helps to increase the survival rate of breast cancer. Currently, the early diagnosis of breast cancer is usually performed by biopsy. In clinical practice, biopsy has three main steps. First, the biopsy materials of breast cancer are obtained by drill-biopsy. Second, histopathology images are stained by hematoxylin and eosin (H&E) staining. Third, pathologists perform early diagnosis of breast cancer by observing the histology images. However, the diagnostic performance relies on the doctors' professional skills and experience, which is typically subjective and maybe inconsistent across different pathologists. To reduce these adverse effects, improve early diagnostic efficiency, and alleviate the workload burden, computer-aided diagnosis (CAD) systems are developed [2]–[5] utilizing image analysis methods.

With the latest development of machine learning and deep learning techniques [6]–[8], the CAD systems can potentially offer more reliable classification methods for the histology images of breast cancer [9]–[15]. These methods are mainly learnt models to classify the histology images of breast cancer into two classes (e.g., carcinomas and non-carcinomas) or four classes (e.g., benign, in situ carcinomas, invasive carcinomas, and normal, Fig. 1). As seen from Fig. 1, these histology images have very large size, uneven H&E staining, and great differences between pathological images from different patients, which have high intra-class differences and low inter-class differences [16]. Therefore, the image preprocessing [12] is desirable by utilizing scale transformation and color enhancement [17], where scale transformation (e.g., downscale and randomly cropped image) is used to solve the problem of very large image size and color enhancement is used to address the problem of uneven H&E staining. The image preprocessing helps to narrow the intra-class differences and increase the inter-class differences.

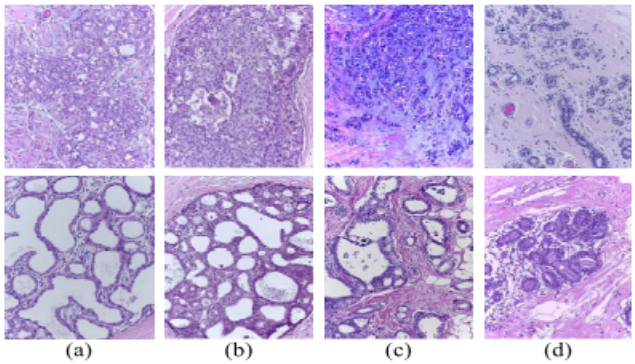


FIGURE 1. Examples of microscopic breast cancer histological images: (a) benign, (b) in situ carcinoma, (c) invasive carcinoma, (d) normal.

Name - Vaasu Bisht
Internship Program – Deep Learning with Computer Vision
Batch – December 2021
Certificate Code – TCRIK01R56
Date of submission – 10/02/2022

It is known that deep convolutional neural networks (DCNNs) have been widely used in many image classification tasks with great successes [18]–[21]. The successes are mainly attributed to the powerful learning ability of DCNN, which can obtain more important feature information. However, they usually only employ single-network features, which can hardly get comprehensive image features and have poor generalization ability. Therefore, the multi network features are obtained by using different DCNNs and different convolution layers, respectively, which can improve performance and enhance generalization ability. As a result, we design a multi-network feature model by using four classical DCNNs (e.g., VGG-16 [18], InceptionV3 [22], ResNet-50 [21], and DenseNet-121 [23]). Accordingly, different networks have unique advantages in their network structures, which allows effective capturing of complemented features.

The VGG-16 network uses a smaller convolution kernel and piecewise convolution to extract the detailed local feature information. In the InceptionV3 network, the mixed modules decompose two-dimensional convolution into two one-dimensional convolutions, which increases the nonlinearity and the width of the network to eliminate representation bottleneck. The ResNet-50 network has a deeper network structure and the residual module [21], which may solve the degradation problem in the optimization process and enhance learning ability. In the DenseNet-121 network, an innovative dense module [23] is proposed, which connects each layer to every other layer in a feed-forward fashion. It relieves the gradient vanishing problem, reinforces feature propagation, encourages feature reuse and substantially cuts down the number of parameters.

To further boost the classification performance, this paper adopts the multi-level InceptionV3 (ML-InceptionV3) network and the multi-level VGG-16 (ML-VGG-16) [12] network by extracting the feature maps of the intermediate layer of InceptionV3 and VGG-16 networks, which are combined with DenseNet-121 and ResNet-50 to obtain multi-network features. Afterward, the features from the preprocessing of scale transformation and color enhancement are encoded via 3-norm pooling [24] and average encoding methods. For the medical image data with small samples, it is well-known that the DCNN models of end-to-end architectures are prone to overfitting. Additionally, the multi network features have high feature dimensions, which leads to higher computational costs. To address these issues, feature selection methods are effective ways. However, the existing methods [25]–[27] have limitations since they mainly consider the relation between the features from the same source and the response variables, which fail to consider the relations among response variables and the complementary relations among the features of two different DCNNs (dual-network). Therefore, we propose a dimension reduction method called dual-network orthogonal low-rank learning (DOLL) inspired by the previous work [28]. Our proposed method utilizes joint low-rank learning and orthogonal rotation among dual-network features, which can consider three relations (e.g., the relation among the features and the response variables, the relation among response variables, and the complementary relation between dual-network features). It can effectively remove redundant features and select important feature information. Also, the softmax layer in DCNN is replaced by ensemble support vector machine (E-SVM) classifiers for classification performance boosting. In summary, we propose a new classification framework to classify breast cancer histological images, which uses multi network features, DOLL method and E-SVM classifier. The main contributions of this paper are as below.

1) We devise a multi-network feature extraction model to obtain more comprehensive feature representations of breast cancer histological images.
2) We develop a DOLL feature selection method, which considers three relationships to remove the redundant features and obtain complementary features.
3) We train an E-SVM classifier with fused features and voting strategy to improve the classification performance. The rest of this paper is organized as follows. In Section II, we briefly review related work of the early diagnosis of breast cancer. In Section III, we describe our proposed method in details. The experiments and comparison results are given in Section IV followed by discussions in Section V. Finally, our conclusions are presented in Section VI.

II. Methodology

A. Notations

*I*n this paper, uppercase boldface letters represent matrices, lowercase boldface letters represent vectors, and ordinary italics represent scalars. For the matrix $\mathbf{X} = [\, x_{i,j} \,]$, its i-th row and j-th column are denoted as x^i and x_j.

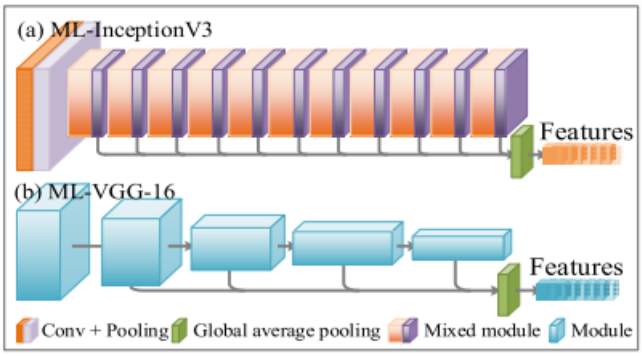
The Frobenius norms l_1, l_2, $l_{2,1}$, and l_F -norm of a matrix X are denoted as $\|X\|_1 = \Sigma_i |\mathbf{x}^i|, \|x^i\|_2 = \sqrt{x^2_{i,j}}$, $\|x^i\|_{2,1} = \Sigma_i \|\mathbf{x}^i\|_2 = \Sigma_i \sqrt{\Sigma_j \mathbf{X}^2_{i,j}}$

respectively. Moreover, X^T, Tr(X), rank(X), and X^{-1} denoted as the transpose, trace, rank, and inverse operators of X, respectively.

B. Figure Extraction Model

Name - Vaasu Bisht
Internship Program – Deep Learning with Computer Vision
Batch – December 2021
Certificate Code – TCRIK01R56
Date of submission – 10/02/2022

In this section, we briefly introduce the image preprocessing and describe how to extract the multi-network features using the four pre-trained DCNNs, and perform the feature encoding.



Feature extraction models of the ML-InceptionV3

C. Doll Feature Selection Method

Full features are extracted by utilizing different DCNNs and different convolutional layers in the same DCNN. However, these features can cause information redundancy and overfitting and reduce the classification accuracy of breast cancer histological images. Therefore, we propose a DOLL feature selection method.

D. Optimization

This Section describes the optimization process, which determines optimal parameters (e.g., Z, b1, b2, A1, and A2). Specifically, we iteratively conduct the following two steps until satisfying predefined conditions. (1) Update Z with fixed b1, b2, A1 and A2. (2) Update b1, b2, A1 and A2 with fixed Z

E. Train E-SVM Classifiers

As shown in Fig below we train the classifiers via fused features and voting strategy to conduct the breast cancer classification. Specifically, the dual-network features are first fused to train SVM classifiers, as shown in Fig. below (a). E-SVM classifier is trained by voting strategy as shown in Fig. below (b). For the features of each dual-network, we can train two SVMs and vote on their predicted score.

We train an E-SVM classifier with high precision and strong robustness by considering the fused features of dual-network and voting strategy for the predicted score of two dual-networks as depicted in Fig. below (c). In our experiments, three E-SVM classifiers are trained. The reason why we only train three E-SVM classifiers is that the features of training each E-SVM classifier must be derived from different DCNNs rather than sharing the features of the same DCNN (e.g., D-R and D-MV shares the features of DenseNet-121), which avoids introducing redundant features.

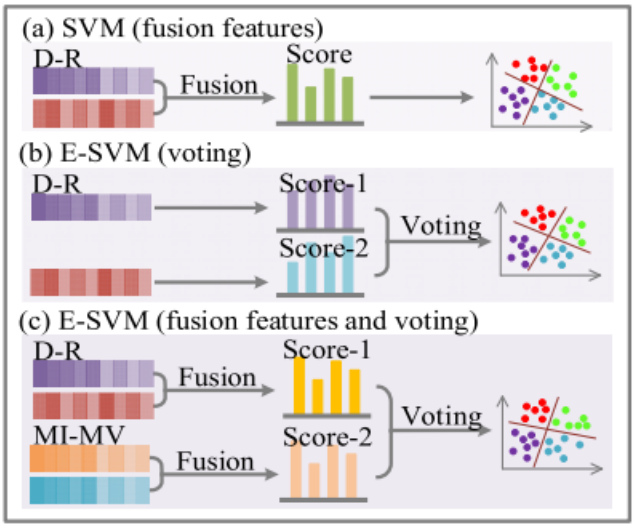


FIGURE Training classifiers: (a) training SVM using fused features of the dual-network; (b) training E-SVM using voting strategy between the dual-network; (c) training E-SVM using fused features and voting strategy between different dual-networks.

III. Conclusion

In this paper, we propose an effective model for the classification of H&E stained histological breast cancer images. To increase the accuracy and robustness of the classifier, we extract image features of the multi-network by using four pre-trained DCNNs. Further, based on three relationships, we devise a new feature selection method of the DOLL algorithm to enhance the classification results by reducing the feature dimension to alleviate overfitting. Moreover, we train the E-SVM classifiers by fused features and voting strategies to improve the classification accuracy. Our proposed model achieves considerable high accuracy and strong robustness. The proposed method is expected to be clinically useful for doctors to achieve the early diagnosis of breast cancer, which can benefit the survival chances of breast cancer patients. In our future work, we will validate our method on clinical data and investigate the efficacy of our method on different types of cancers.

References

Name - Vaasu Bisht
Internship Program – Deep Learning with Computer Vision
Batch – December 2021
Certificate Code – TCRIK01R56
Date of submission – 10/02/2022

[1] C. E. Desantis, J. Ma, A. G. Sauer, L. A. Newman, and A. Jemal, ‘‘Breast cancer statistics, 2017, racial disparity in mortality by state,’’ CA, A Cancer J. Clinicians, vol. 67, no. 6, pp. 439–448, Nov. 2017.

[2] R. M. Rangayyan and J. S. Suri, Recent Advances in Breast Imaging, Mammography, and Computer-Aided Diagnosis of Breast Cancer. Bellingham, WA, USA: SPIE, 2006.

[3] M. King and B. Zhu, “Gaming strategies,” in Path Planning to the West, vol. II, S. Tang and M. King, Eds. Xian: Jiaoda Press, 1998, pp. 158-176.

[4] Z. Gandomkar, P. C. Brennan, and C. Mello-Thoms, ‘‘MuDeRN: Multicategory classification of breast histopathological image using deep residual networks,’’ Artif. Intell. Med., vol. 88, pp. 14–24, Jun. 2018.

[5] A. Pimkin, G. Makarchuk, V. Kondratenko, M. Pisov, E. Krivov, and M. Belyaev, ‘‘Ensembling neural networks for digital pathology images classification and segmentation,’’ in Proc. Int. Conf. Image Anal. Recognit., 2018, pp. 877–886.

[6] Z. Ma and T. Sun, ‘‘Adaptive estimation in two-way sparse reducedrank regression,’’ pp. 1–25, 2014, arXiv:1403.1922. [Online]. Available: https://arxiv.org/abs/1403.1922.

[7] C. Giraud, ‘‘Low rank multivariate regression,’’ Electron. J. Statist., vol. 5, no. 0, pp. 775–799, 2011.

[8] G. Liu and S. Yan, Low-Rank and Sparse Modeling for Visual Analysis. Cham, Switzerland: Springer, 2014.

[9] J. C. Gower and G. B. Dijksterhuis, Procrustes Problems. Oxford, U.K.: Oxford Univ. Press on Demand, 2004.

[10] L. van der Maaten and G. Hinton, ‘‘Visualizing data using t-SNE,’’ J. Mach. Learn. Res., vol. 9, pp. 2579–2605, Nov. 2008.