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A parasitic metric learning net for breast mass classification based on mammography

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ABSTRACT

Accurate classification of different tumors in mammography plays a critical role in the early diagnosis of breast cancer. However, owing to variations in appearance, it is a challenging task to distinguish malignant instances from benign ones. For this purpose, we train a deep convolutional neural networks (CNNs) to obtain more discriminative description of breast tissues. Benefiting from the discriminative representation, metric learning layers are proposed to further improve performance of the deep structure. The best-performing model restricts the depth of backpropagation of joint training in only the metric learning layers. Relation between metric learning layers and tradition CNNs structures seems like parasitism relationship between species, where one species, the parasite, benefits at the expense of the other. Therefore, the proposed method is named as parasitic metric learning net. To confirm veracity of our method, classification experiments on breast mass images of two widely used databases are performed. Comparing performance of the proposed method with traditional ones, competitive results are achieved. Meanwhile, the parameter updating strategy for our parasitic metric net may inspire a way of improving performance of a pre-trained CNNs model on particular medical image processing or other computer vision tasks.

1. Introduction

1.1. Computer-aided diagnosis (CAD) methods for mammography analysis

Breast cancer is the most common non-skin cancer and the second leading cause of cancer-related death in women [1]. According to the statistical data from World Cancer Report, proportion of breast tumor in diagnosed cancers is as high as 22.9%, causing 13.7% cancer related death all over the world. Fortunately, early diagnosis of breast cancer is of great help to treat this disease, relieving both physical pain and mental anguish suffered by patients and their families. In early diagnosis of breast cancer, multi-examinations and related CAD methods have been applied [2–4,6–10]. Among all these inspection strategies, computed tomography (CT) provides high resolution but its radiation is relatively higher than others, making CT not that widely preferred in daily inspection. In addition, magnetic resonance imaging (MRI) does less damage to patients, but the inspection charge of MRI is high, causing not everyone could afford this expensive examination. Owing to its low radiation, low cost, and relatively high resolution, digital mammograms are considered as the gold standard for the early detection and diagnosis of breast cancer [5]. And it is also widely applied in research institutions for study of breast tumors. However, as results of widespread mammography technology, radiologists have to browse and analyze enormous quantities of mammograms day and night. Nevertheless, shortage of experienced doctors makes it become particularly difficult to tackle these images to assist the patients. Meanwhile, this exhausted diagnosis process also bothers the physicians, causing the diagnosis to be highly susceptible to errors. CAD systems have been playing more and more important parts in assisting and improving physicians' work of detecting and classifying breast masses.

Methods representing and distinguishing between benign and malignant tumors are always attracting researchers. And it is popular to contribute to the breast cancer related CAD systems. In the beginning, morphological features are designed to characterize the roughness of tumor boundaries and they are applied in classification tasks [11]. Then more low-level features cooperating with various kinds of classifiers are also reported to achieve improvement in mass classification. The representative work of Ma and co-workers [12,13] contribute to segmentation of pectoral muscle for further detecting and classifying breast tumors in mammograms. In [14], textural features and fractal dimension analysis are combined to tackle this problem. In addition, temporal features, gradient orientation, fuzziness, speculation, and mutual informa-

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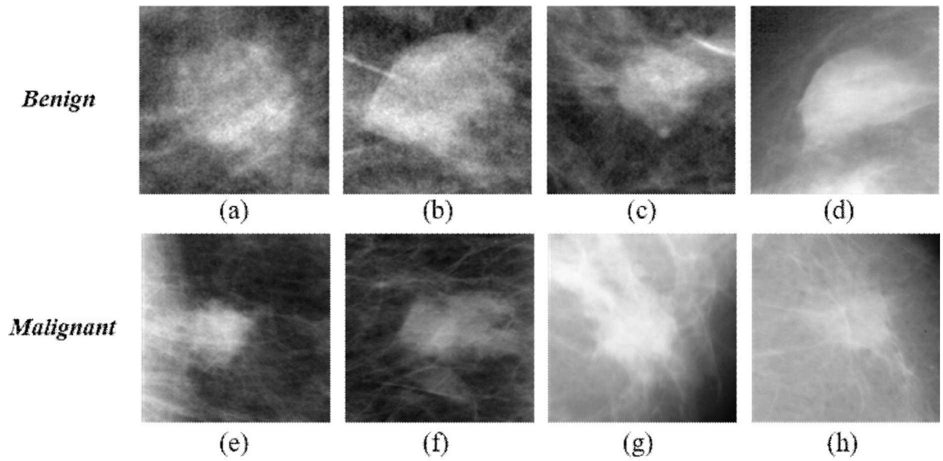

Fig. 1. Instances of benign and malignant breast mass images. Examples in the first row are benign masses while ones in the second row are malignant. Instances in the same row belong to one category of benign or malignant, but they varies in shape, edge, brightness, and so on.

tion are also reported by Timp and co-workers [15,16] to achieve improvement in this area. Meanwhile, frameworks utilizing spatial information and latent feature mining have been introduced to make improvement [17]. More recently, a few of methods inspired by deep learning are proposed to achieve competitive performance in research on mammography. In [18], multi-scale deep belief networks (DBN) are designed to detect suspicious areas, and these areas are processed by a two-level cascade of random forest classifiers to obtain the improved result. CNNs is also introduced to do mass lesion classification, and it is reported to outperform traditional handcraft image features on mammography [19]. Utilizing powerful region-based convolutional networks, a novel system integrating detection and classification of breast tumors is designed in [20]. Experimental results on up-to-date mammogram data shows relatively high accuracy and efficiency of detection and classification. Stacked autoencoder (SAE) model is introduced to this area in [21]. In this work, SAE represents relationships between features of microcalcifications and mass with breast cancer. Performance of the proposed method demonstrates that deep architectures superior to standard methods for the discrimination of microcalcifcations and mass lesions. Mining the discriminative abilities of speed-up robust features (SURF) and local binary pattern (LBP), a framework named DeepCAD is reported in [22]. Core content of this method is training deep belief networks to learn invariant feature transform from hand-crafted features. Performance of classifying benign breast masses and malignant ones shows reliability of the proposed method. Besides, a CNNs model is also introduced in our recent work [23] for feature representation of breast mass, then outcome of various classifiers which focuses on different levels of deep features are analyzed jointly to catalogue instances of breast mass into benign and malignant ones.

1.2. Deep learning on biomedical image and deep metric learning

In the practice of categorizing different kinds of breast tumors, there are a number of challenges. For example, as shown in Fig. 1, because of the diversity in appearance of both low-level (brightness, texture, etc.) and high-level representations (shape, structure, etc.), it is sometimes difficult for traditional means benefitting more from handcrafted features to distinguish some malignant masses from benign ones. Owing to the development of representation learning, deep neural networks [24] make it possible to obtain more useful descriptions of biomedical images. And it has been reported to achieve better performance in biomedical related tasks, such as tissue segmentation, detection, and so on [25–28]. Among these applications, various CNNs are usually trained, validated, and tested on tagged instances of related medical images, or they are trained on both natural image datasets and medical images. In common, specific tasks are transformed into classification problems by operating pretrained networks on testing dataset. The final performance of these frameworks depends heavily on feature representation ability once the network training has been terminated.

Distance metric learning is a problem concerning with learning a distance function tuned to a particular task. And this distance function is helpful to distinguish between instances with different labels in a transformed feature space [29,30]. As the development of huge technology wave named deep learning, deep metric learning attracts more attention in the field of pattern recognition. Metric learning method with hierarchical structures is first introduced to person re-identification problem in [31]. In this work, with help of Siamese deep neural network, color features, texture feature, and metric are learned jointly to deal with variations in person images. Experiments across databases demonstrate both superior performance and good generalization on person re-identification task. In the representative work of Hu et al. [32], a discriminative deep metric learning method is proposed for face verification in the wild. Various face pairs are projected into the same feature subspace via hierarchical nonlinear transformations. And a large margin framework is applied to formulate that the distances between positive pairs of faces are smaller than those between negative ones. Very competitive performances are acquired and analyzed on two widely used datasets of face verification. A more recent work of Lin et al. [33] generalizes linear projection and distance metrics of similarity measure learning into a unified formulation. The proposed method utilizes data from various modalities by training an end-to-end deep architecture. A novel hierarchical metric tree is proposed for large-scale image classification in our recent work [55]. Besides, variations of deep metric learning also have achieved competitive performance on other tasks [34–36].

Inspired by the successes of deep metric learning methods above, we propose a jointly deep metric learning neural network for breast mass classification. The proposed method consists of CNNs layers and metric learning layers to improve classification performance of the whole deep network. Being similar with definition of parasitism in biology [37,38], metric learning layer in our proposed method benefits from the discrimination of features in CNNs layers. The metric learning layers increase both memory usage and number of parameters of the overall network. As a result, this would decrease efficiency of forward and backward