# A Survey of Transfer Learning in Breast Cancer Image Classification

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***Abstract*—Worldwide, breast cancer is one of the leading cancer for female, especially in low and middle income countries. Breast cancer's classification in the early stages plays a pivotal role to improve survival rate. But the training dataset which should be large-scaled and well-annotated is hard to collect because of the limitation of data acquisition and annotation. Transfer learning can transfer the knowledge from target domain to source domain to improve model performance. Thus, the dataset needed for training in target domain can be degraded. For the feature mentioned above, it has become the hot topic for research in machine learning. This survey tries to systematize the current research of transfer learning techniques in the area of breast cancer image classification. And also, highlight several findings for the researchers in future.**

***Keywords—breast cancer, transfer learning, deep learning, classification***

## I. Introduction

Breast cancer is the most common cancer for female. And the clinical reports has proven that the detection and classification of breast cancer has significantly improved the patients treatments[1][2][3][4]. There are two kinds of breast cancer, in-situ and invasive ductal carcinoma(IDC). In-situ accounts for approximately 20%, while IDC almost 80% is the most common type of breast cancer.

In the breast cancer detection and classification, machine learning algorithms are developing rapidly but still. It's highly demanded to develop an application to get the right diagnostic reports automatically[7]. Therefore, machine learning algorithms are required to help doctors to diagnose towards qualitative results. While in traditional machine learning, the tasks like image preprocessing, object segmentation, feature engineering are complex. And these tasks are extremely dependent on experiences on algorithm designer.

To overcome these machine learning's issues, deep learning method has been used for feature extraction for breast cancer detection and classification[8][9]. In deep learning pattern, features are no longer calculated manually instead they're obtained from data sets by training stage. Over the past decade, Convolution Neural Network (CNN) has achieved human level in medical image analysis, like neural membranes segementation[13], mitosis cells detection[10][11], tumor detection[12], skin disease detection and classification[14][15] and quantization of mass in mammograms[16]. Although the CNN strategy works well, its model needs to be trained on large-scaled and well-annotated data sets. Otherwise, it fails.

The most common problem of using deep learning method for breast cancer classification is to construct a labeled data set[17][18][19] for training a classifier. Because, it's really difficult to collect and annotate image data. It's impossible to label TB or PB of image data manually. On the other side, the labeled data is not available for all even when it is built. Transfer learning can solve these issues.

Generally, the data used for training and testing in deep learning should have the same feature space and data distribution. Otherwise, the performance of the model can be degraded[20].

In this survey, we try to systematize the cutting-edge transfer learning techniques in breast cancer image classification, and highlight several improvement areas for other researchers in future.

In Section 2, we describe the method to collect related papers from several searching databases. In section 3, we introduce the breast cancer image databases which are used in related researches. In Section 4, we reviewe the transfer learning techniques of breast cancer image classification. Finally, in Section 5, we provide several opportunities for future research.

## II. Methods

We reviewed papers from 2010 to 2020 from the following two aspects:

- Describe available breast cancer image databases;
- Systematize transfer learning techniques for breast cancer image classification.

We used the keywords to search, like 'transfer learning', 'transfer learning and breast cancer image classification', and 'application of transfer learning in breast cancer image classification'. And the databases we searched are: Web of Science, PubMed, Science Direct, IEEE Xplore Digital Library, Google Scholar, arxiv.

## III. Dataset

### *A. ICIAR 2018 BACH-Challenge*

The data set is composed of Hematoxylin and eosin (H&E) stained breast histology microscopy and whole-slide images. It collects almost 400 microscopy images.

*B. INBreast Database*

The data set consists of 115 patients with 410 breast cancer images. It contains 67 cases negative and 48 cases positive.

*C. The mini-MIAS database of mammograms*

The data set collects 332 mammograms from 161 patients. And it's divided into three categories, fatty, fatty-glandular, and dense-glandular.

*D. DDSM*

The data set is composed of 10,239 images of 2,500 patients with three types: benign, malignant and normal. Breast density labels are divided into four categories, fatty, glandural, dense and extremely dense.

*E. Breast Cancer Histopathological Database (BreakHis)*

The data set contains 9,109 breast cancer images of 82 patients, which was constructed using different magnifying factors. Image labels are categorized into 2 classes: benign(2,480 images) and malignant(5,429 images).

## IV. TRANSFER LEARNING

*A. Definations and Notations*

In transfer learning[21], two components exist in domain $D$:

- Feature Space: $X$ ;
- Marginal Probability Distribution: $P(X)$ ;

where $X = \{x_1, x_2, ..., x_n\}$. $X$ stands for a feature vectors, $x_i$ is the $ith$ dimension of feature vector.

In domain $D$ ( $D = \{X, P(X)\}$ ), two components exist in task:

- Label Space $Y$ ;
- Predictive Function $f(\cdot)$ ;

And the task is denoted by $T = \{Y, f(\cdot)\}$ . The formula can be learned from target domain. The function $f(\cdot)$ predicts the new instance $x's$ label $y$ .

In transfer learning, we note a source domain with learning task as $(D_S, T_S)$, and target domain with learning task $(D_T, T_T)$, respectively. Transfer learning was designed to improve the performance of the target domain's predictive function $f_T(\cdot)$ using the data from source domain, where $D_S \neq D_T$, or $T_S \neq T_T$ .

Domain is defined by $D = \{X, P(X)\}$ . Thus, the formula $D_S \neq D_T$ means either $X_S \neq X_T$ or $P_S(X) \neq P_T(X)$.

Similarly, task is defined by $T = \{Y, P(Y \mid X)\}$ . Thus, the formula $T_S \neq T_T$ means either $Y_S \neq Y_T$ or $P(Y_S \mid X_S) \neq P(Y_T \mid X_T)$ .

When the learning tasks $T_S \neq T_T$ in domains $D_S$ and $D_T$, then either:

- Label Spaces are different: $Y_S \neq Y_T$ ;
- Conditional Probability Distributions are different: $P(Y_S \mid X_S) \neq P(Y_T \mid X_T)$ .

*B. Transfer Learning in Breast Cancer Image Classification*

One of the earliest DNN applications from [22] was on breast cancer image. Nowadays, as the deep learning techniques developing, ROIs[23] detection has achieving the human level. Most breast cancer image collecting methods are two dimensional, therefore, the strategies or algorithms used in 2D images can be applied. Paper [24] proposed a transfer learning algorithm to classify breast cancer. It used a Google's Inception v3 model as a classifier which was pre-trained by non-medical images. And then, fine-tuned stage was carried out with breast cancer images. After that, it used the model for classification of breast cancer. The AUC achieved 0.93. The result shows that transfer learning works in classification of breast cancer image.

Strategies to transfer learning can be categorized into two cases based on "What to transfer" in breast cancer image classification,

- Feature-representation-transfer: Find proper feature representation. Using that feature set for training model can reduce the difference between source and target domains. Make the model trained in source domain can be transferred to target domain.
- Parameter-transfer: Find shared parameters between source domain and target domain models.

*C. Transferring Knowledge of Feature Representations.*

Most feature-representation-transfer strategies to the inductive transfer learning problem try to find proper feature representations to reduce the difference between source and target domains.

Paper [25] proposed a method to extract features from breast cancer images using several pre-trained neural network, GoogLeNet, VGGNet and ResNet. After that, the classifier was trained by features data. The GoogLeNet, VGGNet, ResNet and proposed network achieved the classification accuracy of 93.5%, 94.15%, 94.35% and 97.525%. The result shows that the features in source domain can be transfer to target domain. And the combination of features from different neural network improves the performance of classifier. Moreover, handcrafted features[26] combined with neural networks' feature also increase classification accuracy. In paper [27], feature extraction was applied by DCNN, and feature selection was carried out using the algorithm mentioned in paper [28]. In this scenario, the DCNN was pruned. The computation cost was significant decreased which makes the algorithm more prospective.

### D. Transferring Knowledge of Parameters

Most parameter-transfer strategies to the inductive transfer learning assume that related tasks' model should share some parameters in source and target domains.

Paper [29] analyzed three pre-trained neural networks' training procedure, VGG16, VGG19 and ResNet50. The result proved that the parameters can be transferred between different domains. A fine-tuned pre-trained VGG16 achieved the best performance. The classification accuracy is 92.60%, the AUC is 95.65%, and the APS is 95.95%, respectively. Paper [30] applied the same strategy of paper [29] instead of different neural networks of Google's Inception-V3 and ResNet50. After training, the Google's Inception-V3 network's classifier achieved accuracy of 97.08% for four classes. Moreover, the ResNet50 network achieved accuracy of 96.66%.

### E. Traditional Machine learning Approach

In transfer learning, some traditional machine learning techniques are used. Data augmentation[31] is the one belong to these. It applied several criterions to generate new images to increase the data set[32]. The criterions are composed by geometric transformations(translating, scaling, and rotation), color processing, noise perturbation, etc.

## V. Discussion and Trends

In this survey, we found that many pre-trained networks[24][25] are used for fine-tuning and full-training. Some significant opportunities are:

- Fine-tuned pre-trained network achieves better performance than full-trained network. Because, it's hard to obtain the large-scaled and well-annotated data to fed the network for training in breast cancer classification;
- Lack of data degrades the network performance. Data belong to a particular class extremely small, but the others are not in this situation. Thus, the trained network cannot be equal sensitive to all classes of breast cancer image;
- Simple combination cannot find proper features for transfer learning. Some researcher used pre-trained networks to extract features[27] and add[26] them all for classification to achieve better performance. But, it cannot minimize classification model error.

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