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Survey on deep learning techniques for thorax disease classification task

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Abstract. In recent years, medical image analysis has been widely studied, largely because it provides useful tools to support daily clinical routines. Thorax disease classification (TDC) is an important one among these tools since Chest X-ray (CXR) has become prevalent in daily clinical examinations. It aims to distinguish between normal and abnormal CXR images according to different diseases. To this aim, many thorax disease classification systems have been proposed to increase performance. Most of them adopt deep learning techniques to train a deep neural network (DNN) by using labeled CXR datasets. The TDC performance has been continually refined. Aiming to provide future researchers with the work being done on TDC to date, we review the DNN models for this task. A brief review of each method along with their evaluations on a set of benchmark datasets is included. Moreover, we give a detailed comparison of these methods as well as a conclusion.

Keywords: medical image analysis, Thorax Disease Classification, Deep Neural Networks.

1. Introduction

Chest X-ray (CXR) has become prevalent in daily clinical examinations [1-5]. During the pandemic, such as COVID-19 and SARS, CXR image is extremely helpful to detect non-symptom patients and distinguish very unusual symptoms from a well-known lung infection. On the other hand, when using a CXR image, most clinics still require an expert radiologist to analyze it and manually give a report. Therefore, during the pandemic, many people may not get timely examinations because there is an inadequate expert radiologist. In addition, when a CXR image has some specific diseases, it often contains tiny lesions. Therefore, it is difficult to distinguish between normal and abnormal CXR images even for doctors and this may result in diagnosis errors.

To address the constraints of relying on expert radiologists only, a number of Thorax Disease Classification (TDC) systems [6-25] have recently been designed to support daily clinical routines. They leverage a huge amount of CXR history data to train DNN models. Most existing approaches adopt supervised learning to train a TDC model [8-11]. They first label a CXR dataset (e.g., ChestX-ray14 [6], SYSU [7]) and then train a deep model to capture discriminative features from CXR images. These visual features are finally used to detect diseases from CXR images. DNNs have improved the TDC performance significantly. However, the supervised thorax disease classification methods still face two major limitations in practical applications. First, collecting and manually labeling a large number of CXR images is extremely difficult and time-consuming. In particular, labeling CXR images is much more difficult than natural images because it needs professional knowledge and the participation of expert radiologists. Second, a DNN trained on one dataset using a supervised learning method may have unsatisfactory accuracy when deployed to another dataset because of dataset shift problems [26, 27]. The above limitations severely hinder the usability of supervised methods in the TDC problem.

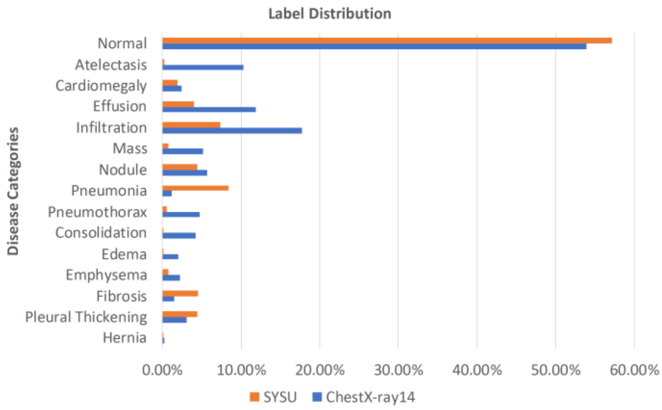

Figure 1. Distribution of 14 disease labels on the ChestX-ray14 and SYSU datasets.

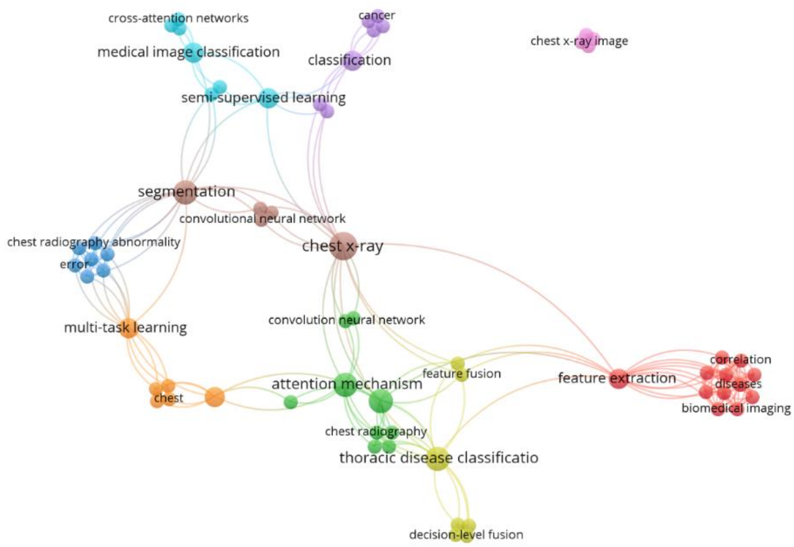

Figure 2. Visual analysis of key words construction using VOS viewer.

Designing a semi-supervised model [28-30] is a common method employed to improve the TDC accuracy. Given a large-scale unlabeled CXR dataset and a small-scale labeled CXR dataset, several attempts [29, 30] have used consistency-enforcing regularization to train a TDC model. However, the performance of these methods relies on the number of the labels. As we mentioned earlier, CXR images often contain tiny lesions of different thorax diseases, which leads to difficult labeling. Moreover, the labeling task requires professional knowledge and the participation of expert doctors. In most scenarios, it may be impractical to label even a small-scale CXR dataset.

Unsupervised Domain Adaptation (UDA) models [31, 32] have been widely used for feature representation learning in recent years. Leveraging a labeled source dataset and an unlabeled target dataset, they simultaneously learn features using the source labels and transfer the learned features to the target dataset. Aiming to mitigate the shifts between source and target domains, most existing works [32-34] directly align the feature distributions of the two domains. In recent years, adversarial domain adaptation [34] has been widely studied in the learning of domain-invariant features because

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of the prevalent generative adversarial networks (GANs) [35]. Although UDA models have achieved very competitive performance in many computer vision tasks, they continue to face two major constraints in thorax disease classification tasks: 1) the source and target CXR datasets often contain large label shifts, which could result in significant performance drops. 2) as shown in Figure. 1, the class imbalance of CXR datasets will deteriorate the quality of feature transferring.

2. Methodologies: a survey

This paper mainly reviews deep learning based TDC works. From the perspective of feature representation learning, we classify existing works into 3 classes, as listed in Table 1: 1) supervised learning based [6-25], 2) semi-supervised learning based [28-30], and 3) unsupervised domain adaptation based [36]. We also give a visualization of key words of reviewed literature using VOSiviewer, as illustrated in Figure 2.

Table 1. Representative methods of TDC.

Category	Method	Highlights	Publication
Supervised	Want et al. [6]	ChestX-ray8 dataset and benchmark	CVPR 2017
	Want et al. [7]	SYSU dataset and benchmark	Nat. Biomed. Eng 2021
	Ranjan et al. [8]	Learning features in the compressed domain	ICVGIP 2018
	Rajpurkar et al. [9]	121-layer DenseNet, ImageNet pre-training	ArXiv 2017
	Chen et al. [10]	Dual DCNN, feature fusion, iterative training	BSPC 2019
	Wang et al. [11]	Text aided, multilevel attention models	CVPR 2018
	Chen et al. [12]	Label co-occurrence learning, GCN	JBHI 2020
	Yao et al. [13]	LSTM, leverage interdependencies among labels	ArXiv 2018
	Gündel et al. [14]	Robust loss function, multi-task learning	Med Image Anal 2021
	Wang et al. [15]	Attention mechanism, weakly supervised learning	JBHI 2020
	Liu et al. [16]	Segmentation guided learning, two-branch network	ArXiv 2018
	Zhang et al. [17]	Mask guided learning, multi-granularity feature	Entropy 2021
	Report [18]	Attention gated network, multi-attention	2021
	Ma et al. [19]	Cross attention, multi-label balance loss	MICCAI 2019
	Wang et al. [20]	Triplet attention, multi-scale ensemble classification	Med. Image Anal 2021
	Huang et al. [21]	Multi-attention, Top-k pooling	ITAIC 2019
	Ma et al. [22]	Feature and space attention, hard example attention	ICASSP 2019
	Guan et al. [23]	Three-branch attention guided network, feature fusion	ArXiv 2018
	Guan et al. [24]	Residual attention,	PR Letter 2020
	Wang et al. [25]	Visual attention, weakly supervised learning	ArXiv 2018

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Table 1. (continued).

Semi-supervised	Rivero et al. [28]	Semi-supervised learning, graphs, transductive learning	MICCAI 2019
	Liu et al.[29]	Sample relation modelling, self-ensembling model	TMI 2020
	Liu et al.[30]	Self-supervised mean-teacher pre-training	ArXiv 2021
UDA	Zhang et al. [36]	Invariant representation learning, cross-domain TDC	PR Letter 2022

2.1. Supervised thorax disease classification

2.1.1. Thorax disease classification via global feature. Using the Convolutional Neural Networks (CNN), researchers have continually refined the image classification performance using since the 2012 ImageNet challenge [37]. In addition, CNNs have been widely used for different tasks because of their generality and good performance. They have been seen as a useful tool to automatically learn feature representation from the input image. For the supervised TDC problem, most existing works directly leverage off-the-shelf CNN models to capture global information from whole CXR images. Different network architectures have been investigated for the TDC problem. For example, [6] leverages AlexNet [38], VGG [39], GoogLeNet [40], and ResNet50 [41] to learn global feature representations. First, the ImageNet dataset is used to pre-train the backbone networks, which are then combined with a transition layer as well as a pooling layer and a fully connected layer to build the TDC models. Third, the CXR datasets are used to fine-tune these TDC models. [9] designs a new CNN architecture named CheXNet, which is a 121-layer network and obtains significant performance. In addition, CheXNet outperform expert radiologists on ChestX-ray14 dataset [6]. [10] designs a two-branch network to learn complementary feature representations. According to the assumption that different thorax diseases contain intrinsic correlation, several works [12, 13] have exploited other DNN architectures to capture the correlation of different thorax diseases. For example, [12] introduces Graph Convolution Networks (GCNs) into feature representation learning. [13] adopts LSTMs to capture correlations among different disease classes. It is well known that pooling layers inside the CNN architecture serve to summarize small patches of the layer below. Since abnormal CXR images contain tiny lesions, the use of pooling layers may lead to losing the detail features thus deteriorating the TDC accuracy. To address this problem, [8] brings the auto-encoder into the CNN architecture to learn detailed features without down-sampling the resolution of input images. Aiming to learn feature representation with auxiliary information, there are some attempts [11, 14] to introduce multi-task learning into the TDC problem. For example, [11] introduces the radiological reports and proposes a TieNet to fuse image features and text embedding. More recently, [14] trains a TDC model by using the semantic segmentation task as a regularization term.

2.1.2. Thorax disease classification via global and local feature. As we mentioned earlier, when a CXR image has some specific diseases, it often contains tiny lesions. A CXR image mainly contains lungs, heart, and other organ tissues, where some local regions belonging to specific organs may have tiny lesions. Therefore, aiming to learn local features for TDC, several methods have been reported [15-17], learn feature representation from local regions of input images. Among these approaches, designing a multi-branch network is a common solution to extract complementary global and local features. For example, [15] designs a CNN with 2 branches, in which one branch network is adopted to learn global representations while another local branch network is adopted to extract local features from a local region. In the training stage, the heatmaps is used to guide the multi-granularity feature representation learning. [16] investigates the scheme of learning the global and local feature representations in a similar way. The difference is that it first generates the lung regions by a semantic

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segmentation network and then obtain local features from the cropped regions. Guan et al. [23] first adopt a global CNN branch to capture global features from whole CXR images. Then, they generate a local patch guided by the heat map produced from the global branch. Third, a local CNN branch is adopted to learn local representations from the cropped local region. Lastly, a fusion branch is designed to concatenate the output features of both the global and local branches for TDC. Very recently, [17] proposes to automatically attend to local regions within different organs. In addition, they adopt multi-task learning in the training stage to avoid introducing extra computation in the testing stage.

2.1.3. Thorax disease classification via attention mechanism. Recently, the attention mechanism has become prevalent in TDC problem. [18] first adopts a pre-trained ResNet followed by a space attention module to extract attentive features. The original CNN features are then fused with the attentive features for TDC. Additionally, an attention-gated module is applied to 2-th and 3-th residual modules of ResNet, which aims to refine the learned feature representation. [19] first extracts features by using two independent feature extraction networks. Then the above features are fused by a cross-attention module to generate more meaningful representations. [20] adopts the backbone of DenseNet [42] to extract features, and designs 3 different attention models to simultaneously refine the extracted features. [21] designs a multi-attention-based CNN architecture that generates multi-attention maps corresponding to the disease categories. In particular, each attention map contains multiple types of features belong to a specific disease class. [22] also designs a multi-attention-based CNN architecture for TDC. This framework contains a space attention, a feature attention as well as a hard example attention. Recently, [17] designs an attention model for multi-granularity feature representation learning. Specifically, a soft attention is added to the 2-th and 3-th block of ResNet50 to refine the learned features progressively. Then it uses an attention model guided by an organ mask to find discriminative regions and features in corresponding organ region.

2.2. Semi-supervised thorax disease classification

2.2.1. Related works. In recent years, semi-supervised learning has been widely used for medical image analysis. For the TDC problem, there are several works [28-30] that have been reported to use a semi-supervised learning paradigm to optimize DNN models. For example, [28] adopts a graph model to construct the correlation between the labeled CXR images and the unlabeled CXR images. Aiming to leverage unlabelled CXR images, [29] presents a new paradigm to construct the correlation among different images, which is named sample relation consistency. Specifically, aiming to guide the learning to capture extra feature representations from unlabelled images, it explicitly applies the consistency regularization among different CXR images under different perturbations. [30] adopts the mean-teacher scheme for the TDC problem.

2.3. Unsupervised domain adaptative thorax disease classification

2.3.1. Related works. To improve the usability of features learned from the labeled source dataset, UDA [31] has been wildly studied in feature presentation learning. Different works have been reported to mitigate the domain shift by using different losses [32-34]. In recent years, several works [27, 36, 43] have been reported to bring UDA into medical image analysis. However, to the best of our knowledge, only one paper has brought UDA into TDC. [36] presents a UDA method for cross-domain TDC. Specifically, a pre-trained ResNet50 is adopted to learn discriminative features with the help of source labels. In addition, three different invariance constraints are aplied to comprehensively guide the network to further learn discriminative and invariant features.

3. Conclusion

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Thorax disease classification is one the most challenging task for medical image analysis system with a wide range of application in daily clinical examinations. It has been widely studied in recent years due to its importance. On the other hand, TDC remains an open research challenge since it is difficult to distinguish between normal and abnormal CXR images even for doctors. In this survey, we reviewed the recent deep learning based approaches for thorax disease classification (TDC) tasks from 2017 until 2022. We have shown the advantages as well as limitations of different learning paradigms for CXR image feature learning, including supervised learning based methods, semi-supervised learning based methods and unsupervised domain adaptation based methods. We have shown different backbone networks for CXR image feature extraction. In addition, we highlighted the latest and most widely used datasets in TDC task, including ChestX-ray14 and SYSU. Further, the comparisons between the above two datasets are also presented, which contains the data size and the distribution of 14 disease labels.

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