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A Deep Learning Technique for Chest Radiograph - based Pneumonia Prediction

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***Abstract*— Pneumonia, a treatable illness, is a leading cause of death. It is crucial to quickly identify pneumonia in order to provide timely intervention. The use of automated diagnosis for pneumonia can greatly improve patient outcomes. However, developing accurate deep learning models for this purpose is challenging because of limited availability of well annotated training dataset. A new technique called deep supervised domain adaptation has been proposed for diagnosing pneumonia using chest x-ray images. The DSDA approach utilizes knowledge from a publicly accessible dataset called ChestX-ray14 and transfers it to a smaller, well-annotated dataset. DSDA guarantees efficient knowledge transfer by lining up the distributions of the source and target domains according to the underlying semantics of the training samples. Two sub-networks—one for the source domain and one for the target domain—are used in the process. Both sub-networks share feature extraction layers and undergo extensive training. This method, in contrast to standard domain adaptation methodologies, focuses on knowledge transfer from a source domain multi-label classification problem to a target domain binary classification task. The proposed technique is evaluated against various existing methods to assess its accuracy. The outcomes demonstrates DSDA method achieves promising performance in automating pneumonia diagnosis. In conclusion, this scholarly article introduces the DSDA method for automated pneumonia diagnosis using chest X-ray images. By effectively transferring knowledge, the proposed method shows potential in improving the accuracy of pneumonia diagnosis.**

***Index Terms*— Deep learning, automated diagnosis, Pneumonia prediction, Transfer learning**

I. INTRODUCTION

Within the realm of digital healthcare, researchers have actively delved into leveraging algorithms for automated diagnosis of diseases. The accomplishments of deep learning in various practical contexts have served as a catalyst for these pursuits. Tang et al. conducted a study where they investigated the utilization of various deep learning models to distinguish abnormal cases in chest X-ray images. Their aim was to assist medical professionals in identifying potential lung abnormalities. In a similar vein, Pan et al. evaluated the effectiveness of deep learning models in categorizing chest X-ray images as either normal or abnormal across different datasets. On the other hand, Stephen et al. introduced a convolutional neural network model that was specifically designed for the classification and detection of pneumonia. In contrast, Liang et al. focused on introducing a transfer learning

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framework to improve the performance of the model in the context of childhood pneumonia detection. Additionally, several other studies have explored the use of modality-specific transfer learning for the analysis of chest X-ray images. The sample images are depicted in figure 1.

In specific domain of chest X-ray (CXR) analysis, researchers have developed deep learning models to address the challenges in this area. An example of a comprehensive CXR database is ChestX-ray14, which has been curated by Wang et al. Pranav et al. introduced ChexNet, a 121-layer convolutional neural network-centered deep learning model that directly identifies lung diseases from unprocessed images. Surprisingly, ChexNet has exceeded the performance achieved based on the F1 score. Guendel et al. introduced a creative technique that combines high-resolution image data with spatial information to diagnose abnormalities, building upon the concept of location-aware Dense Networks (DNetLoc). These advancements in deep learning methods for analyzing medical images, specifically in the domain of chest X-rays (CXRs), offer great promise in improving the accuracy and efficiency of radiology diagnostics.

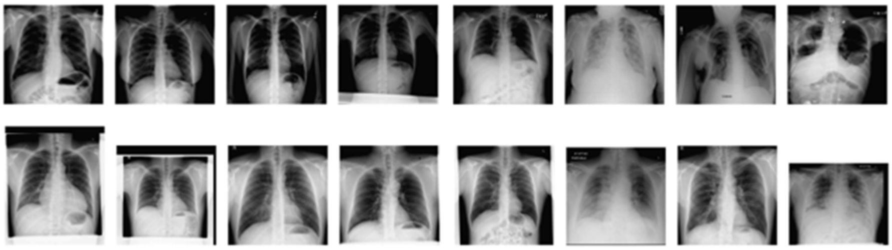

Fig 1. The pneumonia x-ray images present in the dataset.

Although the above methods are renowned for their exceptional performance, they usually necessitate a vast data with dependable ground truth for efficient performance. Regrettably, several establishments encounter difficulties in acquiring such datasets. However, this approach may not work well when there are differences in data distributions between the two domains, leading to difficulties in knowledge transfer. When with multiple labels binary, it is possible for the transferred information to contain more noise than useful signal. To address this issue, a new neural network has been developed that is specifically designed to transfer knowledge between heterogeneous tasks. Within this network, there are two distinct sub-networks, each serving a different purpose. One sub-network manages the source domain, focusing on multi-label classification, while a separate sub-network exclusively handles the target domain, dedicated to binary classification. By using this approach, we can overcome the domain shift issues that arise when using deep learning algorithms on datasets with different visual characteristics.

II. Related Work

Pneumonia constitutes a infection induced by various pathogens, and other microorganisms [1-3]. The advent of COVID-19, has led to worldwide pandemic, encompassing over 185 million verified cases and surpassing 4 million fatalities internationally [4-8]. Early identification and prompt medical intervention for pneumonia have the potential to significantly decrease the mortality rate linked to COVID-19.Imaging techniques such as chest radiography, CT, and USG are commonly used for diagnosing pneumonia, with chest radiography being a widely available and cost-effective method [9-14]. Typically, a thorough assessment and examination of chest X-rays conducted by skilled radiologists is required to identify this condition. The use of computer-assisted methods can enhance the accuracy and efficiency of the diagnostic process, reducing the chances of human error and fatigue.

III. Proposed Method

A. Problem Formulation

Our study endeavors to enhance the effectiveness of the model's application scope through the utilization of knowledge acquired [15-17]. The dataset, denoted as X_s, comprises ns samples. The label vector y_s is a binary vector of length C_s, which represents the categories to which X_s belongs. In the case where X_s is classified under the jth category, Y_s is assigned a value of 1; otherwise Y_s is assigned a value of 0.

B. Framework of DSDA

The primary goal of our methodology is to effectively detect pneumonia within the designated dataset by utilizing the insights obtained. One sub-network is tailored explicitly and other focuses on the binary classification task. Both sub-networks leverage common feature extraction layers from the classification model, employing ResNets [18] and DenseNets [19,20]. Our proposed domain adaptation model, depicted in Figure 2, incorporates these task-specific sub-networks. The initial sub-network concentrates on distinguishing among many diseases, encompassing pneumonia. Meanwhile, the second sub-network aims to differentiate between images depicting pneumonia and those that do not within the desired one. The DSDA model employs to convert samples into a unified space, acquiring features. It's crucial note that the model deliberately aligns with the domains, considering their intrinsic semantics. This alignment ensures that samples from the same class are close together, regardless of their domain, while samples from different classes are far apart. The proposed model differs from the pre-training strategy as it actively learns discriminative features by leveraging knowledge from both domains, thereby enhancing its overall performance is depicted in figure 2.

C. Objective Function

To ensure identification of pneumonia, proposed technique focuses on minimizing the objective function, which is formulated as in equation (1) as follows:

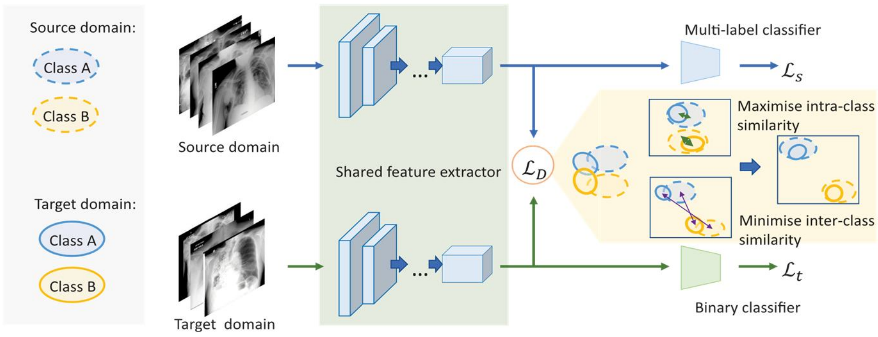

Fig 2. The proposed architecture.

$$L(X_s, X_t, Y_s, Y_t) = L_t + \lambda_1 L_s + \lambda_2 L_D \quad (1)$$

In our model, the encompassing parameters are denoted by Θ, which comprise of the weights and biases. The classification losses observed represented by Ls and Lt, respectively. Additionally, the domain adaptation loss is denoted by LD. The hyper-parameters λ1 and λ2 are utilized to maintain a harmonious equilibrium among the contributions of these three terms. Detailed elucidation regarding the specific characteristics will be presented in the subsequent sections

1) Target domain classification loss:

A proposed technique aims to tackle the problem of class imbalance in the dataset by enhancing the weighted cross-entropy loss (WCEL) for the classifier. By evaluating the WCEL for each sample in the training dataset, we can effectively overcome the challenges posed by the uneven distribution of the data.
To address the uneven distribution of classes within the target domain dataset, our approach emphasizes optimizing the approach. By calculating WCEL, each individual in the training dataset, we are able to effectively overcome the challenges posed by the imbalanced nature of the data.

2) Source Domain Classification loss:

To improve effectiveness of multi-label classifier, employ the BCEWithLogitsLoss. This particular loss function with the BCE Loss for every class. When dealing with an individual sample within the training dataset.

3) Domain Adaptation Loss:

To ensure domain adaptation, we incorporate a domain adaptation loss.

D. Implementation Details

The study's model incorporates either ResNets or DenseNets' convolutional layers as the backbone. Within the source domain sub-network, an augmentation is made by introducing. The neural network is composed of two sub-networks: the source domain sub-network and the target domain sub-network. The source domain sub-network has a fully connected layer with 14 neurons and a linear activation function. On the other hand, the target domain sub-network has a separate fully connected layer with 2 neurons and a Softmax activation function.To initialize the weights of the feature extractor, a pre-trained ImageNet model is used. The network is trained end-to-end using the Adam optimizer with default parameters. A batch size of 32 is used, along with a learning rate of 0.0001. Additionally, regularization parameters $\lambda 1 = 0.5$ and $\lambda 2 = 0.5$ are applied. The model undergoes 20 epochs of training. The highest achieved AUC score on the validation set is used for testing purposes. The training is performed using the PyTorch framework and is accelerated by two NVIDIA Titan XP GPUs.

IV. Experimental Study

The experiments used the ChestX-ray14 dataset as the source dataset and our exclusive TTSH dataset as the target dataset. To assess the effectiveness of the DSDA method, comparisons were made against conventional machine learning techniques, deep learning methods designed for CXRs, and various state-of-the-art domain adaptation methods. The evaluation process aimed to measure the importance of gaining knowledge from the multi-labelled source domain and analyze the impact of using different transfer strategies.

A. Datasets

The TTSH dataset, acquired from Tan Tock Seng Hospital in Singapore, was utilized in the study and comprised a total of 4185 CXRs. A proficient radiologist with extensive expertise meticulously examined each CXR, categorizing them into either pneumonia or non-pneumonia groups. To facilitate further analysis, the dataset was partitioned into three subsets. The ChestX-ray14 dataset, an extensive public repository of CXRs, encompasses 112,120 frontal-view X-ray images obtained from 30,805 patients. This dataset, carefully curated by the NIH, is segregated into training, validation, and test sets, thereby offering a valuable resource for researchers and medical professionals. Each image within this dataset is associated with a maximum of 14 distinct labels, specifically designed to address multi-label classification challenges. The RSNA dataset, which is a subset of ChestX-ray14, specifically focuses on pneumonia detection and serves as an augmented dataset for classification and detection purposes is depicted in the table 1 .

TABLE I. The Dataset Description

Category	n_{train}	$n_{validation}$	n_{test}
Non-pneumonia	2,115	302	604
Pneumonia	825	117	222
Global	2,940	419	826

B. Methods Comparison

Unsupervised domain adaptation methods such as MDD, CDAN, and DAN, have also been compared in this study. The objective of these techniques is to leverage the label information present in the target dataset, which has demonstrated encouraging outcomes in enhancing the efficacy of conventional approaches. Nevertheless, it is crucial to acknowledge that all the domain adaptation methods that were compared necessitated the classifiers of both the source and target datasets to possess identical architecture is depicted in figure 3.
For traditional methods, two types of features were extracted: local descriptors over the ORB feature using the BoW method and CNN-based features using the feature extractor of DenseNet121. These methods were compared with six traditional methods, including SVM, LDA, decision tree, logistic regression, adaBoost classifier, and random forest.

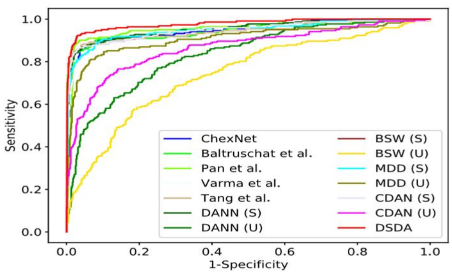

Figure 3. Model comparison and results

In conclusion, this study highlights the importance of utilizing deep neural networks for accurate pneumonia diagnosis from CXRs. Superior performance has been observed in deep X-ray methodologies and domain adaptation techniques when compared to traditional methods. Therefore, it is imperative to conduct further research in this area.

Supervised variations of domain adaptation techniques have demonstrated remarkable performance, even in the absence of label information in the target data. MDD (U), CDAN (U) and DANN (U) have exhibited AU C scores surpassing 83.3%, with MDD (U) achieving an impressive score of 90.96%. The significance of domain adaptation methods is highlighted by these results. However, when label information is available in the target dataset, domain adaptation techniques show even greater improvement. DANN, BSW, MDD, and CDAN achieve notable enhancements ranging from 3.89% to 20.63%. It is important to acknowledge that the performance of domain adaptation methods is adversely affected by the existence of noisy labels in the source domain. Our suggested approach outperforms other methods by a considerable margin, possibly because it can effectively utilize knowledge transfer across various tasks and handle multi-label classification tasks. The ROC curves depicted in Figure 3 clearly demonstrate the superiority of our DSDA method over other techniques, including deep X-ray methods and other domain adaptation approaches.

V. Conclusion

DL models possess the capability to acquire knowledge that can be applied across different domains and tasks. Nevertheless, the challenge of domain shift arises when models trained on one dataset struggle to perform well on another dataset. To tackle this issue, domain adaptation methods have been developed to reduce differences in domains in terms of features. This study introduces a novel conceptual framework that enables the transfer of knowledge from a widely available dataset to a smaller or medium-sized dataset by aligning samples based on their inherent semantics. Unlike traditional pre-training methods, this approach iteratively integrates samples. The empirical results obtained from the X-ray dataset strongly support the effectiveness of this approach in enhancing the model's performance. While CT scans have been employed for COVID-19 diagnosis, chest radiography remains a more prevalent choice settings, Particularly in healthcare systems with limited resources, the effectiveness of CT scans in diagnosing COVID-19 is still uncertain. As a precautionary measure to minimize the risk of transmission within hospitals, chest radiography is favored. However, there have been recent findings suggesting that deep learning models can be helpful for automated identification of covid pneumonia from chest xrays. This advancement holds great potential for enhancing clinical practice.

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