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INTERSTITIAL LUNG DISEASES USING HIGH RESOLUTION COMPUTED TOMOGRAPHY (HRCT) IMAGES

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***Abstract*—** In the past decade years, medical image technologies have been rapidly growing. The x-rays, ultrasound (US), MRI scan and CT scan are the piliminary techniques to examine human diseases and CT techniques have more resolution images compared to other techniques. HRCT is another advanced technology derived from the CT familyand working in 3D to capture the images. HRCT techniques are used to examine all humankind problems like heart, brain, breast, lung, kidney etc. The diagnosis accuracy depends on expert doctors, radiologists or pathologists and wrong judgment leads to wrong treatment or diagnosis. To overcome this, introduce computer-based technology instead of manual operation because of its more efficiency, accuracy and achievedby transfer learning methods, reviewed by the end of the chapter.

***Keywords*—** interstitial lung disease (ILDs), High Resolution Computed Tomography (HRCT), Computed Tomography (CT), quantitative analysis, Convolution Neural Network (CNN), computer aided detection (CAD).

I. INTRODUCTION

Medicine is derived from science, evaluates all humankind's problems, and is directly related to human quality of life and health conditions. Medical-based researchwas supported by the analysis of medical images. Before going to diagnosis, a large amount of research (in terms of research) was conducted in the laboratory [2].

Day-to-day development of medical technology has led to a variety of medical images emerging. The commonly available methods that are available nowadays are Magnetic resonance imaging (MRI), X rays, Computer tomography (CT), and Ultrasound (UT) [1]. The first technique used in medical imaging is X-rays. They are simple to examine, and the cost is lower. Compared to all the techniques, CT provides higher density, higher resolution images, but it depends on the doctor's skill. These two techniques are harmful to the human body and should not be used too often[3]. MRI does not emit radiation and provides a clear image,but it takes longer to investigate, and some patients may suffer due to the longer time it takes to investigate the patients [2-4].

High-resolution computed tomography (HRCT) image is an advanced technology used to capture images in 3D technology and is driven by the CT family, to enhance imageresolution. The spatial resolution method is used to enhance imaging parameters, and the speed of the scan is also enhanced to minimize the size of each pixel. All the techniques have their own characteristics, and the doctor needs to prefer one based on a patent diagnosis.

The transfer learning-based methods are non-invasive class- type techniques, not harmful to the patient's system andapplied to several parts of the human body, such as the brain,lung, kidney, heart, etc. This type of medical analysis is doneby an expert doctor’s team to identify the problem, and a wrong judgment will lead to a wrong diagnosis. To overcome this, scientists and doctors are studying and performing research to introduce computer-based technology instead of manual operation because of its more efficiency and accuracy. The

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growth of the transfer learning method is shown in Fig.1, and data is taken from the web of science journal on transfer learning methods.

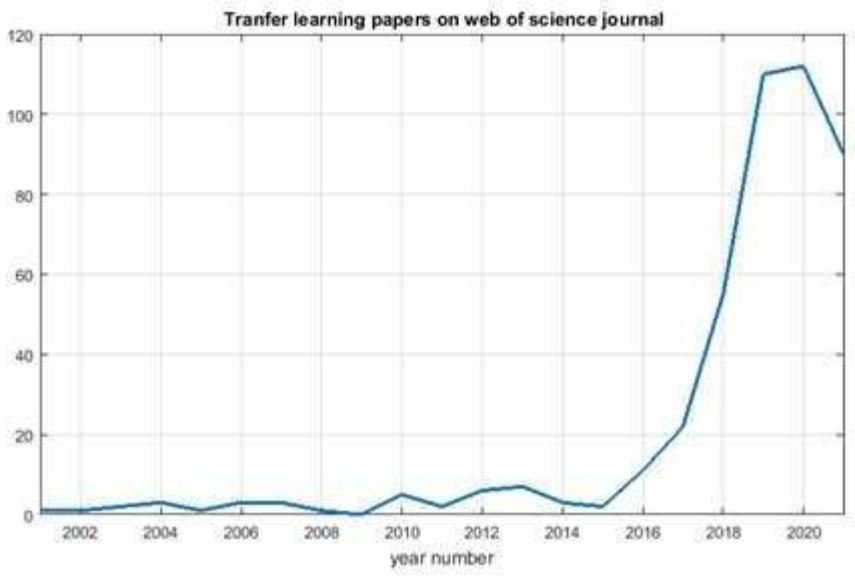

Fig .1: papers published on web of science journals on transfer learningmethods

In this manuscript, a high resolution computed tomography (HRCT) image is described in Section 2. The review of interstitial lung diseases (ILD) is explored in Section 3. Section 4 will give a little overview the Finally, Section 5 gives a clear overview of this review paper that is conclusive and followed by references.

II. HIGH RESOLUTION COMPUTED TOMOGRAPHY

HRCT image is a cutting-edge CT technique that collects images in 3D to improve image clarity by improving image resolution. It makes use of the spatial resolution concept to increase scan speed by reducing pixel size. HRCT images can reveal disease features and use visual patterns to aid in differential diagnosis and narrowing [5].

HRCT's impact on clinical care can be seen in the reduction in the need for surgical lung biopsy, and In 2002, the ATS/ERS consensus statement established a diagnostic approach [6] and more recent evidence-based clinical practice guidelines for diagnosis and management [7-8]. Even when the HRCT scans lack the precise characteristics that suggest fibrosis, cellular infiltration, and architectural distortion with honeycombing that is characteristic of a process like UIP. HRCT is still a valuable non-invasiveapproach for revealing aberrant parenchymal densitiescaused by microscopic morphological changes [9–15]. It canprovide direction for the best spot to get a biopsy of acharacteristic or active disease [12].

Correspondingly, Widely acknowledged that the level ofvisual-abnormalities correlates with the extent of pathogenic participation as well as the brutality of physiologic abnormalities [16], and hence longitudinal-HRCT image is suitable to monitor the therapy response and disease progression [17–19]..

III. INTERSTITIAL LUNG DISEASES

The ILDs are developed jointly by the European Respiratory and the American Thoracic Society and fall into a heterogeneous group, resulting in various forms of lung disorders [20], and ILDs classifications are shown in Fig. 2 [20-23, 27]. The lungs are blocked for inhalation in ILDs, which are classified as pulmonary illnesses such as emphysema and COPD. In some circumstances, the patient isunable to take a full breath due

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to a blockage of airflow in their lungs. ILDs are also caused by pollution in the environment [21, 24-25]. Some cases of ILD do not satisfy the particular definitions for any ILD and are thus classified as 'unclassifiable' [26].

Radiologic examination by high-resolution computed tomography (HRCT) has become more important in defining and classifying ILD. The characteristic imaging features may be diagnostic for several pathologic conditions, including idiopathic pulmonary fibrosis (IPF) and typical interstitial pneumonitis (UIP). Radiologic evaluation's capacity to distinguish between diseases such as UIP, which has an associated mortality of approximately 75% five years following diagnosis, and other diseases with a less alarming prognosis has been critical inpatient care [28]. Several other interstitial lung diseases (ILDs), including non-specific interstitial pneumonitis, desquamative interstitial pneumonitis, acute interstitial pneumonitis, hypersensitivity pneumonitis, respiratory bronchiolitis associated interstitial lung disease, lymphoid interstitial pneumonia, and cryptogenic organizing pneumonitis, can all have distinct HRCT features. These separate disease processes, on the other hand, may share a clinical phototype and can have indeterminate radiographic and pathologic manifestations. Furthermore, some individuals, such as those with combined pulmonary fibrosis and emphysema syndrome[29], can have both restrictive/fibrotic and destructive/obstructive processes,which can confound physiologic testing and cause biopsy results to fluctuate widely depending on the location of sampling. The fundamental clinical problems of detecting, characterizing, and differentiating the many ILDs continue tobe diagnostic hurdles. Nonetheless, each of the major ILD and mixed parenchymal illnesses has a markedly different prognosis and treatment options [30], and it is becoming increasingly obvious that targeting a specific pathogenic process will be critical for modifying the development of these often incurable diseases. Someother ILDs are nonspecific interstitial pneumonitis, hypersensitivity pneumonitis, desquamative interstitial pneumonitis, acute interstitial pneumonitis, respiratory bronchiolitisassociated interstitial lung disease, lymphoid interstitial pneumonia, and cryptogenic organising pneumonitis, can all have distinct HRCT features. A same clinical phenotype can be seen in both the pathology and the radiological findings of several distinct disease processes.

ILD's complex morphological patterns, which might alter magnitude and appearance over time, can be difficult toassess. Similarly, manual classification and evaluation ofextent are time-consuming and unreliable. The diagnosis of ILD is hampered by high inter-and intra-observer variation [31-32]. Even if advances in imaging technology or a physician's training can improve his or her ability to accurately describe and characterise the disease, there are still inherent differences in interpretation, perception of visual disease features, and reader error that may not be overcome [33-35].

Furthermore, the final clinical diagnosis of ILD has beendemonstrated to vary depending on the expertise and experience of radiologists, clinicians, and pathologists working individually or in the multidisciplinary evaluation of disease, even in a well-controlled experiment with clearly defined individuals. These discrepancies are much more common in real world patient care provided by academic andcommunity health center physicians from various specialties [36]. Even if a diagnosis is reached by the consensus of several specialists and the application of methodologies for continuous learning, these do not guarantee reliable outcomes[37].

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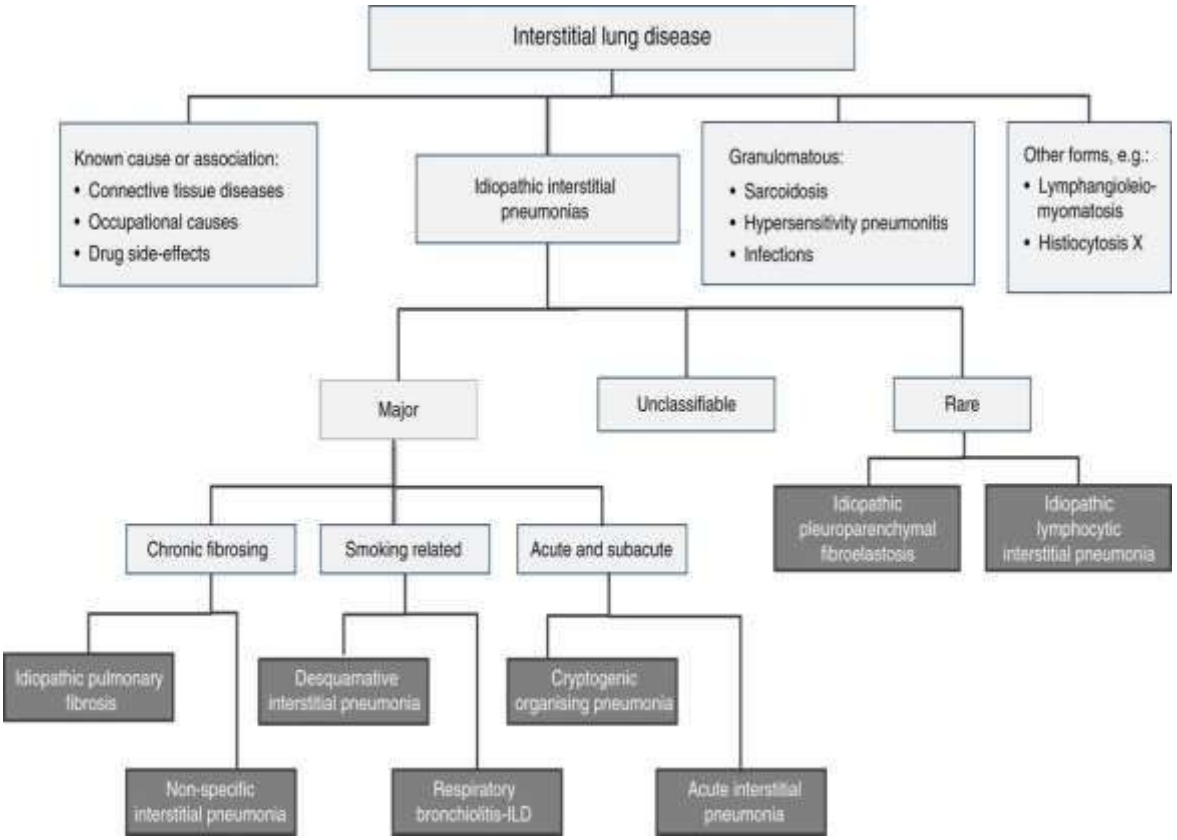

Fig 2. ILDs classification

Variability in clinical assessment of ILD presents an opportunity for automation, computer-aided detection, and quantitative picture analysis. Specifically, there are opportunities to maximise the identification of abnormalitiesrecognised to indicate pathogenic alterations on HRCT and to enable reproducible quantification and characterization of ILD symptoms by utilising existing image processing technology on CT data. These quantitative findings have thepotential to be used as biomarkers, resulting in more consistent diagnosis, more sensitive disease monitoring, and more accurate prognosis determination [38]. Over the last several decades, numerous efforts have been made to robustly identify observable patterns in chest CT scans and x-rays using a variety of different methodologies. As a general rule, the evaluation of data from certain early texturebased analysis is the same: "interstitial lung disease is difficult to classify and quantify, and even expert chest radiologists frequently struggle with differential diagnosis. Automated systems that identify the percentage of afflicted lungs or the likelihood of developing a certain disease would undoubtedly be beneficial, but would require significantly more research " [39].

Fortunately, quantitative approaches for assessing the severity of emphysema and other aspects of COPD on CT images have become additional tough over last two decades, as numerous techniques have evolved and been optimised. These quantitative analytical results may be useful as biomarkers for diagnosing COPD symptoms, monitoring thedisease development, and predicting prognosis [40].

As a result, quantitative CT-based assessments of lung fibrosis have proven more difficult [37–40] and have shown less promising results. The simple methods are whole lung histogram analysis or first-order features based on density masks, pixel counting, multiple higher order features or texture methods and even more so phisticated classification- techniques such as continuous learning with physician in theloop are only partially successful in evaluating specific diseases and even determining normal vs. abnormal regions [41-43]. Additionally, many of the approaches now utilised to evaluate ILD interms of research are computationally

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intensive and require hours or even days of processing. Due to these practical constraints, it is difficult to translate those ideas into everyday clinical practise..

IV. TRANSFER LEARNING

It is incredibly expensive and difficult to maintain and develop a database on medical images. As a result, maintaining the sample data is difficult, and Another approach is to learn from previous tasks before moving on to new ones. This is accomplished by transfer learning, which initializes the target from the existing source domain. The generalized diagram of transfer learning is given in fig.3, and the most widely used transfer learning methods are instant based, parameter-based, feature relying, and relation based.

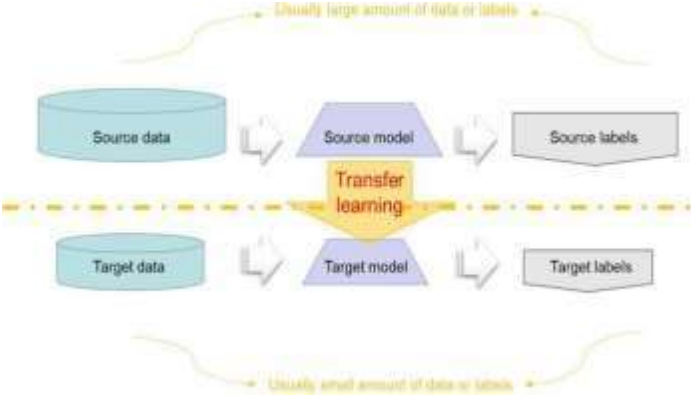

Fig. 3. Working principle of transfer learning

✓ **Instant based Transfer-learning**

This procedure is similar to filtering through the data in the source domain to find the most relevant information for the destination domain and matching it to the target domain. This strategy downside is more empirical, unstable and doesnot always have a subset of data in the source domain that isextremely similar to the destination domains.

✓ **Parameter based transfer learning**

When retraining, use parameters from the source domain as initialization and give them more weight. Using a pre- trained model, it is much easier to train new neural networksat a high pace than it is to start from scratch

✓ **Feature relying transfer learning**

Table 1. Transfer learning method on lung disease

Ref. No.	Disesase Name	Transfer Method
[44-45]	Lung CT/ Diffuse lungdisease	Fine-tuning
[46-49]	Lung CT/ Survival predictionof lung adenocarcinoma VGG / Lung Lesion / lung cancer prediction	Feature extractor

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[50]	Pulmonary nodule classification	Finetuning on ResNet
[51-55]	Lung nodule classification /Lung cancer prognostication	Feature extractor
[59]	Lung cancer	Feature extractor
[56-58]	Lung-nodule classification	Finetuning on DenseNet / Fine-tuning on GoogLeNet / VGG-16as feature extractor
[60-63]	Lung-nodule detection	Finetuning / Fine-tuning on VGG-16 / Fine-tuning on LeNet-5 / Extreme learning applied after feature extraction

The extracting low level feature using CNN was introduced by christodoulidis et. al [46] and used six public texture databases. The CT scanning image database is used in this model and increases the accuracy by 2%. Paul et al.

The premise behind this method is that the two domains those are target and source domain can share some overlapping properties. Using feature transformation, may combine the two domains into a single space. As a result, we may apply machine learning to complete the remaining tasks. The strength of the method is to work effectively, but the weakness is frequently not easy to compute.

- ✓ **Relation based-transfer learning.**

Here, the source and destination domains are compared to find the logical relation between them to share some kind of information. The center concept of this method is the attempt to transfer logical relationships from the source-domain to the target-domain.

The table 1 reveals the data of transfer learning methods applied to lung disease. In the source domain, Sawada et al.[44] introduced the concept of multi-prediction deep boltzman machines to satisfy database requirements and convert them into tuned networks. The x-ray images to identify the lung disease are based on the concept of fine tuning. Shuouno et. al [45] used a deep convolution network, which is a pre-trained network, applied to nonmedical images to extract lung diseases. Better performance is achieved by training the natural images first and then applying the transfer learning method to HRCT images. [47] extract deep features of lung diseases using a pre trained CNN network, and different classifiers are used to achieve the most excellent results in predicting the survival- time of humans with lung diseases. The doctor andresearches are finally conclude that, transfer learning methods is better solution to extract the deep features on lung images [48-50].

The hussein et. al [51] proposed model for lung nodule recognition and the model used here is a three-dimensional CNN network, which acquires the deep features more efficiently. This method is first pre trained on nonmedical images before applying it to CT images. Transfer learning methods are popular nowadays to extract the features inlung images [52-55]. Dey et. al [56], Fang et. al, Nishio et. al introduced algorithms like Dense-Net, Google-Net, and VCG-16 feature extractor for lung nodule classification, andthree

dimensional CT scan images are used in these models.

V. CONCLUSION

In this paper, reviewed the classification of Interstitial Lung Diseases using HRCT images. Firstly, we will discuss the overview of general imaging techniques like CT scan, MRI etc. HRCT is one class of the CT family and provides a higher resolution image because of 3D capturing. The accuracy of the diagnosis depends on expertise in that field, which otherwise leads to the wrong judgment of diseases. To avoid that, transfer learning methods were introduced, predicting the target domain from source data. These can be varied by instant-based or parameter based or feature-based or relation based and finally ended with a discussion of different transfer learning methods used in lung diseases. Furthermore, extend this work with pixel mapping for feature extraction and then followed by transfer learning techniques for better accuracy.

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