A robust deep learning method for radiation induced pulmonary fibrosis disease classification in lung CT-a review

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***Abstract*—A chronic lung condition called pulmonary fibrosis damages the tissues of the lungs by inflaming, scarring, thickening, and hardening them. This uses CT images, which have the potential to be more effective than X-rays. In order to accurately segment the PF lesions for diagnosis and treatment monitoring, CT is crucial in the observation of lung fibrosis brought on by radiation (PF). The work is complicated by the lesions' varied positions and sizes, uncertain boundaries, irregular shapes, and the difficulty of obtaining a sizable collection of volumetric images with annotations for learning. A deep learning model is what we describe in implementation with Framework for semi-supervised learning with iterative confidence-based refinement and weighting of fictitious labels (I-CRAWL) to tackle these problems. Image pre-processing, segmentation, feature extraction, and classification are steps in the process. A number of augmentation and fragmentation approaches are used to produce more accurate results. Based on the classification of the pictures using classification algorithms, the disorders in the CT images were identified.**

Keywords— Pulmonary fibrosis, Image Processing, Feature extraction, Enhancement, Lung CT, Input Image, Pre-processing, Classification, Performance Estimation.

I. Introduction

The usage of image processing methods has increased significantly in the medical field in recent years, allowing for early disease identification and treatment in situations when it is crucial to find the patient's disease as soon as feasible. The likelihood of a successful treatment is considerably increased by early identification. The process of applying different techniques to an image in order to enhance it or extract useful information from it is known as image enhancement or image processing. It is a method of signal processing in which an image serves as the input, and the output may be another image, attributes, or characteristics associated with the input image. One of the technologies that is growing significantly right now is image enhancement. It is a key area of study in both the fields of engineering and research domains. Basically, image enhancement involves the ensuing three actions:

Employing image capturing software to import the image;
Modifying the image after analysis;
Producing a report or altered image as a result of the analysis.
There are five categories for image processing goals. As follows:

1. Visualization - Pay attention to intangible objects.
2. Image restoration and sharpening - To improve the image reliability.
3. Image extraction - Search for the desired image.
4. Sequence Analysis- Measures several objects in an image employing numerous pattern.
5. Image Recognition- Identify the components in an image using image classification, etc.

When lung tissue is injured and destroyed, pulmonary fibrosis is a lung autoimmune disease that occurs. Successful treatment of PF lesions depends greatly on early identification. CT images are mostly used in diagnosis. The process's primary goals are to identify abnormalities in the input and to enhance fine segmentation. to increase the classification process's accuracy.

II. Materials and Method

The classification of pulmonary fibrosis utilizing texture analysis, machine learning, and deep learning has improved in PF lesion detection to a higher extent in early diagnosis, according to a literature review that was conducted. a number of online resources and libraries, including IEEE, ResearchGate, SCOUPS, and MDPI. By utilizing a variety of enhancement and segmentation techniques, the goal of this research is to identify the early stage Pulmonary Fibrosis Disease Classification in Lung CT scans and produce a more accurate result. A total of 50 papers have been evaluated, of which 30 have undergone in-depth analysis in this review article.

III. Proposed Method

A. Pulmonary Fibrosis:

A wider category of more than 200 interstitial lung diseases or ILDs, include pulmonary fibrosis(PF), which is defined by pneumonitis and/or damage. In ILDs, the lung's air sacs' walls, as well as the tissue and area surrounding them, are injured and damaged. Pulmonary fibrosis is the medical term for an infectious respiratory disease that causes scar tissue in the lungs. Pulmonary fibrosis can be brought on by inhaling dangerous chemicals. Additionally, some illnesses, medications, and genetics can contribute to PF. Other types of pulmonary fibrosis, such as hereditary pulmonary fibrosis, pulmonary fibrosis linked to dyskeratosis gene defects or Hermansky Pudlak syndrome, may have a multifactorial etiology. The cause is typically unknown. Idiopathic pulmonary fibrosis is what causes this (IPF).

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TYPES	CAUSES
Triggered by drugs	Amiodarone, nitrofurantoin, chemotherapy, methotrexate, or any other medication known to have an adverse influence on the lungs in the past or the present
Nuclear enhanced	Radiation therapy administered to the chest in the past or present
Environmental(called hypersensitivity aseptic meningitis)	Exposure to animals, fungus, or additional factors
Autoimmune(called fibrous tissue illness)	Joint pain, skin irritation (especially on the fingers and cheeks), sore throat, or altered facial characteristics
Occupational(called aseptic meningitis)	Exposure to particles, fibres, fumes, or vapours that can cause PF in the past or present (such as asbestos, coal, silica and others)
Idiopathic	When there is no apparent cause

B. Symptoms:

PF symptoms sometimes resemble those of other lung conditions. PF symptoms typically appear in patients between the ages of 50 and 70. breathing challenges (Dyspnea). prolonged cough that produces no results, breathing very quickly and shallowly (particularly when walking), gradual unintentional weight loss, increased tiredness/fatigue, and low-grade fevers Joint pain, myalgias in the muscles (arthralgias), the tip of the fingers or toes becoming clubbed (wider and rounded).

The proposed research focuses on pulmonary fibrosis, which is one of the first diseases symptoms to manifest in a patient's lungs. Pre-processing, feature extraction, classification, and performance estimation are the processes via which images of the lung affected by pulmonary fibrosis are processed.

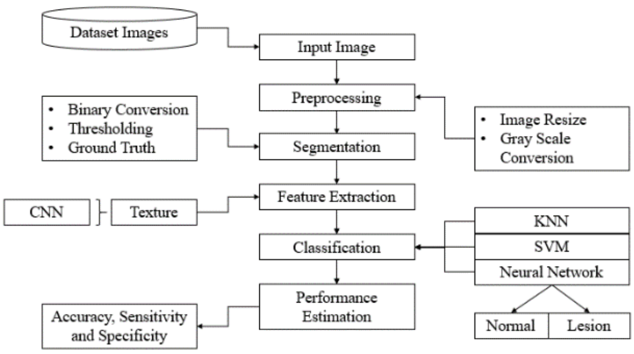

Diagram 1- Depicts the proposed system's schematic diagram.

The initial step entails gathering both normative and atypical CT images from the accessible database. The second step involves the application of picture enhancing techniques. In the third step, the region is extracted from the image using image segmentation algorithms. This makes use of morphological segmentation algorithms, which are advantageous throughout the image processing cascade. The general features are derived from the improved segmented image in the fourth stage. With the use of a classifier, pictures are classified as either normal or malignant during the classification process.

1. ***Input image***: The Lung CT dataset is used as the input image in this example. The input images are captured in ".jpg" or ".png" format. The process of integrating different operations to an image in order to produce an advanced technique used to extract some relevant data from it is known as image enhancement. It is a form of signal analysis where the input is an image, and the output can either be another image or functions/ characteristics related to that image.
2. ***Image Preprocessing:*** The first phase in an image pre-processing is called image enhancement. The purpose of picture enhancement is to give other automated image processing systems greater input. As a result, numerous preprocessing steps have been applied to the complete set of photos. Segmentation, enhancement, and smoothing are all steps in the pre-processing of an image. Preprocessing is applied to the obtained photos. We can use an in the Preprocessing stage. Image Resize is a process of resizing the original image to 256 X 256. Gray Scale Conversion is where the image is changed from colour to grayscale in this process. The input image is converted to grayscale if it has RGB channels.
3. ***Segmentation:*** The initial segmentation is accomplished in this step by comparing the preprocessed image to the background image. The morphological approach is then used to enhance the binary image. An image is segmented into its individual items or areas. Medical professionals can employ the segmentation of 2D medical images slice by slice for a variety of purposes. For the majority of future tasks involving image analysis, image segmentation is a crucial step. Particularly, the outcomes of many of the current methods for image interpretation and recognition heavily rely on fragmentation.
4. ***Feature Extraction:*** When characteristics are being extracted, we can implement the "Convolutional Neural Network algorithm" to gather characteristics from the image. The indicator matrices are then concatenated to produce the test features. The image feature extraction process, which uses methods and algorithms to locate and isolate specific desirable regions or features (characteristics) of an image, is crucial to image processing procedures. The classification procedure is based on these characteristics.
5. ***Feature Classification:*** In this phase, the image is categorized as either "normal" or "lesion" using a

"Neural Network." The phases of pulmonary fibrosis in the lung can be determined by extracting features from the segmented image once the nodule is found during segmentation. KNN, SVM, and NN classification algorithms are implemented, and there are two different forms of classification to differentiate between "normal" and "malignant lesions." The classification outcome displays whether the input is normal or a lesion.

6. ***Performance Estimation:*** The aim of using computer algorithms while enhancing digital images is to strengthen their qualities. Techniques for processing digital images include preprocessing, segmentation, and classification. Performance estimation can be used to gauge these strategies' efficacy. Evaluation of performance is used to assess how well an image processing method achieves desired outcomes. They are the metrics used to compare the effectiveness of various systems. Depending on the stage the estimate methods are used, there are three types of performance estimation in image processing: pre-processing performance estimation, segmentation performance estimation, and classification performance estimation. It estimates performance metrics including "TP, TN, FP, FN, Reliability, Precision, and Specificity."

CONCLUSION

According to the identification of PF lesions in the lungs, pulmonary fibrosis is the deadly and pervasive disease in the world. This indicates us that early diagnosis of this disease is crucial to preventing critical stages and reducing its percentage distribution in the world. Lung cancer risk is also increased by chronic pulmonary fibrosis. As pulmonary fibrosis worsens, it may result in side effects such lung infections, collapsed lungs, or blood clots in the lungs. Work is broken down into the following stages to produce more accurate results: image enhancement, image segmentation, features extraction, feature classification, and performance estimation.

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