

# A Survey On Lung Disease Diagnosis Using Deep Learning

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## **Abstract:**

The COVID-19 epidemic spread rapidly over the world in 2019, which led to a dangerous situation. The virus attacks the respiratory system, resulting in pneumonia along with additional symptoms including fever, dry cough, and exhaustion that can be misdiagnosed as tuberculosis, lung cancer, or pneumonia. Consequently, as COVID-19 can cause patient death, early detection is essential. Even yet, the poor quality of the air is causing many people to have respiratory issues. Numerous lung disorders require early detection and can be caused by a variety of factors, including pollution, changing environmental conditions, and undesired everyday behaviors like drinking and smoking. Deep learning approaches are more promising and effective areas that expand the machine learning domain and can improve medical care. This study looks at the diagnostic potential of different deep-learning algorithms for lung diseases. This paper's main objective is to use deep learning to show the different patterns in lung disease diagnoses and identify current problems.

## **Introduction:**

The development of deep learning algorithms has completely changed the diagnostic landscape for lung disorders. Researchers and medical professionals have created novel methods to improve diagnosis efficiency and accuracy by utilizing the power of neural networks[44]. The purpose of this introduction is to examine how deep learning is revolutionizing the identification and classification of different lung illnesses, opening the door to more effective and prompt medical interventions. Deep learning algorithms have become indispensable instruments in the detection of lung diseases, able to do everything from identifying the minute anomalies in medical imaging to decipher intricate patterns in patient reports.

The application of deep learning algorithms has resulted in a significant evolution in the diagnosis of lung disorders, from pneumonia to lung cancer. Medical imaging, such as X-rays, CT scans, and MRIs, can be analyzed by deep learning models, in particular convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which have shown remarkable abilities in identifying patterns and abnormalities that, may signal different lung ailments.

These models are highly skilled at identifying complex features and patterns in images, which allows them to accurately differentiate between lung tissues that are healthy and those that

are diseased. CNNs can identify minute opacities or infiltrates that indicate infection, for example, in the case of pneumonia, assisting in an accurate and timely diagnosis.

Furthermore, while screening for lung cancer, deep learning algorithms can help distinguish between benign and possibly malignant nodules. These models help radiologists make more educated decisions by helping them identify particular traits associated with different stages or types of lung cancer by evaluating big datasets of imaging scans.

Deep learning is useful not only for imaging but also for interpreting clinical data, including genetic data, biomarkers, and patient histories[42]. These models have the ability to combine many data sources in order to prognosticate, tailor treatment regimens, and forecast the course of diseases.

Still, there remain problems, like the need for large annotated datasets for training and ensuring the reliability and interpretability of these models in real-world clinical settings. Despite these difficulties, using deep learning techniques to identify lung diseases can enhance patient outcomes by boosting productivity, accuracy, and speed[42].

*Mycobacterium tuberculosis* is the bacteria that causes tuberculosis. The World Health Organization lists tuberculosis as one of the top ten causes of death worldwide. In 2017, the disease killed 1.6 million people. Asthma affects approximately 334 million people annually. Additionally, tuberculosis kills 1.4 million people, lung cancer claims 1.6 million lives, and pneumonia claims millions more. The COVID-19 pandemic affected the entire world [18], infecting millions of people and placing a heavy burden on healthcare systems [19]. It is evident that lung diseases are among the leading causes of death and disability worldwide.

Records indicate that poor air quality was a contributing factor in nearly 1.6 million fatalities in 2019. Strokes, diabetes, lung cancer, and myocardial infarctions were among the causes of mortality. Additionally, the State of Global Air 2020 reported that, of all the risk factors for death, air pollution currently has the highest risk.

A physician at Sir Ganga Ram Hospital in Delhi said that the majority of his lung cancer patients were men smokers in their 60s when he first began practicing some 30 years ago. However, the physician recently revealed that 40% of his patients are now women and that the majority of his patients are no longer smokers. He also noted that, with about 10% of the patients in their 30s and 40s, the patients are now much younger. It is now possible to see black deposits in the lungs of teenage patients, something that would have been unimaginable thirty years ago. After heart disease, chronic obstructive pulmonary disease, or COPD, is currently the second leading cause of death.

Intelligent healthcare is being created by DL. Because of this unprecedented plethora of ML-derived understanding, physicians and administrators may now make informed decisions about patient care and operational programs that affect millions of lives[43]. the COVID-19

classification process utilizing convolutional neural networks (CNNs) and additional methods. According to M. Susan Anggreainy et al., CNNs outperform K-NN and SVM in the COVID-19 classification process[11].

### **The basic process to identify lung disease using deep learning:**

#### **Image acquisition**

Within the scope of the research reviewed in this study, photographs will be the pertinent data needed to identify lung illness. Chest X-ray, CT scan, sputum smear microscopy, and histopathology imaging are among the images that might be utilized. This step produces images, which are then utilized to train the model..

#### **Preprocessing**

To increase image quality, the image could be improved or altered. Our objective in pre-processing is to use the combination of optimal filtering to enhance the quality of raw chest X-ray pictures while avoiding data loss. The Convolution Neural Network (CNN) is a popular deep learning method for automatically extracting lung features. [1]

#### **Training**

These include the use of an ensemble, transfer learning, and the choice of deep learning algorithm. Different learning styles are exhibited by different algorithms. Certain algorithms do better with different kinds of data. CNN is especially good when it comes to images. The type of data at hand should be taken into consideration while selecting a deep learning method.

#### **Classification**

The trained model will predict which class an image belongs to in the fourth and final stage, classification. A model should be able to accurately classify test photos—images that the model has never seen before—into healthy and infected lungs, for instance, if it was trained to distinguish between images of healthy and diseased lungs. For each image, the model will provide a likelihood score. The likelihood that an image belongs in a particular class is indicated by the probability score. The image will be categorized at the conclusion of this stage according to the probability score given to it by the model.

### **Different Existing Deep Learning Based Techniques for Lung Disease Detection**

Most present work uses a deep learning framework that may be broadly categorized into three stages. The first step involves preparing respiratory sound using techniques like noise reduction and audio filtering. Using signal processing techniques including spectrum analysis, Cepstrum analysis, wavelet modifications, and statistics, the second phase is feature extraction. Classification is the third stage, and the most popular classifiers to date have been ANN, Gaussian Mixture

models, Support Vector Machines, and K-nearest Neighbors. The suggested method achieved the highest precision of 98.85% and average accuracy of 99.62% in classifying patients based on the various types of lung illnesses.[2]

This paper[3] presented the classification and prediction of lung diseases in chest X-ray pictures using the Keras framework. It was created using deep learning techniques such as MobileNet and Densenet models. The MobileNet model may be used to build a variety of use cases, and an area under the curve (AUC) value of 94% and 96% accuracy can be obtained by applying a case modeling approach. The outcome suggests that the suggested approach would be better able to recognize impurity indicators from a dataset of chest X-ray pictures. Additionally, this study examines a number of performance metrics, including F1-Score, recall, and precision.[3]

According to paper[4], Every dataset utilized in this project is an open source dataset that was made available on the "Kaggle" website. Every image in the dataset was resized to  $224 \times 224$  during preprocessing. A popular technique for increasing the volume of training data is data augmentation, which involves slightly altering an image for each training period. The sequential and functional models of CNN, which combine CNN with data augmentation, have been used to implement the dataset. In this suggested work, three alternative model algorithms were used. Sequential models, functional models, and pre-trained models are among them. The outcomes of using a sequential model in this framework yield better results than other current approaches for tuberculosis and pneumonia in terms of accuracy, recall, and F1 score.[4]

An automated method for the identification of many lung illnesses in CT and X-ray scans is proposed in this work. For picture classification, a novel image enhancement model along with two pre-trained deep learning models and a customized convolutional neural network (CNN) are suggested. Pre-processing and deep learning classification are the two primary components of the suggested lung disease detection method. The k-symbol Lerch transcendent functions model is used in the pre-processing stage to construct the novel image enhancement method, which enhances images based on the likelihood of individual pixels. While the two pre-trained CNN models, Alex Net and VGG16Net, are constructed, the customized CNN architecture is used in the classification step. For the X-Ray image dataset, the results revealed classification accuracy, sensitivity, and specificity of 98.60%, 98.40%, and 98.50%, respectively; for the CT scan dataset, the results showed similar values of 98.80%, 98.50%, and 98.40% [5].

As stated in the paper[6], A deep learning (DL) architecture is suggested for the multi-class categorization of COVID-19, pneumonia, lung cancer, TB, and lung incapacity. The incoming photos go through preprocessing functions such as data image splitting, scaling, and normalization during the first step. The second and third steps then make use of deep learning techniques. Using VGG19 and CNN algorithms, feature extraction is carried out in the second phase. The process of image categorization uses the fully connected network technique. Regarding classification, three convolutional neural network (CNN) blocks were added as a feature extraction and fully connected network at the classification stage, after which a pre-trained model called VGG19 was used. The

VGG19 + CNN exceeded previous research, according to the experimental results, which showed 96.48% accuracy, 93.75% recall, 97.56% precision, 95.62% F1 score, and 99.82% area under the curve (AUC).[6]

In this work [7], The resilience and excellent performance with the least amount of computational labor are the main goals of the Fusion and Normalization Features Based RNNLSTM (F-RNN-LSTM) framework. Applying the median filtering and histogram equalization procedures preprocesses the input raw X-ray image. A dynamic region growth technique has been proposed for images of various modalities and dimensions to extract the area of interest (ROI) from the improved image. In order to improve the detection accuracy, a strong feature normalization method was suggested. Subsequently, a variety of machine learning and soft computing techniques—such as SVM, ANN, KNN, and ensemble classifier—are used for classification. Furthermore, in order to achieve greater accuracy and require less computing work, a deep learning method combining RNN with the LSTM model is created to assess the probability of lung diseases and early prediction.[7]

By merging CNN, VGG, data augmentation, and the spatial transformer network (STN), a new hybrid deep learning framework was suggested. The NIH chest X-ray picture dataset, which was gathered from the Kaggle repository, is subjected to the new model. The best validation accuracy for the complete dataset is 73% for VDSNet; the accuracy values for vanilla gray, vanilla RGB, hybrid CNN VGG, basic CapsNet, and modified CapsNet are 67.8%, 69%, 69.5%, 60.5%, and 63.8%, respectively. Compared to the sample dataset, where the accuracy value was 70.8%, VDSNet shows a validation accuracy score of 73% [8].

Forte et al. have conducted a thorough assessment and meta-analysis of the diagnostic effectiveness of the current DL techniques for identifying lung cancer [10]. The combined sensitivity and specificity of DL techniques for lung cancer identification were 68% and 93%, respectively.

The hybrid technique for tuberculosis X-ray classification tasks [13] by Sahlol, Ahmed T et al. new was proposed for the identification of lung disorders like tuberculosis by first extracting characteristics from X-ray image data using transfer learning. Next, an Artificial Ecosystem-based Optimization approach (AEO) that was recently proposed was used to filter the enormous amount of features that were generated. Our technique achieved over 90% accuracy in two datasets.

In addition to cancer, a neural network was utilized to diagnose pneumonia and COPD (chronic obstructive pulmonary disease). He-xuan Hu et al. [14] proposed a concurrent deep learning model merging a hybrid learning algorithm with DenseNet, which achieved 94% accuracy, to develop the current state-of-the-art in cancer segmentation.

1229 photos from the COVID-Mild, COVID-Medium, COVID-Severe, Normal, Pneumonia, and Tuberculosis categories were collected by Mehta & Mehendale [16]. The quantity

of images was increased using cGAN, and ResNet50, Xception, and DenseNet-169 were trained to accurately classify them. Accuracy for training and validation was 94.21% and 98.20%, respectively.

### Related Work:

The use of deep learning and machine learning methods for lung disease diagnosis has garnered significant attention in recent years. Various computer vision techniques have been blended with machine learning and deep learning approaches.

In this section, we provide an analysis the deep learning techniques by the recently suggested research for the diagnosis of lung diseases depending on types of diseases.

### Summary of papers for lung disease detection using deep learning techniques:

References	Disease	Deep Learning techniques	Features	Dataset
[20]	Tuberculosis	CNN	Feature extracted from CNN	ImageCLEF 2018 dataset
[21]	Tuberculosis	CNN with transfer learning, with demographic data	Features taken from CNN + demographic data	Private dataset
[22]	Tuberculosis	CNN with data augmentation, and ensemble by weighted averages of probability scores	Features taken from CNN	Montgomery, Shenzhen, Belarus, JSRT
[23]	Tuberculosis	CNN	Features extracted from CNN	Private dataset
[24]	Tuberculosis	3D CNN	Features extracted from CNN + lung volume + patient attribute metadata	ImageCLEF 2019 dataset
[25]	Tuberculosis	CNN with transfer learning, and ensemble by majority voting, simple averaging, weighted averaging, and stacking	Features extracted from CNN	Montgomery, Shenzhen, LDOCTCXR, 2018 RSNA pneumonia challenge dataset, Indiana dataset

[26]	Pneumonia	Deep Siamese based neural network	CNN extracted features from the lungs	Kaggle dataset
[27]	Pneumonia	CNN with transfer learning, data augmentation and ensemble by majority voting.	Features taken from CNN	LDOCTCXR
[28]	Pneumonia	CNN with transfer learning, data augmentation and ensemble by combining confidence scores and bounding boxes.	Feature acquired from CNN	Radiological Society of North America (RSNA) pneumonia dataset
[29]	Pneumonia	CNN	Feature acquired from CNN	Mooney's Kaggle dataset
[30]	Pneumonia	CNN with transfer learning	Feature extracted from CNN	LDOCTCXR
[31]	Pneumonia	CNN and LSTM-CNN, with transfer learning and data augmentation	Feature taken from CNN	Mooney's Kaggle dataset
[32]	Pneumonia	Decision Tree, Random Forest, K-nearest neighbour, AdaBoost, Gradient Boost, XGBboost, CNN	Multiple feature	Mooney's Kaggle dataset
[33]	Lung cancer	CNN-long short-term memory network	Features extracted from CNN	NIH-14 dataset
[34]	Lung cancer	CNN	Features acquired from CNN	LIDC-IDRI
[35]	Lung cancer	CNN with transfer learning and data augmentation	Features extracted from CNN	Private Dataset

[36]	Lung cancer	CNN with transfer learning and data augmentation	Features acquired from CNN	JSRT database
[37]	Lung cancer	CNN with data augmentation	Features extracted from CNN	Cancer Imaging Archive
[38]	Covid 19	CNN with transfer learning and location-attention classification mechanism	Features taken from CNN	Private Dataset
[39]	Covid 19	RADLogics Inc., CNN with transfer learning and data augmentation	Features acquired from RADLogicsInc and CNN	Chainz Dataset, A dataset from a hospital inWenzhou, China, Dataset from El-CaminoHospital (CA) and Lung image database consortium (LIDC)
[40]	Covid 19	CNN with transfer learning	Features extracted from CNN	Cohen's Github dataset and LDOCTCXR

## Conclusion

We provided an overview of various deep learning techniques for lung illness diagnosis in this research. Conventional approaches lack expertise and experience with lung disease; radiologists have struggled to diagnose chest X-rays and have occasionally recommended inaccurate results. As a result, a delay in diagnosis and treatment is observed because physicians are not readily available. By analyzing reports of chest X-rays, the suggested model is a potentially automated framework that may identify and diagnose illnesses. With this model, one may ascertain its current state of health. It is also beneficial for physicians to identify the illness in fewer patients and recommend a course of action. The performance matrix, which precisely defines accuracy, specificity, sensitivity, and precision, has been used to evaluate the overall performance of the various deep learning techniques

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