Review Article

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A Comparative Study of Deep Learning Models in Medical Image Analysis for Pulmonary Disease Detection: A Review

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ABSTRACT

This survey provides the view of current scenario of Deep Learning models used to detect pulmonary diseases, Stroke Disease and some other diseases related to blood clots. The diagnosis and categorization of lung disorders using medical images, especially chest X-rays and CT scans, has been greatly improved by recent developments in deep learning. This survey highlights the use of deep learning techniques in the detection of lung diseases by compiling and analyzing 20 research publications published between 2016 and 2020. By offering a thorough taxonomy based on seven essential characteristics—image kinds, features, data augmentation, deep learning models, transfer learning, ensemble methods, and lung disease types—this study fills that gap. Convolutional neural networks (CNNs) dominate, transfer learning models like VGG, ResNet, and Inception-V3 are widely used, and diseases including COVID-19, TB, and pneumonia are the main emphasis, according to key findings. The paper also indicates promising avenues for future research, such as combining clinical and demographic data, creating lightweight models for contexts with limited resources, and implementing ensemble learning techniques.

INTRODUCTION

Pulmonary Diseases such as Covid-19, Pneumonia, Tuberculosis and Pulmonary Embolism (PE) has come up as a life-threatening disease. Covid-19 (Coronavirus disease 2019) is an infectious disease. It was initially found in Wuhan, China and after that it spread all over world and declared. One of its symptoms can be seen in chest CT scan showing pneumonia like features [1]. Now a day's people are threatened by death rate caused by pulmonary diseases. It varies from gentle like common cold to lethal like pneumonia, tuberculosis, Pulmonary embolism and COVID-19 etc. [6]. Around three lakh people, having PE get hospitalized every year in the United States of America. PE is determined by Computed Tomography Pulmonary Angiography (CTPA) that is used by the radiologist to diagnose the disease. Due to slow detection, many people affected by this disease lose their lives. Therefore, it needs to be diagnosed fast to save the life of many people. Sometime Radiologists takes more than 6 days to diagnose this disease and also sometimes they misinterpret it. Thus, the need for automate the diagnosis of this disease arises [18]. Automated detection of these diseases will reduce the time of diagnosis and patient will get the treatment fast. Hence a system is needed which will use

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the combination of clinical information of patients and the images of the disease to predict the disease.

This study compares 20 papers related to the detection of different pulmonary diseases using deep learning models on the basis of sensitivity, specificity and accuracy. It also discusses the Key features, Performance, Key Insights and Gap Identified in these papers.

Section 1. provides the information regarding the need of deep learning models in medical image processing. Section 2. considers the papers related to the detection of different pulmonary diseases using deep learning models. Section 3. provides the percentage of papers considered in this study related to different diseases. Section 4. makes the conclusion of all the papers considered in this research.

LITERATURE REVIEW

COVID 19:

Corona virus was first found in Wuhan, Hubei and China. After that on March 11, 2020 it was declared as a pandemic by World Health Organization (WHO). Therefore, we need an automated system to detect this disease fast and accurately. This section discusses the paper related to this disease and the deep learning techniques used to detect this disease [2].

Salman et al. [1] tried to assist traditional testing in detecting COVID 19. Convolutional Neural Network (CNN) is used to diagnose COVID-19 using X-ray or CT Scan images. Rahaman et al. [2] tried to automat classification of chest X-ray images into COVID-19, pneumonia and normal condition. Used COVID-19 image data collection by Joseph Cohen and from Kaggle pneumonia datasets. Performed augmentation to improve generalization and VGG19, ResNet50, InceptionV3 and Xception models are used for classification. Sahinbas et al. [3] used pre-trained CNNs (VGG16, ResNet50, InceptionV3 and DenseNet) on ImageNet for feature extraction and Fine-Tune the upper layer for classification. This study used publicly available chest X-ray image datasets which contains COVID-19 positive cases, Pneumonia cases and Normal images. Ozturk et al. [4] used custom Deep Neural Network (DNN). They use simple, direct DNN pipeline for Covid-19 classification without leveraging transfer learning. This study uses publicly available dataset of Covid-19.

Table 1. Provides an overview of papers focused on COVID-19.

S. No.	Ref. No.	Key features	Performance	Key Insights	Gap Identified
1	[1]	Reduced the use of RT-PCR tests by enabling image based diagnosis	Accuracy 95%	CNN based classifiers are capable of distinguishing COVID-19 from other lung diseases like pneumonia	Limited dataset and lack of real world implementation
2	[2]	Evaluates multiple pre-trained deep learning models and fine tune them for direct classification	Accuracy 98%	Transfer learning is highly effective on small dataset	Limited Dataset and real time testing is absent
3	[3]	Transfer Learning with CNNs (VGG16, ResNet50, InceptionV3 and DenseNet)	Accuracy 95%	The method used in this study is scalable and can be adapted by other medical image processing tasks.	Limited dataset and no real time deployment
4	[4]	Used Deep Neural Network-Based Classification	Accuracy of 95%	Proposed an automated systems which can aid rapid screening	Dataset Size is limited Clinical Deployment is not Considered

Pneumonia:

In pneumonia lungs get infected due to pathogens such as virus, bacteria and fungi. Sometimes it becomes lethal for infants, people with weak immune system, elderly people, people having disease such as asthma etc. This section discusses about the deep learning techniques used in detecting pneumonia using X-ray images.

Chouhan et al. [5] tried to simplify the pneumonia detection using chest X-ray images. They used transfer learning using AlexNet, DenseNet121, InceptionV3, ResNet18, and GoogLeNet and performed ensemble classification with majority voting. Guangzhou Women and Children's Medical Center dataset is used in this study. Abdulahi et al. [6] tried to develop a deep convolutional neural network (DCNN) model for multiclass classification to accurately detect pulmonary diseases. Model has 26-layer CNN with Conv2D, MaxPooling2D, flatten, and Dense layers. For compilation it used Adam optimizer and categorical cross-entropy loss. Dataset used in this study is consisting of three different diseases: 1. bacterial pneumonia, 2. COVID-19 and 3. viral pneumonia. Tripathi et al. [7] provided a deep convolutional neural network (CNN) to classify chest diseases. They used CapsNet as an alternative algorithm for comparison. They combined patient information with

X-ray data for diagnosis. Acquired a large dataset from Kaggle named Chest X-Ray 14 which consists of 14 classes: Nodule, Pleural Thickening, Pneumonia, Atelectasis, Hernia, Effusion, Infiltration, Pneumothorax, Edema, Mass, Emphysema, Fibrosis, Cardiomegaly, Consolidation and Normal images. Pant et al. [8] Proposed ensemble approach using two deep learning models. Used Kaggle dataset which is collected from Guangzhou Women and Children's Medical Centre in China. This dataset has imbalanced data therefore Dice loss (DL) function is used to handle imbalanced data.

Table 2. Provides an overview of papers focused on Pneumonia.

S. No.	Ref. No.	Key features	Performance	Key Insights	Gap Identified
5	[5]	Used novel ensemble approach using transfer learning Applied majority voting in ensemble approach	- Accuracy: 96.4%	Use of novel ensemble approach using transfer learning with five different neural network architectures shows improved performance.	- Lack of transparency in deep neural networks' decision-making processes Lack of diverse image data for pneumonia pathologies
6	[6]	Used the combination of convolutional, dense, max pooling, and flattened layers for performing multiclass classification model	94%	With radiographic images, achieving high accuracy across multiple classification tasks.	- Dataset lacks diversity and size. - Restricted to only three lung disorders. - Exclusive dependence on X-ray and CT scan images, which have inherent limitations.
7	[7]	- Used CNN + VGG + data + STN model architecture on combination of image data with patient information (age, gender)	- Average accuracy: 89.77%	- Developed a deep convolutional neural network (CNN) to classify chest diseases using X-ray images. - Compared CNN + VGG + data + STN and vanilla CNN models.	- Large datasets is difficult to manage - A better model is needed to handle noisy data.
8	[8]	Used combination of ResNet-34 based U-Net and ensemble it with EfficientNet-B4 based U-Net.	Accuracy 82%	Proposed model Efficientnet-B4 based U-Net provided high precision and decent recall, but the other model, ResNet based U-Net provided high recall but low precision.	Biased dataset and focused only on binary data.

Tuberculosis:

In 2017 around 10 million cases have been registered among them 1.6 million were dead. Correct diagnosis of this disease is not feasible and it is time consuming also [10]. Therefore, an automated system is required to diagnose TB accurately. This section gives the information regarding the advancement of model in diagnosing this disease by discussing the papers related to it.

Heo et al. [9] had the aim of detecting tuberculosis in chest radiographs from annual workers' health examination data by using deep learning algorithm and to compare the performance of CNNs based on images only (I-CNN) and CNNs including demographic variables (D-CNN). Considered demographic variables: age, gender, height, weight. Used stochastic gradient descent with Nesterov momentum for optimization. They used annual workers' health examination data from Yonsei University, starting from 2009, which includes chest X-ray images and demographic information for 39,677 individuals. Murphy et al. [10] tried to evaluate the performance of CAD4TB v6 against previous versions and expert human observers. 500 images were annotated by 5 expert observers for radiological reference standard. Data was collected from TB centers in Karachi, Pakistan, between 2013 and 2015. Pasa et al. [11] tried to develop a simple and efficient convolutional neural network (CNN) architecture to achieve automated diagnosis of tuberculosis from chest X-rays. CNN architecture included 5 convolutional blocks, global average pooling layer, fully-connected softmax layer. They also used saliency maps and grad-CAMs for visualization. They used NIH Tuberculosis Chest X-ray dataset from Montgomery County in Maryland, Shenzhen and Belarus Tuberculosis Portal dataset. Melendez et al. [12] evaluated a machine learning-based combination framework that combines CAD scores and clinical information. They used a database of 392 patient records from TB patients in South Africa's Gugulethu TB clinic. They also combined CAD scores of chest radiographs with 12 clinical features with the help of machine learning. Cao et al. [13] It's primary objective is to improve the accuracy and reliability of tuberculosis diagnostics. They used Montgomery County X-ray Set which contains both normal and TB-infected chest X-rays. Models used in this study are ResNet-50, VGG16 and VGG19 and Custom CNN Architecture. Lopes et al. [14] used Montgomery County X-ray Set and Shenzhen Hospital X-ray Set. Used VGG16, ResNet50, InceptionV3, Xception and DenseNet121 for feature extraction and extracted features are passed to classifiers such as Support Vector Machine, Random Forest and k-NN (k-Nearest Neighbors). Amani et al. [15] tried to provide a simple, effective, and fast system for TB detection. They performed Grayscale conversion of X-ray images and then used Gray Level Co-occurrence Matrix (GLCM) for feature extraction after that Support Vector Machine (SVM) is used for binary classification.

Table 3. Provides an overview of papers focused on Tuberculosis.

S. No.	Ref. No.	Key features	Performance	Key Insights	Gap Identified
9	[9]	- Used VGG19, InceptionV3, ResNet50, DenseNet121, InceptionResNetV2 for feature extraction.	- AUC values for D-CNN models are higher than for I-CNN models. - AUC improvements up to 2.88% with demographic variables.	- Inclusion of demographic variables improves sensitivity and specificity. - Demographic factors improve the diagnosis of tuberculosis when included in CNN models.	-Needs to include more demographic variables into CNN models due to the relatively low number of demographic features compared to feature maps.
10	[10]	- Able to interpret CXR images in under 15 seconds. - More cost-effective and efficient than previous versions.	- Sensitivity: 90% - Specificity: 76% (Xpert reference)	- CAD4TB v6 outperforms previous versions in terms of sensitivity and specificity.	- Need to be compared with other machine-learning systems - Limited to a single population
11	[11]	Included about 230,000 parameters - Trained by using categorical cross-entropy and elastic deformations	- Accuracy: 79.0% (MC), 84.4% (SZ), 86.2% (CB)	- The network has less parameters (230,000) compared to other models, which reduces computational complexity and memory requirements. - Showed training time is about 1 hour on a low-end GPU, and inference time is approximately 5-6 milliseconds.	- Model should be pre-trained and bigger datasets is to be used to improve accuracy and AUC while preserving speed advantage. - Generation of textual annotations for each case to enhance model utility.
12	[12]	Combined CAD score and clinical information for TB diagnosis - Lung auscultation findings	- Specificity at 95% sensitivity: 49% for the combination framework.	- HIV status, lung auscultation findings and axillary temperature are key clinical features that improved the performance by combining with CAD scores.	- Data is used from a single site, which may not be representative of other settings or scenarios.
13	[13]	ResNet and VGG are used to diagnose TB with the help of X-ray	Accuracy 90%	Transfer learning helps to improve the performance in diagnosing the TB data augmentation helps to reduce the over fitting	It does not consider global population diversity or different X-ray acquisition conditions.
14	[14]	Used pre-trained models are used as feature extractors for TB detection from chest X-rays.		Combined deep feature extraction with lightweight ML classifiers	Results are not tested in real-world hospital environments
15	[15]	Enhanced image quality through grayscale conversion, histogram equalization, and noise reduction.	Accuracy 90%	Used Support Vector Machine as main classifier due to its effectiveness on small data	Data set is small and homogeneous

Pulmonary Embolism:

Disease like pulmonary embolism (PE) is not easy to detect and life threatening also. computed tomography pulmonary angiography (CTPA) is used to detect it. Mortality rate is high in PE, but it can be avoided by early diagnosis of this disease. Therefore, we need a system which is capable of detecting PE fast and with accuracy. In this section papers related to the

PE detection using different deep learning approaches have been considered.

Yang et al. [16] used 3D fully CNN, ResNet-18 The model described in this paper is a two-stage convolutional neural network (CNN) for automated detection of pulmonary embolisms (PEs) on CT pulmonary angiography (CTPA) images. They used PE129 as a test dataset from the PE challenge, which consists of 20 CTPA scans. Huang et al. [17] developed PENet (3D CNN with 77 layers) to automatically detect pulmonary embolism (PE) by using volumetric computed tomography pulmonary angiography (CTPA) scans. They used an internal dataset from Stanford University Medical Center, consisting of 1797 CTPA studies from 1773 unique patients, which was split into training, validation, and test sets and external dataset from Intermountain healthcare system, consisting of 200 CTPA studies from 198 patients, which was used for external validation. Huang et al. [18] used 108,991 CTPA studies from Stanford University Medical Center. They manually review and label a subset of 2500 studies as positive or negative for pulmonary embolism by radiologists. They develop and compare several different fusion models that combined information from the CT scans and electronic medical records. Ma et al. [19] used CNN and RNN model for two-phase deep learning for pulmonary embolism (PE) detection and identification. The first phase uses a 3D CNN to extract features from 3D CT scan windows, and the second phase uses a temporal convolutional network (TCN) combined with attention mechanisms to perform sequential learning by using extracted features and predict the presence of PE as well as its properties (position, condition, RV/LV ratio). They used RSNA STR Pulmonary Embolism Detection dataset from the Kaggle competition. Wang et al. [20] used hybrid approach to improve the accuracy of pulmonary disease classification. They combined the output of many models using ensemble learning. This paper used VGGNet, ResNet, Inception and Custom CNN architectures for ensemble learning.

Table 4. Provides an overview of papers focused on Pulmonary Embolism.

S. No.	Ref. No.	Key features	Performance	Key Insights	Gap Identified
16	[16]	Used two-stage CNN for automated detection of pulmonary embolisms - first stage to detect suspected PE cubes - a vessel-aligned 2D classification network in the second stage to remove false positives.	Sensitivity, 0.76 scan at 0mm, 0.789 scan at 2mm and 0.847 at 5mm 2 false positives, localization error.	Fully convolutional neural network (FCN) to extract 3D feature hierarchies, which are combined with location information to generate candidate cubes containing PEs.	limited representation ability of the handcrafted features used in conventional methods, detection of pulmonary embolisms (PEs) on CT pulmonary angiography (CTPA) images often suffer from a high false positive rate.
17	[17]	Used PENet to automatically detect pulmonary embolism (PE). PENet is a 77-layer 3D convolutional neural network (CNN) .	Sensitivity 73% and specificity of 82% for Stanford test data	PENet model achieved an AUROC of 0.85 on an external test set. Interpretability of the PENet model through class activation mapping (CAM), to highlight the regions of the CTPA scan.	An end-to-end deep learning model is needed that can detect pulmonary embolism (PE) on full computed tomography pulmonary angiography (CTPA) scans, with interpretability and robustness .
18	[18]	Developed and comparing different multimodal fusion model architectures that can utilize both CT imaging data and electronic health record (EMR) data to automatically classify pulmonary embolism (PE) cases.	Sensitivity 87% and specificity 90% Achieved AUROC of 0.962 [0.961-0.963] on the test set.	The model used in this study is capable of making predictions based on EMR data alone when CT imaging is not available.	Limited image dataset
19	[19]	Used a two-phase deep learning approach having ability to not only detect the presence of pulmonary embolism PE, but also predict its properties such as position, whether acute or chronic, and the right-to-left ventricle diameter (RV/LV) ratio.	Sensitivity 87% and specificity 99%	In first phase 3D CNN is used to extract features from smaller 3D windows of the CT scan. In second phase attention mechanisms is used to learn the sequential information and predict the study-level labels.	Not Generalized and Limited dataset
20	[20]	Used Convolution Neural Network for feature extraction from X-ray images of pulmonary diseases.	Accuracy 90%	Combine deep learning with ensemble strategies which improves the reliability in detecting the pulmonary diseases.	Due to complexity it is less reliable for real time

Percentage of papers considered in this study related to different pulmonary diseases: Fig 1. Bellow displays that total of 25% papers of Pulmonary Embolism, 20% of Covid-19, 35% of Tuberculosis and 20% of pneumonia have been considered in this study.

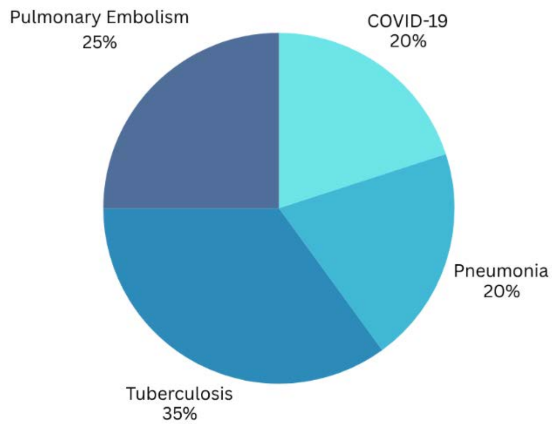

Fig. 1. Percent of papers on the basis of types of pulmonary diseases considered in this study.

CONCLUSION

Automated pulmonary disease detection has shown potential in medical field to enhance the accuracy, saves the time and helps in clinical decision making process. This study discus a wide range of deep learning techniques which are used to detect pulmonary disease by using X-ray and CT images. Many deep learning techniques such as transfer learning and ensemble learning have been compared on the basis of performance where ensemble approach gives the accuracy of 96.4% while detecting pneumonia. Around 20 papers related to deep learning techniques have been discussed on the basis of Key features, Performance, Key Insights and Gap Identified. As it can be seen that still there gaps which has to be filled. In the future some work needs to be done on the dataset, because due to limited dataset deep learning models are not generalized. New models have to be developed which can be installed on the edge devices for easy accessibility.

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