Original Article

MEDICAL IMAGING WITH ARTIFICIAL INTELLIGENCE FOR LUNG DISEASE ANALYSIS: A COMPREHENSIVE REVIEW

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Abstract

Nowadays, to diagnose or detect any diseases in humans, we must have a good diagnosis to predict the disease that is present in the human body. In general, we aim to employ X-Ray, CT, or MRI scan techniques for lung disease prediction. Artificial intelligence and deep learning methods advances have aided in the diagnosis and classification of lung diseases in medical imaging. As a result, there has been a lot of research on utilizing artificial intelligence to identify lung diseases. This article presents deep learning approaches that may be used to identify lung diseases based on medical scans. This study's main objective is to explore pulmonary infection in early stage by making use of a variety of medical images to recognize, diagnose, and classify different types of lung infections via the use of deep learning methods for early detection of lung disease. A detailed description of how these procedures have been used to treat lung nodules, TB, pneumonia, lung cancer, COVID-19, and ILD is also presented. Finally, the application of deep learning algorithms, machine learning algorithms and transfer learning to medical images is reviewed, as well as an appraisal of future difficulties and prospective possibilities.

Keywords: Machine learning; Deep learning; Medical images; Classification.

1. INTRODUCTION

Lung disease refers to a problem with something in the lungs that reduces the proper functioning of the lungs. Lung diseases are pneumonia, tuberculosis, lung nodule, lung cancer, and COVID-19. Asthma is inflammation of the airways in the lungs and narrowing of the small airways. Worldwide, 4.2 million people die from asthma, which causes more than 1,000 deaths per day. Tuberculosis is an infectious disease and 1.5 million people die from this infectious disease [1]. Lung cancer kills 2.21 million people annually, while pneumonia and COVID-19 kill millions. Lung diseases can be easily diagnosed using lung X-rays and CT scan images. Recently, artificial intelligence has shown great potential when used in medical images to diagnose diseases of the lungs. Deep learning then identifies and separates medical images based on numerous imaging modalities, such as baseline, CT/MRI, tomography, ultrasound, and digital pathology.

The neural network of a person is modeled using the deep learning approach. Identify, or classify targets by integrating many layers of asymmetric processing for source data hierarchical abstraction and extracting various degrees of abstraction from data [3].

The risk of lung disease is extremely high, which makes it particularly difficult for middle- and low-income countries. As a result, early lung cancer detection can assist to lessen the severity of the disease. Artificial Intelligence now plays a minor part in foresight. Machine learning has been used effectively to automate the interpretation of lung function tests for the diagnostic process of preventive lung diseases.

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Neural network models for predictive system detection in computed tomography, such as the convolutional Neural Network, are pieces of art in their own right. Nowadays, big data is used to analyze user behavior and make predictions. Because of the huge number of types and the speed with which data is generated, big data finds a great deal of value in this industry. Deep learning is a kind of artificial intelligence algorithm which it executes a challenging task by combining many interconnected blocks. Instead of requiring a pre-programmed instruction set, deep learning algorithms could build a model on their own from huge volume of data.

Combining deep learning with transfer learning is an excellent way to find these tumors and infections. As a result of this technique, it is possible to identify and track sperm, as well as to eliminate bone suppression in X-ray images, for a variety of purposes. Additionally, this approach is applied to segment breast lesions and pulmonary nodules. In contrast, computer vision and deep learning may frequently outperform radiologists when it comes to recognizing a disease. For example, the technique used has a 90% accuracy rate, yet radiologists' diagnoses are only 70% accurate. Machine learning techniques and deep learning techniques are used to diagnose Covid-19, both are useful in medical imaging, particularly CT scans and X-ray images. Deep learning and other computer vision challenges have been greatly simplified by the use of neural networks.

The main purpose of machine learning and deep learning techniques for many lung diseases such as lung nodules, lung cancer, pneumonia, TB, and COVID-19 are outlined in this survey. Most lung cancer deaths and diseases are caused by a combination of risk factors, including outdoor air pollution and the prevalence of tobacco smoking. However, the cost of treating lung cancer is growing, and healthcare systems are trying to find new cancer treatments.

The primary purpose of this research is to investigate pulmonary infection using various medical images to identify, diagnose, and classify lung infections using deep learning, machine learning, and transfer learning algorithms for early detection of lung disease.

In this survey, the method used in the latest Lung Diagnostic Survey using machine learning techniques and deep learning techniques are described. Several successful machine learning algorithms had been advanced in current years, and deep learning algorithms nowadays have a very low error rate

2. Detection of lung disease overview architecture

During this phase, we will investigate how artificial intelligence may be utilized to diagnose lung diseases by looking at medical images. Pre-processing, algorithm development, and disease classification are the three most important procedures. Identifying healthy lungs as compared to diseased, inflamed lungs within the context of an image is the objective of the lung disease detection process. It is essential to practice the classification of lung diseases, which is also often known as a framework. The process through which a neural network acquires the ability to recognize a large number of images is referred to as training. There is a possibility that deep learning will be employed to develop a version that is capable of correctly labeling images according to their class. To use deep learning to identify lung infection, images of diseased lungs must first be collected. This is the first stage in the detection process.

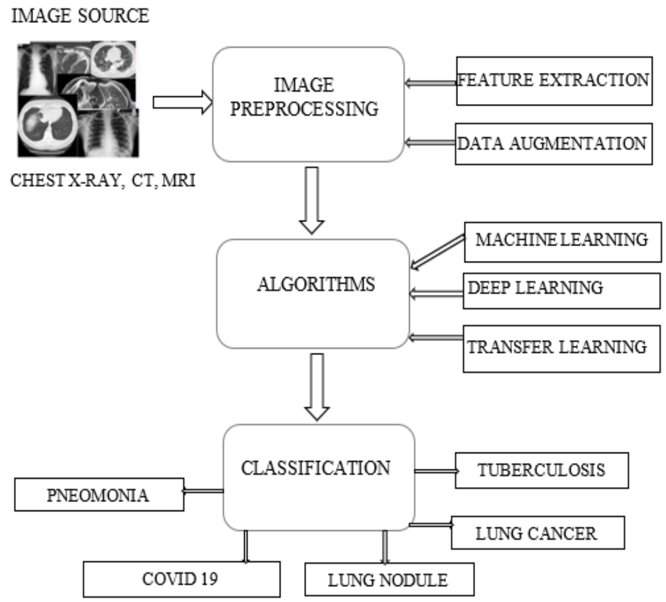

Figure 1. Overview of Architecture

Deep learning methods are now used in a variety of fields to evaluate medical images. Additionally, we must learn about data access, model building with sparse data, making the most of the image shape and accuracy aspects of medical imaging data, and applying these findings to clinical practice. These methods are accurate in a variety of applications, including segmentation and registration. Edge detection filters and a wide range of mathematical algorithms are used in the conventional approach to image segmentation. Deep learning is one of the most effective ways to analyze medical images. For determining target identification, segmentation, object classification, and individual identification are very successful. For example, one dataset and task may be used to train neural network variables for another. So that the network can handle the new data source and purpose efficiently, this is being done. It is common for neural networks trained on images to have a specific purpose. Finally, the network's properties must be entirely translated from broad to more specialized classification. When the size of the target dataset is a small percentage of the overall size of the source dataset, transfer learning may be an effective method for avoiding the use of unevenly distributed datasets. Image-based diagnosis, disease prediction, and risk assessment seem to be picking up steam in the use of machine learning technologies. A variety of scientific and practical issues must be addressed if these models are to be successful. Classifying and assigning images is the last stage. The model can reliably forecast the classification of new images that it has never seen before. An overview of the technique is shown in Figure 1.

3. TYPES OF IMAGES

3.1. X-RAY IMAGES

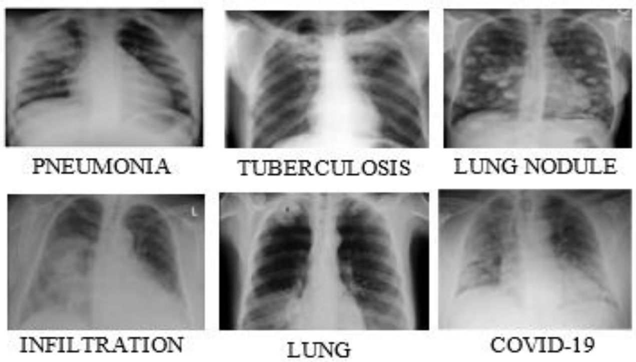

Figure 2. Example X-Ray Images

An x-ray of the chest employs focused radiation to provide images of the patient's heart, lungs, and bones. Healthcare experts use chest X-rays to diagnose and treat conditions such as pneumonia, emphysema, and chronic obstructive pulmonary disease (COPD). Chest X-rays are a simple, quick, and painless diagnostic tool. You have one to two days to find out the results of the chest X-ray that was performed on you. To produce images of the inside structures of the chest, an X-ray makes use of every minute dose of ionizing radiation. The X-ray images of the chest that are shown in Figure 2 were taken from a variety of different datasets.

Medical X-ray pictures are traditionally exposed to photographic images, which must be processed before being viewed. Digital X-rays are used to solve this problem [5]. CNNs have been utilized in investigations to examine chest X-ray images and analyze lung infections like pneumonia and tuberculosis in recent studies.

Deep convolutional neural networks can automatically diagnose TB in chest radiography [6]. Both the previous and new UNet models divided chest X-rays. Deep learning CNNs classified TB and normal chest x-ray images using SqueezeNet, InceptionV3, VGG19, ResNet18, ResNet50, ResNET101, and DenseNet201. Score-CAM methods are also utilized to show that dominant lung regions have superior symptomatic accuracy. CheXNet classified non-segmented images with 97.07% accuracy and DenseNet201 with 99.9%.

Subrato Bharati et al. [7] recommend combining X-rays and a hybrid deep learning architecture to identify lung diseases (VGG Data STN with CNN). Using a hybrid technique, lung infections were diagnosed using X-rays. Kaggle gave NIH chest X-ray images. A hybrid method may detect diseased chest x-ray regions. They resize and prepare X-rays first. The VDSNet system includes spatial transformers, feature extraction, and classification layers. Classification eliminated infected regions' spatial transformer layers.

Pretrained AlexNet was utilized by Abdullahi Umar Ibrahim et al. to identify bacterial, COVID-19, and non-COVID-19 viral pneumonia [8]. A pretrained AlexNet model may be more accurate for image classifications. The output layer, which is the SoftMax layer used for classification, is the last layer to be completely linked. The pre-trained AlexNet model was 99.16% accurate for two-way classification, 94% for three-way, and 93.4% for four-way.

Matthew Zak and Adam Krzyzak et al. utilized ImageNet-trained deep networks to diagnose lung disorders [9]. A pipeline is established for segmentation and classification. Two processes are needed to classify lung symptoms as pneumonia or tuberculosis: X-ray image segmentation and lung disease classification. They employed VGG16, ResNet-50, and InceptionV3 to categorize lung images as pneumonia or TB.

Ying Xie and Wei-Yu Meng [10] suggested interdisciplinary lung cancer early detection approaches. An early detection model for lung tumors was created using KNN, AdaBoost SVM, Random Forest, and Neural Network. Metabolic producers may be utilized to diagnose lung cancer using machine learning. Analyzing metabolic biomarker characteristics using supervised FCBF. Naive Bayes and Neural Networks were used to improve classification precision, accuracy, specificity, sensitivity, and AUC.

Shimpy Goyal and Rajiv Singh et al. developed a technique for diagnosing lung disease using chest X-rays [11]. In the proposed framework, lung-specific characteristics are assessed using considerable image augmentation, ROI-based image retrieval, and normalization. F-RNN LSTM improves classification and minimizes processing complexity. They used a semi-automated strategy for reliable image retrieval and deep learning with limited computational overhead to diagnose lung diseases from X-ray images. Were proposed method for recovering ROI from the enhanced image is the dynamic region growth strategy.

To generate a pseudo lesion, labeled lesion tissue CXR and healthy CXR may be used [17]. The bone suppression mask was produced using the normal CXR from the source. To create a normalized distance map border suppression mask, they used the damaged area's size as a reference. Pseudo-lesion creation was used to balance out the lesion imbalance.

Outlier detection in chest X-rays is based on reducing the dimensions of the image and detecting the edges [22]. High-quality, high-resolution images are converted into lowdimensional data using Line-Feature Analysis, allowing for faster, more accurate data processing. LFA was used to build an RNN-based model. Preprocessing prevents overfitting with RNN.

Fouzia Altaf et al. developed a novel technique for boosting transfer learning when the target domain knowledge is restricted and modal [32]. They tested their recommended technique for classifying COVID-19 patients from chest X-rays. While limited data from the target domain is inadequate for normal transfer learning, this method considerably improves problem performance. Improvements in detecting COVID-19 from lung X-ray images using deep pre-trained models suggest that computer-aided testing will reduce physician work in the future.

Nitha V R at el. developed XRayNet to classify lung diseases [38]. This proposal is multi-class segmentation utilizing the Convolutional Hidden Markov Neural Network (CHMNN) model to identify lung disease. Traditional neural networks initialize weights randomly. They proposed a soft similarity clustering (SSC) approach to discover lung infections. Edge Preserved Median Filter (EPMF) reduces noise, then Contrast Limited Histogram Equalization (CLAHE) boosts contrast. Adaptive Otsu Binarization (AOB), canny edge detection, and convex hull are used to segment images with contrast enhancement. The studies on lung disease detection using X-RAY imaging are in Table 1.

Table 1. Summarizes articles on the identification of lung diseases using X-RAY images.

Author	**Techniques**	**Diseases**	**Accuracy**	**Dataset**
Tawsifur Rahman et al. [6]	Deep CNN	TB	97.07%	NLM dataset, Belarus dataset, and RSNA dataset
Subrato Bharati et al. [7]	VDSNet	Lung diseases	73%	NIH chest X-ray image
Abdullahi Umar Ibrahim et al. [8]	pre-trained AlexNet	COVID-19	99.16%	COVID-19 image: 1292, CAP image: 1735, and normal CT scans image: 1325
Matthew Zak et al. [9]	VGG16, ResNet-50, and InceptionV3	Pneumonia and tuberculosis	93.42%	Shenzhen Hospital dataset (SH)
Ying Xie et al. [10]	Machine learning Algorithms	Lung cancer	0.885	Hubei Taihe Hospital
Shimpy Goyal et al. [11]	Naive Bayes and Neural Networks	Pneumonia	94.31	C19RD and CXIP datasets
CHANG-MIN KIM et al. [22]	LFA	COVID-19	97.5%	Normal image: 482, COVID-19 image: 468
Fouzia Altaf et al. [32]	An augmented ensemble transfer learning technique	COVID-19	99.24%	ImageNet data set
Nitha V R at el. [38]	CHMNN	Lung diseases	97.0%	NIH chest X-ray image

3.2. CT SCAN

CT scans aid in the diagnosis of chest abnormalities and the determination of the cause of unusual coughing, trouble breathing, tightness of the chest, inflammation, and other chest symptoms. CT scan has acquired widespread acceptance for its capacity to provide three-dimensional (3D) images of the chest, resulting in greater resolution of lung disorders. A CT scan is a very effective and accurate way of examining the lungs, and it is frequently used after abnormal chest X-rays. Figure 3 depicts some examples of chest computed tomography (CT) images from datasets. The CT lung scan is a painless, non-invasive process that includes low-dose X-rays to identify lung cancer in only 30 seconds. It utilizes a spiral computed tomography (CT) scanner with multiple slices to detect microscopic tumors or malignancies that ordinary radiographs can't show. In the lungs, a tumor, also known as a nodule, is a cluster of cells.

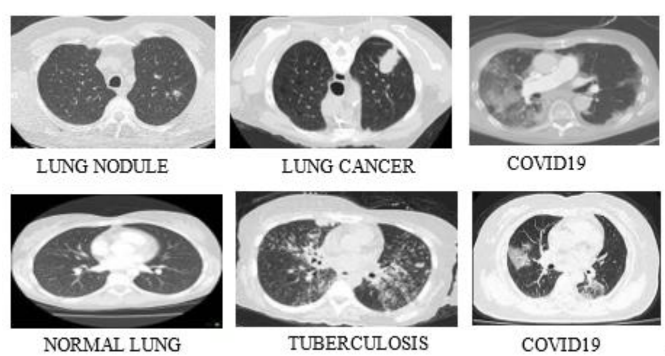

Figure 3. Example CT Scan Images

Longxi Zhou et al suggested a fully automated, rapid, accurate, and machine-agnostic approach for segmenting and detecting infected areas from CT images [12]. Preprocessing process and spatial and signal normalization were proposed. The spatial normalization of CT scan images combines the resolution and size of the images. Competition in lung segmentation and COVID-19 segmentation has been improved by the network developed in this paper.

Many Deep CNN-based methods were used to identify COVID19 from chest CT scans [13]. To identify and classify lung disease, three different DCNN designs were used in CT scans. As developed and tested, the COVID-SegNet is a multi-deep learning network for fragmenting lungs and corona viruses from lung images. COVID-19 infections may be highlighted by the use of ASPP and contrast optimization approaches in the proposed network, which includes pattern variation and ASPP blocks that are impacted by these techniques.

Onur Ozdemir et al. created an extensive CADe/CADx system for minimal CT images [16]. In identifying and diagnosing lung cancer using minimal CT images, CADe and CADx modules outperform 3D convolutional neural networks, while 3D convolutional neural networks improve lung tumor segmentation and aggressiveness classification. For classification and segmentation, the researchers have developed a Computer-Aided Detection module, as well as a Computer-Aided Diagnosis module for classification. It is recommended that the two modules of the CADe/CADx system be created and tested together if they are to be used as an edge automated diagnostic tool for lung cancer diagnosis, according to these studies.

This work used a weakly-supervised deep learning system to classify and identify tumors in COVID-19 [19]. COVID-19 (DeCoVNet) was identified from CT scans using a 3D deep convolutional neural network. Using a pre-trained UNet, we were able to segment the lung. The information has been divided into three DeCoVNet tiers for your convenience. ProClf is replaced with three 3D convolution layers, one of which is a fully connected (FC) layer. When a 3D lung mask is inserted in an input chest CT volume, COVID-19 is further classified. Classification Network Activated Patches and Unsupervised Connected Patches components are used to identify COVID-19 lesions.

TARANJIT KAUR et al. created a standard version based on neural abilities and a Parameter Free BAT (PF-BAT) that supports and facilitates the K-nearest neighbor (PF-FKNN) classifier for finding coronaviruses [23]. They used a transfer learning MobileNetv2 model to identify COVID and non-COVID CT images and then built a PF-BAT augmented FKNN model. As a feature extractor, MobileNetv2 from transfer learning is used in the proposed model. To aid the PF-BAT enhanced FKNN classifier, the trained model's fully connected layer generates discriminative properties.

To detect ILD patterns, S. Agarwala et al. developed a deep learning algorithm [24]. Fully convolutional networks were utilized to recognize ILD patterns from one other. Using deep learning, high-resolution (CT) images may be utilized to detect ILD patterning. Pre-training a model using images and transferring learning to a database provides acceptable results. Multiscale feature extraction improved ILD segmentation. Dilated convolution maintained the feature map's precision and increased the perceptron. In this work, a deregulatory paradigm was established to automatically recognize accumulation, oedema, and stiffness in an HRCT sector.

The radiographic complexity of CT images and varied lung nodule sizes complicate classification [25]. A multi-resolution convolutional neural network (CNN) was suggested to collect features from the network's spatial layers. This knowledge-transfer procedure has three components. They turned a source CNN model for feature extraction into a multi-resolution image classification model. Then, the origin training data was turned into a calculation including the model's lateral branches. This research recommends two neural networks for recognizing lung cancers from CT images.

MRRN (multi-resolution residually connected networks) have been created by Jue Jiang et al. as incremental-MRRN and high-density [28]. In order to identify and segment lung nodules, these networks combine data from a wide range of image resolutions and feature levels by using residual connections. Several residual streams of varying quality were added to two neural networks in this research to separate lung cancers from lung images. According to different datasets, classification performance has improved significantly.

COVID19 was identified in chest CT scans using a variety of Deep CNN-based approaches [29]. There's also an approach called "decision fusion" that combines the predictions of several various aspects to get a final result. It has been exciting to observe how merging different slices from CT scans might assist extract important information from the images. A more efficient approach might be created using COVID19 images and CT scans that include labeled information on different types of pulmonary diseases.

For the detection of COVID-19 severity, Shen et al. (2020) established a quantitative CT analysis technique [35]. These technique segments lungs using an algorithm based on organ correlation. Their approach can effectively evaluate CT abnormalities, GGO accumulation, and disease fibrosis. Consolidation increased with lesion density, but GGO decreased. The retrospective nature, selection bias for severe COVID-19 patients, restricted sample size, and evaluation bias based on CT scores were all limitations of the research.

Inception transfer learning algorithms were used to evaluate CT images by Wang et al. (2020) [36]. It employs a multi-cohort diagnostic paradigm that is retrospective in nature. Accuracy of 0.895 was reached by using this recommended strategy. Internal and exterior CT datasets show a sensitivity of 0.88 and 0.83, respectively, for their screening approach. Table 2 shows an overview of research for detecting lung disease using CT scan images.

Table 2. Summarizes articles on the identification of lung diseases using CT Scan images.

Author	Techniques	Diseases	Result	Dataset
Longxi Zhou et al. [12]	Machine-agnostic segmentation and quantification	COVID-19	0.783 (AUC)	KFSHRC
Qingsen Yan et al. [13]	Deep CNN	COVID-19	0.987 (Dice Coefficient)	Tianyou Hospital
Onur Ozdemir et al. [16]	3D CNN	Lung cancer	0.87 (AUC)	LIDC-IDRI and Kaggle datasets
Xinggang Wang et al. [19]	weakly-supervised deep learning system	COVID-19	90.1 (Accuracy)	Union Hospital, Tongji Medical College, Huazhong University
TARANJIT KAUR et al.[23]	PF-BAT-based FKNN	COVID-19	95.99 (Accuracy)	Multiclass dataset
S. Agarwala et al. [24]	Fully convolutional network and Pre-trained	Lung Diseases	90 (Success Rate)	MedGIFT ILD database
WANGXIA ZUO et al. [25]	CNN	Lung Nodule	97.33 (Accuracy)	LUNA16 and LIDC/IDRI
Jue Jiang, Yu-Chi Hu et al. [28]	Multi-Scale CNN approach	Lung Tumors	0.91 (Detection Rate)	TCIA and MSKCC
Arnab Kumar Mishra et al. [29]	Deep CNN	COVID-19	88.34 (Accuracy)	Tongji Hospital
Wang et al. [36]	DCNN model based on MobileNetV2	COVID-19	85.2 (Accuracy)	Xi'an Medical College

4. METHODOLOGY

4.1. Deep Learning Algorithms

Convolutional neural networks, the most common kind of deep learning, are excellent at image processing, such as X-rays and CT scans. Deep learning methods have enabled CNN to be employed in image recognition applications, where it has shown high levels of accuracy. Image detection and recognition have both been accomplished by using convolutional neural networks, or CNNs. One of the advantages of using medical imaging is the capacity to see infectious diseases using machine vision. This is one of the perks. Deep learning, which is considered to be one of the most efficient methods, is one of the many methods that are used in machine vision.

Recent developments in deep learning, and various Deep CNN architectures might be used in the future. An algorithm known as a convolutional neural network (CNN) is a kind of machine learning system that learns important properties such as the global effect of images. The system then utilizes these variables as weights and biases to differentiate between various images. The use of image analysis is a productive option for the construction of a CNN. During the present COVID-19 outbreak, the implementation of such Deep Learning-based techniques in real-time has become an even more crucial component. Particularly in regard to diagnosing diseases and conducting tests, the efficient use of methods that are based on Deep Learning might be of tremendous benefit. In medical imaging, the process of collecting images and interpreting such images is essential to the effective diagnosis and assessment of diseases. [2] Computer-aided diagnosis, often known as CAD, of clinical images, has been developed to do early clinical issue detection and evaluation using clinical images. Figure 4 shows the results of diagnostic work performed with the assistance of a convolutional neural network. Deep learning methodologies including CNN, Deep CNN, Multilevel CNN, DL-CRC framework, VGG architecture, and ResNet have been used in the process of diagnosing lung diseases.

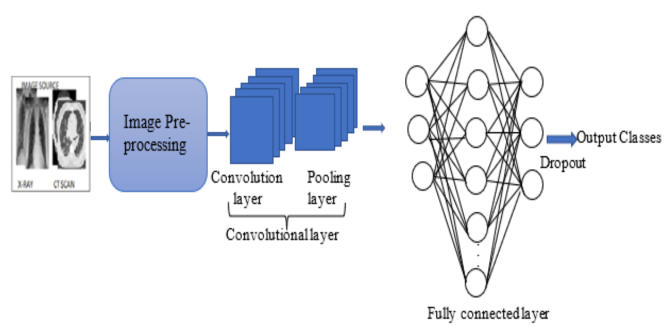

Figure 4. CNN Model for detecting lung disease

Deep CNN is developed for the supervised classification of diseased lung tissue on HRCT slices [14]. This paper proposes a CNN for supervised classification. Instead of decreasing feature maps to improve acceptance, use dilated convolutions. The proposed CNN employs convolutional layers with dilated filters to evaluate lung images and generate labeling maps. An instance variance normalization strategy is used in combination with dilated convolutions to integrate multi-scale properties in the network under study.

SADMAN SAKIB et al. [15] presented a DL-CRC architecture for COVID-19 identification. COVID-19 infected lung X-ray images are generated using an adaptive GAN and generic data augmentation techniques in the suggested framework for the development of a reliable model. Inception ResNet v2, DenseNet, and ResNet were compared to DL-CRC. They constructed a new CNN model using actual and simulated x-ray images, which improved accuracy.

Two-stage convolutional neural networks are used to identify lung nodules [18]. First, they employed ResDense U-Net segmentation to identify lung lesions. Second, the TSCNN design was established to reduce false-positive lung nodules based on the recommended dual pooling design in three 3D-CNN communication networks. The second prediction step is to segment the probable lesion neighborhood effectively. 3D-CNN-based false positive reduction modules include InceptionNet, DenseNet, and SeResNet.

Hoo-Chang Shin et al. [20] introduced CNN architectures for CADe. In this study, two CADe problems, namely thoraco-abdominal lymph node (LN) identification and interstitial lung disease (ILD) classification, are addressed. Based on cross-validation classification methodologies, they were able to accurately predict CT axis slices with ILD categories with the greatest detection performance for LN mediastinum. LN detection using CifarNet. GoogLeNet and AlexNet were altered to test this cutting-edge CNN architecture on CADe problems and datasets and the ImageNet classification assignment.

This research developed an automated lung nodule detection method [21]. This work created an excellent method for detecting pulmonary nodules using multi-region lung radiographs and Frangi filter. Radiologists discovered four-level nodules by combining picture groupings and a convolutional neural network model from four segments. Vascular removal of high-light nodules while weakening arteries is a common pre-processing method. 3D processing

TARANJIT KAUR et al. created a standard version based on neural capacities and a Parameter Free BAT (PF-BAT) classifier [23]. They used a transfer learning MobileNetv2 model and PF-BAT augmented FKNN to classify COVID and non-COVID CT images. Transfer learning is modeled MobileNetv2 extracts features. A fully connected model layer generates discriminative features for the PF-BAT enhanced FKNN classifier.

This study used Deep CNNs to identify COVID19 in lung CT images [29]. An approach called decision fusion is the estimate of various elements to make a final option. Evaluation metrics include VGG16, ResNet50, InceptionV3, DenseNet121, and DenseNet201. In this study, the convolution areas of these evaluation metrics are the same as in the ImageNet competition.

This research used an NU-Net to identify lung cancer candidate nodules to avoid missed diagnoses [30]. The NU-Net, based on U-Net, adds noise to each convolution layer, making it more sensitive to key characteristics. The research found that NU-Net is more accurate in detecting nodules, especially small ones. In this research, the neural network's responsiveness (rate of positive nodule identification) was evaluated.

Classification is complicated by CT image complexity and lung nodule size [25]. For the network's spatial layers, a multi-resolution CNN was recommended. They created a multi-resolution image classification model from a CNN model for feature extraction. Multi-resolution network data enhances lung nodule detection. When combined with asymmetric initial detection, this method improves lung nodule screening.

They constructed, assessed, and implemented two multi-resolution residual deep neural networks [28]. Two internal and two external datasets were utilized to assess the suggested lung tumor segmentation method. Deep learning RF+CRF was compared to CNN. Deep CNN outperforms shallow learning approaches, according to research. These approaches segmented tumors best, regardless of size or location.

Mohammad Rahimzadeh et al. [34] established a fast and accurate approach for recognizing COVID-19 from a chest CT image. First, an image processing approach was proposed to properly filter chest CT images. This method reduces classification errors, particularly for small objects in images. Three deep convolutional networks were developed to classify CT scans as COVID-19 or normal. ResNet50V2, a modified feature pyramid network, performed best. They employed Grad-CAM to measure classification accuracy and identify infection regions in lung CT images.

Lung cancer detection and classification are made easier by Wessam M. Salama's generalized framework [39]. As a first step, they generated an Auto-encoder model that used convolutional variation. Online classification of CXR images is carried out using ResNet50, which was trained offline using massive, balanced datasets. A retraining scenario is described, in which weights from a network previously trained on another dataset are used. Pre- or post-processing, as well as hand-crafted features, are not required, in this work. The robustness of the proposed architecture is put to the test by examining the learning curves. On the basis of these findings, it seems that the deep learning model may be utilized to identify COVID-19 and pneumonia infections from chest x-rays and CT scan results [40]. The ResNet152V2 + GRU and ResNet152V2 + Bi GRU (Bidirectional GRU) architectures were also evaluated in this research. Based on public chest x-ray and CT datasets and four classes, an assessment of several deep learning architectures is offered. The VGG19 +CNN model performed better than the other three models in the experiments. Viral Pneumonia, Bacterial Pneumonia, Normal and Covid-19 were predicted by Dangety Sowjanya et al. using VGG-19 [43]. A high prediction rate is achieved by retrieving anomalous image characteristics using VGG-19 and processing them with Fully Connected Layers. The accuracy rate is 0.94, according to performance measures. Accuracy increases with more data.

For the automatic detection of COVID-19, Masadeh, Mahmoud, et al. presented the CNN model[44]. With automatic feature extraction, the suggested model is completely automated. They achieved 97.44% test accuracy and 97.55% training accuracy in three class classifications i.e., normal vs pneumonia vs COVID-19. A variety of datasets were used to test the proposed framework. Table 3 shows an overview of research for detecting lung disease using deep learning algorithms.

Table 3. Summarizes articles on the identification of lung diseases using Deep Learning algorithms.

Author	Algorithms	Image type	Diseases	Result	Dataset
Marios Anthimopoulos et al.[14]	Deep CNN	CT Scan	Interstitial Lung Diseases	81.8 (Accuracy)	INSEL and HUG hospitals
SADMAN SAKIB et al. [15]	DL-CRC framework and depth-based CNN	X-RAY	COVID-19	94.61 (Accuracy)	Normal Images: 27,228 pneumonia Images: 5,794 and COVID-19 Images: 209
Haichao Cao et al.[18]	TSCNN	CT Scan	Lung Nodule	0.925 (CPM)	Four Different Hospitals
Hoo-Chang Shin et al. [20]	CNN	CT Scan	Interstitial Lung Diseases	0.93 (AUC)	ILD dataset
Hongyang Jiang, He Ma et al. [21]	CNN	CT Scan	Lung Nodule	0.871 (AUC)	LIDC/IDRI
TARANJIT KAUR et al. [23]	PF-BAT-based FKNN	CT Scan	COVID-19	95.99 (Accuracy)	Multiclass dataset
WANGXIA ZUO et al. [25]	CNN	CT Scan	Lung Nodule	97.33 (Accuracy)	LUNA16 and LIDC/IDRI
Jue Jiang, Yu-Chi Hu et al. [28]	CNN	CT Scan	Lung Tumors	0.91 (Detection Rate)	TCIA and MSKCC
Arnab Kumar Mishra et al. [29]	Deep CNN	CT Scan	COVID-19	88.34 (Accuracy)	COVID-CT
WENKAI HUANG et al. [30]	U-Net	CT Scan		98 (Sensitivity)	LUNA16
Mohammad Rahimzadeh et al. [34]	ResNet50V2	CT Scan	COVID-19	98.49 (Accuracy)	Sari in Iran- Negin radiology
Wessam M. Salama et al. [39]	GAN, ResNet50	CXR	Lung Cancer	98.91 (Accuracy)	LIDC/IDRI
Dina M. Ibrahim et al. [40]	ResNet152V2 + Bi GRU	CT Scan	COVID-19	98.05 (Accuracy)	public digital chest x-ray and CT datasets
Dangety Sowjanya et al. [43]	VGG 19	CXR AND CT Scan	COVID-19	94 (Accuracy)	Covid-19 CXR image dataset

4.2. Machine Learning Algorithms

One of the most important technical developments in medical image processing in recent years has been machine learning. This trend has been driven in large part by advances in computer vision. Image registration, fusion, segmentation, and other calculations are assisted by prior information gathered from common scenarios provided by medical professionals. This results in accurate descriptions of the original data and the extraction of appropriate diagnostic signals, which is necessary to accomplish CAD goals.

Supervised learning algorithms that produce a transfer from data input to result from data (labels) from a series of labeled training images have shown outstanding potential in the field of medical image analysis [4]. By applying features that describe local image presentation, pattern segmentation has been used for many decades to identify and define abnormalities in mammograms and lung radiography.

This work used metabolomics and machine learning to identify lung cancer biomarkers [10]. Metabolic signs may help detect lung cancer early. Researchers compared and evaluated machine learning models using a test set and a control experiment. Naive Bayes, sensitive Neural networks, Random Forests, and SVM may accurately identify lung tumors. A fast Correlation-Based Filter determines a metabolic biomarker's relevance. Using chest X-ray pictures, the researchers Shimpy Goyal et al. [11] suggested an F-RNN-LSTM technique for detecting lung disease and classifying cases of Covid-19 and pneumonia.

During training, they used three top classical machine learning algorithms for testing [31]. Fine k-nearest neighbor, gaussian SVM, and ensemble bagged model trees are available. The optimal combination of radiomics characteristics and a machine learning algorithm rapidly detected COVID-19 from a chest radiograph with equal or better specificity and sensitivity than RT-PCR. EBM trees can identify COVID-19 from other lung infection severity levels using radiomics. The method identified COVID-19 even though two skilled doctors couldn't see any abnormalities on the lung Chest radiograph.

To diagnose lung diseases in a publicly accessible CXR dataset, Chandra Mani Sharma et al. employed a combination of machine learning (ML), deep learning (DL), and transfer learning (TL) algorithms [37]. An Inception-ResNet-v2 transfer learning model, along with data augmentation and image improvement, was the most accurate model. Using Amazon IoT Core, a model can automatically identify three types of CXR images: normal, pneumonia, and COVID-19. Balance the unbalanced data using the SMOTE technique. The process of disease classification is made easier with the aid of data augmentation and image improvement. The suggested method has an average accuracy of 98.66 %. Deep learning and machine learning approaches like CNN and Logistic Regression were proposed by Koti Neha et al [42]. Covid-19 must be discovered quickly if it is to remain contained. Using CT-Scan and X-ray images, researchers were able to estimate Covid-19 significantly more rapidly and easily than blood tests.

4.3. Transfer Learning Methods

Transfer learning uses a learned model in another domain. Transfer learning is used in computer vision to create accurate models. Using a pre-trained model, a problem was solved. ImageNet is used to develop new CNN models. Transfer learning applications include fine-tuning and CNN feature extraction. To learn more from training data, a pre-trained model's outer layers must be taught. A huge dataset that can be compared to the dataset of a pre-trained model is a fine fit for this method of training. Transfer learning transfers neural network parameters from one dataset and objective to another. Last network layers transfer characteristics from broad to specific categories.

Transfer learning is a good option if the destination dataset is small compared to the original. This permits trained models without system overload. If the dataset isn't too vast, transfer learning can be effective in CNN applications. The practice of adopting a model learned in one field to another is known as transfer learning. The resource domain is designed in such a manner that there are sufficient training data to create an effective model. With little data, transfer learning is utilized to fine-tune the model's features to the source domain.

This issue is addressed by transfer learning, which employs information gained in one field to resolve problems in another. Transfer learning is useful when working with data with a small sample size because the pre-trained parameters enhance performance and efficiency. The three fully connected layers were augmented by the final layer as a classification layer, and the pre-trained model's initial layers were frozen. Rather than repeating the complete network's weights with FC layers, the weights of the convolution layers have been sent. A depiction of the model is shown in Fig.5.

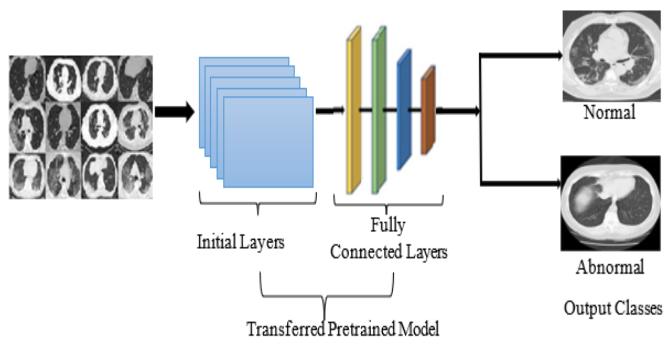

Figure 5. Pre-trained Transfer Learning Model

A fast and easy-to-implement machine learning model for different imaging modalities is provided by the VGG19 classier with transfer learning for identifying COVID-19 [26]. Given the limited quantity of COVID-19 medical images, both VGG16 and VGG19 classifiers performed well in the early model evaluation research. Their false negative rate dropped from 12 to 7 when they used a threshold of 0.7. The concept of this technique was between 83 and 90 %, while the accuracy of its predictions was between 79 and 78 %.

COVID-19-infected patients' classification models are built using the Deep Transfer Learning (DTL) approach [27]. A tenfold cross-validation technique was performed to prevent overfitting. The proposed deep transfer learning-based COVID-19 classification model outperforms earlier supervised learning models in terms of efficiency. Hyper-parameter tuning for the proposed model can be accomplished using a variety of algorithms shortly.

An HRCT segment was used in this research to identify ILD using deep learning [24]. After building the pre-trained model using images, ILD was utilized to fine-tune the model's accuracy. A fully convolutional network is used to distinguish ILD patterns. Multi-scale extracted characteristics improved ILD segmentation. Dilated convolution was used to keep feature resolution while increasing the ROI.

Fouzia Altaf et al. devised a unique method to increase transfer learning when model material is constrained and formatted differently [32]. The suggested approach uses a hierarchical collection of fine-tuned deep-learning models. They tested the technique using pre-trained natural image models using chest x-rays (i.e. ImageNet). They employed hierarchical transfer learning to improve system efficiency.

Vinay Arora et al.utilized CT lung scans and deep learning algorithms to identify COVID-19[33]. These pre-trained models, including Xceptionnet, MobileNet, inceptionV3, Densenet, resnet50, and vgg 16, were used to evaluate whether or not this improved CT scan of COVID-19 was positive or negative. By using a residual dense neural network in the pre-processing step before collecting CT images with super-resolution, the accuracy, F1 score, precision, and recall of the proposed model were all enhanced.

RepVGG pre-trained model was proposed by Trang, Kien, et al. to categorize COVID-19 based CXR images[45]. The suggested RepVGG model attained reasonable accuracy. For the segmentation of the lung, they first trained a U-Net type network. In this study, the last layer in the final step of RepVGG is replaced with a flattened layer for mixing with the encoders.

5. DATASET

This section describes the datasets that were used in the study that was evaluated. The datasets utilized to detect TB, pneumonia, lung cancer, and COVID-19 are presented in Tables 1–3. This is done to provide users with access to information that might be helpful to them about the datasets. The tables only feature public datasets as they are available to the general public, while private databases need authorization.

Table 1 outlines the eight datasets used to diagnose lung disease using X-Ray images. An X-ray of the chest is obtained. The NLM dataset, the Belarus dataset, the RSNA dataset, the NIH dataset, the C19RD dataset, the CXIP dataset, and the ImageNet data collection are all examples of datasets. These datasets have been applied in a variety of studies for lung diseases, which encompass a wide range of ailments. The Montgomery and Shenzhen datasets may now be accessed thanks to the efforts of the National Library of Medicine. The NLM database includes images of normal and TB-infected X-rays. All of the chest images in the Belarus database have been tainted by TB. Chest radiographs with a resolution of 2248x2248 pixels were acquired using the Kodak Point-of-Care system. 344 abnormal X-ray images and X-ray normal images are included in the Kaggle dataset.

Two datasets were used for experimental work. Datasets 1&2 are Chest X-Ray images from the Kaggle repository. Which contains normal, pneumonia, and covid19 images. Dataset collected from https://drive.google.com/drive/folders/1bwldB0owjeroiL8kLJL0NMJHqF4dfyjk?usp=sharing

6. EXPERIMENTAL WORK

CNN models with preloaded weights were tested as a result of the research. The deep learning model was trained using an NVIDIA GeForce RTX 12 GB GPU, 64 GB of RAM, and Windows 10 operating system. A validation loss was assigned as an early endpoint for networks trained for 30 epochs. Python-based deep learning tools like Keras and Tensorflow are used for model building, training, and performance assessment as well as visualization. With the use of data augmentation, more training samples without affecting the image class ratio improve the model's performance. Data-augmented models have lower loss values when actual and intended classes are comparable. When a number of epochs are high, data augmentation creates a large number of training samples. Without data augmentation, each epoch uses the same training samples. As can be seen in part (A), the CNN model's loss and accuracy plots are displayed, while those for VGG16, VGG19, and ResNet50 [41] can be seen in parts B, C, and D of figure 6. Table 4 shows the various metrics for the customized approach's various accuracy measures.

Table 4. Comparison of the performance of various models.

Model	**Class**	**Dataset 1**	**Dataset 2**
		Accuracy	**Accuracy**
CNN	Pneumonia Class Normal Class	0.90	0.95
VGG16	Pneumonia Class Normal Class	0.91	0.99
VGG19	Pneumonia Class Normal Class	0.90	0.99
ResNet 50	Pneumonia Class Normal Class	0.91	0.99

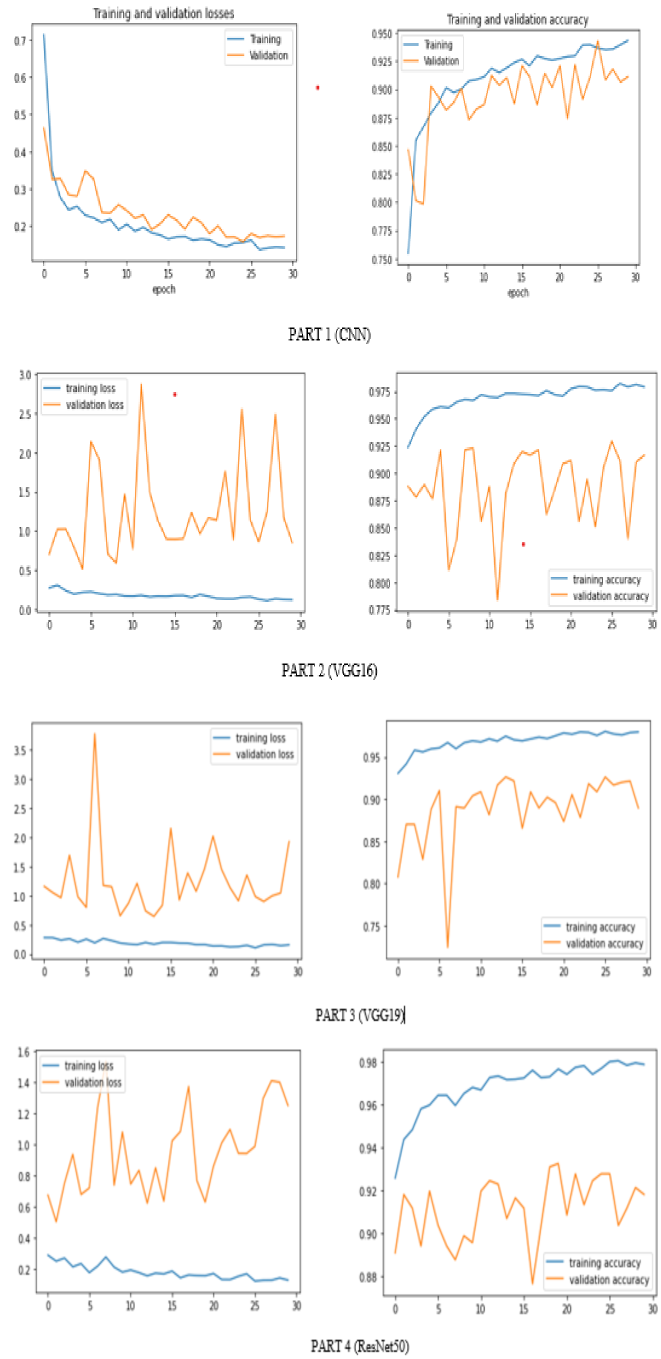

Figure 6. Plots for DL models.

7. Research Gap

Despite the achievement of deep learning approaches in the diagnostic and therapeutic domains, there are significant limitations and challenges. Many times, a significant amount of labeled data is required for a deep learning study. This is a significant challenge when it comes to annotating medical images. Labeling medical images need expert information, such as radiologists' topic experience. If deep learning methods can be used to annotate unlabeled images, it will save a significant amount of time and effort. Deep learning's interpretability is also a challenge. Deep learning techniques are frequently considered a black box, with no means to interpret their success or failure. In medical image processing, clinical deep learning applications are becoming more common as research in these approaches increases. Integrity in the legal and practicality in practice are necessary for the broad use of deep learning in the area of medicine. The most frequent problem with transfer learning is when the network's predicted input parameters differ from the actual dimensions of the samples being utilized in the target domain. In addition, it's possible that the number of class labels predicted for the target domain at the output will change.

8. Conclusion

Over many years, an increasing amount of research on the detection of lung disorders via the use of deep learning has been published. On the degree of analysis and implementation that is now taking place, however, there was a lack of thorough surveys. This survey provides a thorough analysis of lung disease diagnosis and detection utilizing machine learning and deep learning techniques. As more patients are diagnosed with lung diseases, the chances of them being treated and living longer may increase significantly by employing artificial intelligence techniques in this research.

In this comprehensive study, TB, pneumonia, lung cancer, and COVID-19 were all taken into special consideration. Medical image analysis employing lung images, datasets, and measurements was discussed along with classification, detection, and segmentation challenges. Deep learning and transfer learning are now the two technologies that are proving to be the most useful for medical image analysis. In terms of target recognition, target segmentation, target classification, and target registration, they had a great deal of success. The development of deep learning in medicine is dependent on the collection of medical big data, with multi-modal features that contribute to higher accuracy in detecting and classifying lung infections.

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