Grenze International Journal of Engineering and Technology, Jan Issue

Deep Learning Techniques for Detecting Lung Diseases

Juhi Gupta[1], Monica Mehrotra[2] and Arpita Aggarwal[3]
[1-2]Department of Computer Science, Jamia Millia Islamia, Delhi, India
Email: juhi2206453@st.jmi.ac.in, mmehrotra@jmi.ac.in
[3]Department of Computer Science, PGDAV College, University of Delhi, Delhi, India
Email: arpita.aggarwal@pgdav.du.ac.in

***Abstract*— Deep learning has emerged as a powerful tool in the medical imaging field that aims to improve accuracy and speed of diagnosis. It can automatically learn feature representations from images which are then used to classify them as normal or abnormal. Several studies have shown the potential of deep learning in detecting lung diseases with high accuracy, even outperforming human experts in some cases. Deep learning models canalso be used to predict disease progression and treatment outcomes, and to guide personalized treatment plans. This paper presents a study of the major deep learning techniques applied to medical imaging, focusing on pulmonary medical images, datasets, and benchmarks. The techniques include classification, detection, and segmentation tasks for variouslung diseases, such as tuberculosis, lung cancer, pulmonary nodule diseases, pneumonia, asthma, COVID-19 and interstitial lung disease. The paper also discusses the challenges and potential directions for the future application of deep learning techniques in detecting lung disease. Deep learning has been successful in several domains, including acoustics, images, and natural language processing, and has the potential to significantly improve disease screening and diagnosis in the medical field.**

***Index Terms*— Deep Learning, Lung disease detection, CNN, Deep models, Medical images.**

I. I. INTRODUCTION

Lung disease refers to any condition that affects the structure or function of the lungs, including the airways, lung tissue, and blood vessels. These diseases can range from acute infections, such as pneumonia and bronchitis, to chronic conditions, such as chronic obstructive pulmonary disease (COPD) and interstitial lung disease. With the aggravation of air pollution and the increasing number of smokers, respiratory diseases have become a serious threat to people's life and health [27]. Early detection and treatment of lung disease are essential for improving outcomes and preventing complications.

According to a survey conducted by Chest Research Foundation, Pune, India has 18% of the world's population, but accounts for 32% global respiratory diseases. India tops the world in death due to various lung diseases [25]. About 34% of all Chronic Obstructive Pulmonary Diseases (COPD) are due to air pollution. Only 21% of COPD cases are due to smoking. In the health care system, there has been a dramatic increase in demand for medical image services, e.g., Radiography, endoscopy, Computed Tomography (CT), Mammography Images (MG), Ultra-sound images, Magnetic Resonance Imaging (MRI), Magnetic Resonance Angiography (MRA), Nuclear medicine imaging, Positron Emission Tomography (PET) and pathological tests. Besides, medical images can often be

Grenze ID: 01.GIJET.10.1.371

challenging to analyze and time-consuming process due to the shortage of radiologists [22].

Deep learning addresses all these challenges. Deep learning is a type of artificial intelligence (AI) that uses multi-layered neural networks to analyze data and make predictions or decisions. It is a subset of machine learning, which is a broader field of AI that involves the development of algorithms that can learn and improve from experience. The neural networks used in deep learning are inspired by the structure of the human brain, and they are designed to recognize patterns and relationships in data. These networks consist of layers of interconnected nodes,or ”neurons”, that process and transform the input data to produce a desired output. The deep learning algorithm was first applied to medical image processing in 1993, in which the neural network was used for the detection ofpulmonary nodules [17].

Deep learning has emerged as a powerful tool in medical image detection, enabling more accurate and efficient analysis of medical images such as X-rays, CT scans, and MRIs. This is particularly important in the field of medical imaging, where accurate and timely diagnosis of diseases can have a significant impact on patient outcomes.In traditional medical image analysis, radiologists and medical professionals manually analyze images to identify abnormalities and diagnose diseases. However, this process can be time-consuming and error-prone, especially for large datasets or complex images. Deep learning algorithms can automate this process, enabling faster and more accurate analysis of medical images. Deep learning is quickly becoming state of the art, leading to improved performance in numerous medical applications. Consequently, these advancements assist clinicians in detecting and classifying certain medical conditions efficiently [36].

Deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been applied to medical image analysis for a variety of tasks, including image classification, object detection, and segmentation. These techniques have shown promise in detecting and diagnosing a wide range of lung diseases, such as lung cancer, pneumonia, asthma, bronchitis etc. One of the key advantages of deep learning in medical image detection is its ability to learn useful representations of medical images directly from the data [26]. This eliminates the need for feature engineering or manual extraction of features, which can be time-consuming and require domain-specific knowledge. Furthermore, deep learning can be used to analyze large datasets with high accuracy, allowing for more precise diagnosis and personalized treatment plans. A basic framework of application of deep learning models in medical images is presented in Fig. 1.

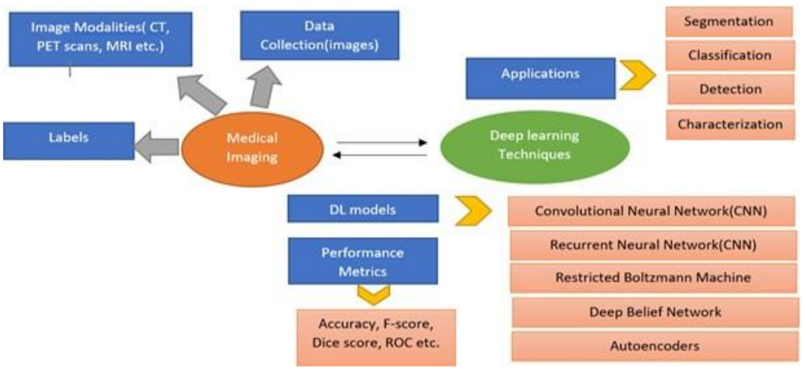

Fig. 1. Framework of application of DL techniques in medical science

Despite the promise of deep learning in medical image detection, there are still challenges that need to be addressed, such as the need for large and diverse datasets, the interpretability of deep learning models, and ethical concerns surrounding the use of patient data. However, ongoing research and development in this field continue to push the boundaries of what is possible with deep learning in medical image detection.

II. RELATED WORK

In this section, the deep learning techniques which have been applied for detecting tuberculosis, pneumonia, lung cancer and COVID-19 are discussed in greater detail. The first three diseases were considered as they are the most common causes of critical illness and death worldwide related to lung [18], while COVID-19 is an ongoing pandemic [35].

A. Deep learning in Tuberculosis detection

Tuberculosis is a disease caused by Mycobacterium tuberculosis bacteria. Murphy et.al [19]used Computer -Aided Detection (CAD4TB) for tuberculosis detection. CAD4TB works by obtaining the patient’s chest X-ray, analyzing the image via CAD4TB cloud server or CAD4TB box computer, generating a heat map of the patient's lung and displaying an abnormality score from 0 to 100. In the literature, numerous studies have utilized convolutional neural networks (CNNs) to classify tuberculosis. Heo et al. [9] introduced a method that incorporated demographic information, such as age, gender, and weight, to enhance the performance of CNN. The findings indicated that the CNN model, when augmented with demographic variables, achieved a higher area under the receiver operating characteristic curve (AUC) score and greater sensitivity compared to a CNN solely based on chest X-ray images. Additionally, Pasa et al. [21] proposed a simple convolutional neural network specifically designed for tuberculosis detection. The approach presented by the authors demonstrated improved efficiency compared to previous models while maintaining their accuracy. This method significantly reduced the memory and computational requirements without compromising the classification performance. Lakhani et. al. [15] proposed two different DC- NNs, AlexNet and GoogleNet to achieve high accuracy in classifying images as TB-positive or TB-negative. A deep learning algorithm using a combination of CNNs and recurrent neural networks (RNNs) for detecting TB in chest radiographs was developed by Zhou et. al. [37]. This model demonstrated high sensitivity and specificity inTB detection.

B. Deep learning in Pneumonia detection

Pneumonia is a lung infection that causes pus and fluid to fill the alveoli in one or both lungs, thus making breathing difficult [34]. Symptoms of pneumonia include severe shortness of breath, chest pain, chills, cough, feveror fatigue. Transfer learning and data augmentation are mostly used in the studies. Tobias et al. [32] employed a CNN in a straightforward manner for their study. In contrast, Stephen et al. [30] trained their CNN from scratch and applied various augmentation techniques, such as rescaling, rotation, width shift, height shift, shear, zoom, and horizontal flip. In the case of pneumonia detection, authors in [2] [6]utilized pre-trained CNNs, and in additionto that, the latter four studies incorporated data augmentation methods into their training datasets.

C. Deep Learning in Lung Cancer Detection

Pulmonary nodules, solid clumps of tissue appearing in and around the lungs, are a significant characteristic of lung cancer [4]. These nodules can be visualized in CT scan images and can be either malignant (cancerous) or benign (not cancerous) [29]. In 2015, Hua et al. [10] utilized models of Deep Belief Networks (DBNs) and Convolutional Neural Networks (CNNs) to classify nodules in CT scans. Their research demonstrated that deep learning techniques enable the extraction of features for classifying lung nodules as malignant or benign without the need for computing morphology and texture features. Rao et al. [23] and Kurniawan et al. [14] applied CNNs straightforwardly to detect lung cancer in CT scans. Furthermore, Song et al. [29] compared the classification performance of CNNs, deep neural networks, and stacked autoencoders (a multilayer sparse autoencoder of a neural network). They concluded that CNNs achieved the highest accuracy among these models.

D. Deep Learning in Covid-19 Detection

COVID-19 is an infectious disease caused by a recently discovered coronavirus [12]. Senior citizens are those at high risk to develop severe sickness, along with those that have historical medical conditions such as cardiovascular disease, chronic respiratory disease, cancer and diabetes [33].

Salman et al. [24] employed a direct method to detect COVID-19 by utilizing a CNN with transfer learning and data augmentation. In their study, they utilized InceptionV3 as a fixed feature extractor for transfer learning purposes. The authors of [20] conducted a 3-class classification task using CNN with transfer learning, aiming to classify X-ray images into normal, COVID-19, and viral pneumonia cases. Similarly, Chowdhury et al. [7] employed CNN with transfer learning and data augmentation to classify X-ray images into the same three categories:normal, COVID-19, and viral pneumonia. The augmentation techniques applied in their study included rotation, scaling, and translation.

III. Deep Learning Models Used In Lung Disease Detection

There are several deep learning models that have been used in the detection and diagnosis of lung diseases. Some of the commonly used models are:

A. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a type of deep learning models that are widely used in image analysis and computer vision tasks. They are capable of automatically learning features and patterns from images througha hierarchical process of convolutions and pooling operations [8]. CNNs consist of multiple layers of interconnected neurons that perform convolutions and nonlinear operations onthe input image. The first layer of a CNN is typically a convolutional layer that applies a set of filters to the inputimage, producing a set of feature maps that highlight different aspects of the input image. The subsequent layers are typically composed of pooling layers that reduce the spatial size of the feature maps, followed by additional convolutional and activation layers that further refine the features.

CNNs are trained using backpropagation, a process that updates the weights of the network based on the error between the predicted output and the true output. The weights are updated using gradient descent, which finds the direction of steepest descent in the error function.

Pros

- *Automatic Feature Learning*: CNNs excel at automatically learning discriminative features from raw input data.
- *Scale-Invariant Representations*: CNNs can learn scale-invariant representations of lung images, making them robust to variations in image sizes and resolutions.
- *Real-Time or Near Real-Time Results:* Once trained, CNN models can provide quick inference on new lung images, enabling real-time or near real-time detection of lung diseases. This speed is crucial in clinical settings where timely diagnosis and treatment decisions are critical.

Cons

- *Data Dependency*: CNNs rely heavily on the availability of large, well-annotated datasets for training. Collecting and annotating such datasets can be time-consuming and expensive, particularly for rare lung diseases.
- *Computational Requirements*: Training and deploying CNN models can demand significant computational resources, including powerful GPUs or dedicated hardware accelerators.

B. Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are a type of deep learning models that are used for processing sequential data, such as time series, natural language, and audio signals. Unlike traditional neural networks, RNNs have loops that allow information to persist over time, making them well-suited for modeling temporal dependencies [16]. RNNs consist of multiple neurons organized in a sequence, where each neuron takes as input the output of the previous neuron in the sequence, as well as an input from the current time step. This allows the network to use information from previous time steps to inform its predictions at the current time step. RNNs can be unfolded intoa series of connected layers, where each layer corresponds to a time step in the sequence.

Pros

- *Sequential Information Processing*: RNNs can capture the temporal patterns and long-range dependencies present in time-series data, such as lung function measurements or longitudinal patient data.
- *Efficient Parameter Sharing*: This parameter sharing property allows RNNs to efficiently handle long sequences and makes them computationally efficient compared to feed-forward neural networks.
- *Suitability for Time-Series Analysis*: RNNs are well-suited for time-series analysis tasks, enabling the detection of temporal patterns and trends in lung disease data.

Cons

- *Difficulty in Capturing Long-Term Dependencies*: Traditional RNN architectures, such as vanilla RNNs, can have difficulty capturing long-term dependencies. This issue, known as the vanishing gradient problem,can limit the ability of RNNs to model long-term temporal patterns in lung disease data.
- *Challenge in Handling Irregular Time Intervals*: RNNs assume a fixed time step between data points, which may not be suitable for lung disease data with irregular time intervals or missing values.
- *Increased Training Time* : The sequential nature of RNNs limits parallelism during training, which can leadto longer training times compared to other neural network architectures.

C. Autoencoders

An autoencoder is a type of neural network that is used for unsupervised learning of data representations [5]. It consists of an encoder and a decoder, both of which are neural networks that are trained to reconstruct the input data. The encoder takes the input data and maps it to a lower-dimensional representation, or code, that captures the most important features of the input data. The decoder then takes this code and maps it back to the original inputdata, with the goal of reconstructing the input as accurately as possible.

Pros

- *Dimensionality Reduction and Data Compression*: Autoencoders can compress high-dimensional lung disease data into a lower-dimensional latent space. This dimensionality reduction can be helpful in reducing noise, removing redundant information, and capturing the most informative features, potentially improvingthe efficiency and effectiveness of subsequent disease detection models.

- *Robustness to Noise and Missing Data*: Autoencoders can handle noisy or incomplete lung disease data by learning to reconstruct the original input from corrupted versions.
- *Transfer Learning*: Pretrained autoencoder models can be used as feature extractors or initialization for downstream disease detection tasks. The learned representations can capture relevant features, aiding in transfer learning scenarios where labelled data for the target disease may be limited.

Cons

- *Difficulty in Capturing Complex Relationships*: Autoencoders might struggle to capture complex relationships in lung disease data, especially when the data exhibits non-linear and high-order interactions.
- *Risk of Overfitting*: Autoencoders can be prone to overfitting, particularly when the model is excessively complex or when the training data is limited.
- *Computationally Expensive Training*: Training autoencoder models can be computationally expensive, especially for large-scale or high-resolution lung disease datasets.

D. Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) are a type of deep learning model that consists of two neural networks:a generator and a discriminator [28]. The generator is trained to generate realistic images from random noise, while the discriminator is trained to distinguish between real images and fake images generated by the generator. In the context of medical imaging, GANs have been used for various applications, including lung disease detection. One approach involves training the GAN to generate synthetic medical images that are similar to real medical images of patients with lung diseases. The generated images can be used to augment the training dataset,which can improve the performance of the deep learning models trained on the dataset. Another approach involves using the GAN as a data augmentation tool to improve the robustness of the deep learning model to variations in the input images. The generator can be trained to generate images that correspondto different variations of the input images, such as different orientations, lighting conditions, or levels of noise. These variations can help the deep learning model to better generalize to new and unseen images.

Pros

- *Improved Discriminative Features*: GANs can learn to generate highly discriminative features specific to lung diseases.
- *Transfer Learning and Domain Adaptation*: GANs can be employed for domain adaptation, where the generator is trained on a source domain and then used to generate lung disease images in the target domain.
- *Rare Disease Detection*: GANs can be beneficial for detecting rare lung diseases.

Cons

- *Training Instability*: GANs can be challenging to train, requiring careful hyperparameter tuning and architecture design to achieve stable convergence
- *Risk of Generating Unrealistic Samples*: GANs may generate synthetic lung disease images that look realistic but do not accurately represent the underlying disease patterns or clinical characteristics.
- *Training Instability*: GANs can be challenging to train, requiring careful hyperparameter tuning and architecture design to achieve stable convergence.

IV. Basic Methodology Used For Detecting Lung Diseases Using Deep Learning

This section describes the process of utilizing deep learning to identify lung disease from medical images, which involves three main steps: image pre-processing, training, and classification [31]. The objective of lung disease detection is typically to classify an image as either healthy or infected with a disease. To achieve this, a lung disease classifier, also known as a model, is trained through a neural network. The deep learning approach enables the model to learn and classify images into their respective labels. To apply this method for lung disease detection, the first step involves gathering images of diseased lungs to be classified. In the next step various pre-processing techniques are applied to images like data augmentation, feature extraction, data cleaning in order to make them suitable for training the model. The third step is to train the neural network to recognize the diseases accurately. Finally, the model is used to classify new images that have not been seen before. The process is illustrated in the Fig. 2.

Fig. 2. Process for detecting Lung Diseases using DL Techniques

V. Evaluation Metrics Used In DL

There are different evaluation metrics which are being used for the purpose of evaluating and measuring the performance of deep learning models. They are used according to some specific regularities and criteria. For example Dice score and F1-score are particularly used for segmentation, accuracy and sensitivity are mostly used for classification tasks [3].

- *Dice Coefficient* : Dice coefficient is a statistic used to find the similarity of two samples. The Dice score is often used to quantify the performance of image segmentation methods [1].
- *Jaccard-index (similarity coefficient) [JAC]:* The Jaccard similarity measures the similarity between two sets of data to see which members are shared and distinct. The Jaccard similarity is calculated by dividing the number of observations in both sets by the number of observations in either set.
- *True-Positive Rate (TPR*): The True positive rate (TPR) gives the proportion of correct predictions in predictions of positive class. Mainly used for binary classification. It is also called sensitivity and recall.
- *Accuracy [ACC]* : Accuracy means exactly how good the DL model at guessing the right labels (ground truth). Accuracy is commonly used to validate the classification task.
- *F1-Score*: The F1-score combines the precision and recall of a classifier into a single metric by taking their harmonic mean. It is primarily used to compare the performance of two classifiers.
- *AUC-ROC*: Receiver-Operating Characteristics Curve (ROC) is a graph between True-Positive Rate (TPR) (sensitivity) and False-Positive Rate (FPR) (1- specificity) by which it shows the performance of classification model, and the plot is characterized at different classification thresholds. The biggest advantage of ROC curve is that its independency of the change in number of responders and response rate.

VI. Research Challenges In Chest Imaging

This section discusses some of the open research challenges in detecting lung diseases using Deep Learning techniques [13]

- *Data Scarcity*: The availability of large and diverse datasets is crucial for training deep learning models. However, obtaining such data for lung disease detection can be challenging due to privacy concerns and limited access to medical images.
- *Data Quality*: Medical images used for training deep learning models need to be of high quality and accurately annotated. However, medical images may contain noise or artifacts that can affect the performance of deep learning models.
- *Generalization:* Deep learning models are known to perform well on the data they were trained on but may not generalize well to new data. This is particularly challenging in lung disease detection where the appearance of diseases can vary significantly across different patients.
- *Explainability:* Deep learning models are often referred to as black boxes as they provide little insight into how they arrive at their decisions. In the context of lung disease detection, explainability is critical for gaining trust and improving clinical decision-making.
- *Interpretability*: Deep learning models can learn complex features from medical images that are difficult for clinicians to interpret. Developing methods to extract and visualize these features can aid clinicians in making more informed decisions.
- *Multi-task Learning*: Lung disease detection may involve multiple tasks, such as identifying the type of

disease, predicting disease progression, and treatment response. Developing multi-task deep learning models that can perform these tasks simultaneously is an active area of research.

- *Transfer Learning*: Transfer learning involves leveraging pre-trained models to perform tasks related to lung disease detection. However, it is challenging to transfer learning from one medical imaging modality to another due to differences in image acquisition and characteristics.

VII. CONCLUSION

In conclusion, deep learning-based detection of lung diseases is a promising approach that has gained significant attention in recent years. Deep learning models have been successfully applied to various lung disease detection tasks, including the detection of lung nodules, lung cancer, and pulmonary embolism.

The literature survey reveals that deep learning models have several advantages over traditional methods, including the ability to learn from large and complex datasets and the ability to capture subtle patterns and features that are difficult to identify by human experts. It is also evident that deep learning-based approaches have shown remarkable performance in the detection of various lung diseases, including lung cancer, pneumonia, and COVID-19. The use of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Hybrid architectures has resulted in high accuracy and sensitivity in the detection of lung diseases. The basic methodology used in implementation of DL models was also discussed.

Finally we discussed few open research challenges in the area that can serve as basis for future research.

REFERENCES

[1] Adekanmi Adeyinka Adegun, Serestina Viriri, and Roseline Oluwaseun Ogundokun. Deep learning approach for medical image analysis. Computational Intelligence and Neuroscience, 2021:1–9, 2021.

[2] Enes Ayan and Halil Murat U¨ nver. Diagnosis of pneumonia from chest x-ray images using deep learning. In 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT), pages 1–5. Ieee, 2019.

[3] Subrato Bharati, Prajoy Podder, and M Rubaiyat Hossain Mondal. Hybrid deep learning for detecting lung diseases from x-ray images. Informatics in Medicine Unlocked, 20:100391, 2020.

[4] Alain C Borczuk. Benign tumors and tumorlike conditions of the lung. Archives of pathology & laboratory medicine, 132(7):1133–1148, 2008.

[5] Min Chen, Xiaobo Shi, Yin Zhang, Di Wu, and Mohsen Guizani. Deep feature learning for medical image analysis with convolutional autoencoder neural network. IEEE Transactions on Big Data, 7(4):750–758, 2017.

[6] Vikash Chouhan, Sanjay Kumar Singh, Aditya Khamparia, Deepak Gupta, Prayag Tiwari, Catarina Moreira, Robertas Damasˇevicˇius, and Victor Hugo C De Albuquerque. A novel transfer learning based approach for pneumonia detection in chest x-ray images. Applied Sciences, 10(2):559, 2020.

[7] Muhammad EH Chowdhury, Tawsifur Rahman, Amith Khandakar, Rashid Mazhar, Muhammad Abdul Kadir, Zaid Bin Mahbub, Khandakar Reajul Islam, Muhammad Salman Khan, Atif Iqbal, Nasser Al Emadi, et al. Can ai help in screening viral and covid-19 pneumonia? Ieee Access, 8:132665–132676, 2020.

[8] Jiuxiang Gu, Zhenhua Wang, Jason Kuen, Lianyang Ma, Amir Shahroudy, Bing Shuai, Ting Liu, Xingxing Wang, Gang Wang, Jianfei Cai, et al. Recent advances in convolutional neural networks. Pattern recognition, 77:354–377, 2018.

[9] Seok-Jae Heo, Yangwook Kim, Sehyun Yun, Sung-Shil Lim, Jihyun Kim, Chung-Mo Nam, Eun-Cheol Park, Inkyung Jung, and Jin-Ha Yoon. Deep learning algorithms with demographic information help to detect tuberculosis in chest radiographs in annual workers' health examination data. International journal of environmental research and public health, 16(2):250, 2019.

[10] Kai-Lung Hua, Che-Hao Hsu, Shintami Chusnul Hidayati, Wen-Huang Cheng, and Yu-Jen Chen. Computer-aided classification of lung nodules on computed tomography images via deep learning technique. OncoTargets and therapy, pages 2015–2022, 2015.

[11] Yuming Hua, Junhai Guo, and Hua Zhao. Deep belief networks and deep learning. In Proceedings of 2015 International Conference on Intelligent Computing and Internet of Things, pages 1–4. IEEE, 2015.

[12] Chaolin Huang, Yeming Wang, Xingwang Li, Lili Ren, Jianping Zhao, Yi Hu, Li Zhang, Guohui Fan, Jiuyang Xu, Xiaoying Gu, et al. Clinical features of patients infected with 2019 novel coronavirus in wuhan, china. The lancet, 395(10223):497–506, 2020.

[13] Stefanus Tao Hwa Kieu, Abdullah Bade, Mohd Hanafi Ahmad Hijazi, and Hoshang Kolivand. A survey of deep learning for lung disease detection on medical images: state-of-the-art, taxonomy, issues and future directions. Journal of imaging, 6(12):131, 2020.

[14] E Kurniawan, P Prajitno, and DS Soejoko. Computer-aided detection of mediastinal lymph nodes using simple architectural convolutional neural network. In Journal of Physics: Conference Series, volume 1505, page 012018. IOP Publishing, 2020.

[15] Paras Lakhani and Baskaran Sundaram. Deep learning at chest radiography: automated classification of pulmonary

tuberculosis by using convolutional neural networks. Radiology, 284(2):574–582, 2017.
[16] June-Goo Lee, Sanghoon Jun, Young-Won Cho, Hyunna Lee, Guk Bae Kim, Joon Beom Seo, and Namkug Kim. Deep learning in medical imaging: general overview. Korean journal of radiology, 18(4):570–584, 2017.
[17] Shih-Chung Benedict Lo, Jyh-Shyan Lin, Matthew T Freedman, and Seong Ki Mun. Computer-assisted diagnosis of lung nodule detection using artificial convoultion neural network. In Medical Imaging 1993: Image Processing, volume 1898, pages 859–869. SPIE, 1993.
[18] Darcy D Marciniuk and Dean E Schraufnagel. The global impact of respiratory disease. European Respiratory Society, 2017.
[19] Keelin Murphy, Shifa Salman Habib, Syed Mohammad Asad Zaidi, Saira Khowaja, Aamir Khan, Jaime Melendez, Ernst T Scholten, Farhan Amad, Steven Schalekamp, Maurits Verhagen, et al. Computer aided detection of tuberculosis on chest radiographs: An evaluation of the cad4tb v6 system. Scientific reports, 10(1):1–11, 2020.
[20] Ali Narin, Ceren Kaya, and Ziynet Pamuk. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. Pattern Analysis and Applications, 24:1207–1220, 2021.
[21] F Pasa, V Golkov, F Pfeiffer, D Cremers, and D Pfeiffer. Efficient deep network architectures for fast chest x-ray tuberculosis screening and visualization. Scientific reports, 9(1):6268, 2019.
[22] Muralikrishna Puttagunta and S Ravi. Medical image analysis based on deep learning approach. Multimedia tools and applications, 80:24365–24398, 2021.
[23] Prajwal Rao, Nishal Ancelette Pereira, and Raghuram Srinivasan. Convolutional neural networks for lung cancer screening in computed tomography (ct) scans. In 2016 2nd international conference on contemporary computing and informatics (IC3I), pages 489–493. IEEE, 2016.
[24] Fatima M Salman, Samy S Abu-Naser, Eman Alajrami, Bassem S Abu-Nasser, and Belal AM Alashqar. Covid-19 detection using artificial intelligence. 2020.
[25] Sundeep Salvi, G Anil Kumar, RS Dhaliwal, Katherine Paulson, Anurag Agrawal, Parvaiz A Koul, PA Mahesh, Sanjeev Nair, Virendra Singh, Ashutosh N Aggarwal, et al. The burden of chronic respiratory diseases and their heterogeneity across the states of india: the global burden of disease study 1990–2016. The Lancet Global Health, 6(12):e1363–e1374, 2018.
[26] Dinggang Shen, Guorong Wu, and Heung-Il Suk. Deep learning in medical image analysis. Annual review of biomedical engineering, 19:221–248, 2017.
[27] Rebecca L Siegel, Kimberly D Miller, Stacey A Fedewa, Dennis J Ahnen, Reinier GS Meester, Afsaneh Barzi, and Ahmedin Jemal. Colorectal cancer statistics, 2017. CA: a cancer journal for clinicians, 67(3):177–193, 2017.
[28] Youssef Skandarani, Pierre-Marc Jodoin, and Alain Lalande. Gans for medical image synthesis: An empirical study. Journal of Imaging, 9(3):69, 2023.
[29] QingZeng Song, Lei Zhao, XingKe Luo, and XueChen Dou. Using deep learning for classification of lung nodules on computed tomography images. Journal of healthcare engineering, 2017, 2017.
[30] Okeke Stephen, Mangal Sain, Uchenna Joseph Maduh, Do-Un Jeong, et al. An efficient deep learning approach to pneumonia classification in healthcare. Journal of healthcare engineering, 2019, 2019.
[31] Ashitosh Tilve, Shrameet Nayak, Saurabh Vernekar, Dhanashri Turi, Pratiksha R Shetgaonkar, and Shailendra Aswale. Pneumonia detection using deep learning approaches. In 2020 international conference on emerging trends in infor- mation technology and engineering (ic-ETITE), pages 1–8. IEEE, 2020.
[32] Rogelio Ruzcko NMI Tobias, Luigi Carlo M De Jesus, Matt Ervin G Mital, Sandy C Lauguico, Marielet A Guillermo, Edwin Sybingco, Argel A Bandala, and Elmer P Dadios. Cnn-based deep learning model for chest x-ray health classification using tensorflow. In 2020 RIVF International Conference on Computing and Communication Technologies (RIVF), pages 1–6. IEEE, 2020.
[33] Thirumalaisamy P Velavan and Christian G Meyer. The covid-19 epidemic. Tropical medicine & international health, 25(3):278, 2020.
[34] Tessa M Wardlaw, Emily White Johansson, and Matthew J Hodge. Pneumonia: the forgotten killer of children. Unicef, 2006.
[35] WHO. World health organization: Coronavirus disease 2019 (covid-19) situation report, 2020.
[36] Chunxue Wu, Chong Luo, Naixue Xiong, Wei Zhang, and Tai-Hoon Kim. A greedy deep learning method for medical disease analysis. IEEE Access, 6:20021–20030, 2018.
[37] Wen Zhou, Guanxun Cheng, Ziqi Zhang, Litong Zhu, Stefan Jaeger, Fleming YM Lure, and Lin Guo. Deep learning-based pulmonary tuberculosis automated detection on chest radiography: Large-scale independent testing. Quantitative Imaging in Medicine and Surgery, 12(4):2344, 2022.