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Deep Learning Paradigms for Existing and Imminent Lung Diseases Detection: A Review

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ABSTRACT

Diagnosis of lung diseases like asthma, chronic obstructive pulmonary disease, tuberculosis, cancer, etc., by clinicians rely on images taken through various means like X-ray and MRI. Deep Learning (DL) paradigm has magnified growth in the medical image field in current years. With the advancement of DL, lung diseases in medical images can be efficiently identified and classified. For example, DL can detect lung cancer with an accuracy of 99.49% in supervised models and 95.3% in unsupervised models. The deep learning models can extract unattended features that can be effortlessly combined into the DL network architecture for better medical image examination of one or two lung diseases. In this review article, effective techniques are reviewed under the elementary DL models, viz. supervised, semi-supervised, and unsupervised Learning to represent the growth of DL in lung disease detection with lesser human intervention. Recent techniques are added to understand the paradigm shift and future research prospects. All three techniques used Computed Tomography (C.T.) images datasets till 2019, but after the pandemic period, chest radiographs (X-rays) datasets are more commonly used. X-rays help in the economically early detection of lung diseases that will save lives by providing early treatment. Each DL model focuses on identifying a few features of lung diseases. Researchers can explore the DL to automate the detection of more lung diseases through a standard system using datasets of X-ray images. Unsupervised DL has been extended from detection to prediction of lung diseases, which is a critical milestone to seek out the odds of lung sickness before it happens. Researchers can work on more prediction models identifying the severity stages of multiple lung diseases to reduce mortality rates and the associated cost. The review article aims to help researchers explore Deep Learning systems that can efficiently identify and predict lung diseases at enhanced accuracy.

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1 Introduction

The growing stress of air pollution, climate change, lifestyle disorder, decrease in immunity, bad habits like smoking, etc., burden the health of one of the vital organs, the lung, leading to an increase in respiratory disorders. According to the Journal of the Forum of International Respiratory Societies (FIRS) (2021), respiratory diseases enact a massive worldwide health burden. Among lung diseases, COPD, asthma, pneumonia, tuberculosis and lung cancer are five common reasons for severe ailment and global deaths (WHO factsheets 2020, 2021; Allemani et al. 2018; Vos et al. 2020; Wang et al. 2016). According to an estimation, COPD is the third-leading reason of death globally (Meghji et al. 2021; GBD study 2020; Li et al. 2020), with 3.2 million (out of 200 million having COPD) death each year. Asthma is a persistent and prolonged illness in children (Global Asthma Report 2018), affecting over 350 million people worldwide. For decades, the most common reason for demise or disability in children and adults is acute lower respiratory tract infections or pneumonia. In 2021, the mortality rates of tuberculosis (T.B.) enhanced due to COVID-19, and 1.4 million deceased in 2019 because of T.B. (WHO Annual Report 2021; Global Tuberculosis Report 2020). In 2020, lung cancer led to the loss of 1.8 million persons (Sung et al. 2021).

Looking at the paramount burden of respiratory diseases, it is necessary to equip the current health systems with technologies that enable early diagnosis and better treatment. With the development of tools like Deep Learning (DL) and machine learning, lung diseases using medical images can easily be identified and classified. Computer-Aided diagnosis (CAD) technology improved lung disease patients' survival rate. Current CAD methods apply deep learning to medical images to pre-process, segment lungs, reduce false positives and detect, classify and retrieve lung nodules. Particular classification studies using deep learning of pulmonary nodules achieve accuracy from 75.01 to 97.58% (Gu et al. 2021; Ursuleanu et al. 2021). Deep Learning is more beneficial in the handling of pulmonary nodule image data as compared to traditional methods.

Furthermore, deep learning approaches that belong to other disciplines (Di Mauro et al. 2021; Padmapriya and Sasilatha 2023; Mohapatra et al. 2022) can be easily transferred to the domain of pulmonary nodule CAD as compared to traditional ML models because the foundation knowledge of ML paradigms in distinct disciplines is diverse (Kalra et al. 2021; Mohapatra et al. 2022). Optimization of hyper-parameters (size and number of filters, depth, learning rate, activation function, number of hidden layers, etc.) can increase the preformation of the deep learning model (Pandey et al. 2022)

Centred on the theory of adversarial training, General Adversarial Network (GAN) attracted many medical imaging researchers that produce novel images like original images through training, which add to the existing data. Optimization algorithms employed in this study for networks correspond to learning rate =0.00005 and stochastic gradient descent (learning rate=0.0001) (Onishi et al. 2020). Earlier old machine learning (ML) algorithms, such as active contour, region growth, and fuzzy c-means techniques, were commonly applied in CAD for lung nodule segmentation. The algorithms included in traditional ML classifiers used for lung nodule CAD are support vector machine (SVM) and random forest. Currently, the combination of deep neural networks and these classifiers is being used by many researchers. One of the numerous limitations of traditional classifiers is the problematic usage of SVM in dealing with extensive training samples and manifold classification problems (Chauhan et al. 2019).

In a deep learning model, the most challenging aspects are eliminated by the automatic extraction of elements of the initial nodule images through a neural network represented in Figure 1. In comparison, deep neural network classifier work surpasses SVM with sufficiently large training and verification data. Another

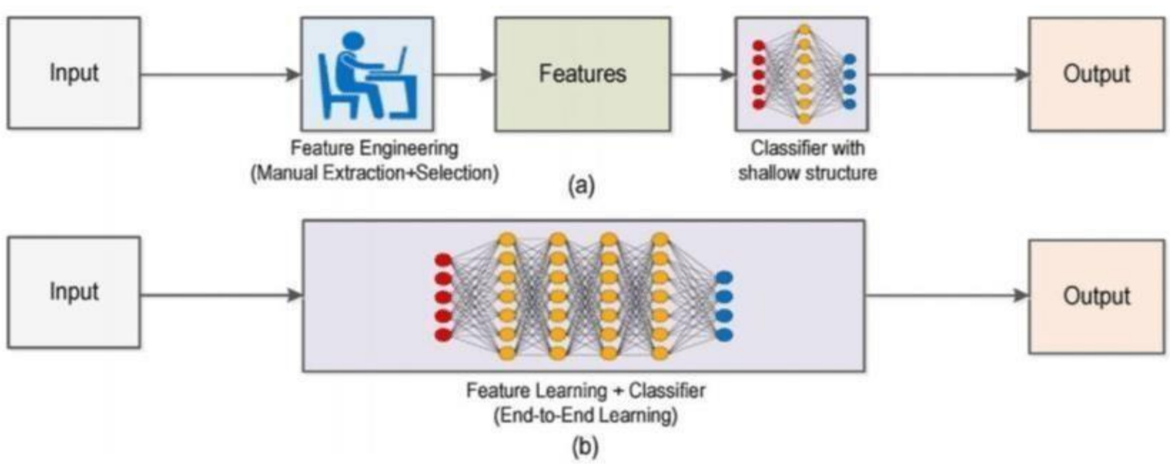

Figure 1 Difference between classical ML and Deep Learning approaches (Source: Del Real et al. 2020)

shortcoming of classical ML methods is achieving excellent outcomes with complex and lengthy procedures of handcrafted feature extraction, which requires proficiency and persistence. An add-on challenge is the complex features of the pulmonary nodule.

2 Deep Learning Methods based on Training Samples

DL methods can be categorized into three main classes: supervised, partially supervised (semi-supervised), and unsupervised.

2.1 Deep supervised Learning

The deep supervised method works with labelled data where the environs have inputs and resultant outputs. The agent informs the network factors to better estimate the desired outcomes. Through constructive training results, the agent can get the correct answers to the questions from the environment. Recurrent neural networks (RNN), convolutional neural networks (CNN), and deep neural networks (DNN) are some supervised learning techniques represented in Figure 2 (Ursuleanu et al. 2021). Inputs given to each layer of a DNN are used through changes parametrized by several weights. Although deep approaches are very promising, the vast number of hyper-parameters makes tuning very hard (Di Mauro et al. 2020). RNN includes recurrent gated units (GRU) and long short-term memory (LSTM) methodologies. The key benefit of deep supervised Learning is that output data can be collected or generated from previous knowledge, but the decision boundary might be over-strained when the training array needs more examples of a particular class. This learning method is simple yet performs extraordinarily.

2.1.1 Convolutional neural networks

Convolutional neural networks (CNN) are most comprehensively applied in deep learning algorithms applied to pulmonary nodules. In the 2017 DSB competition, the winning team used a CNN model (Liao et al. 2019), and Google developed an algorithm that overtook six skilful radiologists, a CNN model published in *Nature*. Hua et al. (2015) first time used the Deep belief network (DBN), while Kumar et al. (2015) first time applied autoencoder (A.E.) in the pulmonary nodule CAD to separate benign and malignant pulmonary nodules. A sliced recurrent neural network (RNN) model was presented by Wang and Chakraborty (2019), in which training efficacy has been increased by simultaneous training of diverse layers of the RNN. A large quantity of information is requisite for training a deep learning model. However, because of limited labelled datasets for researchers, this work is time-consuming and needs specialists (Di Mauro et al. 2020).

CNN has distinctive benefits in processing images over other network types, which makes it the most chosen technique. An arrangement of CNN can unambiguously communicate the local weights of images and their learning features. Typical CNN architecture has three layers, namely convolutional, pooling, and fully connected, as shown in Figure 3, briefly discussed below.

The convolutional layer takes out the facets from the stored image, for example, the lung nodule image. The features of the nodule image are extracted by convolution operations, carried out by convolutional kernels in this layer, similar to filtering. Any slight change in the selected hyper-parameter values will affect the general CNN performance. In traditional filters, weights must be placed manually, whereas CNN learns these weights automatically (Gu et al. 2021).

The pooling layer's primary function is to choose several features and reduce feature map size by filtering the information. With the pooling operation, the outcome of a particular point is replaced with a value (for example, an average value or maximum) in the

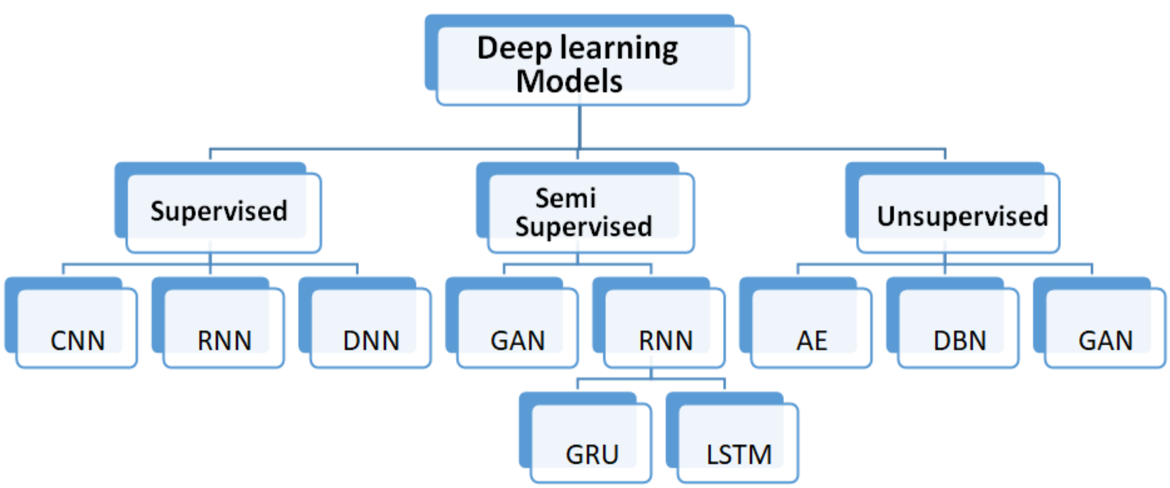

Figure 2 Different models of Deep Learning

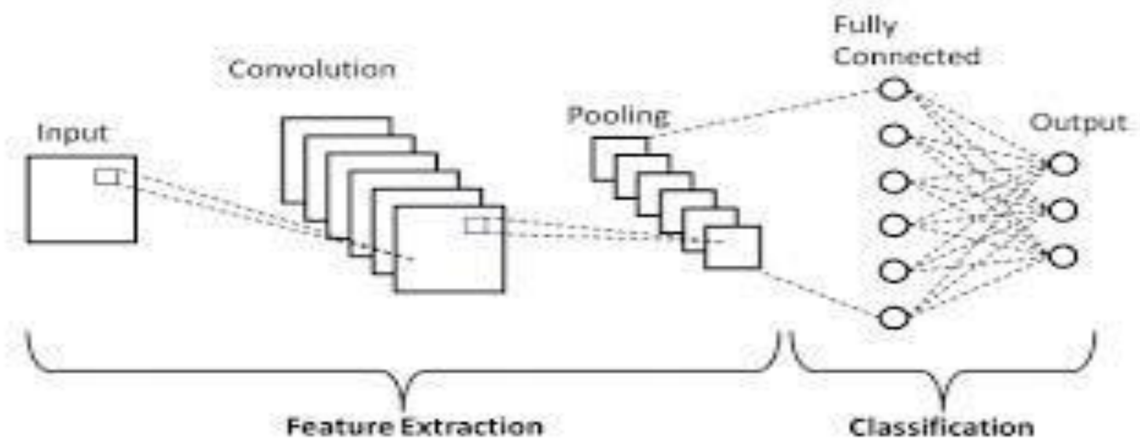

Figure 3 Layers of Convolution Neural Network (Source: Sharma et al. 2020)

feature map representing the adjacent region. However, the dimensionality reduction process degrades image quality and leads to the loss of some information by a pooling layer. Therefore, a pooling layer is not frequently used for processing medical images when the GPU capacity is satisfactory. Stridden convolution (Ayachi et al. 2018) and dilated convolution (Zhang et al. 2018) can replace the pooling layer to decrease feature map size. The fully connected (F.C.) layer joins the extracted elements non-linearly to get the output, the same as the hidden layer in a conventional artificial neural network (Gu et al. 2021).

2.1.2 Recurrent Neural Networks (RNN)

RNN are eminent in the natural language processing (NLP) field. RNN can appropriately process sequential data, as the embedded part delivers valuable information in the data sequence; these paradigms and the variations are extensively used in various applications having text, audio, and video analysis. To conclude the implication of a particular word in a sentence, the context of the sentence should be known. "Hidden-to-Hidden," "Hidden-to-Output," and "Input-to-Hidden" three deep RNN techniques are proposed by Pascanu et al. (2013). These three more profound RNN techniques make learning less difficult in the deep network. However, the central concern with this approach is exploding gradient and vanishing problems (Glorot and Bengio 2010), to which RNN is sensitive. More precisely, the repetitions of numerous large or small derivatives may lead to exponential explosion or falloff of the gradients during the training process. This sensitivity decays over time, as with fresh inputs, the network halts reasoning about the preliminary inputs. Moreover, this problem can be dealt with Long Short-Term Memory (LSTM)(Gao et al. 2019). Repeated links are offered to memory blocks in the network in this approach (Di Mauro et al. 2021). Many memory cells in every memory block can store the network's temporary state and control the information flow through gated units. Although using a huge quantity of data increases the time complexity of LSTM, this problem is solved by Gated Recurrent Unit (GRU). The GRU comprises a reset gate that decides the amount of information transmitted from past to future and the amount of information that can be forgotten from the past by updating the gate. In profound networks, the vanishing gradient issue impact can be reduced considerably with residual connections (Piccialli et al. 2021). RNN has been applied in pulmonary nodule CAD tools (Wang and Chakraborty 2019), segmentation (Messay et al. 2015), detection and diagnosis (Abbas 2017a) of the pulmonary nodule.

2.2 Deep Semi-supervised Learning

Deep semi-supervised learning systems require partially annotated datasets. Generative adversarial networks (GAN), DRL, and RNN, including GRU and LSTM, are sometimes used as semi-supervised methods (Alzubaidi et al. 2021). This technique requires less labelled data, but extra input could deliver inappropriate decisions, while data training is represented in Figure 2 (Ursuleanu et al. 2021). Text document classifier is a general application of partially supervised Learning extraordinary.

2.2.1 Generative adversarial networks (GAN)

The GAN is a highly significant network in the deep learning domain. An extensive dataset is required for training a deep neural network. Still, available datasets are narrow, mainly for medical imagery, such as pulmonary nodule C.T. The operational procedure of the GAN paralleled a minimax game of two players: an adversarial process used to train the network. Generative model G produces fabricated data by capturing data distribution. The discriminative model D aimed to precisely discriminate between genuine and fabricated input data. The G designed the training process to extend the likelihood of D producing inaccuracies. The fundamental notion of GAN evolved from the Nash equilibrium in game theory. Regular optimization of G and D is required to improve their abilities to generate and discriminate. This learning optimization course implicates a Nash equilibrium between G and D (Goodfellow et al. 2014). Using latent distribution (Ngo et al. 2017; Hsieh et al. 2020), synthetic training data can be generated from original data. Two problems of GAN are mode collapse and instability.

2.3 Deep Unsupervised Learning

With this method, the learning process is implemented without labeled data. In input data, it is essential to ascertain the anonymous arrangement or associations, and that association is given through the critical features or interior image acquired by an agent. In unsupervised Learning, clustering, generative network methods, and dimensionality reduction are often summed up. Auto-encoders restricted Boltzmann machines, and GAN beat non-linear dimensionality reduction and clustering tasks. GRU and LSTM methodologies incorporated with RNN are also applied for unsupervised Learning in many fields. However, unsupervised Learning needs to give precise data organization information and is computationally demanding. Clustering is one of the widespread unsupervised learning methods extraordinary (Alzubaidi et al. 2021).

2.3.1 Deep Belief Networks(DBN)

Probabilistic generative models have several restricted Boltzmann machines (RBM) (Abbas 2017b; Smolensky 1986; Freund and Haussler 1991). These networks of two layers adhere to the encoder–decoder paradigm (Hinton 2002). In diverse categories of data, RBM is used as generative models but most significantly applied as components of a DBN.

The DBN has two networks that form each other, whereas an acyclic graph denotes beliefs (Ranzato et al. 2007). Stochastic binary units with weights and their weighted connections form layers of this graph, RBM, which is stochastic (Ngo et al. 2017). Applications of DBN include recognizing images and speech, classifying lesions in medical diagnosis, a person's presence in video recognition (Pandey et al. 2022), understanding omitted words in a sentence in speech recognition, and applying physiological indications that identify human emotion.

2.3.2 Auto-encoders (A.E.)

A.E. created by Wang et al. (2017), contain an encoder and decoder. Important images are used to reduce data size and learn data features to reconstruct outputs. A.E. is applied in the analysis of medical image processing of natural language and video analysis (Rumelhart et al. 1985). With AE, the input signal can be reconstructed perfectly by mapping itself. A.E.'s operation basis is first mapping an input vector to a hidden depiction via deterministic mapping. Then "reconstructed" input vector is mapped back from the following underlying illustration a. As so, an enhanced representation of the input could be learned by the hidden layer of the A.E. The A.E. is an unsupervised learning method in which the network uses many data points for endways training to increase accuracy.

3 Predicting Lung Diseases via DL Models

Deep Learning has been extended from automatic detection to the prediction of lung diseases. Various models were developed using supervised, semi-supervised and unsupervised methods, as summarized in Tables 1, 2, and 3. Automated deep learning techniques play a significant role in accurately predicting lung diseases (Wang et al. 2022b; Li et al. 2022; Walsh et al. 2022; Mohamed 2022). Predicting progressive fibrotic lung disease enhances outcomes with deep learning-based usual interstitial pneumonia probability on High-Resolution CT (Walsh et al. 2022). COPD causes fast progress of heart problems and other respiratory infections if not discovered and treated timely. Prediction with PNN (Probabilistic Neural Network) helps predict COPD severity stages (Mohamed 2022).

Table 1 Supervised Approach

S.No.	Dataset	Type of Image used	Method used	References
1	LIDC-IDRI	CT scans	VCNet	Tandon et al. 2022
2	GitHub	X-rays	DenseNet	Anitha et al. 2022
3	RSNA & other reliable sources	X-rays	VGG19+CNN	Alshmrani et al. 2023
4	LUNA16	CT scans	3D multi-scale deep CNN	Peng et al. 2021
5	Public dataset	C.T. scans X-rays	hybrid 2D/3D CNN architecture	Bayoudh et al. 2020
6	NIH	X-rays	*VGG Data STN* with *CNN* (VDSNet)	Bharati et al. 2020
7	LUNA16 DSB2017	CT scans	3-D deep neural network	Liao et al. 2019
8	LIDC-IDRI	CT scans	hierarchical (sliced) RNN	Wang and Chakraborty 2019

LIDC-IDRI: Lung Image Database Consortium Image Database Resource Initiative; DSB: Data Science Bowl; LUNA: Lung Nodule Analysis; RSNA: Radiological Society of North America

Table 2 Semi-Supervised Approach

S. No.	Dataset	Type of Image used	Method used	References
1	LUNA16; NLST	CT scans	Semi-supervised 3D deep neural network for Data-driven segmentation	Liu et al. 2020
2	DSB; LUNA	CT scans X-rays	Semi-supervised Learning for 3D medical image detection	Wang et al. 2020
3	LIDC-IDRI	CT scans	Adversarial autoencoder-based unsupervised reconstruction supervised classification	Xie et al. 2019

LIDC-IDRI: Lung Image Database Consortium Image Database Resource Initiative; DSB: Data Science Bowl; LUNA: Lung Nodule Analysis; NLST: National Lung Screening Trial

Supervised Deep Learning Models provide promising results in detecting and classifying various lung diseases at an early stage. For example, using C.T. images, multi-scale Res2Net achieved a sensitivity of 98.3% with fewer false positive nodules (Peng et al. 2021). Anitha et al. (2022) concluded that ResNet is more efficient, with a validation accuracy of 98.33%, in identifying Covid19. Bharati et al. (2020) proposed CO-ResNet that adjusts hyperparameters for optimization. It overtook other classic ResNet models with COVID- 19 detection rate of 98.74% in ResNet101 assessment data. In most situations, deep CNN is used for detecting the region of the main module of the lung, but performance degrades when there are differences in image characteristics. A hybrid model named VCNet combining VGG-16 and capsule network address the shortcomings of CNN and detects Lung Cancer with an accuracy of 99.49% (Tandon et al. 2022). Qin et al. (2020) combined PET and C.T. scan information to validate a DL architecture for the sensitive detection of lung cancer. During the pandemic, the more extensive availability of X-rays leads to experimenting COVID-19 radiographs to identify the disease. Bayoudh et al. (2020) achieved an accuracy of 96.91% with both C.T. and X-rays for detecting COVID-19 and ensured a tradeoff between accuracy and complexity by reducing the false negative rate and the computational time.

Semi-supervised methods partially automate the detection process of lung disease and also reduce the cost, as annotating medical images is a costly process. Deep convolutional neural networks always require a massive set of labelled training data to classify benign and malignant lung nodules. A semi-supervised adversarial classification (SSAC) model achieved an accuracy of 92.53% by training labelled and unlabeled data for the variety of benign and malignant lung nodules (Xie et al. 2019) using the LIDC-IDRI dataset. The cost of annotating medical images can be reduced with the help of semi-supervised Learning (SSL) to detect 3D medical images. With 400 unlabeled C.T. images, Wang et al. (2020) achieved a 17.3% improvement over supervised learning methods. A semi-supervised 3D deep neural network can solve the problem of weak label information obtained from C.T. The semi-supervised model trains the network with image-level tag annotations from the dataset and outputs all suspicious nodules for a subject. The semi-supervised 3D deep neural network performed excellently with C.T. and radiographs in pulmonary nodule detection(Liu et al. 2020).

Annotating medical images is costly, but the advent of unsupervised deep learning models reduces the burden. The GAN-based data augmentation method called forward and backward GAN (Zhao et al. 2018), expands the dataset by generating high-quality synthetic medical images that improve the performance of pulmonary nodules classification. Forward and backward GAN has an accuracy of 95.24% and a sensitivity of 98.67%. In subsequent years, accuracy in classifying pulmonary nodules has increased to 95.3% using unlabeled C.T.

Table 3 Unsupervised Approach

S.No.	Dataset	Type of Image used	Method used	References
1	Anonymous	CT scans X-rays	Deep Learning based Medical Image Interpretation	Wang et al. 2022a
2	Mendeley	CT scans X-rays	Unsupervised Deep Learning Based feature Fusion	Ravi et al. 2022
3	RSNA	X-rays	auto-encoding generative adversarial network (α-GAN) framework	Nakao et al. 2021
4	Hospitals in China	CT scans	convolutional autoencoder deep learning framework	Chen et al. 2021
5	LIDC	CT scans	convolutional autoencoder deep learning framework with Clustering Augmented Learning Method (CALM) classifier	Ghoshal et al. 2020
6	LIDC	CT scans	3D conditional GAN-based DA approach	Han et al. 2019
7	LIDC	CT scans	Forward and Backward GAN	Zhao et al. 2018

RSNA: Radiological Society of North America; LIDC-IDRI: Lung Image Database Consortium Image Database Resource Initiative images. Ghoshal et al. (2020) introduced Clustering Augmented (CALM), in which the features acquired from a convolution encoder using simultaneous clustering and classification to learn deep feature representation resulted in an overall accuracy of 95.3%. An unsupervised detection method requires standard images for training and evaluate its performance on a large dataset of chest radiographs. VAE-GAN model successfully detected several diseases or anomalies in chest radiographs (Nakao et al. 2021). The Deep MRD, a deep learning-based medical interpretation system developed by Wang et al. (2022c), demonstrated the potential to facilitate early diagnosis of major respiratory diseases that helps improve diagnosis and decision-making. The performance of Deep MRD was evaluated for abnormality identification and disease diagnosis on C.T. and chest X-rays datasets from two different institutes. This system achieved a 95% confidence level for abnormality identification of primary respiratory disease. Automated deep learning techniques play a beneficial role in detecting disease or abnormalities, which help medical experts make decisions or prepare accurate treatment scheduling (Quazi et al. 2022).

4 Future Perspective

This paper studied the growth of deep learning methods in lung disease detection, as demonstrated in Table 1-3. Unlike semi-supervised and unsupervised, supervised methods achieve more accurate results but depend on labelled data. Earlier research focuses on increasing models' efficacy in detecting one or two diseases, usually with C.T. scans. More research is needed to diagnose lung diseases through one deep learning system without supervision using X-rays. X-rays help in the economical early detection of lung diseases that will save lives by providing early treatment. In future, more accurate prediction models are required to identify the severity and the stages of multiple lung diseases to reduce mortality rates and the associated cost.

Conclusion

Deep Learning models have grown to acceptable outcomes with numerous applications to detect and diagnose lung diseases early. Deep learning offer automatic, prompt, and trusty detection of lung diseases through medical images. Unambiguously, convolutional neural networks achieved promising outcomes in revealing diseases. However, collecting labelled data is costly and tiresome, specifically for a new disease. Regardless of the performance of supervised models, their dependence on extensive labelled data leads to the proposal of various methods that can learn with less and with other types of supervision with optimized parameters and less time consumption. Therefore, a deep unsupervised framework could help classify lung disease from chest C.T. and X-ray images and predict lung disease more accurately and efficiently.

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References

Abbas, Q. (2017a). Lung-deep: a computerized tool for detection of lung nodule patterns using deep learning algorithms Detection of Lung Nodules Patterns. *International Journal of Advanced Computer Science and Applications*, *8*(10), 2017. http://dx.doi.org/10.14569/IJACSA.2017.081015.

Abbas, Q. (2017b). Nodular-deep: classification of pulmonary nodules using deep neural network, *International Journal of Medical Research & Health Sciences*, *6*(8), 111–118.

Allemani, C., Matsuda, T., Di Carlo V., et al. (2018). Global surveillance of trends in cancer survival 2000-14 (CONCORD-3): analysis of individual records for 37 513 025 patients diagnosed with one of 18 cancers from 322 population-based registries in 71 countries. *The Lancet*, *391*(10125), 1023-1075.

Alshmrani, G. M. M., Ni, Q., Jiang, R., Pervaiz, H., & Elshennawy, N. M. (2023). A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images. *Alexandria Engineering Journal*, *64*, *923–935*. https://doi.org/10.1016/j.aej.2022.10.053

Alzubaidi, L., Zhang, J., Humaidi, A. J., Duan, Y., et al. (2021). Review of deep Learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, *8*(1), 1-74. https://doi.org/10.1186/s40537-021-00444-8

Anitha, J., Kalaiarasu, M., Kumar, N. Suresh & Sundar, G. Ram (2022). Detection and classification of lung diseases using deep Learning. *AIP Conference Proceedings*, *2519*, 030001. https://doi.org/10.1063/5.0109980

Ayachi, R., Afif, M., Said, Y., & Atri, M. (2018). Strided Convolution Instead of Max Pooling for Memory Efficiency of Convolutional Neural Networks. In: M. Bouhlel, S. Rovetta, (eds) Proceedings of the 8th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT'18), Vol.1. SETIT 2018. Smart Innovation, Systems and Technologies, vol 146. Springer, Cham. https://doi.org/10.1007/978-3-030-21005-2_23

Bayoudh, K., Hamdaoui, F., & Mtibaa, A. (2020). Hybrid COVID: a novel hybrid 2D/3D CNN based on cross-domain adaptation approach for COVID-19 screening from chest X-ray images, *Physical and Engineering Sciences in Medicine*, 43, 1415–1431. https://doi.org/10.1007/s13246-020-00957-1

Bharati, S., Podder, P., & Mondal, M. R. H. (2020). Hybrid deep Learning for detecting lung diseases from X-ray images. *Informatics in Medicine Unlocked*, *20*, 100391. https://doi.org/10.1016/j.imu.2020.100391

Chauhan, V.K., Dahiya, K., & Sharma, A. (2019). Problem formulations and solvers in linear SVM: a review. *Artificial Intelligence Review*, *52*, 803–855.

Chen, M., Shi, X., Zhang, Y., Wu, D., & Guizani, M. (2021). Deep Feature Learning for Medical Image Analysis with Convolutional Autoencoder Neural Network. *IEEE Transactions on Big Data*, *7*(4), 750-758. DOI:10.1109/TBDATA.2017.2717439.

Del Real, A.J., Dorado, F, & Durán, J. Energy Demand Forecasting Using Deep Learning: Applications for the French Grid. *Energies*, *13*, 2242.

Di Mauro, M., Galatro, G., Fortino, G., & Liotta, A. (2021). Supervised feature selection techniques in network intrusion detection: A critical review. *Engineering Applications of Artificial Intelligence*, *101*, 104216. https://doi.org/10.1016/j.engappai.2021.104216

Di Mauro, M. & Galatro, G. & Liotta, A. (2020). Experimental Review of Neural-Based Approaches for Network Intrusion Management. *IEEE Transactions on Network and Service Management*, *17*(4), 2480-2495. https://doi.org/10.1109/TNSM.2020.3024225

Forum of International Respiratory Societies (2021). The global impact of respiratory disease. Third Edition. European Respiratory Society. Retrieved from http://firsnet.org/images/publications/FIRS_Master_09202021.pdf

Freund, Y., & Haussler, D. (1991). Unsupervised Learning of distributions on binary vectors using two layer networks, *Advances in Neural Information Processing Systems*, *4*, 912–919.

Gao, C., Yan J., Zhou, S., Varshney, P.K., & Liu H. (2019). Long short-term memory based deep recurrent neural networks for target tracking. *Information Sciences*, *502*, 279– 96. DOI:10.1016/j.ins.2019.06.039.

GBD Chronic Respiratory Disease Collaborators (2020). Prevalence and attributable health burden of chronic respiratory diseases, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. *The Lancet Respiratory Medicine*, *8*(6), 585-596.

Ghosal, S.S., Sarkar, I., & Elhallaoui, I. (2020). Lung Nodule Classification Using Convolutional Autoencoder and Clustering Augmented Learning Method (CALM), *HSDM 2020 Workshop on Health Search and Data Mining*.

Global Asthma Report (2018). Global Asthma Network. Retrieved from http://globalasthmareport.org/burden/burden.php

Global Tuberculosis Report (2020). World Health Organization Global Tuberculosis Program. World Health Organization. Retrieved from https://www.who.int/publications/i/item/9789240013131

Glorot, X., & Bengio, Y. (2010) Understanding the Difficulty of Training Deep Feedforward Neural Networks. Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics. *Proceedings of Machine Learning Research*, *9*, 249-256. http://proceedings.mlr.press/v9/glorot10a.html

Goodfellow, I.J., Pouget-Abadie, J., Mirza, M, et al. (2014) Generative Adversarial Nets. *Proceedings of the 27th International Conference on Neural Information Processing Systems*, *2*, 2672-2680. https://dl.acm.org/doi/10.5555/2969033.2969125

Gu, Y., Chi, J., Liu, J., Yang, L., Zhang, B., et al. (2021). A survey of computer-aided diagnosis of lung nodules from C.T. scans using deep Learning. *Computer in Biology and Medicine*, *137*:104806.

Han, C., Kitamura, Y., Kudo, A., Ichinose, A., Rundo, L. et al. (2019). Synthesizing Diverse Lung Nodules Wherever Massively: 3D Multi-Conditional GAN-based CT Image Augmentation for Object Detection. *arXiv*. https://doi.org/10.48550/arXiv.1906.04962

Hinton, G.E. (2002). Training products of experts by minimizing contrastive divergence. *Neural Computation, 14*, 1771–1800.

Hsieh, Y.J., Tseng, H.C., Chin, C.L., Shao, Y.H., & Tsai, T.Y. (2020) Based on DICOM RT Structure and Multiple Loss Function Deep Learning Algorithm in Organ Segmentation of Head and Neck Image. In: K.P. Lin, R. Magjarevic, & P. de Carvalho (Eds.), *Future Trends in Biomedical and Health Informatics and Cybersecurity in Medical Devices*. *ICBHI 2019. IFMBE Proceedings, 74, Springer, Cham*, 428-435. https://doi.org/10.1007/978-3-030-30636-6_58

Hua, L., Hsu, H., Hidayati, S. C., Cheng, H., & Chen, J. (2015). Computer-aided classification of lung nodules on computed tomography images via deep learning technique. *OncoTargets and therapy*, *8*, 2015-2022.

Kalra, V., Kashyap, I., & Kaur, H. (2021). Machine Learning and Its Application in Monitoring Diabetes Mellitus. In B. Patil & M. Vohra (Eds.), *Handbook of Research on Engineering, Business, and Healthcare Applications of Data Science and Analytics* (pp. 228-288). *IGI Global Publisher of Timely Knowledge*. https://doi.org/10.4018/978-1-7998-3053-5.ch012

Kumar, D., Wong, A., & Clausi, D.A. (2015). Lung nodule classification using deep features in C.T. images, in 12th Conference on Computer and Robot Vision, IEEE, 2015, pp. 133–138.

Li, X., Cao, X., Guo, M., Xie, M., & Liu, X. (2020). Trends and risk factors of mortality and disability adjusted life years for chronic respiratory diseases from 1990 to 2017: a systematic analysis for the Global Burden of Disease Study 2017. *BMJ*, *368*, 234

Li, L., Ayiguli, A., Luan, Q., Yang, B. et al. (2022). Prediction and Diagnosis of Respiratory Disease by Combining Convolutional Neural Network and Bi-directional Long Short-Term Memory Methods. *Frontiers in Public Health*. https://doi.org/10.3389/fpubh.2022.881234

Liao, F., Liang, M., Li, Z., Hu, X., & Song, S. (2019). Evaluate the malignancy of pulmonary nodules using the 3-D deep leaky noisy-or network. *IEEE transactions on neural networks and learning systems*, *30*(11), 3484–3495.

Liu, M., Jiang, X., Liu, Y., Zhao, F., & Zhou, H. (2020). A semi-supervised convolutional transfer neural network for 3D pulmonary nodules detection. *Neurocomputing*, *391*, 199-209. https://doi.org/10.1016/j.neucom.2018.12.081

Meghji, J., Mortimer, K., Agusti, A. et al. (2021). Improving lung health in low- and middle-income countries: from challenges to solutions. *The Lancet*, *397*(10277), 928-940.

Messay, T., Hardie, R. C., & Tuinstra, T. R. (2015). Segmentation of pulmonary nodules in computed tomography using a regression neural network approach and its application to the Lung Image Database Consortium and Image Database Resource Initiative dataset. *Medical Image Analysis*, *22*(1), 48-62.

Mohamed I. (2022). Prediction of Chronic Obstructive Pulmonary Disease Stages Using Machine Learning Algorithms. *International Journal of Decision Support System Technology*, *14*(1), 1-13. DOI: 10.4018/IJDSST.286693

Mohapatra, R. K., Pal, M., Parija, S., Panda, G., & Dhama, K. (2022). Machine learning for the classification of breast cancer tumor: a comparative analysis. *Journal of Experimental Biology and Agricultural Sciences*, *10*(2), 440–450.

Nakao, T., Hanaoka, S., Nomura, Y. *et al.* (2021). Unsupervised Deep Anomaly Detection in Chest Radiographs. *Journal of Digital Imaging*, *34*, 418–427. https://doi.org/10.1007/s10278-020-00413-2

Ngo, T.A., Lu, Z., & Carneiro, G. (2017). Combining Deep Learning and Level Set for the Automated Segmentation of the Left Ventricle of the Heart from Cardiac Cine Magnetic Resonance. *Medical Image Analysis*, *35*, 159–171. https://doi.org/10.1016/j.media.2016.05.009

Onishi,Y., Teramoto, A., Tsujimoto, M., Tsukamoto, T., et al. (2020). Multiplanar analysis for pulmonary nodule classification in C.T. images using deep convolutional neural network and generative adversarial networks. *International Journal of Computer Assisted Radiology and Surgery*, *15*, 173–178.

Padmapriya J., & Sasilatha T., (2023). Deep Learning based multi-labelled soil classification and empirical estimation toward sustainable agriculture. *Engineering Applications of Artificial Intelligence*, *119*, 105690. https://doi.org/10.1016/j.engappai.2022.105690

Pandey, B., Pandey, D.K., Mishra, B.P. & Rhmann, W. (2022). A Comprehensive Survey of Deep Learning in the Field of Medical Imaging and Medical Natural Language Processing: Challenges and Research Directions. *Journal of King Saud University-Computer and Information Sciences, 34(8), 5083-5099*. https://doi.org/10.1016/j.jksuci.2021.01.0007

Pascanu, R., Gulcehre, C., Cho, K., & Bengio, Y. (2013). How to Construct Deep Recurrent Neural Networks. *ArXiv*. https://doi.org/10.48550/arXiv.1312.6026

Peng, H., Sun, H., & Guo, Y. (2021). 3D multi-scale deep convolutional neural networks for pulmonary nodule detection. *PLoS ONE*, *16*(1), e0244406. https://doi.org/10.1371/journal.pone.0244406

Piccialli, F., Di Somma, V., Giampaolo, F., Cuomo, S., & Fortino, G. (2021). A Survey on Deep Learning in Medicine: Why, How and When*? Information Fusion*, *66*, 111-137.

Qin, R., Wang, Z., Jiang, L., Qiao, K., Hai, J., Chen, J., et al. (2020). Fine-grained lung cancer classification from PET and C.T. images based on multidimensional attention mechanism. *Complexity*, *2020*:165–75. DOI: 10.1155/2020/6153657

Quazi, S., Saha, R. P., & Singh, M. K. (2022). Applications of Artificial Intelligence in Healthcare. *Journal of Experimental Biology and Agricultural Sciences*, *10*(1), 211–226.

Ranzato, M.A., Boureau, Y.L., & LeCun, Y. (2007). Sparse feature learning for deep belief networks. *Advances in Neural Information Processing Syst*ems, *20*, 1185–1192.

Ravi, V., Narasimhan, H., Chakraborty, C., & Pham, T.D. (2022). Deep learning-based meta-classifier approach for COVID-19 classification using C.T. scan and chest X-ray images. *Multimedia Systems*, *28*(4), 1401-1415. DOI: 10.1007/s00530-021-00826-1.

Rumelhart, D.E., Hinton, G.E. & Williams, R.J. (1985) Learning Internal Representations by Error Propagation. In: Rumelhart, D.E., McClelland, J.L. and the PDP Research Group, Eds., *Parallel Distributed Processing: Exploration in the Microstructure* *of Cognition.* Volume I: *Foundations, MIT Press, Cambridge*, MA, 318-362.

Sharma, D., Dutta, S. & Bora, D. (2020). REGA: Real-Time Emotion, Gender, Age Detection Using CNN—A Review. *The International Conference on Research in Management & Technovation, 24,* 115-118. DOI: 10.15439/2020KM18.

Smolensky, P. (1986), Information Processing in Dynamical Systems: Foundations of Harmony Theory. Chapter 6 of D.E. Rumelhart, J.L. McClelland, and the PDP Research Group, *Parallel Distributed Processing: Exploration in the Microstructure of Cognition.* Volume I: Foundations. Cambridge, MA: MIT Press/Bradford Books.

Sung, H., Ferlay, J., Siegel, R. L., et al. (2021). Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA: A Cancer Journal of Clinicals*, *71*(3), 209-249.

Tandon, R., Agrawal, S., Chang, A., & Band, S. S. (2022). VCNet: Hybrid Deep Learning Model for Detection and Classification of Lung Carcinoma Using Chest Radiographs. *Frontiers in Public Health*. https://doi.org/10.3389/fpubh.2022.894920

Ursuleanu, T.F., Luca, A.R., Gheorghe, L., et al. (2021). Unified Analysis Specific to the Medical Field in the Interpretation of Medical Images through the Use of Deep Learning. *E-Health Telecommunication Systems and Networks*, *10*, 41-74. https://doi.org/10.4236/etsn.2021.102003

Vos, T., Lim S. S., Abbafati, C., et al (2020). GBD 2019 Diseases and Injuries Collaborators. Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, *396*(10258), P1204-1222.

Walsh, S.L.F., Mackintosh, J.A., Calandriello, L., Silva, M., et al. (2022). Deep Learning-based Outcome Prediction in Progressive Fibrotic Lung Disease Using High-Resolution Computed Tomography. *American Journal of Respiratory and Critical Care Medicine*, *206*(7), 883–891. DOI: 10.1164/rccm.202112-2684OC.

Wang, C., Ma, J., & Zhang, S. *et al.* (2022a). Development and validation of an abnormality-derived deep-learning diagnostic system for major respiratory diseases. *NPJ Digital Medicine, 5*(1), 124. https://doi.org/10.1038/s41746-022-00648-z

Wang, C., Ma, J., Shao, J., Zhang, S., Li, J. et al. (2022b). Non-Invasive Measurement Using Deep Learning Algorithm Based on Multi-Source Features Fusion to Predict PD-L1 Expression and Survival in NSCLC. *Frontiers in Immunology,* https://doi.org/10.3389/fimmu.2022.828560

Wang, C., Ma, J., Shao, J., Zhang, S., Liu, Z. et al. (2022c). Predicting EGFR and PD-L1 Status in NSCLC Patients Using Multitask A.I. System Based on C.T. Images. *Frontiers in Immunology,* https://doi.org/10.3389/fimmu.2022.813072

Wang, D., Zhang, Y., Zhang, K., & Wang, L. (2020). FocalMix: semi-supervised Learning for 3Dmedical image detection, *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Seattle, WA, USA, 3950–3959. http://doi.org/10.1109/CVPR42600.2020.00401

Wang, H., Naghavi, M., Allen, C., et al (2016). GBD 2015 Mortality and Causes of Death Collaborators. Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: A systematic analysis for the Global Burden of Disease Study 2015. *The Lancet*, *388*(10053), 1459-1544.

Wang, J., Ding, H., Bidgoli, F.A., Zhou, B., Iribarren, C., & Molloi, S. (2017). Detecting Cardiovascular Disease from Mammograms with Deep Learning. *IEEE Transactions on Medical Imaging*, *36*, 1172–1181, https://doi.org/10.1109/TMI.2017.265548

Wang, W., & Chakraborty, G. (2019). Evaluation of malignancy of lung nodules from C.T. image using recurrent neural network, *IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Bari, Italy, pp. 2992–2997, https://doi.org/10.1109/SMC.2019.8913885

World Health Organization. Indoor air pollution and household energy (2021). Retrieved from https://www.who.int/heli/risks/indoorair/indoorair/en/

World Health Organization. The top 10 causes of death (2020). Retrieved from https://www.who.int/news-Room/factsheets/detail/the-top-10-causes-of-death

Xie, Y., Zhang, J., Xia, Y. (2019). Semi-supervised adversarial model for benign-malignant lung nodule classification on chest C.T. *Medical Image Analysis*, *57*, 237–248. DOI: 10.1016/j.media.2019.07.004.

Zhang, J., Xia, Y., Zeng, H., & Zhang, Y. (2018). NODULe: combining constrained multi-scaleLoG filters with densely dilated 3D deep convolutional neural network for pulmonary nodule detection, *Neurocomputing*, *317*, 159– 167.

Zhao, D., Zhu, D., Lu, J., Luo, Y., & Zhang, G. (2018). Synthetic medical images using F&BGAN for improved lung nodules classification by multi-scale VGG16, *Symmetry*, *10*, 519.