International Conference on Recent Trends in Data Science and its Applications
DOI: rp-9788770040723.012

A Study on the Pulmonary Diseases using Deep Learning

M.Beulakutti
Research Scholar, Department of computer science and Engineering, SRMIST,
Kattankulathur, Chennai, India
bm3895@srmist.edu.in

Dr.T.Karthick
Assistant Professor, Department of Data science and Business system,
School of Computing, SRMIST,
Kattankulathur, Chennai, India
karthict@srmist.edu.in

Abstract–*Deep learning current advancements help to identify and classify pulmonary disease in medical images. Therefore, various studies can be discovered in the literature to identify lung illness via deep learning. The present study offers an investigation of deep learning in medical images for pulmonary disease diagnosis. Only two study papers on deep learning focused on the way to the identification of lung illnesses were published in the recent five years. Yet the taxonomy and analysis of the current work trend are not presented in their study. As a starting point, this study intends to present taxonomy of current systems for the diagnosis of deep lung disease, as well as a view of current domain work as well as probable future directions in this subject. It's possible that other scholars will make use of the taxonomy provided to organize their own work. With the given probable future route, deep learning applications that aid in the detection of lung ailments may become even more efficient and numerous.*

Keywords– Deep learning, Pulmonary disease, Taxonomy, diagnosis, lung ailments, Medical Images.

I. INTRODUCTION

Disorders of the cardiovascular system, such as those affecting the lungs, can damage the airways and other parts of the lungs. The Lung disorders are such as bronchitis, tuberculosis, and coronavirus illness (COVID-19). The Federation of International Respiratory Associations [1] reports that there are more than 334 million individuals with asthma worldwide, that 1.4 million people are dying annually from bronchitis, and that 1.6 million people die annually from lung cancer. Because of the widespread spread of the COVID-19 pandemic [2], millions of people became ill and healthcare costs skyrocketed [3]. Undoubtedly, lung illness is one of the leading global killers and disablers. Enhancing long-term recovery and survivability prospects requires early identification [4, 5]. Traditional methods for diagnosing lung disease have included skin testing, complete blood count, sputum sample tests, chest X-rays, and computerized tomography (CT) scanning [6, 7]. Furthermore, supervised learning has shwed a significant amount of promise in diagnostic imaging disease detection, notably for respiratory problems.

Most instances of TB are due to a bacteria known as Mycobacterium tuberculosis. Inhalation of germs through the lungs is the supreme communal route of entry [8]. Inflammation of the lungs is a life-threatening illness [9]. Furthermore, early identification and treatment might result in complete recovery. Pneumonia, according to Er et al. [8], is an infection or inflammation of the lungs, most frequently brought on by a bacterium or a viral infection. In addition, ingesting vomit or other foreign things might induce Pneumonia. Asthma is a chronic illness that causes episodes of shortness of breath and wheezing, according to Er et al. [8]. Asthma attacks cause swelling of the bronchial tube lining, which narrows the airways and reduces the amount of air that can flow into and out of the lungs at the same time. COPD is a condition that may be prevented and treated, but the airway restriction is permanent [8]. Tobacco smoking's impact on lung capacity is also cumulative, and it's linked to the tissues' abnormal inflammatory response to inhaled toxins.

Sputum examination, computed tomography (CT), magnetic resonance imaging (MRI), and chest radiography are all frequent diagnostic tools for emphysema. Moreover, the abovementioned operations take a significant amount of time, are sometimes located some distance from the patient, and are typically thought to be expensive. In furthermore, the aforesaid methods are able to detect tumors at a preliminary phase, which is the stage at which a patient's probabilities of survival are quite low. For the most part, researchers are working hard to spot the early signs of pulmonic cancers. The processing of pictures and the use of Artificial Neural Networks improve medical diagnostics research [10]. Medical diagnostics have benefited greatly from the use of image processing and soft computing tools during the last few years.

Build a graphical representation of the current state of deep learning systems for lungdiagnosing; catalogue the recent advances made in this field; list the obstacles still to be overcome; describe potential future strategies for overcoming these issues. The documentation is organized in the following manner. The survey's limitations are discussed in detail in Section 2, which offers related works on employing DL methods to diagnose lung disease. In Section 3, we look at how deep learning can be used to spot lung disease in medical imaging. Detailed explanations of each specific topic are provided in Section 4, which presents the taxonomy. Knowledge about the datasets can be found in Section 5. The development of supervised learning in the detection of lung diseases and the research gaps that exist

DOI: rp-9788770040723.012

are discussed in Section 6 and 7 of this work. The paper comes to a close in Section 8.

II. Literature Review

To handle small databases and the idiosyncrasies of CT TB images with only anomalies in a few particular places, a 3D block-based residual deep learning structure with depth information injection at every layer (depth-ResNet) was chosen. Methods that utilize deep learning have quickly become a powerful tool for both early detection and accurate diagnosis of ailments. Data-driven feature representations can lead to significant medical advancements in this procedure. In medical imaging, deep learning has been utilized extensively to improve picture analysis. This research takes a deep dive into the field of machine learning, and it summarizes some of the most important contributions and cutting- edge results from this field thus far.

For the diagnosis of many malignancies in chest X-ray images, ShuaijingXu and coworkers [12] present an attention-driven ensemble learningand association context model. The CNN- ATTENTION-LSTM (CAL) network at first integrates a CNN model with a long short-term memory mechanism to identify items in both texts and images [13, 14]. In addition, a mining approach of implicit association intensity guides CAL network training to generate a chest lesion association structure (CLA).

There must be an effective cancer prediction system that utilizes a computer assisted automated detection (CAD) method at the clinical center. Enhanced lung image processing algorithms [15] are being utilized to probe the body's internal workings, recover features, retrieve vital info, and create an informed method for identifying lung disease. Some of the many processing methods utilized for lungs include: preprocessing, injured portion separation, extraction of features, and lung cancer diagnosis. Segmentation is one step in the process since it analyses each pixel in the lung imagery to determine which cells are linked to cancer and which are not, allowing for a more accurate classification of the both.

To enhance tumor categorization, Sarfaraz Hussein et al. [13] recommended different machine learning techniques. The first method relies on supervised learning; deep learning approaches such a 3D Convolutional Neural Network (CNN) and Transfer Learning have demonstrated significant improvements. Then, it is shown how to integrate task-dependent feature representations into CNN architecture via a graph-regularized sparse Multi-Task Learning (MTL) technique informed by radiologists' interpretations of the scans. When labeled training data is scarce, unsupervised learning methods can be utilized to improve medical imaging applications. Multiple instances learning (MIL) is an example of a minimally supervised classification that may prove useful here. One such approach to addressing problems is active in the learning process. Medical imaging problems can only beaddressed with the development of unsupervised learning systems.

Approaches for identifying COPD were proposed by Ran Du et al. [14], who suggested employing deep convolutional neural systems to assess 3D lung bronchial tree branches from the viewpoint of machine vision. CT images are used to extract airway trees, which are then 3D visualized in ventral, dorsal, and isometric views. A Bayesian optimization approach is used to build a single deep CNN model that can identify COPD.

In order to evaluate the effectiveness of medication adherence over time, Xiaohong W. Gao and colleagues [11] looked at how CT respiratory imaging may be used to detect and categorize tuberculosis across five severities.

III. Common Detection System for Pulmonary Disease

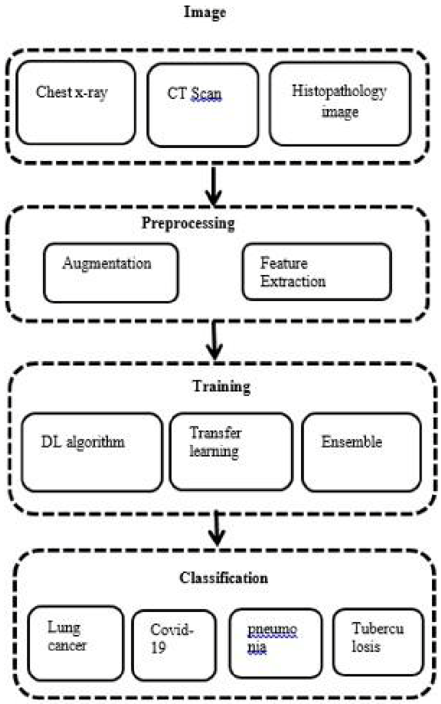

Fig. 1. Common Prediction Framework

1. *Image Acquisition*

The utilization of deep learning to analyze clinical images as a diagnostic tool for respiratory problems has been explained in depth. Two out of the three main processes are learning and classification. It is usual practice in the diagnosis of respiratory illness to characterize images as normal lungs and contaminated lung imagery. Training is necessary for the development of the lung disease classifier, or model. A neural network can be taught to recognize a certain sort of image when it is trained. Classifying images into their respective categories is a task well- suited for deep learning. The first step in applying deep learning to pulmonary disease diagnosis is the collection of imaging modalities of affected lung. Diseases can be identified once the neural network is trained.

Images are the first step. For a computer to create a classification model, it has to learn from its experiences. It takes a lot of photos for the computer to recognize an object. Deep learning models can be trained using a variety of data formats, including time series and speech recordings. Lung disease can be detected using photographs, which are essential data in this paper's context. Some types of images

DOI: rp-9788770040723.012

that might be utilized are those obtained via radiograph, CT scan, mucus smears microscope, and histopathological screening. This step generates photos that will be fed into the model's learning process.

2. Pre-Processing

The sharpness of a visual can be improved by enhancement or modification. CLAHE is a contrast enhancement algorithm. The region of interest for lung disease diagnosis can be found by image processing techniques including lung segmentation and bone eradication. Data can also be represented in a different way, and edge detection can help with that. The images might be enhanced to provide more information. Adeep learning model can recognize a specific entity in a variety of ways, including by retrieving relevant attributes from the data set. This stage has resulted in the improvement of these images or the removal of unwanted elements from them.

3. Training

In training, there are three ways to look at it. When deciding on a deep neural network algorithm, it's important to take into account a variety of factors, such as the application of learning algorithms and ensembles. Algorithms learn in a variety of ways. Specific algorithms are better suited to certain sorts of data. CNN excels in using images to convey information. In this case, a deep learning method should be used. In this method of learning, information is passed from one model to the next in a logical chain of reasoning. The phrase "ensemble" refers to the classification of data using multiple models. Learning time is reduced; classification performance is enhanced, and over fitting is avoided by utilizing learning algorithm and evolutionary algorithms.

4. Classification

When an image is presented in a certain way, the trained model will be able to estimate which class it belongs to. According to the model, the likelihood score for the image will be determined. Using the probability score, you may determine how likely it is that an image belongs to a given category. When we nearing the edge of this phase, the image will be categorized according to the probability score that the machine learning strategy assigned to it.

IV. Taxonomy of Lung Disease Detection

Among the many things this study adds to the conversation is a classification of existing deeplearning projects for diagnosing lung diseases. The purpose of the taxonomies is to identify and categorize the most pertinent questions and areas of emphasis in the current scientific literature. The taxonomy's seven characteristics were determined. These traits were selected because they are ubiquitous and can be observed in every object of investigation. The seven aspects of the taxonomies include image classes, attributes, up-sampling, deep learning method types, learning techniques, the ensemble of classifiers, and lung cancer diagnoses. Figure 3 depicts the current lung disease detection taxonomy based on deep learning.

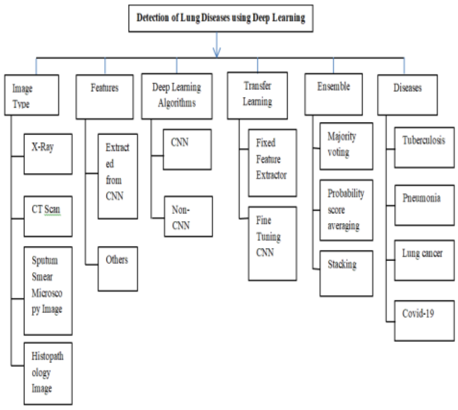

Fig. 2. Distinct Features of Deep Learning for Respiratory Disorders

4.1 Kinds of Images

TABLE 1. Types of Various Lung Images

S. No	Image Type	Description	Sample Image
1	Chest X-Rays [26]	1. Anatomical details such as images of blood arteries and lungs can be gleaned throughthisprocedure.	
		2. In order to examine X-ray images, they must first be processed onphotographic film.	
2	CTScan [25 23]	1. For radiographic imaging that uses computer processing. 2. From photographs taken from a variety of angles around the patient's body, create sectional views of varying depths. 3. It provides more information than X- rays, which are lessprecise.	
3	Sputu m Smea r Micro scopyImages [27]	1. Lungs and airways breathing tubes produce thick fluid. 2. For sputum examination, the illustration is placed on a glass slide witha very thin layer.	
4	Histopatho logy Images [2833,2934]	1. Glass slides are used for microscopic assessment of a biopsy or surgical specimen to study the signs of a disease. 2. One or more stains are used to highlight the tissue's variouscomponents.	

4.2 Methods and Importance of Features

In machine vision, characteristics are numerical measurements extracted from images that canbe employed to address certain challenges. Structures such as points, edges, colors, shapes, or objects can be used to depict features in the image. [16] The categories of images have a logical effect on the quality of attributes. It is possible to generate new features from existing ones by using feature transformations. However, in a different context, they may have a greater ability to discriminate than the original traits did. When transforming features, the purpose is to give a machine learning system for object identification a more usable feature.

4.3 Augmentation

DOI: rp-9788770040723.012

When the number of observations in each category is equal or balanced, deep learning algorithms function best. In order to increase the size of the training dataset, it is not necessary to constantly add new images. Through the process of image augmentation, the source images undergo alterations. The effect is accomplished by employing the use of distortion, revolutions, flipping, translations, and digital zoom. Figure 8 displays a variety of enhanced photos.

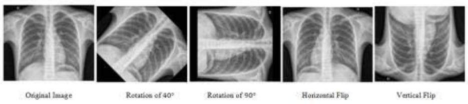

Fig. 3. Augmentation of Lung Images

4.4 Deep Learning Methods

"Deep learning" refers to a subfield of learning algorithms inspired by the structure of the human brain. The strong performance of this method is useful in many different areas, including medical imaging processing. Deep learning methods are used to sift through medical databases for relevant information. The application of deep learning techniques has improved the categorization, delineation, and identification of lesions in medical information. Diagnostic imaging information from MRIs, CT scans, and X-rays was analyzed using deeplearning methods. These discoveries have made it easier to detect and diagnose diseases like diabetes, brain tumors, melanoma, and breast cancer.

4.5 Lung Disease Detection

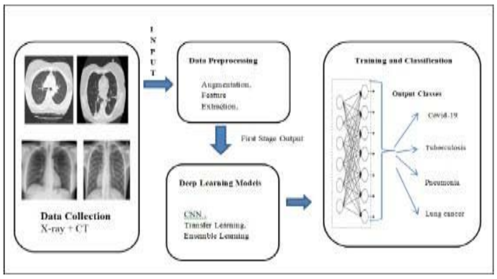

Fig. 4.Common Methodology of Lung Disease Detection using Deep Learning

Deep neural networks (DNNs) can be utilized to address picture recognition difficulties using convolutional neural networks [17]. When it comes to CNN's operation, computers must be able to recognize and interpret images presented as input. In order to make use of the photos, they must first be transformed to a matrix format. On the basis of disparities in picture and matrix, the system identifies what image is associated with what label. These variations in labelling are learned during training, and then applied to new images in order to create predictions.

Convolutional, pooling, and fully connected layers are all part of CNN's three-layer structure. The feature extraction approach includes both convolutional and pooling layers. However, categorization is done in the fully linked layer.

4.6 Transfer Learning

Due of its ability to create accurate models, transfer learning has become an increasingly used technique in computer vision [18]. Withtransfer learning, a model learnt in one field can be applied to another. A pre-trained model or not, transfer learning can be accomplished. Pre- trained models are those that were built to solve a comparable problem. It is preferable to Pre- trained models are those that were built to solve a comparable problem. Starting over with a difficult aspect in consideration is better to starting over with a particular challenge. In most instances, it was found that using a system that had been pre-trained on a different task than the current task improved performance.

Through some kind of series including forward and backward repetitions, the objective of the process of developing a deep learning algorithm is to locate the appropriate weights to apply to the nodes of the network. They are a valuable source of current situation information thanks to these pre-trained models Transfer learning may be applied in two ways as a feature extractor using CNN, which I fine-tune. [19] Some of the weighting in the early levels come straight from the pre-trained CNN model, whereas higher levels require optimizing weights. Typically algorithms can only be trained up at the base level, meaning just the weights at the top of the model are changed. It is possible to use first-layer data for a wide variety of purposes since it contains generic qualities. To acquire more advanced features unique to the specific dataset, it is necessary to educate the model's upper layers. However, CNN employs a feature extractor. The fully- connected levels can be removed, and the network can be used as a fixed feature representation for the new set of information.

4.7 Classifier Ensemble

Ensemble categorization is the outcome of using the outputs of multiple classifiers together. The forecasts of ensembles are much more reliable than those of a unified framework. A sampling of ensemble voting techniques comprises qualified majority, probabilistic score averaging, and stacking. In amajority vote, each system assigns a class label to a test case and then forecasts the class label that gets the most votes [20]. There are some models that have their votes counted more heavily than others when it comes to the majority vote. Probabilistic score aggregating is a statistical method for combining and dividing the predictions from many systems. In its place, weighted aggregating can be used to calculate an average by multiplying the prediction score of each modeling by its weight. [21] An approach called stacking ensembles takes the results of multiple less accurate models and tries to combine them in the best way possible so that the final forecast is more accurate.

4.8 Types of Diseases

This study details the use of deep learning techniques for the identification of TB, bronchitis, emphysema, and COVID-19. People with lung disease are more likely to die from COVID-19 than any of the other three diseases on this list because it's a pandemic that is still going on.

4.8.1 Tuberculosis

The World Health Organization [22] reports that TB is a major killer worldwide. In 2017, 1.6 million individuals all over the world passed away due to tuberculosis. The likelihood of a successful recovery from tuberculosis is greatly increased when the disease is discovered early on. In the literature, CNN has been used to classify TB. Improve the CNN's accuracy by factoring in user-provided age,

DOI: rp-9788770040723.012

sexual identity, and bodyweight information. Computer-aided diagnosis (CAD) was used with clinical data to score the chest X-rays. This combination enhanced precision and specificity when compared to using either type of information alone.

4.8.2 Pneumonia

As the most prevalent kind of pneumonia, bacterial pneumonia has more significant indications and requires medical attention.Although bacterial pneumonia can present itself gradually or quickly, the symptoms are often similar. There may be excessive sweating and rapid breathing and heart rate as well as a dangerously high fever of 105 degrees F. Lips and nail beds may turn blue if oxygen levels in the blood drop too low. A patient's psychological condition may be unclear or delusional. Pneumonia is difficult to diagnose because its signs are nonspecific and may be mistaken for those of a common cold or influenza.

4.8.3 Lung Cancer

The most frequent forms of lung cancer are small cell pulmonary cancer and non-small cell lung cancer [23]. Signs of lung cancer have included a persistent cough that produces blood, chest pain, fatigue, appetite loss and breathing difficulties or weakness [24]. The survivability rate increases from 15% to 50% with early identification [25]. Yet, this rate of survival must be raised above its present level. X-rays, CT scans, MRIs, and other noninvasive imaging methods aid in the early diagnosis of lung cancer. CT scanning is the gold standard for creating 3D lung pictures [25]. It is possible to lower mortality rates with early diagnosis and treatment. The method of early identification of cancer is crucial in stopping the progress of the disease cells. The accuracy of current lung cancer detection methods is inadequate. Therefore, it is crucial to find novel means of detecting lung cancer at its earliest stages.

4.8.4 Covid 19

COVID-19 is an infectious disease brought on by the SARS-CoV-2 virus. The majority of persons who contract this virus will have mild to moderate respiratory symptoms and will improve without any particular therapy. Some, though, will become gravely ill and necessitate professional medical care. People over the age of 65 and those who already have illnesses like high blood pressure, hypertension, asthma, ormalignancy are at a higher risk of becoming seriously ill. At any age, someone who has COVID-19 infection has the potential to become gravely ill or perhaps die.

V. Knowledge of Dataset

The LIDC-IDRI image review synthesizes thoracic CT images with annotated lesions for diagnostic and screening purposes. It is a worldwide internet-based resource for the creation, training, and evaluation of computer- aided diagnostic methods for the recognition and diagnosis of lung diseases. Nodular, non- nominal or nodule > 3 millimeters in diameter are all three categories that radiologists assign to CT scans in this initial step (NMD). The datasets utilized to detect lung disease are summarized in Table 2. Only public datasets are included.

TABLE 2. Summary of Dataset for Lung Disease Detection

Name of the Dataset	Image Category	Total Images	Reference
JSRT dataset	X-ray and CT	154 nodule & 93 non-nodule	[11]
LIDC-IDRI	CT	1018	[12, 15]
NIH-14 dataset	X-ray	112,120	[13]
ELVIRA Biomedical Data Repository	X-ray and CT	203	[14]

VI. Challenges and Future Scope

Despite the accomplishments of deep learning technology from a medical and therapeutic perspective, numerous limits and problemsremain. Deep learning usually necessitates the use of a huge volume of labeled data. Medical image annotation faces a significant problem in meeting this need. Radiologists, for example, have extensive domain expertise that is required for labeling medical pictures. An adequate medical picture annotation is therefore labor- and time-intensive [26]. Regardless of the challenges of annotating medical information, a large number of clinical images are stored in PACS for an extended period of time. This results in a large number of images that do not have any labels attached to them. Deep learning algorithms might make use of the unlabeled pictures, saving a lot of time and effort in the annotation process. More training data sets will be used in the future, and the model's parameters will be tweaked to improve speed in the model. Some of the measures' settings will be put to the test as well. To enhance the accuracy, we can run experiments on a pre- trained classic. The representation of deep learning is another problem that needs to be addressed. The application of deep learning in the analysis of medical images is becoming increasingly popular, and additional research is being conducted to get it ready for clinical deployment [27]. Legal openness and interpretability would be required if deep learning applications were widely used in the medical industry.

VII. Conclusion

A current issue of discussion in the fields of medicine and information technology is the application of deep learning to the evaluation of medical images. Consequences of study in these areas are described extensively in this article: Initially, the neural network framework for deep learning was introduced, which was actively investigated. Classical models utilized in medical imaging were also included as part of the network's deep structure. In the beginning, neural networks were used in the treating a wide variety of respiratory illnesses. Analysis and categorization as well as a deep assessment of the framework advancement aregiven in this report to lay a substantial basis for future researchers in deep neural networks for various disease-related jobs. Also included in this work are some commonly used datasets on a variety of disorders, so that others might conduct similar investigations.

References

DOI: rp-9788770040723.012

[1] Forum of International Respiratory Societies. The Global Impact of Respiratory Disease, 2nd ed.; European Respiratory Society, Sheffield, UK, pp. 5–42, 2017.

[2] World Health Organization. Coronavirus Disease 2019 (COVID-19) Situation Report; Technical Report March; World Health Organization: Geneva, Switzerland, 2020.

[3] M.M.Rahaman, C.Li, Y.Yao, F.Kulwa, M.A.Rahman, Q.Wang, S.Qi, F.Kong, X.Zhu,and X.Zhao,"Identification of COVID-19 samples from chest X-Ray images using deep learning: A comparison of transfer learning approaches", J. X-Ray Sci. Technol., vol. 28, pp. 821–839, 2020.

[4] A.Yahiaoui, O.Er,and N. Yumusak, "A new method of automatic recognition for tuberculosis disease diagnosis using support vector machines", Biomed. Res.,vol. 28, pp. 4208–4212, 2017.

[5] Gomathy, V., Janarthanan, K., Al-Turjman, F., Sitharthan, R., Rajesh, M., Vengatesan, K., &Reshma, T. P. (2021). Investigating the spread of coronavirus disease via edge-AI and air pollution correlation. ACM Transactions on Internet Technology, 21(4), 1-10.

[6] A.A.A.Setio, A.Traverso, T.de Bel, M.S.Berens, C.van den Bogaard, P.Cerello, H.Chen, Q.Dou, M.E.Fantacci, and B.Geurts, et al.,"Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: The LUNA16 challenge," Med. Image Anal.,vol. 42, pp. 1–13, 2017.

[7] D.Shen, G.Wu,and H.I.Suk,"Deep Learning in Medical Image Analysis",Annu. Rev. Biomed. Eng.,vol. 19, pp. 221–248, 2017.

[8] G. A. Carpenter,et al., "Fuzzy ARTMAP: A Neural Network Architecture for incremental supervised learning of analog multidimensional maps," IEEE Transactions on Neural Network, 1992.

[9] S. Durga, and K. Kasturi, "Lung disease prediction system using data mining techniques," Journal of Adv Research in Dynamical & Control Systems, 2017

[10] N.Bhaskar, and BodduChaitanya, "A Survey on Early Detection and Prediction of Lung Cancer," (IJTIMES), June-2018.

[11] Xiaohong W. Gao, Carl James-Reynolds, and Edward Currie, "Analysis of tuberculosis severity levels from CT pulmonary images based on enhanced residual deep learning architecture," Neurocomputing,2019,DOI:https://doi.org/10.1016/j.neucom.2018.12.086.

[12] ShuaijingXu, JunqiGuo, Guangzhi Zhang and RongfangBie, "Automated Detection of Multiple Lesions on Chest X-ray Images: Classification Using a Neural Network Technique with Association-Specific Contexts," Applied Sciences, vol. 10, iss. no.5,2020,DOI:https://doi.org/10.3390/app10051742.

[13] Sarfaraz Hussein and PujanKandel, Candice W. Bolan, Michael B. Wallace, and UlasBagci, "Lung and Pancreatic Tumor Characterization in the Deep Learning Era: Novel Supervised and Unsupervised Learning Approaches," IEEE Transactions on Medical Imaging, 2019, DOI:10.1109/TMI.2019.2894349.

[14] Ran Du, Shouliang qi, jiefeng, Shuyuexia, Yan kang, Wei qian and Yu-dong yao, "Identification of COPD From Multi-View Snapshots of 3D Lung Airway Tree via Deep CNN," IEEE Access, vol.8,2020,DOI: 10.1109/ACCESS.2020.2974617.

[15] Rajesh, M., &Sitharthan, R. (2022). Introduction to the special section on cyber-physical system for autonomous process control in industry 5.0. Computers and Electrical Engineering, 104, 108481.

[16] N. O'Mahony, S.Campbell, A.Carvalho, S.Harapanahalli, G.V.Hernandez, L.Krpalkova, D.Riordan,and J. Walsh, "Deep Learning vs . Traditional Computer Vision," Adv. Intell. Syst. Comput., pp. 128–144, 2020.

[17] N. Jmour, S. Zayen, and A. Abdelkrim,"Convolutional neural networks for image classification," In: International conference on advanced systems and electric technologies, Hammamet, Tunisia, pp 397–402, 2018.

[18] X. Cao, D.Wipf, F. Wen, G.Duan,and J.Sun,"A practical transfer learning algorithm for face verification," In Proceedings of the IEEE International Conference on Computer Vision, Sydney, Australia, pp. 3208–3215, 1–8 December, 2013.

[19] N. Tajbakhsh, J.Y.Shin, S.R.Gurudu, R.T.Hurst, C.B.Kendall, M.B.Gotway, and J.Liang,"Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?" IEEE Trans. Med. Imaging, vol. 35, pp. 1299–1312, 2016.

[20] L.G.Kabari,and UOnwuka,"Comparison of Bagging and Voting Ensemble Machine Learning Algorithm as a Classifier", Int. J. Adv. Res. Comput. Sci. Softw. Eng.,vol. 9, pp. 1–6, 2019.

[21] F.Divina, A.Gilson, F.Goméz-Vela, M.G.Torres,and J.F. Torres, "Stacking Ensemble Learning for Short-Term Electricity Consumption Forecasting," Energies,p. 11, 2018.

[22] World Health Organisation. Global Health TB Report; World Health Organisation: Geneva, Switzerland, p. 277, 2018.

[23] A.M. Mesleh, Jordan Journal of Biological Sciences, vol. 10, p.239, 2017,[Google Scholar]

[24] Anjali Sevani, et al. International Journal of Advance Engineering and Research Development, vol. 5, p. 792, 2018,[Google Scholar]

[25] B. Abdillah, et al. The Asian Journal, p. 893:1, 2016,[doi-10.1088/17426596/893/1/012063] [Google Scholar]

[26] K. Ananthajothi, and M. Subramaniam, "CLDC: Efficient Classification of Medical Data Using Class Level Disease Convergence Divergence Measure," International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN 2278-3075, vol. 8, no. 10, pp. 2256-2262, 2019.

[27] D. Divya,and T. R.Ganeshbabu,"Fitness Adaptive Deer Hunting-Based Region Growing and Recurrent Neural Network for Melanoma Skin Cancer Detection," International Journal of Imaging Systems and Technology, ISSN 0899-9457, E.ISSN 1098-1098, vol. 30, issue no. 3.2020.