DETECTION OF PULMONARY DISEASES USING DEEP LEARNING

[1]P.Vijay Bhaskar Reddy, [2]Y.V.Ramesh

Faculty
CSE Department
GIST, Nellore.

***Abstract*- Lung disease is common throughout the world. These include chronic obstructive pulmonary disease, pneumonia, asthma, tuberculosis, fibrosis, etc. Timely diagnosis of lung disease is essential. Many image processing and machine learning models have been developed for this purpose. Different forms of existing deep learning techniques including convolutional neural network (CNN), vanilla neural network, visual geometry group based neural network (VGG), and capsule network are applied for lung disease prediction. The basic CNN has poor performance for rotated, tilted, or other abnormal image orientation and VDSNet hybrid model is not efficient for large datasets. Therefore, we use DenseNet a CNN architecture to detect lung diseases from chest x-ray images.This deep learning model is very dense network which helps the doctors to diagnosis the disease more efficiently.**

***Keywords*- Computer Vision, Pulmonary Diseases,Deep Learning,DenseNet,CNN.**

I. INTRODUCTION

Lung disease is common throughout the world. These include chronic obstructive pulmonary disease, pneumonia, asthma, tuberculosis, fibrosis, etc. Timely diagnosis of lung disease is essential. Many image processing and machine learning models have been developed for this purpose. Different forms of existing deep learning techniques including convolutional neural network (CNN), vanilla neural network, visual geometry group based neural network (VGG), and capsule network are applied for lung disease prediction. The basic CNN has poor performance for rotated, tilted, or another abnormal image orientation.

Therefore, we are using DenseNet model to improve the accuracy for detecting lung diseases. The goal of this project is to develop a lung diseases detection model from x-ray images. The system provides a platform where users can identify the lung diseases by just providing the x-ray images as input and hence the lung disease which the patient is suffering is displayed.

II. LITERATURE REVIEW

Using deep learning for classification of lung nodule on computed tomography images.

This paper was proposed by Song Q, Zhao L, Luo X, Dou X. Lung cancer is the most common cancer that cannot be ignored and cause death with late health care. Currently, CT can be used to help doctors detect the lung cancer in the early stages. In many cases, the diagnosis of identifying the lung cancer depends on the experience of doctors, which may ignore some patients and cause some problems. Deep learning has been proved as a popular and powerful method in many medical imaging diagnosis areas. In this paper, three types of deep neural networks (e.g., CNN, DNN, and SAE) are designed for lung cancer calcification. Those networks are applied to the CT image classification task with some modification for the benign and malignant lung nodules. Those networks were evaluated on the LIDC-IDRI database. The experimental results show that the CNN network archived the best performance with an accuracy of 84.15%, sensitivity of 83.96%, and specificity of 84.32%, which has the best result among the three networks.

Deep-learning framework to detect lung abnormality a study with chest X-Ray and lung CT scan images

This paper was proposed by Bhandary Abhir, et al. Lung abnormalities are highly risky conditions in humans. The early diagnosis of lung abnormalities is essential to reduce the risk by enabling quick and efficient treatment. This research work aims to propose a Deep-Learning (DL) framework to examine lung pneumonia and cancer. This work proposes two different DL techniques to assess the considered problem: (i) the initial DL method, named a modified AlexNet (MAN), is proposed to classify chest X-Ray images into normal and pneumonia class. In the MAN, the classification is implemented using with Support Vector Machine (SVM), and its performance is compared against Softmax. Further, its performance is validated with other pre-trained DL techniques, such as AlexNet, VGG16, VGG19 and ResNet50. (ii) The second DL work implements a fusion of handcrafted and learned features in the MAN to improve classification accuracy during lung cancer assessment. This work employs serial fusion and Principal Component Analysis (PCA) based features selection to enhance the feature vector. The performance of this DL frame work is tested using benchmark lung cancer CT images of LIDC-IDRI and classification accuracy (97.27%) is attained.

Comparative performance analysis of different classification algorithm for the purpose of prediction of lung cancer
This paper was proposed by Bharati S, Podder P, Mondal R, Mahmood A, Raihan- Al-Masud M. Visual inspection of histopathology slides is one of the main methods used by pathologists to assess the stage, type and subtype of lung tumors. Adenocarcinoma (LUAD) and squamous cell carcinoma (LUSC) are the most prevalent subtypes of lung cancer, and their distinction requires visual inspection by an experienced pathologist. In this study, we trained a deep convolutional neural network (inception v3) on whole-slide images obtained from The Cancer Genome Atlas to accurately and automatically classify them into LUAD, LUSC or normal lung tissue. The performance of our method is comparable to that of pathologists, with an average area under the curve (AUC) of 0.97. Our model was validated on independent datasets of frozen tissues, formalin-fixed paraffin-embedded tissues and biopsies. Furthermore, we trained the network to predict the ten most commonly mutated genes in LUAD. We found that six of them—STK11, EGFR, FAT1, SETBP1, KRAS and TP53—can be predicted from pathology images, with AUCs from 0.733 to 0.856 as measured on a held-out population. These findings suggest that deep-learning models can assist pathologists in the detection of cancer subtype or gene mutations.

Fully convolutional networks for semantic segmentation
This paper was proposed by Shelhamer E, Long J, Darrell T. Convolutional networks are powerful visual models that yield hierarchies of features. We show that convolutional networks by themselves, trained end-to-end, pixels-to-pixels, improve on the previous best result in semantic segmentation. Our key insight is to build "fully convolutional" networks that take input of arbitrary size and produce correspondingly-sized output with efficient inference and learning. We define and detail the space of fully convolutional networks, explain their application to spatially dense prediction tasks, and draw connections to prior models. We adapt contemporary classification networks(AlexNet, the VGG net, and GoogLeNet) into fully convolutional networks and transfer their learned representations by fine-tuning to the segmentation task. We then define a skip architecture that combines semantic information from a deep, coarse layer with appearance information from a shallow, fine layer to produce accurate and detailed segmentations. Our fully convolutional networks achieve improved segmentation of PASCAL VOC (30% relative improvement to 67.2% mean IU on 2012), NYUDv2, SIFT Flow, and PASCAL- Context, while inference takes one tenth of a second for a typical image.

Lung cancer recognition and prediction according to random forest ensemble and RUSBoost algorithm using LIDC data
This paper was proposed by Bharati S, Podder P, Paul PK.. In most patients presenting with respiratory symptoms, the findings of chest radiography play a key role in the diagnosis, management, and follow-up of the disease. Consolidation is a common term in radiology, which indicates focally increased lung density. When the alveolar structures become filled with pus, fluid, blood cells or protein subsequent to a pulmonary pathological process, it may result in different types of lung opacity in chest radiograph. This study aims at detecting consolidations in chest x-ray radiographs, with a certain precision, using artificial intelligence and especially Deep Convolutional Neural Networks to assist radiologist for better diagnosis.

Deep 3D dual path nets for automated pulmonary nodule detection and classification
This paper was proposed by Zhu W, Liu C, Fan W, Xie X. In this work, we present a fully automated lung computed tomography (CT) cancer diagnosis system, Deep Lung. Deep Lung consists of two components, nodule detection (identifying the locations of candidate nodules) and classification (classifying candidate nodules into benign or malignant). Considering the 3D nature of lung CT data and the compactness of dual path networks (DPN), two deep 3D DPN are designed for nodule detection and classification respectively. Specifically, a 3D Faster Regions with Convolutional Neural Net (R-CNN) is designed for nodule detection with 3D dual path blocks and a U-net-like encoder-decoder structure to effectively learn nodule features. For nodule classification, gradient boosting machine (GBM) with 3D dual path network features is proposed. The nodule classification sub network was validated on a public dataset from LIDC-IDRI, on which it achieved better performance than state-of-the-art approaches and surpassed the performance of experienced doctors based on image modality. Within the Deep Lung system, candidate nodules are detected first by the nodule detection sub network, and nodule diagnosis is conducted by the classification sub network. Extensive experimental results demonstrate that Deep Lung has performance comparable to experienced doctors both for the nodule-level and patient-level diagnosis on the LIDC-IDRI dataset.

III. METHODOLOGY
The proposed methodology goes in the below mention step wise manner.

The execution of the process will be explained clearly with the help of the continuous screenshots. The whole process includes the uploading the x-ray image which is the random image to test the type of the lung disease.

Each figure mentioned below are the simultaneous process of the screening outputs screen. The entire process occurs in three simple steps in the case of frontend.The visible interface has one display screen and three button clicks for their respective operation such as: Upload Image which is responsible for taking an image which is to be tested, Model Load which is responsible for loading the dataset available in the system in the format of .h5 file and Predict Image which is responsible for comparing the initially uploaded image with the dataset of lung disease x-ray images which are in .h5 format and then predict the type of the disease.

The display screen is responsible for displaying all respective actions on the screen for better understanding of the user. The interface was designed by using Tkinter and the whole dataset was imported from the kaggle dataset which has the four types of lung disease images. It is a large pool of dataset having chest x-ray images. Keras was used which mainly deals with the all type of libraries related to deep learning. Similarly, computer vision library is used to implement the interface and aligning the buttons accordingly.Here, the below screenshot Figure 1 represents the home page of the execution process. The first step of the process is to upload the image and the path of the image which is the internal address of the image will be displayed under the section (button key of the upload image file). The path that set under the button of upload image will be latterly compared with the whole dataset of the chest x-ray images which are imported from kaggle dataset. It is ready for the furtherprocess. Here the image is uploaded from the test image folder.

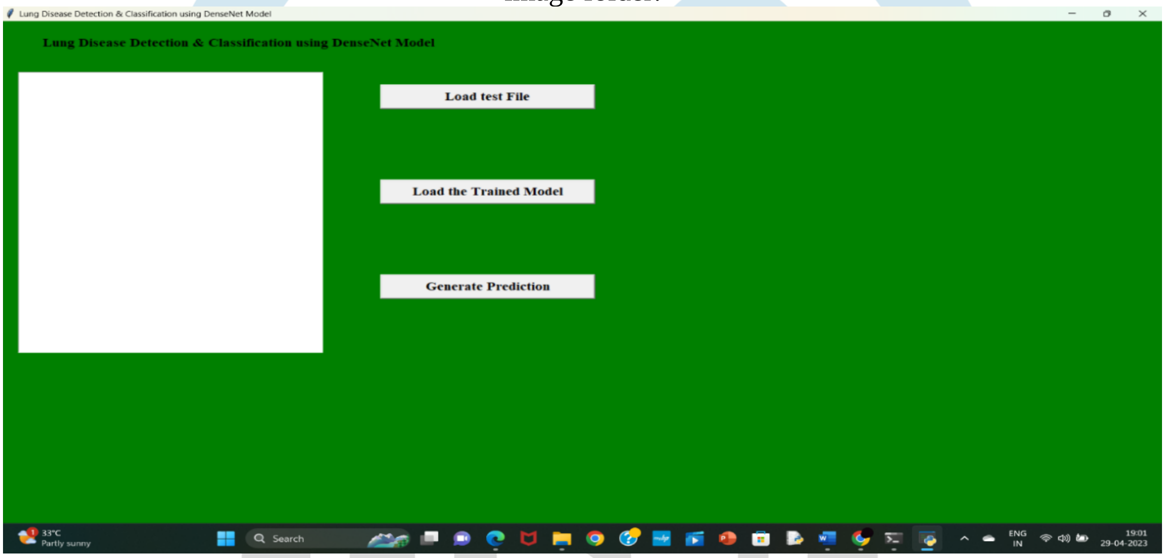

Fig 1 Model GUI

In the above screen, click on "load test file" to upload a chest x-ray image

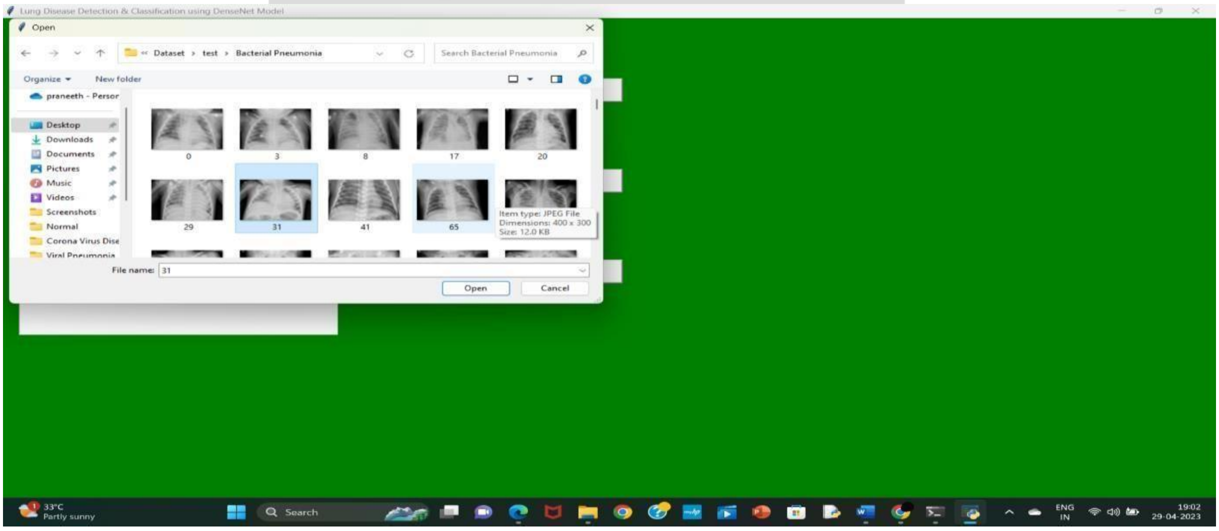

Fig 6.2 uploading Lung x-ray image

After click on the "load test file" button select the chest x-ray image from test folder

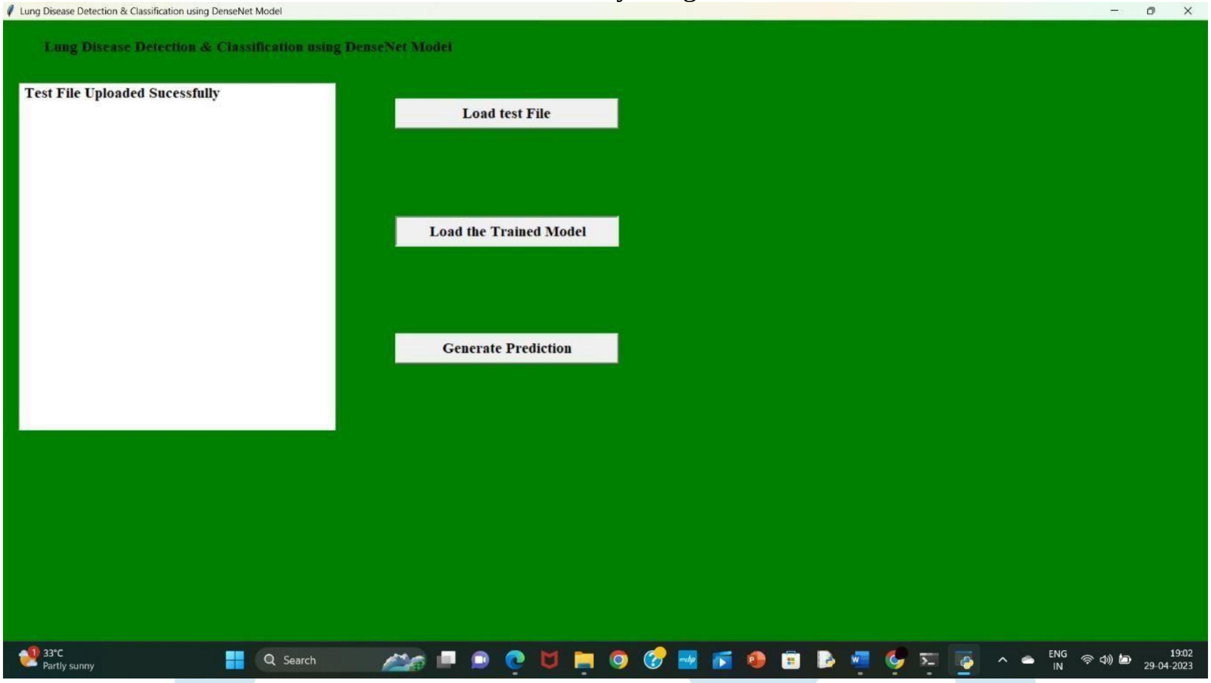

Fig 6.3 Test File is uploaded

After successfully upload of test image we get "Test File Uploaded Successfully" on Screen

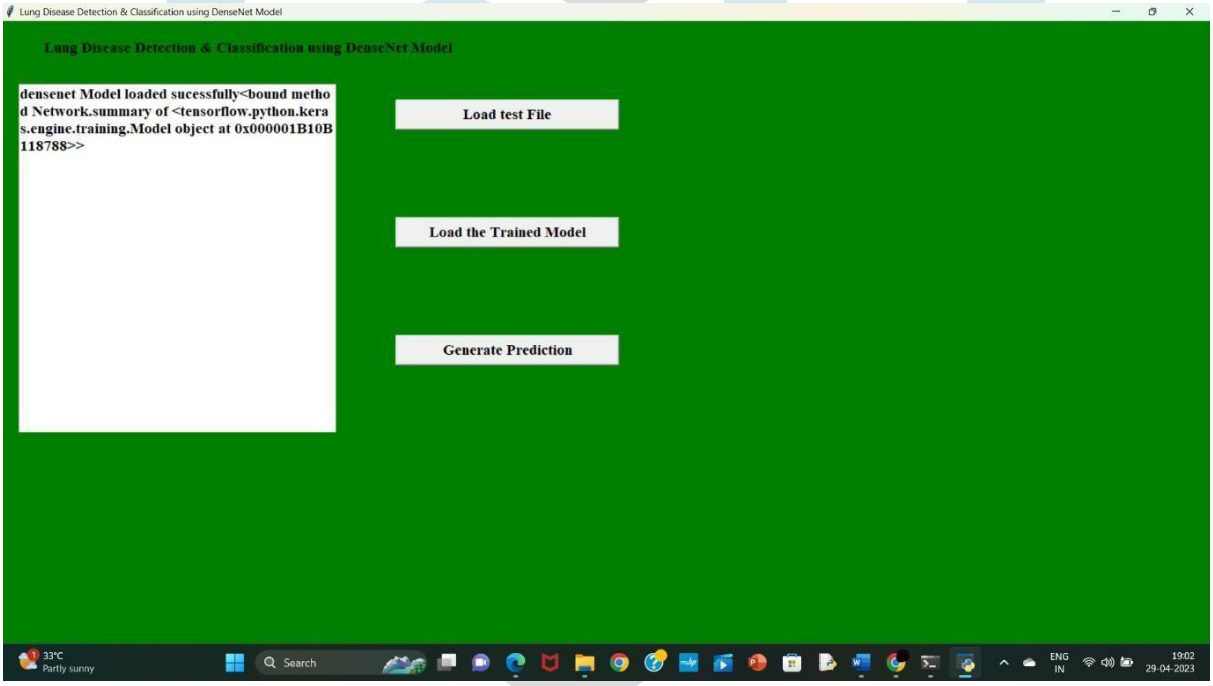

Fig 6.4 Load the trained model

Now, click on the "Load the Trained Model" to load the model. After successful load of trained model, we get "denseNet Model loaded successfully" on the screen
After that click on "Generate Prediction" to predict the lung disease from chest x-ray image.

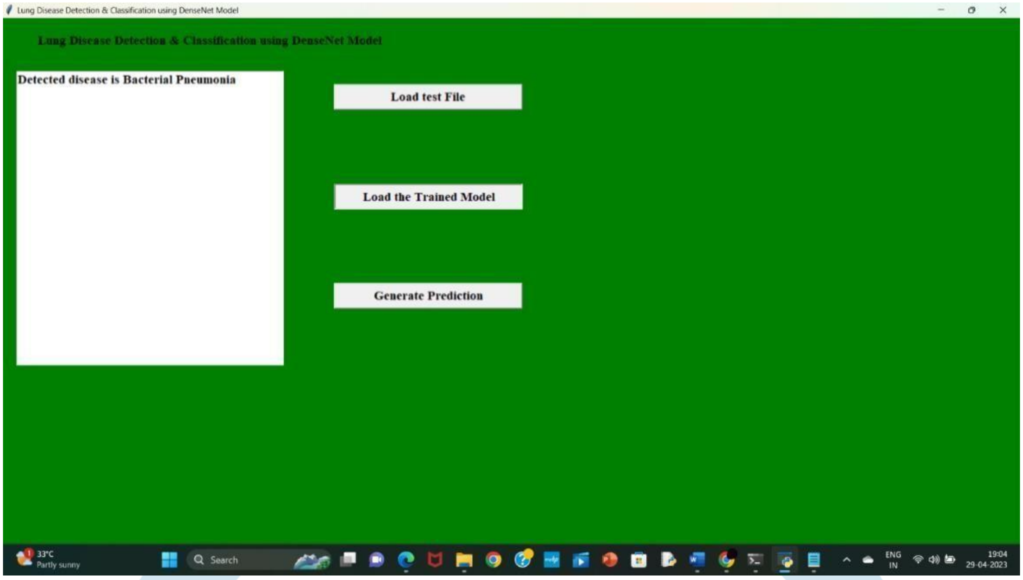

Fig 6.5 Prediction of Lung disease

Now, we can see "Detected disease is Bacterial Pneumonia" on screen. since, we have uploaded bacterial pneumonia patient chest x-ray image from test folder, we get the output like that. Likewise, we can upload different chest x-ray images from test folder to predict the accurate disease. For example, if the patient is healthy and we upload the chest x-ray image of that patient and we get "Patient is healthy" as output.

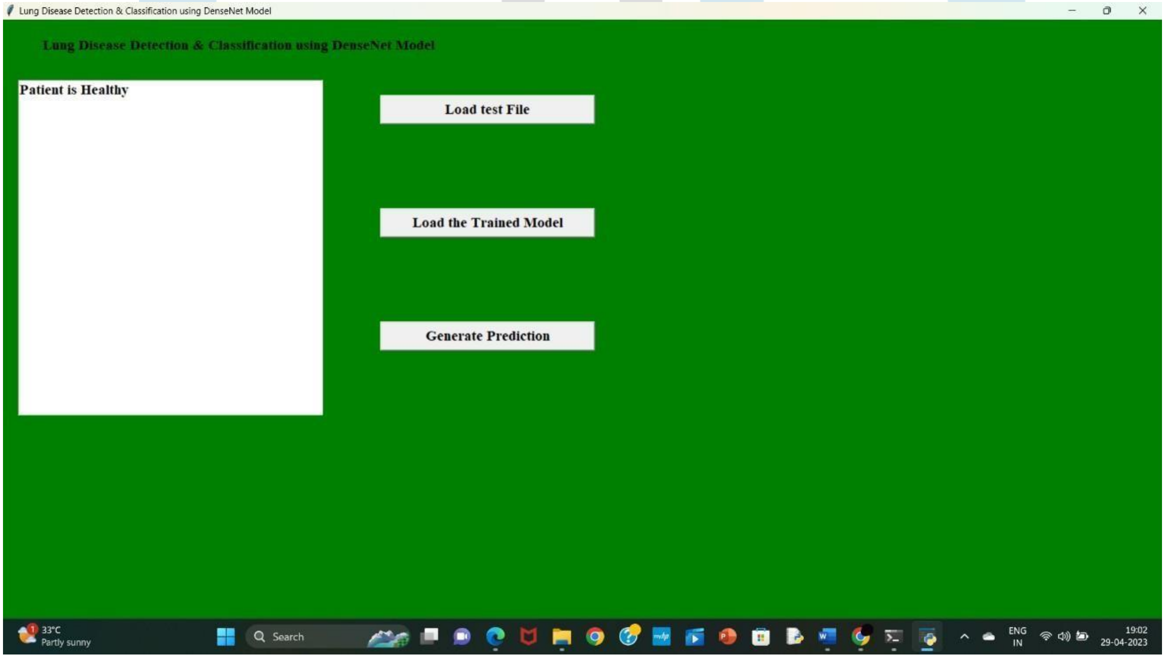

Fig 6.6 Output for a Healthy Patient

IV. CONCLUSIONS

In this project, we used DenseNet a CNN architecture to train lungs x-ray images dataset and after training we can use this model to detect the lung diseases from new x-ray images. To train the DenseNet model we used lung disease dataset from kaggle. The existing system to detect lung diseases from x-ray images uses a hybrid VDSNet model exhibits an accuracy of 73%.whereas the proposes model which uses DenseNet has an accuracy of 87.4%. Therefore we can say our proposed model which uses DensNet is an efficient model to detect lung diseases from x-ray images.

REFERENCES:

1. Bharati S, Podder P, Mondal R, Mahmood A, Raihan-Al-Masud M. Comparative performance analysis of different classification algorithm for the purpose of prediction of lung cancer. Advances in intelligent systems and computing, vol. 941. Springer; 2020. p. 447–57. https://doi.org/10.1007/978-3-030-16660-1_44.

2. Coudray N, Ocampo PS, Sakellaropoulos T, et al. Classification and mutation prediction from non–small cell lung cancer histopathology images using deep learning. Nat Med 2018;24:1559–67. https://doi.org/10.1038/s41591-018-0177- 5.
3. Mondal MRH, Bharati S, Podder P, Podder P. "Data analytics for novel coronavirus disease", informatics in medicine unlocked, 20. Elsevier; 2020. p. 100374. https:// doi.org/10.1016/j.imu.2020.100374.
4. Kuan K, Ravaut M, Manek G, Chen H, Lin J, Nazir B, Chen C, Howe TC, Zeng Z, Chandrasekhar V. Deep learning for lung cancer detection: tackling the Kaggle data science bowl 2017 challenge. https://arxiv.org/abs/1705.09435; 2017.
5. Sun W, Zheng B, Qian W. Automatic feature learning using multichannel ROI based on deep structured algorithms for computerized lung cancer diagnosis. Comput Biol Med 2017;89:530–9.
6. Song Q, Zhao L, Luo X, Dou X. Using deep learning for classification of lung nodules on computed tomography images. Journal of healthcare engineering 2017: 8314740. https://doi.org/10.1155/2017/8314740.
7. Sun W, Zheng B, Qian W. Computer aided lung cancer diagnosis with deep learning algorithms. In: Proc SPIE. Medical Imaging, 2016, 9785. Computer-Aided Diagnosis; 2016. 97850Z. https://doi.org/10.1117/12.2216307.
8. NIH sample Chest X-rays dataset. https://www.kaggle.com/nih-chest-xrays/sa mple. [Accessed 28 June 2020].
9. NIH full Chest X-rays dataset. https://www.kaggle.com/nih-chest-xrays/data. [Accessed 28 June 2020].
10. Wang X, Peng Y, Lu L, Lu Z, Bagheri M, Summers RM. ChestX-Ray8: hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization
11.
12. of common thorax diseases. In: 2017 IEEE Conference on computer Vision and pattern recognition (CVPR); 2017. p. 3462–71. https://doi.org/ 10.1109/CVPR.2017.369.
13. Gu Y, Lu X, Yang L, Zhang B, Yu D, Zhao Y, Gao L, Wu L, Zhou T. Automatic lung nodule detection using a 3D deep convolutional neural network combined with a multi-scale prediction strategy in chest CTs. Comput Biol Med 2018;103:220–31.
14. Setio AAA, Traverso A, de Bel T, Berens MSN, van den Bogaard C, Cerello P, Chen H, Dou Q, Fantacci ME, Geurts B, et al. Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: the LUNA16 challenge. Med Image Anal 2017;42: 1–13.
15. Zhu W, Liu C, Fan W, Xie X DeepLung. Deep 3D dual path nets for automated pulmonary nodule detection and classification. In: Proceedings of the IEEE winter conference on applications of computer vision (WACV); 12–15 March 2018. p. 673–81. Lake Tahoe, NV, USA.
16. Kong W, et al. YOLOv3-DPFIN: a dual-path feature fusion neural network for robust real-time sonar target detection. IEEE Sensor J 1 April1 2020;20(7): 3745–56. https://doi.org/10.1109/JSEN.2019.2960796
17. . [15] Ronneberger O, Fischer P, Brox T. U-net: convolutional networks for biomedical image segmentation. In: International conference on medical image computing and computer-assisted intervention, vol. 9351. Berlin/Heidelberg, Germany: Springer; 2015. p. 234–41.
18. Kallianos K, Mongan J, Antani S, et al. How far have we come? Artificial intelligence for chest radiograph interpretation. Clin Radiol 2019;74(5):338–45. https://doi.org/10.1016/j.crad.2018.12.015.
19. Irvin J, Rajpurkar P, Ko M, Yu Y, Ciurea-Ilcus S, Chute C, Marklund H, Haghgoo B, Ball r, Shpanskaya K, et al. Chexpert: a large chest radiograph dataset with uncertainty labels and expert comparison. 2019. arXiv:1901.07031.
20. Ren S, He K, Girshick R, Sun J. Faster r-cnn: towards real-time object detection with region proposal networks. Adv Neural Inf Process Syst 2015:91–9.
21.
22. Shelhamer E, Long J, Darrell T. Fully convolutional networks for semantic segmentation. IEEE Trans Pattern Anal Mach Intell 2017;39(4):640–51. https:// doi.org/10.1109/TPAMI.2016.2572683.
23. He K, Gkioxari G, Dollar P, Girshick R. Mask r-cnn. Proceedings of the IEEE International Conference on Computer Vision 2017:2961–9.
24. Huang J, Rathod V, Sun C, Zhu M, Korattikara A, Fathi A, Fischer I, Wojna Z, Song Y, Guadarrama S, et al. Speed/accuracy trade-offs for modern convolutional object detectors. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition 2017:7310–1.
25. Shrivastava A, Sukthankar R, Malik J, Gupta A. Beyond skip connections: topdown modulation for object detection. 2017. arXiv:1612.06851.

26. Nasrullah N, Sang J, Alam MS, Xiang H. Automated detection and classification for early stage lung cancer on CT images using deep learning. Proc SPIE 13 May 2019; 10995:109950S. Pattern Recognition and Tracking XXX.
27. Bhandary Abhir, et al. Deep-learning framework to detect lung abnormality – a study with chest X-Ray and lung CT scan images. Pattern Recogn Lett January 2020;129:271–8. https://doi.org/10.1016/j.patrec.2019.11.013.
28. Bharati S, Podder P, Paul PK. Lung cancer recognition and prediction according to random forest ensemble and RUSBoost algorithm using LIDC data. Int J Hybrid Intell Syst 2019;15(2):91–100. https://doi.org/10.3233/HIS-190263.
29. Behzadi-khormouji H, et al. Deep learning, reusable and problem based architectures for detection of consolidation on chest X-ray images. Comput Methods Progr Biomed 2019. https://doi.org/10.1016/j.cmpb.2019.105162.
30. Liang C-H, et al. Identifying pulmonary nodules or masses on chest radiography using deep learning: external validation and strategies to improve clinical practice. Clin Radiol 2019. https://doi.org/10.1016/j.crad.2019.08.005.
31. Chouhan V, et al. A novel transfer learning based approach for pneumonia detection in chest X-ray images. Appl Sci 2020;10(2):559. https://doi.org/ 10.3390/app10020559.
32.
33. Rajaraman S, Antani SK. Modality-specific deep learning model ensembles toward improving TB detection in chest radiographs. IEEE Access 2020;8:27318–26. https://doi.org/10.1109/ACCESS.2020.2971257.
34. Takaki T, et al. Calculating the target exposure index using a deep convolutional neural network