THORAX DISEASE CLASSIFICATION BASED ON PYRAMIDAL CONVOLUTION SHUFFLE ATTENTION NEURAL NETWORK

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ABSTRACT

One of the most used radiological tests for detecting thoracic illnesses is the chest X-ray. Even though convolution neural network-based algorithms have made significant progress in classifying thoracic diseases from chest X-ray pictures, the scale variety of the pathological anomalies in various thoracic diseases remains a challenge. This research suggests a convolutional neural network model built on a VGG 19 considering the aforementioned issues. When compared to the traditional 3x3 convolution, the VGG 19 model is specifically designed to extract more distinguishing characteristics of pathological abnormality; and it allows the VGG 19 model to concentrate on more characteristics of pathological abnormality. The rigorous testing on the ChestX-ray14 and COVIDx datasets shows that the VGG 19 model outperforms other cutting-edge techniques in terms of performance. The ablation study further establishes the effectiveness of VGG 19, a convolutional neural network-based model, in improving the efficiency of thoracic illness classification.

INTRODUCTION

A chest X-ray (CXR) is a reasonably priced and cost-effective diagnostic imaging technique that is primarily used for the early detection of disorders of the thorax, heart, lung tissue, and other organs, including pneumonia, heart failure, lung cancer, and so forth. Each year, more than 1 million adults are admitted to hospitals with pneumonia, and just in the United States, this illness claims the lives of almost 50,000 victims. Most chest X-ray images typically rely mostly on manual inspection by a qualified radiologist. Because of the intricate pathological anomalies and subtle structural alterations caused by different thoracic disorders, even radiologists with expert clinical training occasionally make mistakes. There are reports of 20–50% of lung nodules being overlooked or misdiagnosed. A serious misdiagnosis of 3-6 percent will occasionally be made by even the finest radiologists. In order to aid in the clinical diagnosis of thoracic disorders, it is crucial that chest X-ray pictures be classified and localised precisely.

The chest X-ray image classification has advanced significantly since the earlier efforts. For instance, while publishing the ChestX-ray14 dataset, Wang et al. assessed the classification results of four classical CNN models, AlexNet, GoogleNet [6], VGGNet-16, and ResNet-50 on the chest X-ray pictures. By altering the fully connected layer of DenseNet-121 and loss function, Rajpurkar et alCheXNet .'s model was able to accurately classify thoracic disorders. In particular, the accuracy of the diagnosis of pneumonia reached 88.87 percent, exceeding the level of human diagnosis at the time. However, because illness pathological anomalies are so complicated, classifying chest X-ray images remains difficult. On the one hand, the pathological anomalies in different thoracic disorders vary on a clear scale. The "pneumonia" and "cardiomegaly" almost completely engulf the left lung and the entire heart, respectively, whereas "nodule" and "mass" are significantly less severe. As a result, while dealing with pathological defects of diverse thoracic diseases, the typical 3x3 convolution may not be able to adjust to the scale change of discriminative features. However, because there are comparable organs and tissues in each chest X-ray image, it is challenging for convolution neural networks to develop discriminative representations of the complex pathologic anomalies in thoracic disorders. The large-scale diversity of the pathological abnormalities in different thoracic diseases and the similarity of the distinguishing features in each chest X-ray image make it a difficult task to classify chest X-ray images. Deep learning has significantly improved many aspects of medical image analysis in recent years, including lesion region segmentation and disease categorization picture alignment. High-resolution feature maps and conventional convolution neural networks were utilized in earlier works to detect pathological abnormalities and classify diseases. To extract aberrant abnormality features from four high-resolution feature maps, for instance, uang et al. presented a high-resolution network (HRNet). Convolutional neural networks (CNNs) are used by the feature embedding module of Guan and Huang's category-wise residual attention learning (CRAL) architecture to learn high-level features. In this paper, we propose a multi-label chest X-ray image classification convolutional neural network model based on VGG 19. The VGG 19 model used to diagnose thoracic illness. However, conventional convolution neural networks and high-resolution feature maps can only learn single-scale aspects of clinical disorders. The VGG 19 model uses pyramid convolution instead of the traditional 3x3 convolution to identify distinguishing characteristics of clinical abnormalities from chest X-ray pictures. The most recent shuffle attention mechanism is also presented to concentrate on additional pathological abnormality aspects. Numerous experiments show that the model significantly enhances the ability to classify thoracic disorders from chest X-ray pictures; on the chest, the AUC can reach 82.5 percent.

OBJECTIVE

This study's goal is to present a VGG-19 model for illness feature extraction that can extract multi-scale pathological abnormality-related features. The VGG 19 model includes the shuffle attention to concentrate on more pathological abnormality aspects. The large-scale diversity of the pathological abnormalities in different thoracic diseases and the similarity of the distinguishing features in each chest X-ray image make it a difficult task to classify chest X-ray images.

PROBLEM STATEMENT

The world's most difficult issue is novel coronavirus illness (nCOVID-19). The severe acute respiratory syndrome coronavirus-2 (SARS-COV-2) is what causes the illness, which has a high morbidity and fatality rate throughout the world. The study demonstrates that specific radiographic visual characteristics, coupled with fever, dry cough, lethargy, dyspnea, etc., are present in infected patients. One of the crucial non-invasive clinical adjuncts that is crucial in the identification of such visual reactions connected to SARS-COV-2 infection is the chest X-ray (CXR). The primary obstacles to manual diagnosis continue to be the scarcity of qualified radiologists who can read CXR pictures and the subtlety of disease radiographic responses.

EXISTING SYSTEM

The challenge of thoracic disease classification in chest X-ray (CXR) pictures is the main topic of this research. A reliable and consistent CXR image analysis system should take into account the special qualities of CXR images in contrast to the generic image classification task. It should be able to, in particular, 1) Automatically focus on the illness-critical regions, which are typically limited in size; and 2) Adaptively capture the intrinsic correlations among various disease traits and use them to jointly increase the multi-label disease detection rates. In this research, we propose to simultaneously accomplish those two goals by learning discriminative features with Consult Net's two branches.

Disadvantage Of Existing System

- Difficulty in diagnosing diseases.
- Lower performance is expected.
- Discovery of disease-unrelated zones.

PROPOSED SYSTEM

In this study, we suggest a VGG 19 model for classifying chest X-ray images with multiple labels. The illustration of the VGG 19 model for thoracic illness diagnosis However, single-scale features of pathological abnormalities are all that the high-resolution feature maps and conventional convolution neural network can learn.

The standard 3x3 convolution is used by the VGG 19 model to extract distinguishing characteristics of pathological abnormalities from chest X-ray pictures. Numerous trials show that the model significantly enhances the ability to classify thoracic disorders from chest X-ray pictures.

Advantages of Proposed System

- It can be applied to traditional backbones to boost performance with no computational overhead.
- Instead, then concentrating on the entire set of data, it aids in drawing attention to the pertinent information.
- VGG-19 is renowned for its superior picture categorization accuracy.

RELATED WORKS

A. THORACIC DISEASE CLASSIFICATION ON THE CHEST X-Ray IMAGE

The study of computer-aided thoracic illness diagnosis has received a lot of attention recently. The method based on deep learning for thoracic illnesses classification has become a research hotspot with the release of the ChestX-ray14 dataset and obtained good classification performance. By examining the most appropriate loss function, Kumar et al [26].'s proposal for an improved cascade network for thoracic illness classification. In order to learn discriminative features, Guan et al. [16] introduced a two-branch architecture called ConsultNet that extracts crucial disease-specific features and strengthens potential semantic relationships in the feature space. In order to investigate the pertinent pathological information, Chen et al. [27] included a graph convolution network (GCN) to the classification of thoracic disorders.

A self-activated CNN technique was suggested by Rehman et al. [28] for the identification of several thoracic illnesses, including COVID-19. Li et al. [29] developed a unified approach for thoracic disease detection and localization using class information and constrained positional annotation due to the expensive human annotation of chest X-ray images. Based on a well-posed loss function and an architecture for patch non-independence and shift invariance, Rozenberg et al. [30], inspired by [29], provided an approach for thoracic illness localization with little annotation. It is important to note that [30] uses substantially less expensive picture annotations rather than a small number of bounding box annotations. In order to outperform earlier research, the VGG 19 model contains a convolution module and a shuffle attention module.

B. ATTENTION MECHANISM IN CHEST X-ray IMAGE ANALYSIS

In the fields of computer vision and natural language processing, attention methods have been effectively investigated. To distinguish between different thoracic diseases, the multi-label chest X-ray picture classification job necessitates learning more discriminative aspects of clinical abnormalities. For the categorization and localisation of thoracic diseases, Ma et al. [31] suggested a multi-attention convolution neural network using a multi-attention mechanism and the merging of global and local information. For identifying lung disorders and locating suspicious lesion locations, Yan et al. [32] suggested a weakly supervised deep learning system outfitted with the SE-blocks, multimap transfer, and max-min pooling. For the classification of lung diseases, Wang et al. [17] suggested a triple attention learning model that combines the three attention modules of channel level, element level, and scale level into a single framework. In order to solve the problem of abnormality localization, Ouyang et al. [33] suggested an attention-driven weakly supervised algorithm that uses a hierarchical attention mining framework to integrate activation and gradient-based visual attention. To improve the classification performance of thoracic diseases using chest X-ray pictures, this research introduces a shuffle attention technique that concentrates on more discriminative characteristics of pathological abnormalities.

METHODLOGY OF PROJECT

The general description of the project is classified Chest X-ray, VGG 19 Convolution Neural Network, thoracic disease classification.

1. Dataset:

In the first module, we developed the system to get the input dataset for the training and testing purpose. We have taken the dataset for deep similarity in images.

The image Thorax dataset consists of 14327 images of 12 different categories.

1) **Atelectasis**: Atelectasis is a condition in which one or more areas of the lungs collapse or do not inflate properly.
2) **Cardiomegaly**: Cardiomegaly is a condition in which the heart is enlarged.
3) **Consolidation**: Consolidation is a condition in which the lung tissue becomes filled with fluid and blood cells.
4) **Edema**: Edema is a condition in which excess fluid accumulates in the body's tissues
5) **Effusion**: Effusion is a condition in which excess fluid accumulates in the body's cavities, such as the lungs or chest.
6) **Emphysema**: Emphysema is a condition in which the air sacs in the lungs are damaged and enlarged, leading to breathing difficulties.
7) **Fibrosis**: Fibrosis is a condition in which the lung tissue becomes scarred and stiff, leading to breathing difficulties.
8) **Infiltration**: Infiltration is a condition in which the lung tissue becomes inflamed and filled with fluid or other substances.
9) **Mass**: Mass is a general term that refers to a lump or growth in the body.
10) **Nodule**: A nodule is a small, round growth in the lung tissue that may be cancerous or non-cancerous.
11) **Pneumonia**: Pneumonia is a lung infection that can be caused by bacteria, viruses, or other microorganisms.
12) **Pneumothorax**: Pneumothorax is a medical condition in which air leaks into the pleural space, the space between the lungs and the chest wall.

2. Importing the necessary libraries

We will be using Python language for this. First, we will import the necessary libraries such as keras for building the main model, and splitting the training and test data, for image processing tasks and other libraries such as pandas, numpy, matplotlib and tensorflow.

3. Retrieving the images

We will retrieve the images and their labels. Then resize the images to (224,224) as all images should have same size for recognition. Then convert the images into numpy array.

4. Splitting the dataset

- Split the dataset into train and test. 80% train data and 20% test data.

A. Convolutional Neural Networks

- The objectives behind the first module of the course 4 are:
- To understand the convolution operation
- To understand the pooling operation

- Remembering the vocabulary used in convolutional neural networks (padding, stride, filter, etc.)
- Building a convolutional neural network for multi-class classification in images.

5. Building the model

For building the model we will use sequential model from keras library. Then we will use VGG 19 model consists of a deep convolutional neural network (CNN) that takes an input image of a face and outputs a vector of features that represent the face. The VGG 19 is trained on a large dataset images expression. The resulting feature vectors have the property that image from the same person are mapped to similar vectors, while trained image from user enter image are mapped to dissimilar vectors. This makes it possible to perform image recognition by comparing the feature vectors of two images and computing the distance between them.

6. Apply the model and plot the graphs for accuracy and loss

We will compile the model and apply it using fit function. Then we will plot the graphs for accuracy and loss.

7. Accuracy on test set

We got an accuracy of 99% on test set.

8. Saving the Trained Model

Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a .h5 or .pkl file using a library like pickle .
Make sure you have pickle installed in your environment.
Next, let's import the module and dump the model into.h5 file

DATA FLOW DIAGRAM

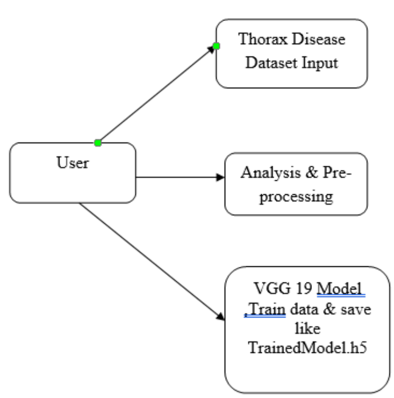


Fig:7 Flow Diagram Of Modules

SYSTEM ARCHITECTURE

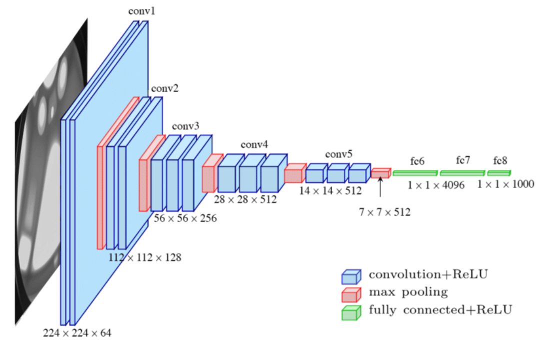
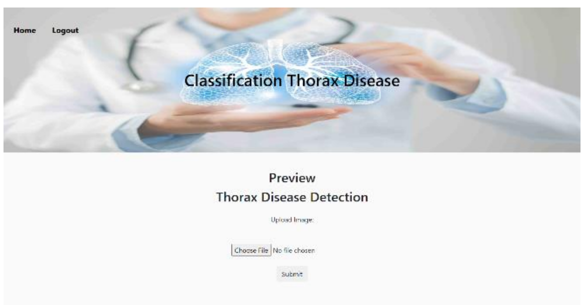


Fig:8 SYSTEM ARCHITECTURE OF PROJECT

RESULTS AND DISCUSSION

In the section, we present results for the ChestX-ray14 dataset using the VGG 19 model. Fig. 9 displays the AUC scores for each pathology. The VGG 19 model, in particular, scored highly with an AUC of 0.825. Table.2 provides a summary of the findings from the comparison with earlier publications. The classification of thoracic disorders in the CNN classic models AlexNet [5], GoogleNet [6], VGGNet-16 [7], and ResNet-50 [8] were examined by Wang et al. [4]. The impact of non-image variables on the classification of thoracic diseases was fully taken into account by Baltruschat et al. [39], who also added angle, gender, and other features to the model. Yao et al[40] .'s outstanding classification outcomes were made possible by the generation of higher resolution salient maps while learning multi-scale features. An approach for thoracic illness diagnosis and localisation using class information and constrained positional annotation was put out by Li et al. [29]. The global branch and local branch of the two-branch CNN architecture proposed by Wang et al. [41] learn features from global images and local regions, with the help of heatmaps created by class activation mapping (CAM). For diagnosing chest X-ray images, Huang et al. [24] presented a fused high-resolution network (FHRNet) combining global and local feature extractors with a global average pooling layer. Lietal Comparing the VGG 19 model to earlier works, significant progress has been made. In comparison to [39] and [40], the VGG 19 model performs 3.6 and 7.8 percent better overall. The VGG 19 model outperforms the second-best model (Huang et al. [24]) in 12 different illness classifications: "Atelectasis," "Cardiomegaly," "Effusion," "Nodule," "Pneumonia," "Pneumothorax," "Consolidation," "Edema," "Emphysema," "Fibrosis," "Infiltration," "Mass," and "Pleural Thickening."



FUTURE ENHANCEMENT

The research will proceed in two directions in the future. Due to the costly bounding box, weakly supervised precision localization techniques will be examined first. In order to get a more accurate localization and diagnosis of pathological abnormalities, picture segmentation techniques are applied in the second place. Further evidence that VGG 19 can successfully enhance thoracic disease classification performance comes from the ablation trial.

CONCLUSION

For the classification of multiple-label chest X-ray images, we suggest the VGG 19 model. Numerous studies have demonstrated that the VGG 19 model can correctly categories chest X-ray pictures, with an AUC score on the Chest X-ray14 dataset that can reach 82.5 percent. The experiment's findings also show that our VGG 19 model can extract multi-scale features that can differentiate between different clinical problems.

REFERENCES:

[1] N.(Oct. 2021). Pneumonia Can be Prevented-Vaccines Can Help. National Center https://www.cdc.gov/pneumonia/prevention.html

[2] H. Chen, C. Shen, J. Qin, D. Ni, L. Shi, J. C. Cheng, and P.-A. Heng,‘‘Automatic localization and identification of vertebrae in spine CT via a joint learning model with deep neural networks,’’ in Proc. Int. Conf. Med. Image Comput. Comput. Assist. Intervent., Nov. 2015, pp. 515–522.

[3] M. A. Bruno, E. A. Walker, and H. H. Abujudeh, ‘‘Understanding and con-fronting our mistakes: The epidemiology of error in radiology and strategies for error reduction,’’ Radiographics, vol. 35, no. 6, pp. 1668–1676, 2015.

[4] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, ‘‘ChestX-ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases,’’ in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2017, pp. 2097–2106.

[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ‘‘ImageNet classification with deep convolutional neural networks,’’ in Proc. Adv. Neural Inf. Pro-cess. Syst.(NIPS), vol. 25. Red Hook, NY, USA: Curran Associates, 2012, pp. 1097–1105.

[6] K. Simonyan and A. Zisserman, ‘‘Very deep convolutional networks for large-scale image recognition,’ 2014, arXiv: 1409.1556.

[7] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V.Vanhoucke, and A. Rabinovich, ‘‘Going deeper with convolutions,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2015, pp. 1–9.

[8] K. He. X. Zhang, S. Ren, and J. Sun, ‘‘Deep residual learning for image recognition,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Dec. 2016, pp. 770–778.

[9] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. Langlotz, K.Shpanskaya, M. P. Lungren, and A. Y. Ng, ‘‘CheXNet: Radiologist-level pneumonia detection on chest X-Rays with deep learning,’’ 2017, arXiv: 1711.05225.

[10] G. Huang, Z. Liu, and L. van der Maaten, ‘‘densely connected convolutional networks,’’ in Proc. IEEE

Conf. Comput. Vis. Pattern Recognit. (CVPR), Jul. 2017, pp. 4700–4708.

[11] H. Wang, D. Zhang, S. Ding, Z. Gao, J. Feng, and S. Wan, ‘‘Rib segmen-tation algorithm for X-ray image based on unpaired sample augmentation and multi-scale network,’’ Neural Comput. Appl.pp. 1–15, Sep. 2021.

[12]M. F. Rahman,Y. Zhuang, T.-L. Tseng, M. Pokojovy, P. McCaffrey, E.Walser, S. Moen, and A. VO, ‘‘Improving lung region segmentation accuracy in chest X-ray images using a two-model deep learning ensem-ble approach,’’ J. Vis. Commun. May 2022.

[13] K. Kondo, M. Ishii, S. Fujimoto, M. Tanaka, M. Kiyono, H. Itoh, and H.Kimura, ‘‘Chest X-ray anomaly detection based on changes in anatomical structures due to disease,’ Med. Image Technol., vol. 39, no. 5, pp. 229–242, Nov. 2021.

[14] C. Xue, L. Zhu, H. Fu, X. Hu, X. Li, H. Zhang, and P.-A. Heng,‘‘Global guidance network for breast lesion segmentation in ultrasound images,’’ Med. Image Anal., vol. 70, May 2021, Art. no. 101989.

[15] M. A. Khan, K. Muhammad, M. Sharif, T. Akram, and V.H. C. D. Albuquerque, ‘‘Multi-class skin lesion detection and classification via teledermatology,’’ IEEE J. Biomed. Health Informant.vol 25, no. 12, pp. 4267–4275, Dec. 2021.

[16] Q. Guan, Y. Huang, Y. Luo, P. Liu, M. Xu, and Y. Yang, ‘‘Discriminative feature learning for thorax disease classification in chest X-ray images,’’ IEEE Trans. Image Process., vol. 30, pp. 2476–2487, 2021.

[17] H. Wang, S. Wang, Z. Qin, Y. Zhang, R. Li, and Y. Xia, ‘‘Triple attention learning for classification of 14 thoracic diseases using chest radiography,’’ Med. Image Anal., vol. 67, Jan. 2021.

[18] S. Z. Y. Zaidi, M. U. Akram, A. Jameel, and N. S. Alghamdi, ‘‘Lung segmentation-based pulmonary disease classification using deep neural networks,’’ IEEE Access, vol. 9, pp. 125202–125214, 2021.

[19] B. Chen, J. Li, G. Lu, and D. Zhang, ‘‘Lesion location attention guided network for multi-label thoracic disease classification in chest X-rays,’’ IEEE J. Biomed.Health Informant. vol. 24, no. 7, pp. 2016–2027, Jul. 2020.

[20] Y. Mao, Y. He, L. Liu, and X. Chen, ‘‘Disease classification based on synthesis of multiple long short-term memory classifiers corresponding to eye movement features,’’ IEEE Access, vol. 8, pp. 151624–151633, 2020.

[21] A. Bessadok, M. A. Mahjoub, and I. Rekik, ‘‘Brain graph synthesis by dual adversarial and target graph prediction from a source graph,’’ Med. Image Anal., vol. 68, Feb. 2021, Art. No: 101902.

[22] M. Blendowski, L. Hansen, and M. P. Heinrich,‘‘Weakly-supervised learning of multi-modal features for regularised iterative descent in 3D image registration,’’ Med. Image Anal., vol. 67, Jan. 2021, Art. no. 101822.

[23] F. Zhu, X. Zhu, Z. Huang, M. Ding, Q. Li, and X. Zhang, ‘‘Deep learning based data-adaptive descriptor for non-rigid multi-modal medical image registration,’’ Signal Process., vol. 183, Jun. 2021, Art. no. 108023.

[24] Z. Huang, J. Lin, L. Xu, H. Wang, T. Bai, Y. Pang, and T.H. Meen, ‘‘Fusion high-resolution network for diagnosing ChestX-ray images, ’’ Electronics, vol. 9, no. 1, p. 190, Jan. 2020.

[25] Q.Guan and Y. Huang, ‘‘Multi-label chest X-ray image classification via category-wise residual attention learning,’’ Pattern Recognit. Lett., vol. 130, pp. 259–266, Feb. 2020.

[26] P. Kumar, M. Grewal, and M. M. Srivastava, ‘‘Boosted cascaded Convnets for multilabel classification of thoracic diseases in chest radiographs,’’ in Proc. Int. Conf. Image Anal. Recognit.(ICIAR). Cham, Switzerland: Springer, Jun. 2018, pp. 546–552.

[27] B. Chen, J. Li, G. Lu, H. Yu, and D. Zhang, ‘‘Label co-occurrence learning with graph convolutional networks for multi-label chest X-ray image classification,’’ IEEE J. Biomed. Health Informat., vol. 24, no. 8, pp. 2292–2302, Aug. 2020.

[28] N.U. Rehman, M. S. Zia, T. Meraj, H. T. Rauf, R. Damaševičius, A.M. El-Sherbeeny, and M. A. El-Meligy, ‘‘A self-activated CNN approach for multi-class chest-related COVID-19 detection,’’ Appl. Sci., vol. 11, no. 19, p. 9023, Sep. 2021.

[29] Z. Li, C. Wang, M. Han, Y. Xue, W. Wei, L.-J. Li, and L. FeiFei, ‘‘Thoracic disease identification and localization with limited supervision,’’ in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., Jun. 2018, pp. 8290–8299.

[30] E. Rozenberg, D. Freedman, and A. A. Bronstein, ‘‘Learning to localize objects using limited annotation, with applications to thoracic diseases,’’ IEEE Access, vol. 9, pp. 67620–67633, 2021.

[31] Y. Ma, Q. Zhou, X. Chen, H. Lu, and Y. Zhao,‘‘Multi-attention network for thoracic disease classification and localization,’’ in Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP), May 2019, pp. 1378–1382.

[32] C. Yan, J. Yao, R. Li, Z. Xu, and J. Huang, ‘‘weakly supervised deep learning for thoracic disease classification and localization on chest X-rays,’’ in Proc. ACM Int. Conf. Bioinf., Comput. Biol.Health Informant. Aug. 2018, pp. 103–110.

[33] X. Ouyang, S. Karanam, Z. Wu, T. Chen, J. Huo, X. S. Zhou, Q. Wang, and J.-Z. Cheng, ‘‘Learning hierarchical attention for weakly-supervised chest X-ray abnormality localization and diagnosis,’’ IEEE Trans. Med. Imag., vol. 40, no. 10, pp. 2698–2710, Oct. 2021.

[34] L.Wang, Z. Q. Lin, and A. Wong, ‘‘COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images,’’ Sci. Rep., vol. 10, no. 1, pp. 1–12, Dec. 2020.

[35] J. P. Cohen, P. Morrison, L. Dao, K. Roth, T. Q. Duong, and M. Ghassemi, ‘‘COVID-19 image data collection: Prospective predictions are the future,’’ 2020, arXiv: 2006.11988.

[36] M. E. H. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M. A. Kadir, Z. B. Mahbub, K. R. Islam, M. S. Khan, A. Iqbal, N. A. Emadi, M.B. I. Reaz, and M. T. Islam, ‘‘Can AI help in screening viral and COVID-19 pneumonia?’’ IEEE Access, vol. 8, pp. 132665–132676, 2020.

[37] T. Rahman, A. Khandakar, Y. Qiblawey, A. Tahir, S. Kiranyaz, S. B. A. Kashem, M. T. Islam, S. A. Maadeed, S. M. Zughaier, M. S. Khan, and M. E. H. Chowdhury, ‘‘Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images,’’ Comput. Biol. Med., vol. 132, May 2021, Art. no. 104319.

[38] M. de la Iglesia Vayá, J. M. Saborit, J. A. Montell, A. Pertusa, A. Bustos, M.Cazorla, J. Galant, X. Barber, D. Orozco-Beltrán, F. GarcíaGarcía. M. Caparrós, G. González, and J. M. Salinas, ‘‘BIMCV COVID-19+: A large annotated dataset of RX and CT images from COVID-19 patients,’’ 2020, arXiv: 2006.01174.

[39] I. M. Baltruschat, H. Nickisch, M. Grass, T. Knopp, and A. Saalbach, ‘‘Comparison of deep learning approaches for multi-label chest X-ray classification,’’ Sci. Rep., vol. 9, no. 1, pp. 1–10, Dec. 2019.

[40] L. Yao, J. Prosky, E. Poblenz, B. Covington, and K. Lyman, ‘‘weakly supervised medical diagnosis and localization from multiple resolutions,’’ 2018, arXiv: 1803.07703.

[41] H. Wang, H. Jia, L. Lu, and Y. Xia, ‘‘Thorax-Net: An attention regularized deep neural network for classification of thoracic diseases on chest radiography,’’ IEEE J. Biomed. Health Informat., vol. 24, no. 2, pp. 475–485, Feb. 2020.

[42] J. Deng, W.Dong,R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, ‘‘ImageNet: A large-scale hierarchical image database,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2009, pp. 248–255.

[43] D. P. Kingma and J. Ba, ‘‘Adam: A method for stochastic optimization,’’ 2014, arXiv: 1412.6980.

[44] S. Minaee, R. Kafieh, M. Sonka, S. Yazdani, and G. Jamalipour Soufi, ‘‘Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning,’’ Med. Image Anal., vol. 65, Oct. 2020, Art. No: 101794.

[45] H. Panwar, P. K. Gupta, M. K. Siddiqui, R. Morales-Menendez, and V.Singh, ‘‘Application of deep learning for fast detection of COVID-19 in X-Rays using nCOVNet,’’ Chaos, Solitons Fractals, vol. 138, Sep. 2020, Art. No: 109944.

[46] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. R. Acharya, ‘‘Automated detection of COVID-19 cases using deep neu-ral networks with X-ray images,’’ Comput. Biol. Med., vol. 121, Jun. 2020, Art. No: 103792.