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SURVEY ON DEEP LEARNING-BASED CHEST X-RAY IMAGE ANALYSIS FOR COVID-19 DETECTION

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Abstract

A new virus called COVID-19 infects the lungs as well as the upper respiratory system. Daily increases in cases and fatalities have reached pandemic proportions. Images from chest X-rays have proved helpful for keeping a check on several lung conditions, including the COVID-19 illness recently. Recent advances in deep learning have shown encouraging outcomes in several medical image analytics. The most common radiographic examination, chest radiographs, is an especially important modality for which numerous applications have been looked at. There have been more articles on the topic as an outcome of the recent disclosure of multiple large chest X-ray datasets. The following tasks are categorized in this study's analysis of all papers that employed deep learning to analyze chest radiographs: segmentation, localization, image production, domain adaption, and image prediction (classification and regression). All publicly available datasets as well as comprehensive descriptions of all commercial systems in the region are supplied. We conclude with a synopsis of the state of the art at the moment, a critical evaluation of outstanding problems, and suggestions for further research.

Keywords, deep learning, COVID-19, chest X-ray, medical image analysis

1. INTRODUCTION

“Chest radiography (chest X-ray, CXR)” has been a mainstay of radiological imaging for many years. Developed countries report an average of 238 erect-view CXR images collected every thousand residents each year in radiological exams done across the globe (Lim and Young [8]). In 2006, the United States alone produced 129 million CXR images, according to estimates. CXR images' popularity and accessibility may be due to their affordability, minimal radiation exposure, and adequate sensitivity to a broad range of diseases. For the screening, diagnosis, and treatment of several different circumstances, The CXR is typically the initial imaging test requested (Ahmed et al. [1]).

There are three basic types of chest X-rays: "posteroanterior, anteroposterior, and lateral," which take the patient's position and orientation taking into consideration the X-ray source and detector panel. Since the “X-ray” source is positioned either behind or in front of the patient, the "posteroanterior (PA) and anteroposterior (AP)" views are also referred to as frontal views. Patients are normally in the supine posture for the acquisition of the AP image

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and upright for the collection of the "PA image". Usually, the "lateral image" is obtained together with a "PA image". The X-ray is typically projected from the patient's right side to the left.

Due to the superimposition of anatomical components along the projection direction, reading a chest radiograph may be difficult. This impact may make it exceedingly difficult to identify little or subtle anomalies, detect changes in specific areas, or precisely discriminate among distinct clinical patterns. These factors account for the significant levels of inter-observer variability that radiologists often exhibit while analyzing CXR images (Lee et al. [9]).

It has long been understood how many CXR images are acquired, how challenging it is to interpret them, and how crucial they are to clinical practice. Automated CXR analysis methods were developed by driven researchers. Since the first studies proving this phenomenon, this has been a subject of interest in research an automated approach for detecting abnormalities in CXR images was published in the 1960s (van [24]; Hosny et al. [30]; and Mohanned et al. [10]). The advantages of automatic CXR are enhanced sensitivity for small results, prioritizing cases with a short deadline, automation of time-consuming everyday duties, and providing analysis when there are no radiologists present.

In recent years, deep learning has produced a considerable influence on the field of medical imaging and has become the go-to technique for image processing tasks (Wang et al. [32]). The distribution of multiple sizable labeled datasets in recent years, which helped the CXR research community, has been primarily attributed to the development of labels by radiology report parsing by machines. Deep learning is generally recognized to be data-hungry. Utilizing the publication, 112,000 images from the "NIH" clinical center in 2017, and this trend started. Three labeled datasets, including "MIMIC-CXR" (Johnson et al. [25]), offered more than 755,000 photos in only 2019 alone. In this research, they demonstrate how these data releases impact the industry's availability of deep learning papers.

Previous reviews on medical image analysis (van [33]; Feng et al. [26]), as well as deep learning diagnosis for CXR, have been published (Qin et al. [28]; Anis et al. [16]). The studies that have been done so far on deep learning in CXR are currently not finished. Concerning the study and methodology used, the explanation of the publicly accessible datasets, or the evaluation of prospective outcomes and advancements in the area. The major goal of the classification and analysis is to locate pneumonia in various datasets with a global distribution. The texture is one of the primary visual qualities observed in chest X-ray images when they are evaluated.

2. OVERVIEW OF DEEP LEARNING METHODS

The network designs that are most often seen in the literature this study has looked at are highlighted in the section on deep learning for image analysis. In numerous other articles, incorporating a current study on deep learning for analyzing a medical image, completed connected and CNN are formally defined and given more thorough mathematical justifications. The only things they do in this article are providing a quick summary of these essential facts and send readers who are interested in classic literature in the correct way.

Machine learning, which refers to learning algorithms in general, includes deep learning as a subset. The neural network, in this example created with several hidden layers, is the technique that underpins all deep learning systems. A network's "architecture" refers to its overall design, which may be constructed using several layers and different construction methods.

An X-ray machine is made up of an image recording plate that is placed underneath the patient, a film container that holds X-ray film, and an X-ray tube that is attached to a fixed or flexible arm that is 6 ft. away from the patient. The rapid, simple process, which requires around 15 min's to perform. Radiological images are the main screening tool, and deep learning-based solutions for quick and accurate testing for COVID-19 may be identified using open sources. The overall opacity score, which represents the degree of opacity, has a range from 0 to 6. To detect acute and chronic illnesses of all the organs in the thoracic cavity, a posterior-anterior projection view CXR is taken of the patient while they are standing (Goodfellow et al. [43]).

2.1 Convolutional Neural Networks

Convolutional layer networks for image analysis were originally proposed in the 1980s and the concept was refined throughout the next years (Li et al. [11]). Almost all deep learning image analysis tasks now start with these convolutional layers as their foundation. Neurons in convolutional layers are only connected to a tiny portion of the preceding layer's "receptive field". Since these neurons work as sliding windows across all areas and can efficiently identify the same local pattern everywhere, they are utilized in various portions of the preceding layer. This method transmits both the learned weights and the spatial data.

A CNN automatically learns filters that serve as feature extractors as it is trained. These ingrained filters aid the model's comprehension and differentiation of the many kinds of input images. In this work, CXR (Chest X-Ray) images are classified into three classes: Normal, Pneumonia (Non-COVID-19), and COVID-19 using CNN architecture. For this, they use the Efficient Net CNN architecture.

2.2 Transfer Learning

The process of transferring information from one domain to another is the subject of transfer learning research. Pre-training is one of the transfer learning techniques that are most often used in CXR analysis. This technique entails initializing the network architecture for the subsequent job with the learned weights after training the network architecture on a big dataset for a separate task to fine-tune it. All layers can need to be retrained, or simply the topmost (completely linked) layer, based on the data from the target domain's availability. Due to the considerable low-level features that are obtained from the source domain data, this technique allows neural networks to be educated for new tasks with a far smaller dataset. Using the ImageNet dataset for pre-training (for categorization of natural images) is helpful for chest radiography analysis (Steinmeister et al. [27]), and this kind of transfer learning is heavily used in the studies reviewed in this article. In much architecture, well-known deep learning frameworks have pre-trained ImageNet versions that are publicly available. Along with more widely used techniques like random forests or support vector machines, The pre-trained architectures might be used to retrieve features.

2.3 Image-level Prediction Networks

The term "image-level prediction" is used in this study to describe tasks that execute the analysis of a whole CXR image to predict a category label (classification) or continual value (regression). These techniques are separate from those that make assumptions about discrete areas or tiny sections of images. Since regression and classification problems often employ the same sorts of design, except for the final output layer, they are combined in this study. One of the first successful deep convolutional architectures for image-level identification was Alex

Net, which consisted of five convolutional layers followed by three fully connected layers. It had a big influence on the literature when Alex Net easily outperformed every other competitor in the ILSVRC (ImageNet) competition in 2012 (Ke et al. [29]). There have been several deep convolutional neural network topologies suggested since then. The VGG family of models employs 3 fully-connected layers after 8 to 19 convolutional layers. The Inception architecture, first disclosed in 2015, was built using stacked blocks of different convolutional filter sizes called Inception modules (Szegedy et al. [40]). The ResNet family of models started to gain traction and outperform earlier benchmarks in 2016. These models define residual blocks with skip connections that often enhance model performance and are made up of numerous convolution processes. Skip connections were extensively used in several designs after ResNet's breakthrough. In addition to using skip connections between blocks, “DenseNet models” (Huang et al. [34]); launched in 2017, also link all layers to one another inside blocks.

2.4 Segmentation Networks

Segmentation, which may also be thought of as pixel categorization, is the process of giving each pixel a category name. This process, known as "semantic segmentation" in natural image analysis, often demands that each pixel in the image belong to a certain category. These labels often refer to anatomical characteristics (such as the “heart, lungs, or ribs”), abnormalities (such as tumours or opacities), or foreign items in the context of medical imaging (e.g., "tubes, catheters”). In the literature on medical imaging, it is normal practice to segment just one item of interest and labels the remaining pixels as "other".

Segmentation techniques for deep learning in the past employed common convolutional networks intended for classification applications. These were used in a sliding window technique to categorize each pixel in a patch. The fundamental flaw with this method is the extreme pixel overlap between adjacent patches, which makes it inefficient to employ the same convolutions again. Furthermore, the approach handles each pixel independently, making it computationally costly and limited to tiny images or portions of images.

2.5 Localization Networks

This research is known as "localization," which is the method of locating a specific region inside an image, which is often expressed by a bounding box or a point position. Localization may be used in the medical field to separate anatomical areas, abnormalities, or structures from foreign things. Although the CXR literature examined here doesn't include many publications that focus explicitly on a localization technique, they group these works because they are all related to medical imaging and because localization is a crucial task that may be simpler to complete than precise segmentation.

In 2014, "RCNN (Region Convolutional Neural Network)" was presented (Girshick et al. [42]). It can recognize interesting areas in an image and then use CNN architecture to derive properties from those regions. The regions were categorized utilizing a support vector machine based on the features that were obtained. This procedure is quite slow and requires multiple steps. Later, faster-RCNN and fast-RCNN (Girshick [41]) replaced them, which sped up processing, did away with the need for SVM classification or initial area identification, and improved speed and performance. A new faster-RCNN enhancement was created in 2017 to enable the segmentation of the object found in the box borders to be done more accurately. Mask R-CNN is the name of this approach. For the sake of this discussion, they have categorized this network even though it is a segmentation network belonging to the RCNN family. The YOLO (You Only Look Once) architecture is another one that has gained popularity in the field of object localization. It was first presented as a single-stage object identification algorithm in 2016

(Redmon et al. [39]) and improved in subsequent iterations in 2017 and 2018. The original YOLO architecture is far faster than its predecessors but not as accurate as its competitors. To identify outputs, it employed a single CNN and an image grid. Versions were improved such that they would continue to outperform the competition yet offer cutting-edge performance. They did this by using training data for detection and classification as well as several training improvement adjustments. RetinaNet is a final localization network mentioned in the literature on medical imaging. In addition to introducing the idea of a focused loss function, this single-stage detection forces the network to focus during training on increasingly challenging events. It is comparable to YOLO. The majority of the localization initiatives included in this research using one of the aforementioned frameworks (Heusel et al. [35]).

2.6 Image Generation Networks

Creating fresh, realistic images using data from a training set is Creating new images for training purposes is one of the activities for which deep learning has often been utilized (data augmentation), generating new, more understandable images, or altering existing images to resemble the appearances of objects from a different domain are just a few of the many reasons for creating images in the medical domain (domain adaptation). Several generating approaches have also been employed to enhance the effectiveness of tasks like segmentation and anomaly detection (Arjovsky et al. [36]).

In 2014, the generative adversarial network was introduced, and the popularity of image generation started to increase. An image generator, a discriminator that attempts to discriminate among false and actual images, and two network topologies make up the GAN. The discriminator reacts by steadily enhancing its capacity to discern between actual and manufactured images, whereas the generator tries to deceive the discriminator by learning which images are highly convincing (Odena et al. [37]). A competitive method was used to train these two networks. Numerous scholars have investigated the dependability and advancements of the basic approach since the training procedure for possibly unsteady GANs and convergence is not guaranteed. By including class labels, image-to-image translation (in this example, conditional on an image), and unpaired image-to-image translation, GANs have also been modified to conditional data creation. Many publications suggesting uses for GANs in medical image analysis have recently been published. The field of medical imaging has been quite interested in GANs. According to the research, some of the image-generating initiatives used GAN-based architectures.

2.7 Domain Adaptation Networks

"Domain Adaptation" refers to techniques used in this study to address the problem that systems when evaluated on data from various "domains," Models that were developed using just data from one "domain" often performed badly. The definition of "domain" in the context of medical imaging is ambiguous; it might relate to information from a particular piece of hardware (a scanner), a set of collecting parameters, a reconstruction technique, or even an entire hospital. Less often, it could also be connected to demographic characteristics like age, gender, ethnicity, or even a specific disease strain that is found in the dataset.

For an image analysis task, a network that has been trained on data from one domain and how to effectively execute that assessment on data from a different domain is both taken into consideration by methods for domain adjustment (Zhu et al. [38]). These methodologies, which are being investigated for a variety of CXR applications ranging from organ segmentation to multi-label abnormality classification, can be categorized into "supervised, unsupervised, and semi-supervised" groups depending on the availability of labels from the target domain.

To achieve the goal of learning to evaluate images from various domains, designs are merged in a variety of ways. No architecture is common for domain adaptation. There are three basic categories for resolving this problem, according to (Wang and Deng's [31]) classification: discrepancy-based, reconstruction-based, and adversarial-based.

By changing the detection of a discrepancy among the two domains and increasing the image analysis network, discrepancy-based solutions make an effort to align the source and destination domains in some feature space. The goal of reconstruction-based techniques, in contrast, is to develop a common encoder-based domain invariant representation. An additional encoder-decoder reconstruction network is used in such techniques. Adversarial-based approaches discriminate among samples from the source and target domains using a discriminator network. These methods promote the adoption of domain-invariant features by basing their approach on adversarial training from GANs. Instead of relying on adversarial training and using the labels from the source domain to build domain-invariant descriptions, this collection of techniques, which includes generative and non-generative models, is the most often used in CXR analysis. Non-generative models aggressively alter source image pixels to resemble the target image while using labels from the source domain.

3. CHEST X-RAY-BASED METHODS

Chest X-rays were used to identify and categorize COVID-19 patients using several AI-based techniques. To distinguish COVID-19 CXRs from "CXRs" for the common cold and pneumonia, an image net CNN was developed (Goel et al. [17]). The CNN network was able to achieve high accuracy because of the swarm intelligence (SI) optimization technique that was used during training. The selection of the appropriate optimizer settings using this approach is quite challenging. With little data, transfer learning techniques may aid with the training. To provide the groundwork for future studies on hyper parameter tweaking and the creation of comparable detection algorithms, (Jain et al. [18]) the effectiveness of three different pre-trained CNN networks was assessed.

The Deep-COVID (Minaee et al. [19]), which was developed with four other pre-trained networks to get over the COVID-19 class's short sample size, is another deep transfer learning method for detecting COVID-19 CXRs. Random patches were taken from the lung-segmented CXRs to address the issue of small sample sizes. To get the classes, an already-trained CNN was trained on the extracted patches. Through the use of the saliency mapping methodology, this method also visualizes how the CNN operates. The increase in performance was often proposed in many of the deep transfer learning algorithms that were given based on the addition of new data and hyper parameter adjustment. A technique for enhancing the deep transfer of gained features while using machine learning classifiers was reported by (Kumar et al. [20]). The limitation of the imbalance in data samples among the classes was also addressed by this solution using a similar methodology. Turkoglu et al. [21] suggested a different method for enhancing transfer learning, one that included extracting and combining information from every layer of the pre-trained network. Only significant characteristics were chosen from these combined data using a feature selection technique, and the COVID-19 CXRs were then classified using an SVM classifier. There is a significant likelihood of discrepancies between the classes in the dataset in applications involving medical imaging. DeTrac CNN, which applies the class decomposition approach to features learned from pre-trained networks, was proposed by (Abbas et al. [22]) as a remedy for these limitations. Classification accuracy has been outperformed by the combined cost-sensitive learning technique, excluding the use of these fine-grained classification techniques. The majority of methods now in use have drawbacks in terms of comprehensive datasets as well as small positive class samples. It was suggested to use a synthetic augmentation strategy with a CycleGAN to address differences between data samples in classes (Li et al. [23]). The quality of the data produced by using GAN to create COVID-19 X-rays is never definite.

4. COMPARATIVE ANALYSIS OF EXISTING ALGORITHMS

A deep learning-based feature fusion strategy for large-scale learning for COVID-19 classification using stacked ensemble meta-classifiers. Kernel principal component analysis (PCA) was used to minimize the dimensionality of the features retrieved from the penultimate layer (global average pooling) of Efficient Net-based pre-trained models (Ravi et al. [12]).

A deep learning-based method that uses chest X-ray pictures to locate Covid-19 and no-finding instances. Here, using the fivefold cross-validation approach, the classification performance of the Bi-LSTM network on the deep features was compared to that of the Deep Neural Network (Akyol and Şen [2]).

It explains how to construct deep learning-based computer-aided diagnostic systems for endoscopy, radiology, pathology, and dentistry (Tsunekiet al. [3]).

Practitioners choose the most effective and efficient real-time procedures, analyze accessible datasets, and comprehend findings. Several strategies exist for detecting pneumonia; however, a literature evaluation is needed (Khan et al. [13]).

To design software that combines Machine Learning and Deep Learning methods like Radial Basis and Back Propagation Network to automatically diagnose pneumonia from medical pictures like X-Rays and compare which algorithm works better. Radiotherapists will evaluate pneumonia X-rays (Latta et al. [14]).

FM-HCF-DLF is a deep learning-based fusion model for diagnosing COVID-19. The FM-HCF-DLF model uses Gaussian filtering for preprocessing, FM for feature extraction, and DLF for classification (Shankar and Perumal [15]).

The chapter uses machine learning methods (Self-Organizing Maps) to detect clusters across Italian areas, which might help explain the pandemic's diverse behavior throughout the nation. It looked at regional demographic, healthcare, and political data to determine their interconnections (Resta [4]).

Hyper parameter adjusted deep belief network with hosted cuckoo optimization algorithm classifies COVID-19. Preprocessing removes noise from chest x-rays (Gampala et al. [5]).

Convolutional Neural Networks (CNN) is utilized to classify patients as COVID-19 diseased or not utilizing chest CT scans. Wide-ranging investigations are done in light of expected and modest classification strategies using the Covid-19 dataset (Jayashree [6]).

Implementation of an automated detection model, CADTra, to rapidly identify pneumonia related disorders. This model is based on classification, denoising auto encoder, and transfer learning. First, pre-processing is used to produce medical images (Shafai et al. [7]).

The comparison of existing methods and their drawbacks is shown in Table 1.

Table 1: Comparison of Existing algorithms

S.no	Reference	Methodology used	Drawbacks
1	Ravi et al. [12]	Convolutional Neural Networks (CNNs)	CNN models couldn't differentiate.
2	Akyol and Şen [2]	Long Short Term Memory Networks (LSTMs)	Disaster for hardware designers.
3	Tsunekiet al. [3]	Recurrent Neural Networks (RNNs)	Computations go slowly.
4	Khan et al. [13]	Generative Adversarial Networks (GANs)	GANs are challenging to train.
5	Latta et al. [14]	Radial Basis Function Networks (RBFNs)	RBF had training concerns.
6	Shankar and Perumal [15]	Multilayer Perceptrons (MLPs)	MLP is sensitive to feature scaling.
7	Resta [4]	Self Organizing Maps (SOMs)	Neuron weights should cluster inputs.
8	Gampala et al. [5]	Deep Belief Networks (DBNs)	DBN's data models are sophisticated.
9	Jayashree [6]	Restricted Boltzmann Machines(RBMs)	Training is more challenging.
10	Shafai et al. [7]	Auto encoders	Inadequate training data.

5. CONCLUSION

Deep learning algorithms are being used in more and more applications. It would be advantageous to use such techniques to improve sustainability efforts for chest X-ray image analysis. It has mostly been directed by the data and labels that are now accessible instead of the demands of the radiologist. This research investigates several deep learning methods. Nowadays, deep learning is used by everyone, whether consciously or unconsciously. Deep learning techniques are used, particularly in the biomedical sector, for the categorization of images in chest X-ray detection. Ten distinct deep learning algorithms used for categorization were systematically reviewed in this research. All of the strategies are evaluated for their drawbacks. The clinical requirements for CXR interpretation should be a more explicit emphasis in the future study in data supply and labeling as well as deep learning.

REFERENCES

[1] Ahmed, M.K., Bayoumi, H.A., Abdelaleem, N.A. and Mohamed, M.N., 2022. Could chest ultrasonography replace chest radiography in outpatient chest clinics; *The Egyptian Journal of Chest Diseases and Tuberculosis*, *71*(2), p.213.

[2] Akyol, K. and Şen, B., 2022. Automatic Detection of Covid-19 with Bidirectional LSTM Network Using Deep Features Extracted from Chest X-ray Images. *Interdisciplinary Sciences: Computational Life Sciences*, *14*(1), pp.89-100.

[3] Tsuneki, Masayuki. "Deep learning models in medical image analysis." *Journal of Oral Biosciences* (2022).

[4] Resta, M., 2022. Pandemic Spreading in Italy and Regional Policies: An Approach with Self-organizing Maps. In *Handbook of Artificial Intelligence in Healthcare* (pp. 199-213). Springer, Cham.

[5] Gampala, V., Rathan, K., Shajin, F.H. and Rajesh, P., 2022. Diagnosis of COVID-19 patients by adapting hyper parameter tuned deep belief network using a hosted cuckoo optimization algorithm. *Electromagnetic Biology and Medicine*, pp.1-15.

[6] Jayashree, R., 2022. Enhanced Classification Using Restricted Boltzmann Machine Method in Deep Learning for COVID-19. In *Understanding COVID-19: The Role of Computational Intelligence* (pp. 425-446). Springer, Cham.

[7] El-Shafai, W., Abd El-Nabi, S., El-Rabaie, E., Ali, A., Soliman, F., Algarni, A.D. and Abd El-Samie, F.E., 2022. Efficient Deep-Learning-Based Autoencoder Denoising Approach for Medical Image Diagnosis. *CMC-COMPUTERS MATERIALS & CONTINUA*, *70*(3), pp.6107-6125.

[8] Lim, Young Khi. "Recent Trend of Occupational Exposure to Ionizing Radiation in Korea, 2015-2019." *Journal of Radiation Protection and Research* 46, no. 4 (2021): 213-217.

[9] Lee, S., Yim, J.J., Kwak, N., Lee, Y.J., Lee, J.K., Lee, J.Y., Kim, J.S., Kang, Y.A., Jeon, D., Jang, M.J. and Goo, J.M., 2021. Deep Learning to Determine the Activity of Pulmonary Tuberculosis on Chest Radiographs. *Radiology*.

[10] Mohanned, H.H., Sürücü, S. and Choupani, R., 2021, September. Lung Inflammatory Classification of Diseases using X-ray Images. In *2021 6th International Conference on Computer Science and Engineering (UBMK)* (pp. 548-553). IEEE.

[11] Li, S., Huang, H. and Lu, W., 2021. A Neural Networks Based Method for Multivariate Time-Series Forecasting. *IEEE Access*, *9*, pp.63915-63924.

[12] Ravi, V., Narasimhan, H., Chakraborty, C. and Pham, T.D., 2021. Deep learning-based meta-classifier approach for COVID-19 classification using CT scan and chest X-ray images. *Multimedia systems*, pp.1-15.

[13] Khan, W., Zaki, N. and Ali, L., 2021. Intelligent pneumonia identification from chest x-rays: A systematic literature review. *IEEE Access*, *9*, pp.51747-51771.

[14] Latta, A., Avhad, S., Mahajan, D. and Shintre, R., 2021. Comparative Study of Pneumonia Detection Using Supervised Learning (Feed Forward Back Propagation) and Unsupervised Learning (Radial Basis Function). *International Research Journal of Engineering and Technology*.

[15] Shankar, K. and Perumal, E., 2021. A novel was hand-crafted with deep learning features-based fusion model for COVID-19 diagnosis and classification using chest X-ray images. *Complex & Intelligent Systems*, *7*(3), pp.1277-1293.

[16] Anis, S., Lai, K.W., Chuah, J.H., Shoaib, M.A., Mohafez, H., Hadizadeh, M., Ding, Y., Ong, Z.C., 2020. An overview of deep learning approaches in the chest radiograph. IEEE Access doi:10.1109/access.2020.3028390.

[17] Goel, T., Murugan, R., Mirjalili, S., Chakrabartty, D.K.: OptCoNet: an optimized convolutional neural network for an automatic diagnosis of COVID-19. Appl. Intell. 1–16 (2020)

[18] Jain, R., Gupta, M., Taneja, S., Hemanth, D.J.: Deep learning based detection and analysis of COVID-19 on chest X-ray images. Appl. Intell. 1–11 (2020)

[19] Minaee, S., Kafieh, R., Sonka, M., Yazdani, S., Soufi, G.J.: Deep-COVID: predicting COVID-19 from chest X-ray images using deep transfer learning. (2020).

[20] Kumar, R., Arora, R., Bansal, V., Sahayasheela, V.J., Buckchash, H., Imran, J., Raman, B.: Accurate prediction of COVID-19 using chest X-ray images through deep feature learning model with SMOTE and machine learning classifiers. (2020).

[21] Turkoglu, M.: COVIDetectioNet: COVID-19 diagnosis system based on X-ray images using features selected from pre-learned deep features ensemble. Appl. Intell. 1–14 (2020)

[22] Abbas, A., Abdelsamea, M.M., Gaber, M.M.: Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. (2020).

[23] Li, T., Han, Z., Wei, B., Zheng, Y., Hong, Y., Cong, J.: Robust screening of COVID-19 from chest X-ray via discriminative cost-sensitive learning. (2020).

[24] Van Ginneken, B., 2019. Deep learning for triage of chest radiographs: should every institution train its system; *Radiology*, *290*(2), pp.545-546.

[25] Johnson, A.E.W., Pollard, T.J., Berkowitz, S.J., Greenbaum, N.R., Lungren, M.P., ying Deng, C., Mark, R.G., Horng, S., 2019. MIMIC-CXR, a de-identified publicly available database of chest radiographs with free-text reports. Scientific Data 6. doi:10.1038/s41597-019-0322-0.

[26] Feng, Y., Teh, H.S., Cai, Y., 2019. Deep learning for chest radiology: A review. Current Radiology Reports 7. doi:10.1007/s40134-019-0333-9.

[27] Baltruschat, I.M., Steinmeister, L., Ittrich, H., Adam, G., Nickisch, H., Saalbach, A., von Berg, J., Grass, M., Knopp, T., 2019. When Does Bone Suppression And Lung Field Segmentation Improve Chest X-Ray Disease Classification?, in: 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), IEEE. pp. 1362–1366. doi:10.1109/ISBI.2019.8759510.

[28] Qin, C., Yao, D., Shi, Y., Song, Z., 2018. Computer-aided detection in chest radiography based on artificial intelligence: a survey. BioMedical Engineering OnLine 17. doi:10.1186/s12938-018-0544-y.

[29] Ke, Q., Liu, J., Bennamoun, M., An, S., Sohel, F., and Boussaid, F., 2018. Computer vision for human-machine interaction. In *Computer Vision for Assistive Healthcare* (pp. 127-145). Academic Press.

[30] Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L.H. and Aerts, H.J., 2018. Artificial intelligence in radiology. *Nature Reviews Cancer*, *18*(8), pp.500-510.

[31] Wang, M., Deng, W., 2018. Deep visual domain adaptation: A survey. Neurocomputing 312, 135–153. doi:10.1016/j.neucom.2018.05.083

[32] Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., Summers, R.M., 2017. Chest x-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases, in IEEE Conference on Computer Vision and Pattern Recognition, pp. 2097–2106. doi:10.1109/ cvpr.2017.369.

[33] van Ginneken, B., 2017. Fifty years of computer analysis in chest imaging: rule-based, machine learning, deep learning. Radiological Physics and Technology 10, 23–32. doi:10.1007/s12194-017-0394-5.

[34] Huang, G., Liu, Z., v. d. Maaten, L., Weinberger, K.Q., 2017. Densely connected convolutional networks, in IEEE Conference on Computer Vision and Pattern Recognition, pp. 2261–2269. doi:10.1109/CVPR.2017.243.

[35] Heusel, M., Ramsauer, H., Unterthiner, T., Nessler, B., Hochreiter, S., 2017. Gans trained by a two-time-scale update rule converges to local nash equilibrium, in Proceedings of the 31st International Conference on Neural Information Processing Systems, p. 66296640.

[36] Arjovsky, M., Chintala, S., Bottou, L., 2017. Wasserstein generative adversarial networks, in: Proceedings of the 34th International Conference on Machine Learning, PMLR. pp. 214–223.

[37] Odena, A., Olah, C., Shlens, J., 2017. Conditional image synthesis with auxiliary classifier GANs, in Proceedings of the 34th International Conference on Machine Learning, pp. 2642–2651.

[38] Zhu, J.Y., Park, T., Isola, P., Efros, A.A., 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks, in 2017 IEEE International Conference on Computer Vision (ICCV), IEEE. pp. 2223–2232. doi:10.1109/iccv.2017.244.

[39] Redmon, J., Divvala, S., Girshick, R., Farhadi, A., 2016. You only look once: Unified, real-time object detection, in the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE. pp. 779–788. doi:10.1109/cvpr.2016.91.

[40] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A., 2015. Going deeper with convolutions, in IEEE conference on computer vision and pattern recognition, pp. 1–9.

[41] Girshick, R., 2015. Fast r-CNN, in 2015 IEEE International Conference on Computer Vision (ICCV), IEEE. pp. 1440–1448. doi:10.1109/iccv.2015.169

[42] Girshick, R., Donahue, J., Darrell, T., Malik, J., 2014. Rich feature hierarchies for accurate object detection and semantic segmentation, in 2014 IEEE Conference on Computer Vision and Pattern Recognition, IEEE. pp. 580–587. doi:10.1109/cvpr.2014.81.

[43] Goodfellow, I.J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative adversarial nets, in Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2, MIT Press. pp. 2672–2680.

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