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by Pneumonia Paper

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Application of Deep Learning Techniques for Pneumonia Detection using Chest X-ray Images

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Abstract

Pneumonia is one of the major diseases affecting the large proportion of the population. Our respiratory system is very capable of fighting of the microbes that enter in our lungs through the nasal passage. Some of the mechanical techniques include coughing and sneezing, but sometimes these microbes are successful in colonizing the areas of alveoli and bronchioles which leads to pneumonia. The detection of pneumonia can be done by the X-ray scan of the patient which is observed by a radiologist to look for abnormalities that are indicative of pneumonia. This observation is highly subjective and depends on the experience of the radiologist. This may lead to ambiguity in appropriate diagnosis and may produce some false negatives. To overcome these issues, it is imperative that the radiologists be provided with a tool that acts as a 2nd set of eyes for them and helps them gain confidence in their diagnosis. Keeping in view the aforementioned objectives, many researchers have proposed various computer-assisted classification (CAC) systems based on machine learning and deep learning methods. The present work compared the performance of MobileNetv2, VGG16 and XceptionNet for classifying chest X-ray images into normal and pneumonia classes, reporting the highest accuracy of 96.0 % using VGG16.

Keywords: Chest X-rays, Pneumonia, Deep Learning, VGGNet, MobileNet, XceptionNet

1. Introduction

Pneumonia is a dangerous disease that affects our body in a severe manner. It is a harmful illness in which the air sacs present in the lungs are filled with different liquids which causes difficulty in breathing [27]. These microbes causing pneumonia go into the lungs and then to alveoli. Alveoli functions like an exchange-point where there is continuous exchange of blood and air from the outside world. When pathogens enter the lungs, the immune system start releasing white blood cells (WBCs) for alveoli to help and as these WBC cells fight the pathogens, it leads to inflammation. As the level of carbon-di-oxide keeps on rising the body breathes more quickly to clear out and get more oxygen in. Thus, common symptoms of pneumonia include heavy breathing. Pneumonia is found predominantly in young adults, with a high mortality rate of 5% of inpatients [28]. The germs that cause pneumonia in children and adults are the same, and many respiratory viruses are successfully transmitted from one generation to another between families. In growing countries, in which diagnosis and treatment are behind schedule because of a scarcity of experienced radiologists, pediatric pneumonia is related to alarming mortality charges. The large gap between the quantity of physicians and the population of a specific vicinity also hinders well timed diagnosis. 800,000 children who are less than 5 every year old are killed or affected by pneumonia in their life. This includes over 153,000 newborns [29].

Timely diagnosis and appropriate treatment of the disease leads to increased survival rates. Different methods are available for lung imaging to diagnose pneumonia in patients; however, chest X-rays (CXRs) are widely used. The study of the X-ray scan for accurate diagnosis may be a difficult problem even for knowledgeable radiologists due to the presence of noise and artifacts [1]. Therefore, to overcome these challenges and assist radiologists in their diagnosis, researchers have used a variety of computer-assisted classification (CAC) systems to identify chest X-ray images into various stages of common pneumonia. We are able to distinguish normal and pneumonia cases of patients by observing the opacities present in the chest X-ray. In pneumonia cases we get the darker elements near the spine which shows the presence of the disease [30]. Sample chest X-ray images indicating healthy lungs and lungs affected by viral and bacterial pneumonia are shown in Fig. 1.

Normal Viral Pneumonia Bacterial Pneumonia

Fig. 1 Sample chest X-ray images indicating healthy lungs and lungs affected by viral and bacterial pneumonia

In Fig. 1, normal chest X-rays indicate the blood vessels and the movement of the hemidiaphragm which shows the healthy and proper functioning of lungs. For viral pneumonia chest X-ray it is observed that virus affects both side of the lungs which causes to increase in cellular debris and mucus where previously open lung pockets were present. In the case of bacterial pneumonia chest X-ray we it is observed that a white condensed area or opacity is present on one side of lung. The reason for this is that bacteria attack on one side of the lung that causes inflammation which take over the cells that are filled with air.

2. Related work

Many researchers have attempted to build unique CAC systems for the identification of results. We have given a detailed study of the papers we studied in the field of pneumonia detection using deep learning in Table 1.

Table 1 Brief description of previous related studies carried out on chest X-rays

Reference No.	**Author (Year)**	**Dataset Description**	**Methodology**
[2]	Xianghong et al. (2018)	4513 Images (Bacterial/Viral)	Segmentation: AlexNet FCN Features: Deep features + Handcrafted features Classifier: SVM (Ac.: 80.4 %)
[3]	Rajaraman et al. (2018)	5856 Images (Normal/Pneumonia)	Classifier: Customized VGG16 (Ac.: 96.2 %)
[4]	Ayan et al. (2019)	5856 Images (Normal/Viral/ Bacterial)	Classifier: VGG16 (Ac.: 87.0 %)
[5]	Jain et al. (2019)	5840 Images (Normal/Pneumonia)	Classifier: VGG19 (Ac.: 88.7 %)

[6]	Sousa et al. (2019)	3883 Images (Viral/Bacterial pneumonia)	Classifier: Self-designed CNN (Ac.: 83.1 %)
[7]	Varshni et al. (2019)	2862 Images (Normal/Pneumonia)	Features: Deep features using DenseNet169 Classifier: SVM (Ac.: 80.02 %)
[8]	Stephen et al. (2019)	5856 Images (Normal/Pneumonia)	Classifier: Self-designed CNN (Ac.: 93.73 %)
[9]	Chouhan et al. (2020)	5856 Images (Normal/Pneumonia)	Classifier: Ensemble model of DL networks (Ac.: 96.4 %)
[10]	Togacar et al. (2020)	5849 Images (Normal/Pneumonia)	Features: Deep features from AlexNet, VGG16, VGG19 Feature selection: mRMR Classifier: LDA (Ac.: 99.41 %)
[11]	Rahman et al. (2020)	5247 Images (Normal/Pneumonia)	Classifier: DenseNet201 (Ac.: 98.0 %)
[12]	Irfan et al. (2020)	25,596 Images (Normal/Pneumonia) 203 Images (Normal/Pneumonia)	Classifier: DenseNet121 (Ac.: 71.0 %) Classifier: DenseNet121 (Ac.: 76.0 %)
[13]	Sharma et al. (2020)	5863 Images (Normal/Pneumonia)	Classifier: Self-designed CNN (Ac.: 90.68 %)
[14]	Yue et al. (2020)	5840 Images (Normal/Pneumonia)	Classifier: MobileNet (Ac.: 92.98 %)
[15]	Al Mamlook et al. (2020)	5856 Images (Normal/Pneumonia)	Classifier: Self-designed CNN (Ac.: 98.46 %)
[16]	Hashmi et al. (2020)	5836 Images (Normal/Pneumonia)	Classifier: DL models based weighted classifier (Ac.: 98.43 %)
[17]	Liang et al. (2020)	5856 Images (Normal/Pneumonia)	Classifier: Self-designed CNN (Ac.: 90.5 %)
[18]	Ebiele et al. (2020)	17050 Images (Normal/Pneumonia)	Features: PCA Classifier: SVM (Ac.: 90.0 %)
[19]	Habib et al. (2020)	5856 Images (Normal/Pneumonia)	Pre-processing: HE Classifier: CheXNet (Ac.: 92.6 %) Pre-processing: HE Features: Deep features using ChexNet Feature selection: PCA Classifier: LR (Ac.: 96.1 %)
[20]	Elshennawy et al. (2020)	5856 Images (Normal/Pneumonia)	Classifier: ResNet152v2 (Ac.: 99.2 %)
[21]	Wu et al. (2020)	5863 Images (Normal/Pneumonia)	Pre-processing: Adaptive median filter Features: Deep features from self-designed CNN Classifier: RF (Ac.: 96.85 %)
[22]	Ferreira et al. (2020)	5856 Images (Normal/Pneumonia)	Pre-processing: CLAHE Segmentation: U-Net Features: VGG16 based deep features Classifier: MLP (Ac.: 97.4 %)
[23]	Dey et al. (2021)	7150 Images (Normal/Pneumonia)	Features: Deep features using VGG19 + handcrafted features Feature selection: PCA Classifier: RF (Ac.: 97.94 %)

[24]	Chowdhary (2021)	5863 Images (Normal/Pneumonia)	Features: Deep features using VGG16 Classifier: SVM (Ac.: 96.61 %)
[25]	Naveen et al. (2021)	5216 Images (Normal/Pneumonia)	Classifier: VGG16 (Ac.: 95.67 %)
[26]	GM et al. (2021)	5863 Images (Normal/Pneumonia)	Classifier: Self-designed CNN (AUC: 0.9582)

Note: FCN: Fully convolutional network, SVM: Support vector machine, Ac.: Accuracy, CNN: Convolutional neural network, DL: Deep learning, mrMR: Minimal redundancy maximal relevance, LDA: Linear discriminant analysis, PCA: Principal component analysis, HE: Histogram equalization, LR: Logistic regression, RF: Random forest, CLAHE: Contrast limited adaptive histogram equalization, MLP: Multi-layer perceptron, AUC: Area under the curve.

Recent improvements in deep learning models and the availability of large datasets have made algorithms perform better in detecting pneumonia. As can be seen from the recent studies carried out for classification of chest X-ray images (2018-2021), most of the studies have been carried out using deep learning based techniques [3-6, 8, 9, 11-17, 19, 20, 25, 26]. It can also be observed that very few studies have made use of hybrid classification methods, wherein the features from the images have been computed using deep networks while classification has been done using conventional machine learning classifiers [2, 7, 10, 19, 21-24]. It has been observed that highest accuracy of 99.4 % has been obtained by Togacar et al. [10] using a combined deep feature set obtained from AlexNet, VGG16 and VGG19 networks. The obtained feature set was then subjected to minimal redundancy maximal relevance (mRMR) for selection of optimal features which were further fed to linear discriminant analysis (LDA) classifier. Habib et al. (2020) [19] in their study compared the performance of deep learning method and hybrid classification method using images pre-processed by histogram equalization (HE) technique. In the deep learning technique pre-trained CheXNet network has been used for classification of normal and pneumonia chest X-ray images achieving an accuracy of 92.6 %. In case of hybrid branch, the deep features computed from CheXNet were reduced using principal component analysis (PCA) and fed to logistic regression (LR) classifier achieving an accuracy of 96.1 %.

As observed from Table 1, most of the studies have been carried out for classifying chest X-rays into normal and pneumonia classes therefore, in the present work performance of different deep learning models has been compared to classify chest X-rays into normal and pneumonia classes.

3. Methodology

The present work aims to propose a technique for classifying chest X-ray images into normal and pneumonia classes based on state-of-the-art deep learning networks. The workflow of the proposed methodology is shown in Fig. 2.

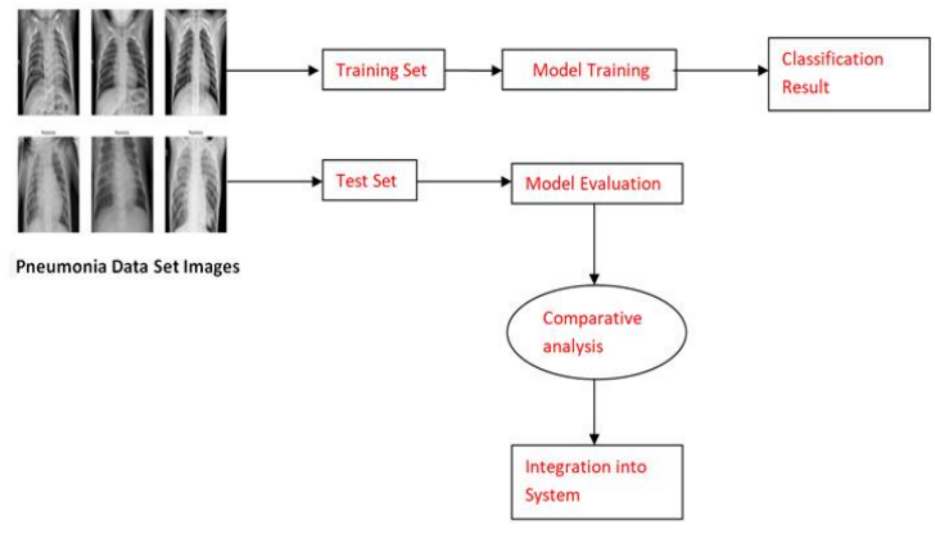

Fig. 2 Workflow of the proposed methodology for classification of chest X-ray images

3.1. Dataset Description

The labelled dataset of chest X-rays has been taken from an online available source provided on the Kaggle website [31]. This dataset contains a total of 5856 chest X-rays images where 1583 chest X-ray images are of normal patients and 4273 files are of patients with pneumonia.

3.2. Data Pre-processing

In the present work, different deep learning models have been trained which have many trainable parameters and need large amounts of data to train efficiently otherwise the problem of overfitting occurs. Basic pre-processing of data in order to avoid this problem is.

3.2.1. Data Compression and resizing

In the present work, the data has been compressed to reduce irrelevance and redundancy of the images to store or transmit data in an efficient form. We need to understand that image resizing is one of the most important steps for preprocessing. The data has been resized to 512 × 512 pixels for our models to train faster in comparison to the data without resizing.

3.2.2. Data Balancing

Balancing training data is an important part of data preprocessing. Data imbalance can lead to potential risks in training a model. We have total of 5856 images of chest X-rays out of which 1583 are normal and 4273 images of pneumonia affected patients. After resizing we have balanced the data of both classes by using 1583 normal images and 1598 pneumonia images. In the next step we have split the training set, validation set and testing set in the ratio of 7:1:2 respectively.

3.3. Convolutional Neural Networks

The CNNs are said to be multi-layer perceptrons which will readily identify the important distinctions from the input image. One of the most important features of CNN is that when we take any image as input, we are able to assign the weights and also differentiate objects from other [32]. The convolutional layer and the pooling layer are two additional layers that distinguish the CNN. There is also a completely linked layer and a RELU (rectified linear unit) layer. As data passes through each layer of the network, the RELU layer acts as an activation function, maintaining non linearity. The dataset will be classified with the help of a fully connected layer. The most crucial layer is the convolution layer, which applies a filter to an array of image pixels, resulting in a convoluted feature map. The pooling layer minimizes the sample size of a given road map and speeds up processing by minimizing the number of parameters that the network must process. The filters are what actually detect the pattern. Pattern could be of any type so it may be called edge detector. Earlier these filters were able to only detect specific objects like eyes, nose, and ear but later on they were able to detect the sophisticated images like cat, dog etc. While adding convolutional layer to the model it should also be specified that how many filters and layers to have in the network. There are many layers comprising of filters which have their own parameters, and we get a deep insight of inside volume but it also comprises of small receptive field. The activation layer comes in handy because it can be used to approximate practically any nonlinear function. The activation layer receives the feature map from the convolutional layer as input [32]. The basic flow of a deep CNN network for image classification is shown in Fig. 3.

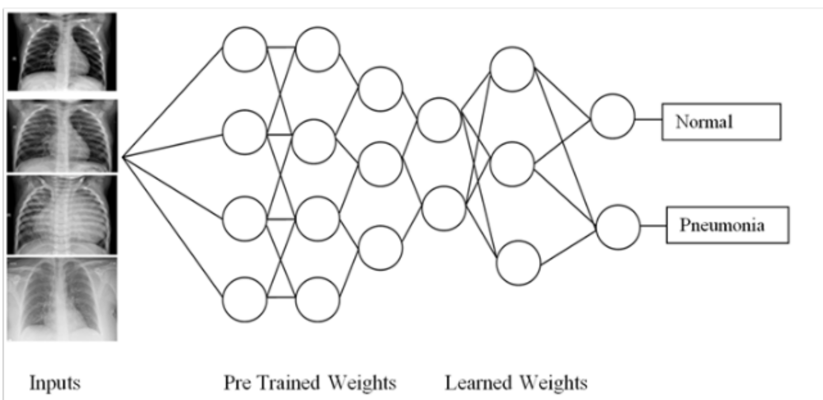

Fig. 3 The basic flow of a deep CNN network for image classification

3.3.1. Pre-trained neural networks and transfer learning

Pre-trained neural networks are the deep learning networks that have already been trained on a large dataset for the identification and extraction of important underlying features in images useful for the differentiation between objects of distinct classes. These networks serve as a starting point for making a network learn a new task. This is the main idea behind the process of transfer learning.

We are successful in the determination of the classification performance of three pre-trained networks namely VGG16, XceptionNet and MobileNet that are able to differentiate between pneumonia and normal classes.

(*a*) VGG16: VGGNet may be a classical convolutional neural specification designed as an improvement over the preliminary deep network AlexNet. The VGGNet model, employs 3 × 3 convolutional filters instead of big filter sizes. This leads to the reduced number of parameters required which successively leads to faster convergence and reduced overfitting. For detailed architecture, readers are directed to [33].

(*b*) XceptionNet: François Chollet created Xception in 2017, drawing inspiration from the architecture of Inception V3 [34]. The Xception model's main contribution is that it employs a slightly modified depthwise separable convolution process. Depth wise separable convolution is reversed in the Xception architecture. There are 14 modules in each of the convolutional layers, which has linear residual connections. For detailed architecture, readers are directed to [34]

(*c*) Mobile Net V2 - A CNN that can be said as mobile friendly is MobileNetv2. The MobileNet model is a network model in which the basic unit is a light-weight depthwise convolution. It also helps in reducing the network size and the number of parameters. For detailed architecture, the readers are directed to [35].

4. Results and Discussion

The performance of three different pre-trained networks namely VGG16, XceptionNet and MobileNetv2 has been compared. The classification results of each of these networks are shown in Fig. 4.

Classification Report

	precision	recall	f1-score	support
NORMAL	0.97	0.95	0.96	300
PNEUMONIA	0.95	0.97	0.96	300
accuracy			0.96	600
macro avg	0.96	0.96	0.96	600
weighted avg	0.96	0.96	0.96	600

Classification report of VGG16

Classification Report

	precision	recall	f1-score	support
NORMAL	0.94	0.95	0.95	300
PNEUMONIA	0.95	0.94	0.95	300
accuracy			0.95	600
macro avg	0.95	0.95	0.95	600
weighted avg	0.95	0.95	0.95	600

Classification report of XceptionNet

Classification Report

	precision	recall	f1-score	support
NORMAL	0.92	0.92	0.92	300
PNEUMONIA	0.92	0.92	0.92	300
accuracy			0.92	600
macro avg	0.92	0.92	0.92	600
weighted avg	0.92	0.92	0.92	600

Classification report of MobileNetv2

Fig. 4 Classification performance of pre-trained networks

As seen from Fig. 4, it is noted that VGG16 achieves maximum accuracy of approximately 96.0% for classification of chest X-rays into normal and pneumonia classes. Out of the total of 600 testing instances, a total of 23 instances were misclassified out of which 15 normal instances were misclassified while 8 misclassified cases belonged to pneumonia class.

The accuracy and loss values for VGG16 are shown in Fig. 5 for training and validation datasets, indicating the performance of the pre-trained network.

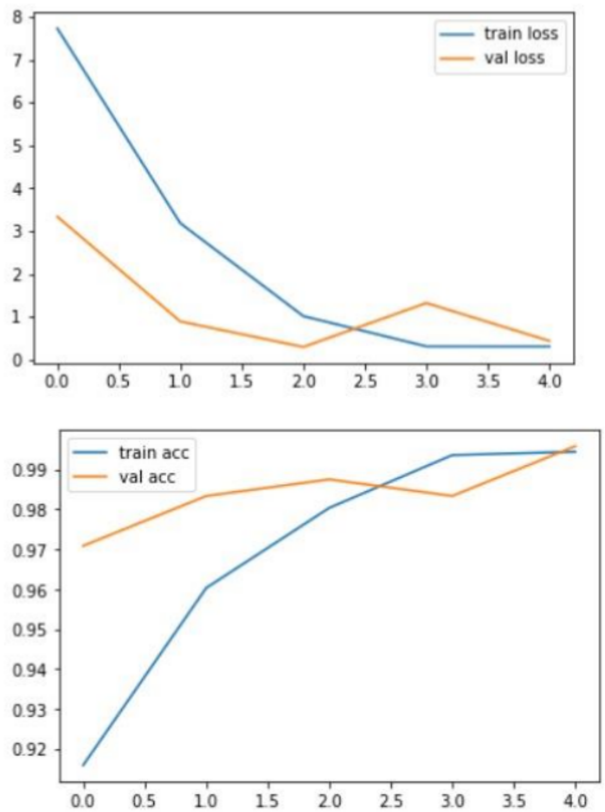

Fig. 5 Performance of pre-trained network VGG16, indication accuracy and loss values for training and validation datasets.

5. Conclusion and future scope

Pneumonia is one of the dangerous diseases and we should detect it by observing any symptoms and plan for a medication in order to improve the likelihood of survival. However, the visual analysis of the chest X-rays is a subjective task and highly operator dependent which might sometimes result in misdiagnosis. To overcome these issues, researchers have tried to develop various CAC system designs useful in diagnosis of abnormalities through X-ray images. The present work also tries to portray a simple and effective algorithm for the identification of chest X-rays into normal and pneumonia classes. The authors compare the classification performance of three pre-trained networks, and it was observed that the best accuracy of 96.0 % has been achieved using VGG16.

One of the future directions for extending the present work and increasing the utility of the proposed system is to integrate the CAC system as an algorithm into the X-ray imaging machines used in routine medical practice by radiologists. In that case, the radiologist can input the captured image into the system wherein the underlying algorithm runs the trained model on the captured image and outputs the probable predicted class as normal or pneumonia based on the captured features. This will prove helpful to the radiologists in their diagnosis as a 2nd opinion can be obtained by the radiologists using this system thus gaining confidence in their own diagnosis. The work can also be further extended by using the deep features extracted from the VGG16 and feeding them to classical machine learning classifiers for differentiation between normal and pneumonia chest X-rays, thus forming a hybrid CAC system design.

References

[1] Sousa, A. S., Ferrito, C., & Paiva, J. A. (2018). Intubation-associated pneumonia: An integrative review. *Intensive and Critical Care Nursing*, 44, 45-52.

[2] Gu, X., Pan, L., Liang, H., & Yang, R. (2018, March). Classification of bacterial and viral childhood pneumonia using deep learning in chest radiography. In *Proceedings of the 3rd International Conference on Multimedia and Image Processing* (pp. 88-93).

[3] Rajaraman, S., Candemir, S., Kim, I., Thoma, G., & Antani, S. (2018). Visualization and interpretation of convolutional neural network predictions in detecting pneumonia in pediatric chest radiographs. *Applied Sciences*, 8 (10), 1715.

[4] Ayan, E., & Ünver, H. M. (2019, April). Diagnosis of pneumonia from chest X-ray images using deep learning. In *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)* (pp. 1-5). IEEE.

[5] Jain, R., Nagrath, P., Kataria, G., Kaushik, V. S., & Hemanth, D. J. (2020). Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning. *Measurement*, 165, 108046.

[6] Sousa, G. G. B., Fernandes, V. R. M., & Paiva, A. C. D. (2019, August). Optimized deep learning architecture for the diagnosis of pneumonia through chest x-rays. In *International Conference on Image Analysis and Recognition* (pp. 353-361). Springer, Cham.

[7] Varshni, D., Thakral, K., Agarwal, L., Nijhawan, R., & Mittal, A. (2019, February). Pneumonia detection using CNN based feature extraction. In *2019 IEEE International*

Conference on Electrical, Computer and Communication Technologies (ICECCT) (pp. 1-7). IEEE.

[8] Stephen, O., Sain, M., Maduh, U. J., & Jeong, D. U. (2019). An efficient deep learning approach to pneumonia classification in healthcare. *Journal of Healthcare Engineering*, 2019, doi: https://doi.org/10.1155/2019/4180949.

[9] Chouhan, V., Singh, S. K., Khamparia, A., Gupta, D., Tiwari, P., Moreira, C., ... & De Albuquerque, V. H. C. (2020). A novel transfer learning based approach for pneumonia detection in chest X-ray images. *Applied Sciences*, 10 (2), 559.

[10] Toğaçar, M., Ergen, B., Cömert, Z., & Özyurt, F. (2020). A deep feature learning model for pneumonia detection applying a combination of mRMR feature selection and machine learning models. *IRBM*, 41 (4), 212-222.

[11] Rahman, T., Chowdhury, M. E., Khandakar, A., Islam, K. R., Islam, K. F., Mahbub, Z. B., ... & Kashem, S. (2020). Transfer learning with deep convolutional neural network (CNN) for pneumonia detection using chest X-ray. *Applied Sciences*, 10 (9), 3233.

[12] Irfan, A., Adivishnu, A. L., Sze-To, A., Dehkharghanian, T., Rahnamayan, S., & Tizhoosh, H. R. (2020, July). Classifying pneumonia among chest x-rays using transfer learning. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* (pp. 2186-2189). IEEE.

[13] Sharma, H., Jain, J. S., Bansal, P., & Gupta, S. (2020, January). Feature extraction and classification of chest x-ray images using CNN to detect pneumonia. In *2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence)* (pp. 227-231). IEEE.

[14] Yue, Z., Ma, L., & Zhang, R. (2020). Comparison and validation of deep learning models for the diagnosis of pneumonia. *Computational Intelligence and Neuroscience*, 2020, doi: https://doi.org/10.1155/2020/8876798.

[15] Al Mamlook, R. E., Chen, S., & Bzizi, H. F. (2020, July). Investigation of the performance of machine learning classifiers for pneumonia detection in chest x-ray images. In *2020 IEEE International Conference on Electro Information Technology (EIT)* (pp. 098-104). IEEE.

[16] Hashmi, M. F., Katiyar, S., Keskar, A. G., Bokde, N. D., & Geem, Z. W. (2020). Efficient pneumonia detection in chest xray images using deep transfer learning. *Diagnostics*, 10 (6), 417.

[17] Liang, G., & Zheng, L. (2020). A transfer learning method with deep residual network for pediatric pneumonia diagnosis. *Computer Methods and Programs in Biomedicine*, 187, 104964.

[18] Ebiele, J., Ansah-Narh, T., Djiokap, S., Proven-Adzri, E., & Atemkeng, M. (2020, September). Conventional machine learning based on feature engineering for detecting pneumonia from chest X-rays. In *Conference of the South African Institute of Computer Scientists and Information Technologists 2020* (pp. 149-155).

[19] Habib, N., Hasan, M. M., & Rahman, M. M. (2020). Fusion of deep convolutional neural network with PCA and logistic regression for diagnosis of pediatric pneumonia on chest X-rays. *Network Biology*, 10 (3): 62-76.

[20] Elshennawy, N. M., & Ibrahim, D. M. (2020). Deep-pneumonia framework using deep learning models based on chest x-ray images. *Diagnostics*, 10 (9), 649.

[21] Wu, H., Xie, P., Zhang, H., Li, D., & Cheng, M. (2020). Predict pneumonia with chest X-ray images based on convolutional deep neural learning networks. *Journal of Intelligent & Fuzzy Systems*, 39 (3), 2893-2907.

[22] Ferreira, J. R., Cardenas, D. A. C., Moreno, R. A., de Sá Rebelo, M. D. F., Krieger, J. E., & Gutierrez, M. A. (2020, July). Multi-view ensemble convolutional neural network to improve classification of pneumonia in low contrast chest x-ray images. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* (pp. 1238-1241). IEEE.

[23] Dey, N., Zhang, Y. D., Rajinikanth, V., Pugalenthi, R., & Raja, N. S. M. (2021). Customized VGG19 architecture for pneumonia detection in chest X-rays. *Pattern Recognition Letters*, 143, 67-74.

[24] Chowdary, G. J. (2021). Impact of machine learning models in pneumonia diagnosis with features extracted from chest x-rays using VGG16. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, 12 (5), 1521-1530.

[25] Naveen, P., & Diwan, B. (2021, March). Pre-trained VGG-16 with CNN Architecture to classify X-Rays images into Normal or Pneumonia. In *2021 International Conference on Emerging Smart Computing and Informatics (ESCI)* (pp. 102-105). IEEE.

[26] GM, H., Gourisaria, M. K., Rautaray, S. S., & Pandey, M. A. N. J. U. S. H. A. (2021). Pneumonia detection using CNN through chest X-ray. *Journal of Engineering Science and Technology (JESTEC)*, 16 (1), 861-876.

[27] Chu, Daniel KW, et al. "Molecular diagnosis of a novel coronavirus (2019-nCoV) causing an outbreak of pneumonia." Clinical chemistry 66.4 (2020): 549-555.

[28] Mayo clinic staff, Pneumonia (June 2022), Available online at: https://www.mayoclinic.org/diseases-conditions/pneumonia/symptoms-causes/syc-20354204·

[29] WHO, Pneumonia (November 2021), Available online at: https://www.who.int/news-room/fact-sheets/detail/pneumonia.

[30] UNICEF, Pneumonia (April 2021), Available online at: https://data.unicef.org/topic/child-health/pneumonia/.

[31] Bian X, Pneumonia prediction using deep learning. Available online at: https://www. kaggle.com/code/therealcyberlord/pneumonia-detection-using-deep learning/data.

[32] Yamashita, R., Nishio, M., Do, R. K. G., & Togashi, K. (2018). Convolutional neural networks: an overview and application in radiology. *Insights into Imaging*, 9 (4), 611-629.

[33] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

[34] Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1251-1258).

[35] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 4510-4520).

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