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DEEP ARCHITECTURE FOR DIAGNOSIS OF PNEUMONIA IN THORACIC IMAGES

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ABSTRACT
Bacterial infection in the lungs is the major reason of the fatal thoracic illness pneumonia. Chest radiography is a common diagnostic procedure to find pneumonia infection in lung. Localizing and diagnosing pneumonia clouds on the chest X-ray is assisted by radiologists or skilled medical professionals. Due to the shortage of specialists, rising patient loads, and the subjectivity of human perception, radiology practice is prone to errors. The current computer-aided pneumonia diagnostic methods struggle with problems like an unbalanced pneumonia dataset, poor chest radiograph quality, pathological irregularities, in homogeneities in X-Ray imaging, loud contextual noise, overlaid patterns of opacities, and anatomical changes brought on by incorrect body positioning. In this work Computer-aided deep learning based pneumonia discovery from a chest radiograph is utilized to decrease the prevalence of investigative errors and to simplify the work of radiologists. Spatial features learned on publicly available large-scale datasets by pretrained CNN architectures like DenseNet201, Inceptionv3, VGG16, VGG19 and Inception_Resnet_V2 are used to classify healthy and pneumonia affected chest X-Rays. The statistical findings from the demonstrations support the analytical selection of the best pre-trained deep network models to be used, specifically for the identification of pneumonia. This research work also suggests suitable preprocessing and augmentation techniques before extracting the global and local statistical features. The VGG16 architecture exhibited a high accuracy of 92.95% in classifying pneumonia from thoracic images whereas DenseNet201 exhibited poor validation performance over prediction accuracy.

Keyword: pneumonia, computed tomography, CNN, deep learning, chest X-Ray diagnosis.

I. INTRODUCTION
The leading cause of adult as well as children mortality and morbidity worldwide is pulmonary pneumonia. Pneumonia illness of the lower respiratory tract is typically brought on by a bacteria or virus. The pulmonary alveoli, which are little balloon shaped sacs at the bronchioles end, are typically the target of this illness. Lung have 5 lobes, pneumonia usually attacks any of these 5 lobes and Sometimes many lobes in a persistent illness become infected.

Chest radiograph, CT scans [1], and magnetic resonance imaging-MRI, Volume Sweep Imaging (VSI) and Lung Ultrasound (LUS) are different possible pneumonia diagnostic thorax screenings. Choices for treatment, recovery, and medicine of pneumonia heavily relies on radiological findings in thorax imaging. Table 1 shows comparison between different imaging modality used for pneumonia diagnosis.

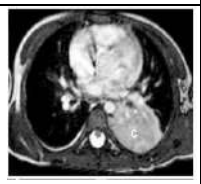
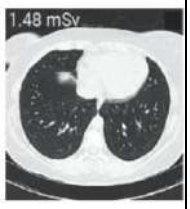
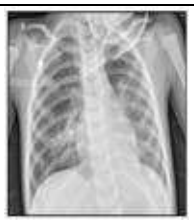
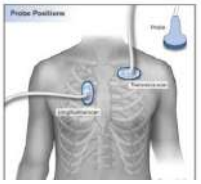
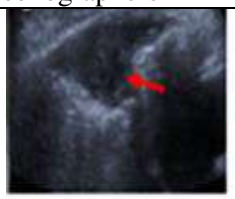
A. Chest Radiograph:
The expert physician usually uses chest X-ray images as a routine diagnostic test to study lung inflammation, abscesses, pneumonia, and enlarged lymph nodes [1]. Chest X-ray diagnostic is largely utilized for thoracic diagnosis because it has more specificity than other thoracic imaging modalities and less false-positive findings. In this paper lung related chronic life frightening disease pneumonia is focused and reviewed by considering given chest X-Ray input for diagnosis of pneumonia [2].

B. Computed Tomography (CT):
Early imaging appearance is ground glass opacity could be missed by chest X-ray due to its projection overlapping and low-resolution nature. Hence, the screening of pneumonia for patients with suspected infection and its complications, computed Tomography is recommended [10]. Despite clear diagnostic advantages, computed tomography is a matter of concern in children or adults as multiple screenings are often required during complications and recovery measurement in pneumonia thus increasing ionizing radiation exposure.

C. **Magnetic Resonance Imaging:**

Magnetic Resonance Imaging has replaced Computed tomography overcoming issues related to ionizing radiation. It is the first-line cross-sectional imaging outside the chest test and a correct, sensitive and potential pneumonia screening in its complications. However, the use of MRI images in diagnosis of pneumonia [20-21] in children is limited by technical factors like fast signal dephasing at air-tissue interfaces, and artefacts in proton poor lung from cardiac and respiratory motion in routine clinical practice [13].

Table 1: Comparative analysis of thoracic imaging modalities

Thoracic Imaging	**Magnetic resonance imaging (MRI)**	**computerized tomography (CT),**	**Chest X-Ray (CXR)**	**Volume Sweep Imaging (VSI)**	**Lung Ultrasound (LUS)**
Affordability	Costly	Costly	Economic	Economic	Economic
Accessibility	Only Available at big hospital	Only Available at big hospitals	Available at diagnostic center	Available at diagnostic centers	Only Available at centers and hospitals
Possibility in Critical/ICU	Not possible	Not possible	Possible	Possible	Possible
Portability	Non Portable	Non Portable	Portable	Portable	Portable
Recommended	In case of complications	In case of complications	Initial Scan and recovery tracking	Useful in rural areas	In case of pediatric pneumonia confirmation and recovery
Disadvantage	Rapid signal dephasing at air-tissue interphases	Requires a larger amount of ionizing radiation	Ground glass opacities are not detected	Literature on VSI is scarce	Good interrater reliability (IRR) and poor specificity, lack of sonographers
Images	 An 8-year-old girl with left lower lobe bacterial pneumonia. MR image shows left lower lobe superior segment round consolidation (C)	 False positive case CT of 28-year-old female patient, showed no signs of pneumonia in the standard dose	 Chest Radiograph. CXR of pneumonia affected patient	 Probe position in longitudinal and transverse scans in Volume Sweep Imaging.	 False positive case, the lung abscess cavity (containing a gas-fluid level) demarcates barley and was not diagnosed initially (red arrow) in lung ultrasound.

D. **Lung Ultrasound:**

LUS, a portable and reasonably priced imaging modality with approximately 95% sensitivity and specificity, has the potential to replace chest X-ray in identifying pneumonia in rural regions. Due to their tiny thoracic diameter

and the fact that ultrasound does not expose kids to ionizing radiation, it is excellent to use it to diagnose pneumonia in children. Nevertheless, results exhibit the poor specificity of lung ultrasound. The current limiting factor to LUS is the lack of trained sonographers. Hence LUS might work better as a screening tool, while chest X-Ray is kept reserved for the confirmation of disease pneumonia [18].

E. **Volume Sweep Imaging:**

Volume sweep imaging of the intended organ. is obtained using an ultrasound probe sweeps and arcs over various exterior body landmarks. Six sections make up each hemi thorax like two laterals, two laterals and two posteriors. Operators get images through a series of movements to completely cover the lung. VSI can be taught to anyone with a little ultrasound or medical experience, marginal technical skill and anatomical knowledge. Hence it is useful in rural areas for pneumonia diagnosis [15].

II. DEEP LEARNING FOR PNEUMONIA SURVEY

D. Kermany and M. Goldbaum suggested a transfer learning framework for pneumonia patients screening through the deep learning network pretrained on detection of retinal diseases reaching performance equivalent to that of human professionals [22-25].

W. Khan and N. Zaki studied different feature extraction methods, data augmentation techniques, datasets, problems in imbalanced dataset, random sampling, feature selection, deep network and machine learning architectures [17]. The algorithms implementing these techniques were also analyzed using goodness factors, usability, and computational complexities.

Ansh Mittal and Deepika Kumar have made a mixture of convolution and capsule to gain two deep models. This ensemble of convolution with capsule and integration of capsule with convolution predicted pulmonary pneumonia with a testing accuracy of 95.33% [15].

Confidence aware abnormality detection- CAAD model was designed by Jianpeng Zhang and Yutong Xie, consisting of a shared feature extractor unit, a confidence forecast unit and an abnormality detection module working on X-VIRAL dataset to detect viral pneumonia patients from healthy ones. This methodology achieved an AUC of 83.61% and sensitivity of 71.70% [25].

A level set formulation suggested by B. LI and J.QIN segmenting certain images by means of competition in fuzzy region. Selective breakdown is capable of tracking and detecting the random combination of image component or selected objects, overcoming the issues with noise and ambiguity, and inhomogeneity in existing level set methods and evolutionary strategies [11].

Pretrained deep convolutional neural nets like AlexNet, DenseNet201, SqueezeNet and ResNet18 were made use for transfer learning by Tawsifur Rahman and M. Chowdhury. 5247 Chest radiograph images of viral, bacterial, and healthy patients were preprocessed [19] and trained for classification into bacterial and viral pneumonia [14].

T. Gabruseva and Dmytro Poplavskiy developed the analytical tactic for pneumonia cloud detection based on squeeze-and-extinction single shot detectors, deep neural networks, and multi task learning and augmentations. Various encoders like ResNet-34, Xception, NASNetAMobile, SEResNext-50, DualPathNet, InceptionResNet-V2 and PNASNet5Large architectures have been tested from global image classification [8].

The dissimilarity issues like region of interest position, resolution, and brightness in binary chest X-rays opacity classification was modelled by Amit Kumar Jaiswal, Prayag Tiwari using pixel-wise disease segmentation and Mask R-CNN encoder. This algorithmic approach also identifies potential pneumonia caused by the use of Faster-RCNN encoder [9].

M. Togaçar , B. Ergen , secured 300 deep features from three different deep network models, and combined these features to act as an input to many machine learning-ML algorithms like linear regression, decision trees, LDA, k-nearest neighbors, and support vector machines. Ultimately, every model secured favorable results, particularly linear discriminant analysis received the maximum effectual accuracy of 99.41% [16].

III. METHODOLOGY

A. Proposed Architecture

Deep Learning based lung infection identification on thoracic imaging is shown in Figure 1. Architecture is Divided into five different parts such as dataset collection, data preprocessing, data augmentation, feature extraction [3-7], [12] and disease classification module for prognosis.

A. Preprocessing: Second stage of computer aided diagnosis is preprocessing publically available standard chest X-ray datasets. Usual image preprocessing techniques, such as image contrast enhancement, Noise suppression, segmentation, resizing, rescaling and bone suppression can be practiced to chest radiograph.

All 5,863 chest X- Ray dataset, for the purpose of producing a uniform quantification, photos are solely cropped. To provide the necessary input for deep architectures, all photos are scaled to 150*150 square pixels. Every single input image given to the encoder models will undergo these preprocessing operations. during training and evaluation phases. The input dataset is divided into three portions for testing, training, and validation: 85:10:5.

a) **Augmentation:** Techniques for universal data expansion like random clipping, left-right, zooming, up-down flipping, and mirroring operation were achieved on input chest X-Ray images to make more training samples available while avoiding data overfitting.

b) **Shear Transformation:** A shear recording (0.2 range) in plane geometry is a linear transformation of spatial pixels in a specific static direction proportionate to its associated signed distance. This shear transformation mapping helps in overcoming data imbalance problems majorly experienced in medical datasets.

c) **Zooming:** A zoom augmentation with a range of 0.2 stretches the image and adds additional pixels at random.

d) **Shift Augmentation:** Horizontal flippant augmentation and vertical flippant augmentation reverses the rows and columns of an image pixel either horizontally or vertically.

B. **Deep Learning Architecture:** Deep architecture encoders pre trained on medical images such as DenseNet201, Inceptionv3, VGG16, VGG19 and InceptionResnetV2 are an important breakthrough in the domain of artificial intelligence, has widespread potential at extracting minute features in medicinal image analysis. These systems offer enormous potential for identifying important details in images and investigating fundamental spatial forms for the diagnosis of pneumonia. For simple pneumonia disease prognosis, these structures give a budding feature map of encoded features.

C. **Disease Classification Module:** The output labels for the feature-based illness classification module for a particular input chest X-ray image are either pneumonia or healthy. In order to assess and gauge the diagnostic performance, this module categorizes and forecasts chest X-rays autonomously while measuring % accuracy, recall, precision and F1-Score.

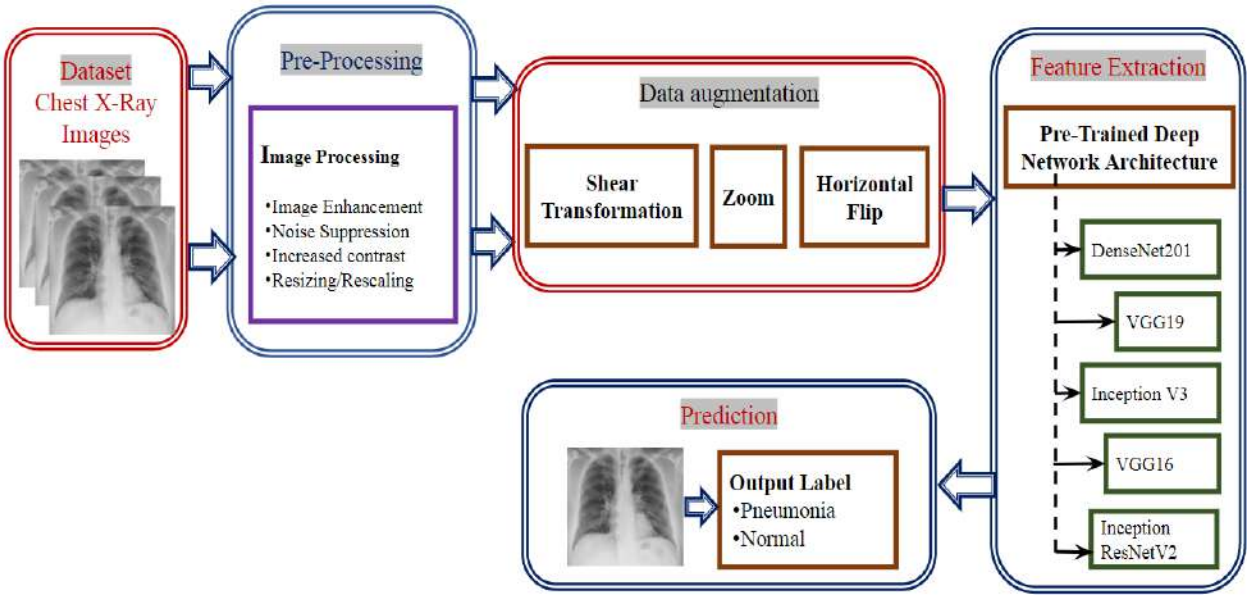


Fig 1. Deep architecture in detection of pneumonia disease using Chest X-Ray.

IV. RESULT AND DISCUSSION

Performance investigation of several taxonomy models is displayed graphically in Figure 2 clearly shows VGG16 network has better validation accuracy comparatively. VGG16 deep neural network has accomplished steady and increasing validation accuracy of 92.95 % over the increasing epochs. The other evaluation metrics used for comparing other classical deep classification models for segmentation performance analysis are sensitivity, F1-score and specificity. Comparative analysis of several classification models is shown in table 2. Table illustrates effects of deep networks in diagnosing with the performance evaluation metric encoder accuracy, recall, precision, and F1 Score respectively. Table clearly shows that the VGG16 network has consistently outperformed other deep architectures in terms of accuracy.

Figure 3 shows Confusion matrix of VGG19 deep network in pneumonia detection shows Image rates for true positive, false positive, true negative and false negative in diagnosis of pneumonia.

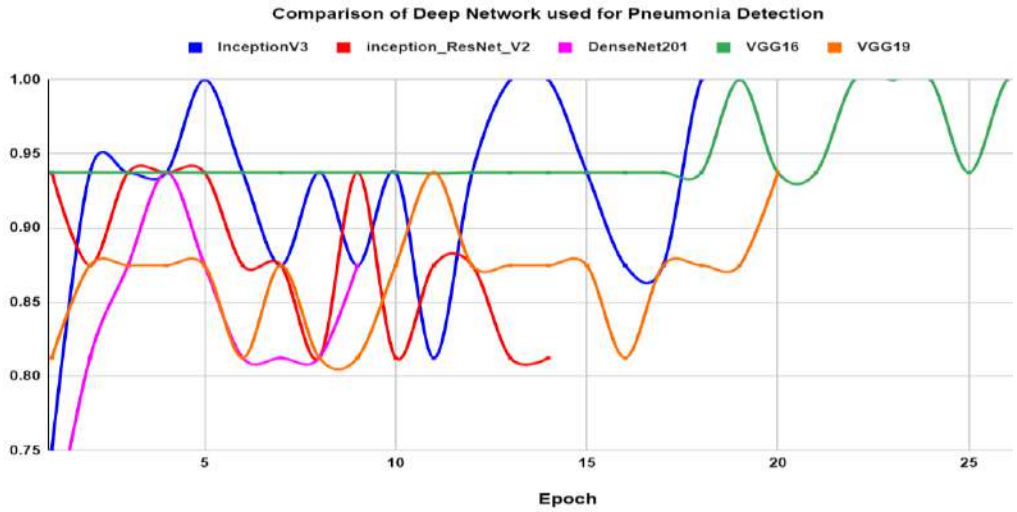


Fig 2. Average validation accuracy of deep neural networks (DenseNet201, Inceptionv3, VGG16, VGG19 Inception Resnet V2) on over the number of Epochs is shown as comparative performance Analysis

Table 2: Diagnostic performance measurement of Deep Network in Diagnosis of Pneumonia

Deep Learning Models	Loss	Accuracy	Precision	Recall	F1-Score
DenseNet201	0.26	90.71	95.36	89.49	92.33
Inceptionv3	0.34	90.54	88.76	97.18	92.78
VGG16	0.21	92.95	91.59	97.69	94.54
VGG19	0.22	91.67	90.82	96.41	93.53
Inception_Resnet_V2	0.3	91.19	93.06	92.82	92.94

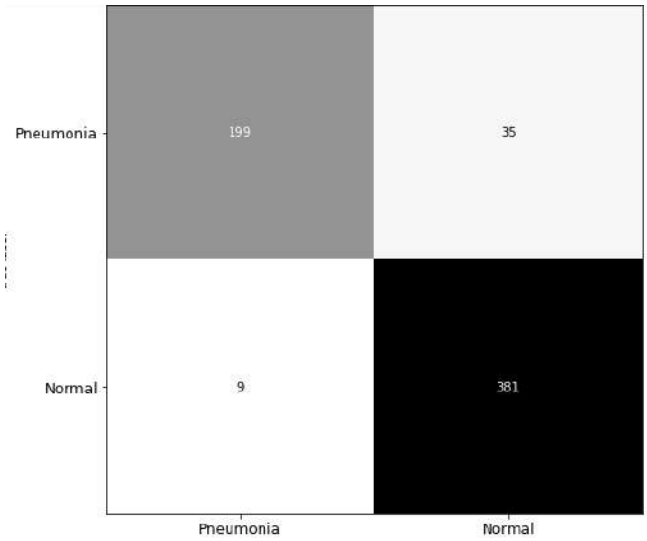


Fig 3: Confusion matrix obtained for pneumonia disease detection using VGG-16 deep architecture.

Figure 4 illustrates the false positives and negatives as well as true positives and true negatives classification results attained in pneumonia detection using deep architecture. VGG16 Model Accuracy obtained during instruction and approval is shown in Figure 5. The validation and training loss of VGG16 model pretrained on ImageNet is also shown graphically.

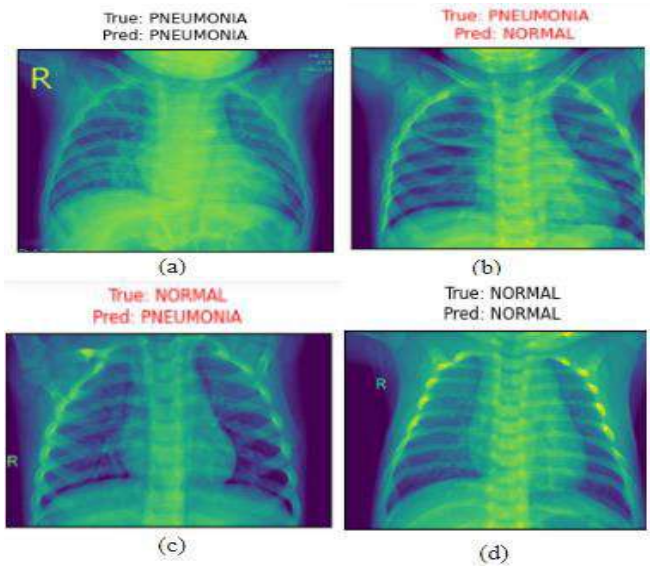


Fig 4: (a) True Positive (b) True Negative (c) False Positive (d) False Negative Prediction Results through deep network model.

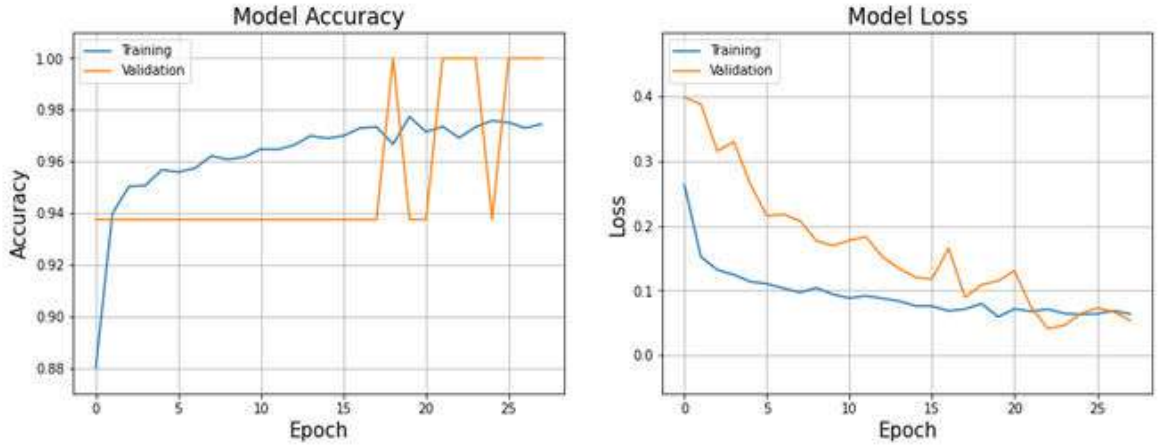


Fig 5: Model Accuracy and Model Loss during training and validation using VGG 16 deep architecture pre trained on ImageNet for pneumonia disease detection from chest X-Ray images.

V. CONCLUSION

In this research the survey of different thoracic imaging modality used for pneumonia disease diagnosis is carried out. Classification of pneumonia affected or healthy lungs were enlightened with pre-trained deep network architecture using chest X-Ray images. The prospective and progress reviews of various deep models for classification, including DenseNet201, Inception Resnet V2, Inception Resnet V3, VGG16 and VGG19, were thoroughly investigated. DenseNet201, Inceptionv3, VGG19 Inception Resnet V2 and DenseNet201 have accuracy values of 90.71, 90.54, 91.67, and 91.19, respectively. The VGG16 architecture exhibited a high accuracy of 92.95% in classifying pneumonia from thoracic images. The VGG16 vision architecture has shown to an excellent vision architecture for identifying pneumonia from chest X-rays due to its architectural simplicity and layer wise detailed feature construction.

An improved high-class model for improvising training, segmentation and classification accuracy with a larger standard data set considering complex overlapping clinical situations needs to be established.

REFERENCES

[1] P. Alongi et al., “Radiomics Analysis of Brain [18 F]FDG PET/CT to Predict Alzheimer’s Disease in Patients with Amyloid PET Positivity: A Preliminary Report on the Application of SPM Cortical Segmentation, Pyradiomics and Machine-Learning Analysis,” Diagnostics, vol. 12, no. 4, pp. 1–13, 2022, doi: 10.3390/diagnostics12040933.

[2] Dabre Kanchan, Satishkumar L. Varma, and Pankaj B. Patil. "RAPID-Net: Reduced architecture for pneumonia in infants detection using deep convolutional framework using chest radiograph." Biomedical Signal Processing and Control 87 (2024): 105375.

[3] E. A. Collisson et al., “Comprehensive molecular profiling of lung adenocarcinoma: The cancer genome atlas research network,” Nature, vol. 511, no. 7511, pp. 543–550, 2014, doi: 10.1038/nature13385.

[4] J. Peng et al., “Development and validation of a pyradiomics signature to predict initial treatment response and prognosis during transarterial chemoembolization in hepatocellular carcinoma,” Front. Oncol., vol. 12, no. October, pp. 1–13, 2022, doi: 10.3389/fonc.2022.853254.

[5] L. Lu et al., “Radiomics prediction of egfr status in lung cancer—our experience in using multiple feature extractors and the cancer imaging archive data,” Tomography, vol. 6, no. 2, pp. 223–230, 2020, doi: 10.18383/j.tom.2020.00017.

[6] H. Horng et al., "Generalized ComBat harmonization methods for radiomic features with multi-modal distributions and multiple batch effects," Sci. Rep., vol. 12, no. 1, pp. 1–12, 2022, doi: 10.1038/s41598-022-08412-9.

[7] L. Duff et al., "A methodological framework for AI-assisted diagnosis of active aortitis using radiomic analysis of FDG PET–CT images: Initial analysis," J. Nucl. Cardiol., vol. 29, no. 6, pp. 3315–3331, 2022, doi: 10.1007/s12350-022-02927-4.

[8] Tatiana Gabruseva, Dmytro Poplavskiy, and Alexandr Kalinin. Deep learning for automatic pneumonia detection. IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, June:1436-1443, 2020.

[9] Amit Kumar Jaiswal, Prayag Tiwari, Sachin Kumar, Deepak Gupta, Ashish Khanna, and Joel J.P.C. Rodrigues. Identifying pneumonia in chest X-rays: A deep learning approach. Measurement: Journal of the International 25l Measurement Confederation, 145:511-518, 2019.

[10] Wasif Khan, Nazar Zaki, and Luqman Ali. Intelligent Pneumonia Identification from Chest X-Rays: A Systematic Literature Review. medRxiv preprint, pages 1-13, 2020.

[11] Bing N A N Li, Senior Member, Jing Qin, Rong Wang, Meng Wang, and Xuelong Li. Selective Level Set Segmentation Using Fuzzy Region Competition. IEEE Access, 4:4777-4788, 2016.

[12] C. Ortiz-Toro, A. García-Pedrero, M. Lillo-Saavedra, and C. Gonzalo-Martín, "Automatic detection of pneumonia in chest X-ray images using textural features," Comput. Biol. Med., vol. 145, Jun. 2022, doi: 10.1016/j.compbiomed.2022.105466.

[13] Gaobo Liang and Lixin Zheng. A transfer learning method with deep residual network for pediatric pneumonia diagnosis. Computer Methods and Programs in Biomedicine, Elsevier, 187:1-9, 2020.

[14] Tawsifur Rahman, Muhammad E H Chowdhury, and Amith Khandakar. Applied sciences Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using. MDPI, J. app Sci., 3233:1-17, 2020.

[15] T. J. Marini et al., "Lung Ultrasound Volume Sweep Imaging for Pneumonia Detection in Rural Areas: Piloting Training in Rural Peru," J. Clin. Imaging Sci., vol. 9, no. xx, p. 35, 2019.

[16] Deep Feature Learning Model for Pneumonia Detection Applying a Combination of mRMR Feature Selection and Machine Learning Models. Irbm, 41(4):212-222, 2020.

[17] R. Abdala, M. Gonzalez, M. B. Zanchetta, V. Longobardi, M. Sesta, and J. M. Massa, "Classification of DXA Samples Into TBS Ranges Using Machine Learning and Pyradiomics," p. 70.

[18] J. peng Wu et al., "Radiomics analysis of ultrasound to predict recurrence of hepatocellular carcinoma after microwave ablation," Int. J. Hyperth., vol. 39, no. 1, pp. 595–604, 2022, doi: 10.1080/02656736.2022.2062463.

[19] D. E. Wright and D. Ph, "Reproducibility in medical image radiomic studies: contribution of dynamic histogram binning. (arXiv:2211.05241v1 [eess.IV])", [Online]. Available: http://arxiv.org/abs/2211.05241

[20] N. Aggarwal and R. K. Agrawal, "First and Second Order Statistics Features for Classification of Magnetic Resonance Brain Images," J. Signal Inf. Process., vol. 03, no. 02, pp. 146–153, 2012, doi: 10.4236/jsip.2012.32019.

[21] W. Lin, K. Hasenstab, G. Moura Cunha, and A. Schwartzman, "Comparison of handcrafted features and convolutional neural networks for liver MR image adequacy assessment," Sci. Rep., vol. 10, no. 1, Dec. 2020, doi: 10.1038/s41598-020-77264-y.

[22] J. Naranjo-Alcazar, S. Perez-Castanos, P. Zuccarello, and M. Cobos, "Acoustic Scene Classification with Squeeze-Excitation Residual Networks," Mar. 2020, doi: 10.1109/ACCESS.2020.3002761.

[23] Z. Ren and Y. Zhang, "LCDAE : Data Augmented Ensemble Framework for Lung Cancer Classi fi cation," 2022, doi: 10.1177/15330338221124372.

[24] S. Wang, D. Ranjan, D. S. Guttery, and X. Zhang, "COVID-19 classification by CCSHNet with deep fusion using transfer learning and discriminant correlation analysis," Inf. Fusion, vol. 68, no. September 2020, pp. 131–148, 2021, doi: 10.1016/j.inffus.2020.11.005.

[25]. Amit Kumar Jaiswal, Prayag Tiwari, Sachin Kumar, Deepak Gupta, Ashish Khanna, and Jo-el J.P.C. Rodrigues. Identifying pneumonia in chest X-rays: A deep learning approach. Measurement: Journal of the International Measurement Confederation, 145:511-518, 2019.