Cascaded Deep Learning Model for Detecting Lung Infections Using Chest X-Rays

Akash Chaturvedi
M. Tech Scholar
Department of CSE
Oriental Group of Institutes,
Bhopal, M.P., India
chaturvediakash5@gmail.com

Prof. Shivank Soni
Assistant Professor
Department of CSE
Oriental Group of Institutes,
Bhopal, M.P., India

Abstract: This work focuses on efforts for accurately predicting lung diseases like omicron and pneumonia using chest X-ray imaging, a reliable method in this domain. The work adopts a transfer learning model for lung infection predictions from chest X-ray images. The proposed architecture encompasses both training and testing functions, with key steps including pre-processing, deep feature extraction, and classification. Initially, each X-ray image is enhanced through digital filtering for quality improvement. These processed images are then input into a robust, step-wise learning model that efficiently facilitates the automatic learning of features. The highlight of this approach is the Cascaded learning model, which not only achieves a high accuracy rate of 99% but also significantly reduces computational complexity. This is evidenced by a lower number of training parameters, making the model both more efficient and lightweight, and hence more practical for clinical applications in differentiating between omicron and pneumonia.

Keywords: Chest X-Rays, Lung Infection, Transfer Learning, Cascaded Learning.

I. INTRODUCTION

Lung diseases fall into categories like lung tissue diseases, bronchitis, and circulatory issues affecting the lungs. Early detection of lung infection is crucial for effective treatment and control. However, identifying early indicators and biomarkers is challenging, necessitating expert medical care and integrated health systems for timely diagnosis and treatment. For example, Misdiagnosing omicron as pneumonia can lead to incorrect treatments and increased costs. Diagnostic imaging, particularly X-ray, is key in differentiating among lung diseases. The advent of artificial intelligence (AI), including deep learning, holds promise for improving early detection, especially in resource-limited settings. Computer-aided diagnostics (CAD) tools aid radiologists by identifying areas of interest in chest X-rays, extracting image features, and employing techniques like texture and radiograph analysis [1]. Diagnostics (CAD) tools aid radiologists by identifying areas of interest in chest X-rays, extracting image features, and employing techniques like texture and radiograph analysis [1].

Deep learning, particularly through convolutional neural network (CNN) models, has demonstrated success in image recognition and classification, highlighting its potential in lung infection diagnosis and the promise of future advancements. Although deep neural networks offer potential for lung infection detection, the lack of peer-reviewed research comparing the efficacy of different deep learning systems in identifying lung infection abnormalities remains a gap in the field [2]. The challenge in addressing lung infections, revolves around developing an accurate and efficient detection method using deep learning models. This new approach aims to surpass the limitations of traditional radiological imaging and laboratory tests, which are often time-consuming and resource-intensive [3]. The potential of deep learning in accurately identifying and differentiating between various types of lung infections, including viral and bacterial, and specifically distinguishing TB from other conditions, marks a significant advancement in medical diagnostics [4]. However, research gaps remain, notably in evaluating the strengths and limitations of existing deep learning models, comparing their performance to traditional diagnostic methods, and exploring the integration of deep learning with conventional image processing techniques for improved outcomes [5].

Key challenges include the complexity of chest X-ray interpretation, which traditionally requires a radiologist's expertise, the underutilization of image enhancement techniques that could illuminate specific image characteristics for better diagnosis, and the increased computational demands these technologies impose. Addressing these challenges is crucial for leveraging deep learning in the fight against TB and other lung infections, especially in settings where resources are scarce and the burden of disease is high.

II. LITERATURE REVIEW

Goyal et al. [1] introduce a framework that combines neural networks and machine learning, particularly RNN and LSTM, for diagnosing lung diseases from chest X-rays by extracting and normalizing visual, shape, texture, and intensity features. Yenurkar et al. [2] propose the FusionNet Model for omicron detection from CXR images, achieving high classification accuracy through preprocessing, feature extraction using the Parallel Attention Layer (PAL), and optimal feature selection with the Entropy Correlation score and Emperor Salp Algorithm. J Zhang et al. [3] present the confidence-aware anomaly detection (CAAD) model, a one-class anomaly detection approach for viral pneumonia detection, demonstrating comparable performance to radiologists. Singh et al. [4] proposed a deep learning-based solution using chest X-rays to triage omicron patients, incorporating image enhancement, segmentation, and a modified stacked ensemble model for high classification accuracy. Okolo et al. [5] evaluate eleven deep convolutional neural network architectures for classifying chest X-ray images into categories of healthy, omicron infected, and viral pneumonia, achieving notable classification accuracy and F1-scores. Jaiswal et al. [6] emphasize machine learning for patient triage with the COVIDPEN model, a transfer learning approach using a Pruned EfficientNet model, demonstrating effectiveness and interpretability in detecting omicron from imaging data. V Guarrasi et al. [7] address the generalization issue of CNNs in omicron detection from chest X-rays by introducing a late fusion technique for constructing an optimal ensemble, achieving high recognition rates. P Saha et al. [8] propose Graph Covid Net, utilizing a Graph Isomorphic Network to detect omicron in CT scans and CXRs, achieving impressive accuracy and offering the source code for broader application. S Ahmed et al. [9] introduce ReCoNet, a novel CNN architecture for omicron detection from CXR images, focusing on preprocessing to enhance omicron patterns, achieving high accuracy, sensitivity, and specificity. M Ahishali et al. [10] explored Machine Learning techniques for early omicron detection through chest X-ray images, introducing the Convolutional Support Estimator Network and achieving exceptional performance, highlighting the potential for early diagnosis. Alharbi et al. [11] explored chest X-ray analysis using deep learning for omicron detection, achieving 99% accuracy with their CNN model, suggesting its potential as a cost-effective and efficient diagnostic method. Gourdeau et al. [12] utilized bedside CXR images with deep transfer learning to predict mortality after mechanical ventilation in omicron ICU patients, finding that incorporating CXR images improves predictive accuracy for ICU triage. Elsharkawy et al. [13] developed a CAD system using chest X-ray data to assess mortality risk in omicron patients, achieving high accuracy and suggesting its usefulness in evaluating disease severity and informing patient care. Kumar et al. [14] proposed a machine learning approach with deep feature extraction for early omicron detection via chest X-rays, showing high accuracy and highlighting its potential for early outbreak prediction. Muhammad et al. [15] advocated for integrating IoT, AI, and 5G technologies for pandemic response, demonstrating the effectiveness of their approach in analyzing cough sounds and chest X-ray images for omicron detection. Gulati et al. [16] introduced LungAI, a CNN model for omicron detection from chest X-rays, achieving remarkable accuracy and showing promise as a rapid and reliable detection method. Gupta et al. [17] focused on enhancing pneumonia diagnosis accuracy with an AI system, outperforming previous methods and underscoring the potential of AI in improving diagnostic outcomes during the pandemic. Alkindi et al. [18] examined the association between omicron vaccines and rare complications, advising caution and awareness, especially for individuals with pre-existing conditions like sickle cell disease. Ahmed et al. [19] explored the use of deep learning models for omicron screening from chest X-rays, suggesting their potential as an effective alternative in regions with limited testing resources. Gidde et al. [20] addressed the challenge of limited training data for AI-based omicron diagnosis using X-ray images by introducing CovBaseAI, an explainable diagnostic tool. This tool combines an ensemble of deep learning models with an expert decision system (EDS), trained on pre-omicron datasets to diagnose COVID-Pneumonia. CovBaseAI's effectiveness is validated on two datasets, achieving an accuracy of 87% and a high negative predictive value of 98% in a dataset from an Indian quarantine center. Abdulah et al. [21] presented a two-module pipeline leveraging convolutional neural networks and advanced processing techniques for distinguishing between COVID and non-COVID cases in CXRs. Their approach includes generating lung masks, applying the Wavelet Scattering Transform, and utilizing an ensemble model for classification. This method, supported by a user-friendly graphical interface, also provides high-resolution heat maps to identify affected lung areas. Gao et al. [22] introduced a diagnostic platform using a deep convolutional neural network to assist radiologists in differentiating between omicron pneumonia and non-omicron pneumonia from chest X-ray images. Their CNN model, trained on a diverse dataset, demonstrates a potential to significantly improve the accuracy and efficiency of CXR interpretation for omicron detection. Panwar et al. [23] explored omicron detection using Convolutional Neural Networks within a deep learning framework, aiming to distinguish omicron cases from other respiratory conditions. Their CNN models achieve an impressive accuracy rate of approximately 98% on a test dataset, highlighting the efficacy of deep learning in diagnosing omicron from chest X-rays.

III. RESEARCH METHODOLOGY

In this paper, a three-layered model is presented in fig 1. for lung infection detection. Their layers are described below in sub-sections. Figure 1 shows the architecture of the proposed detection model for automatic lung disease classification

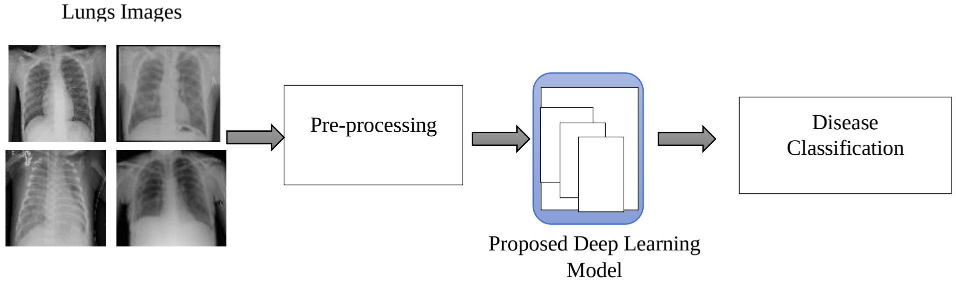


Figure 1: System Architecture

The flowchart of the working is presented below in figure 2.

The proposed architecture has demonstrated both training and testing functions for lung disease detection using the main steps such as pre-processing, deep features extraction and classification. For quality improvement, each chest X-ray image has first pre-processed using digital filter. The improved chest X-ray image has further fed to the robust stepwise learning model for the estimation of the features. The proposed step-wise learning model effectively assists the automatic features learning from the pre-processed chest X-ray images.

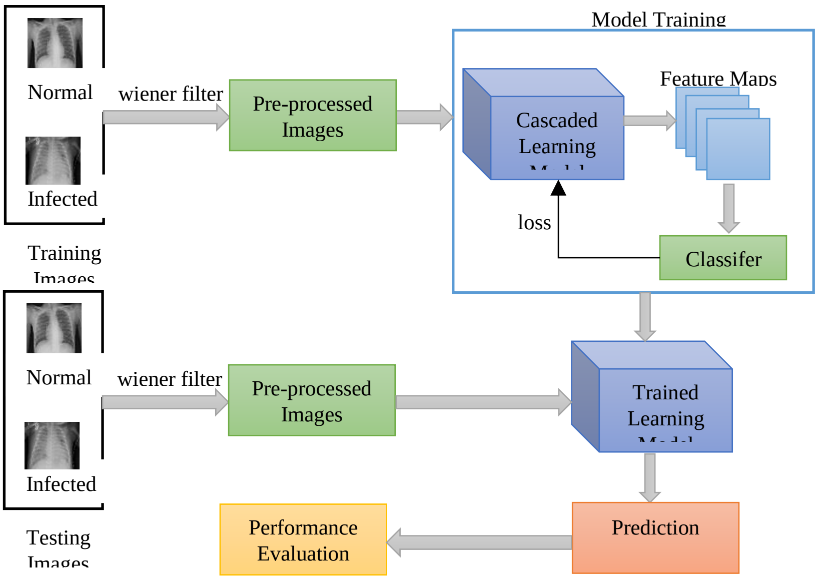


Figure 2: Flowchart of Working

Pre-Processing: The input lung disease images are resized in size 224×224×3. Each image in each disease type contains different samples. In this step wiener filter is used to enhance the image quality. The wiener filter computes the local variance and mean around each pixel and then applied pixel-wise wiener filtering to produce the filtered image.

Fine-tuned Cascaded Learning: In this work a cascaded transfer learning model is presented, as illustrated in Fig 3.

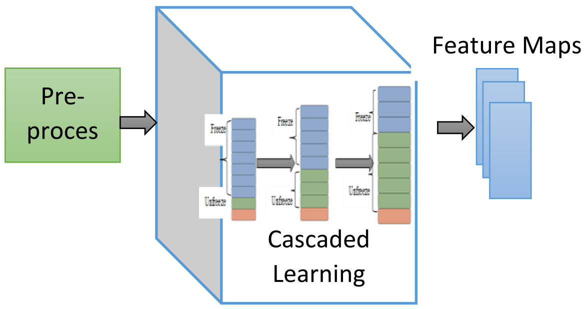


Figure 3: Fine-tuned Cascaded Learning

As illustrated in Fig. 3, fine-tuned cascaded learning model is presented in which some layers are gradually freezeout.

Initially, all layers except the last of a pre-trained ResNet50 model are frozen, with a dense layer added to the unfrozen last layer. As training progresses, additional layers are gradually unfrozen, retrained, and information is exchanged sequentially to subsequent layers. This process continues until the final layer, where more layers are unfrozen and a classifier is introduced for disease classification. The model's novel approach lies in its focus on efficient information exchange and faster training, different from the traditional Freeze out method which primarily aims at

A Residual Neural Network (ResNet) is a type of Artificial Neural Network that utilizes residual blocks to build deep network architectures. ResNet-50, a specific variant, follows this design:

• Initial Convolution and Pooling: The network begins with a convolution layer using a 7×7 kernel with 64 filters and a stride of 2. This is followed by max pooling with a stride of 2.

• Residual Blocks: The architecture comprises several residual blocks arranged in phases:

• The first phase has three blocks, each with three layers of convolutions: 1×1 (64 filters), 3×3 (64 filters), and 1×1 (256 filters), totaling nine layers.

• The second phase repeats a similar structure four times, but with different filter sizes: 1×1 (128 filters), 3×3 (128 filters), and 1×1 (512 filters), resulting in 12 layers.

• The third phase includes six blocks with the layers 1×1 (256 filters), 3×3 (256 filters), and 1×1 (1024 filters), adding up to 18 layers.

Parameters

$$\text{Accuracy} = (\text{TP} + \text{TN})/\text{TP} + \text{TN} + \text{FP} + \text{FN} \quad (1)$$

Recall / Detection Rate = TP/ (TP+FN) (2)

Precision = TP/ (TP+FP) (3)

F1_Score = 2* (Precision* Recall) / (Precision + Recall) (4)

Dataset Used: For simulation and experimental analysis, this work has used the x-ray images. The dataset consists of x-ray images specifically from the omicron Radiography Database [24][25]. This indicates that the study utilizes x-ray imaging to analyze aspects related to omicron.

speed. This stepwise transfer learning approach not only ensures faster convergence and reduced training time but also maintains the pre-trained weights in the frozen layers. The total trainable parameters are computed by summing up the parameters at each training step and dividing by the total number of steps, ensuring that retraining occurs only on the unfrozen layers.

In this cascaded learning pre-trained ResNet-50 model is used.

• The final phase has three blocks of 1×1 (512 filters), 3×3 (512 filters), and 1×1 (2048 filters) convolutions, contributing nine layers.

• Ending Layers: The network concludes with an average pooling layer, a fully connected layer of 1000 nodes, and a softmax function, comprising one layer.

In total, the ResNet-50 architecture includes 50 layers, leveraging the residual connections to enable training of deeper networks without the vanishing gradient problem.

4. Results and Discussion

The paper presents the implementation detail of the models presented. In this work, simulation experiments are presented under following hardware and software requirements.

- 16GB RAM
- 1TB HDD
- Windows 64 bit
- Python

Performance

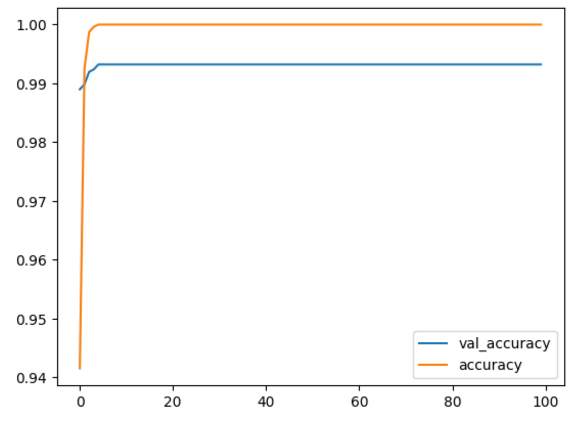


Figure 4: Training Accuracy Performance of Proposed Model

Figure 4 shows the training and validation accuracy of the proposed model in which the model have achieved approx. 99% accuracy. Similarly, figure 5 presents the training loss graph. Fig 6 shows the Receiver Operating Characteristic (ROC) analysis of the proposed model for different classes and shows higher prediction accuracy. Table 1 shows the testing result of the proposed model with approx. 99% accuracy.

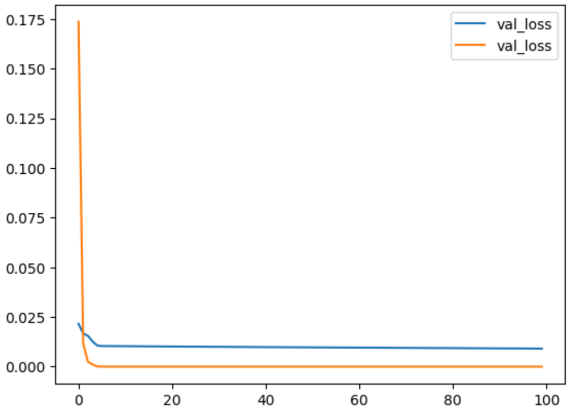
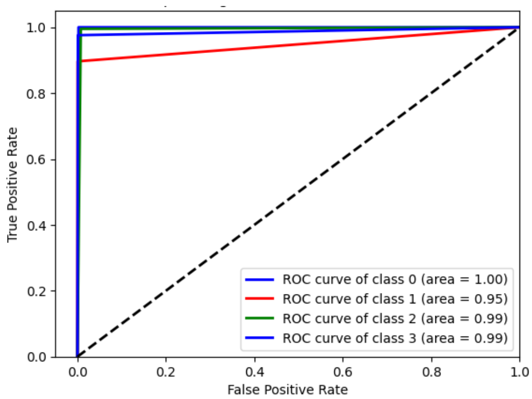


Figure 5: Training Loss Performance of Proposed Model



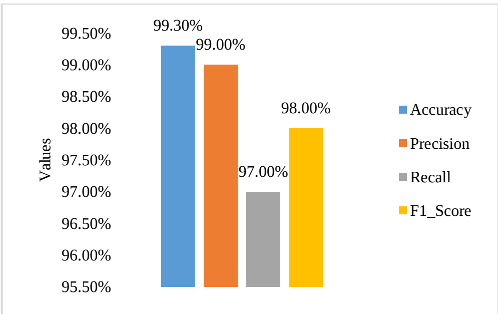


Figure 7: Testing Performance Analysis

Figure 7 presented the performance analysis for lung infection chest x-ray detection on performance parameters such as accuracy, precision, recall and f1-score. The Fig 7 indicates highly effective performance of a lung infection detection system using chest X-rays. The system demonstrates high accuracy (99.3%), precision (99%), and a good balance between recall (97%) and F1 score (98%), suggesting it is reliable in identifying lung infection cases with minimal false positives and a strong ability to identify true cases.

Figure 6: ROC Curve of Proposed Model

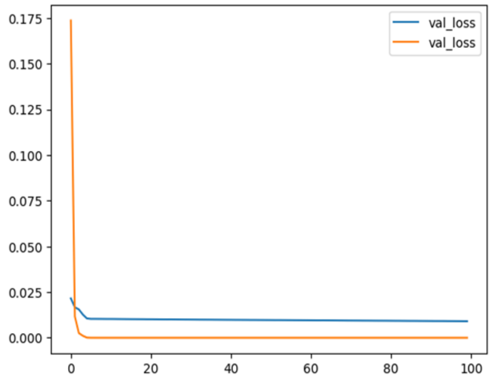


Table 1: Performance Analysis of Proposed Model

Disease	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Pneumonia	99.3	99.87%	99.87%	99.87%
Omicron (coronavirus)		98.00%	90.00%	94.00%
Normal		99.00%	99.87%	99.00%
Tuberculosis		99.00%	98.00%	98.00%

The comparative analysis presented in Table 2. It highlights the performance of different models in lung disease detection from X-ray images. The proposed Cascaded ResNet50 model, incorporating Wiener Filter pre-processing, achieves a high accuracy and precision (99%) comparable to the existing ResNet50 model, with significantly low training parameters. This shows that the proposed model is lightweight. It supports multi-class classification, unlike the binary classification of the existing ResNet50, and outperforms the RNN-LSTM model in accuracy, precision, and recall. This indicates the proposed model's efficiency and effectiveness in diagnosing various lung diseases.

Table 2: Comparative Analysis

Features	Existing [1]	Existing [10]	Proposed
Model	RNN-LSTM	ResNet50	Cascaded ResNet50
Pre-processing	-	No	Wiener Filter
Accuracy	94.31	99	99

Precision	88.89	-	99
Recall	95.41	92	97
Classification	Multi	Binary	Multi
Training Parameters	-	23M	0.4M

V. CONCLUSION AND FUTURE SCOPE

In conclusion, this study represents a significant advancement in the field of medical imaging, particularly in the accurate prediction and differentiation of lung diseases such as omicron and pneumonia using chest X-ray images. The adoption of a transfer learning model, complemented by a robust step-wise learning approach, effectively addresses the challenges faced by medical experts in distinguishing between these two closely related lung conditions. The key to the model's success lies in its

meticulous pre-processing phase, where digital filtering enhances the quality of X-ray images. This enhancement is critical for the subsequent deep feature extraction and classification stages, leading to the automatic and effective learning of features from the processed images. Then deep feature is passed to Cascaded learning model, which not only demonstrates an impressive accuracy rate of 99% but also significantly reduces computational demands through a lower number of training parameters. This reduction in complexity makes model both efficient and lightweight, making it a highly valuable tool for healthcare professionals. The model's efficiency, coupled with its high accuracy offering a reliable and efficient method for early detection and diagnosis of critical lung diseases. In future, this work will be extended to identify the percentage infected portion of lungs and its severity level for recommendation of treatment in real-time application over cutting edge technologies such as IoT.

Conflict of Interest: The corresponding author, on behalf of all authors, confirms that there are no conflicts of interest to disclose.

REFERENCES

[1] Goyal, Shimpy, and Rajiv Singh. "Detection and classification of lung diseases for pneumonia and Covid-19 using machine and deep learning techniques." Journal of Ambient Intelligence and Humanized Computing 14.4 (2023): 3239-3259.

[2] Yenurkar, G. K., & Mal, S. (2022). Effective detection of COVID-19 outbreak in chest X-Rays using fusionnet model. The Imaging Science Journal, 70(8), 535-555.

[3] Zhang, J., Xie, Y., Pang, G., Liao, Z., Verjans, J., Li, W., ... & Xia, Y. (2020). Viral pneumonia screening on chest X-rays using confidence-aware anomaly detection. IEEE transactions on medical imaging, 40(3), 879-890.

[4] Singh, R. K., Pandey, R., & Babu, R. N. (2021). COVIDScreen: explainable deep learning framework for differential diagnosis of COVID-19 using chest X-rays. Neural Computing and Applications, 33, 8871-8892.

[5] Okolo, G. I., Katsigiannis, S., Althobaiti, T., & Ramzan, N. (2021). On the use of deep learning for imaging-based COVID-19 detection using chest X-rays. Sensors, 21(17), 5702.

[6] Jaiswal, A. K., Tiwari, P., Rathi, V. K., Qian, J., Pandey, H. M., & Albuquerque, V. H. C. (2020). Covidpen: A novel covid-19 detection model using chest x-rays and ct scans. Medrxiv, 2020-07.

[7] Guarrasi, V., D'Amico, N. C., Sicilia, R., Cordelli, E., & Soda, P. (2022). Pareto optimization of deep networks for COVID-19 diagnosis from chest X-rays. Pattern Recognition, 121, 108242.

[8] Saha, P., Mukherjee, D., Singh, P. K., Ahmadian, A., Ferrara, M., & Sarkar, R. (2021). Retracted article: Graphcovidnet: A graph neural network based model for detecting COVID-19 from ct scans and x-rays of chest. Scientific reports, 11(1), 8304.

[9] Ahmed, S., Yap, M. H., Tan, M., & Hasan, M. K. (2020). Reconet: Multi-level preprocessing of chest x-rays for covid-19 detection using convolutional neural networks. medrxiv, 2020-07.

[10] Ahishali, M., Degerli, A., Yamac, M., Kiranyaz, S., Chowdhury, M. E., Hameed, K., ... & Gabbouj, M. (2021). Advance warning methodologies for covid-19 using chest x-ray images. Ieee Access, 9, 41052-41065.

[11] Alharbi, R. S., Alsaadi, H. A., Manimurugan, S., Anitha, T., & Dejene, M. (2022). Multiclass classification for detection of COVID-19 infection in chest X-rays using CNN. Computational Intelligence and Neuroscience, 2022.

[12] Gourdeau, D., Potvin, O., Biem, J. H., Cloutier, F., Abrougui, L., Archambault, P., ... & Duchesne, S. (2022). Deep learning of chest X-rays can predict mechanical ventilation outcome in ICU-admitted COVID-19 patients. Scientific Reports, 12(1), 6193.

[13] Elsharkawy, M., Sharafeldeen, A., Taher, F., Shalaby, A., Soliman, A., Mahmoud, A., ... & El-Baz, A. (2021). Early assessment of lung function in coronavirus patients using invariant markers from chest X-rays images. Scientific reports, 11(1), 12095.

[14] Kumar, R., Arora, R., Bansal, V., Sahayasheela, V. J., Buckchash, H., Imran, J., ... & Raman, B. (2020). Accurate prediction of COVID-19 using chest X-ray images through deep feature learning model with SMOTE and machine learning classifiers. MedRxiv, 2020-04.

[15] Muhammad, G., Alqahtani, S., & Alelaiwi, A. (2021). Pandemic management for diseases similar to COVID-19 using deep learning and 5G communications. Ieee Network, 35(3), 21-26.

[16] Gulati, A. (2020). LungAI: A Deep Learning Convolutional Neural Network for Automated Detection of COVID-19 from Posteroanterior Chest X-Rays. MedRxiv, 2020-12.

[17] Gupta, A., Sheth, P., & Xie, P. (2022). Neural architecture search for pneumonia diagnosis from chest X-rays. Scientific reports, 12(1), 11309.

[18] Alkindi, S., Elsadek, R. A., & Pathare, A. V. (2021). Safety warning for ChAdOx1 nCov-19 vaccine in patients with sickle cell disease. Mediterranean Journal of Hematology and Infectious Diseases, 13(1).

[19] Ahmed, F., Bukhari, S. A. C., & Keshtkar, F. (2021). A deep learning approach for COVID-19 8 viral pneumonia screening with x-ray images. Digital Government: Research and Practice, 2(2), 1-12.

[20] Gidde, P. S., Prasad, S. S., Singh, A. P., Bhatheja, N., Prakash, S., Singh, P., ... & Dash, D. (2021). Validation of expert system enhanced deep learning algorithm for automated screening for COVID-Pneumonia on chest X-rays. Scientific Reports, 11(1), 23210.

[21] Abdulah, H., Huber, B., Abdallah, H., Palese, L. L., Soltanian-Zadeh, H., & Gatti, D. L. (2022). A hybrid pipeline for Covid-19 screening incorporating lungs segmentation and wavelet based preprocessing of chest X-Rays. MedRxiv, 2022-03.

[22] Gao, T., & Wang, G. (2020). Chest X-ray image analysis and classification for COVID-19 pneumonia detection using Deep CNN. medRxiv, 2020-08.

[23] Panwar, A., Dagar, A., Pal, V., & Kumar, V. (2021, May). COVID 19, pneumonia and other disease classification using chest X-ray images. In 2021 2nd international conference for emerging technology (INCET) (pp. 1-4). IEEE.

[24] M. E. H. Chowdhury et al., "Can AI Help in Screening Viral and COVID-19 Pneumonia?," in IEEE Access, vol. 8, pp. 132665-132676, 2020, doi: 10.1109/ACCESS.2020.3010287.

[25] El-Shafai, W., Abd El-Samie, F.: Extensive COVID-19 X-ray and CT chest images dataset. Mendeley Data V3 (2020)