LUNGCAREAI: INNOVATING RESPIRATORY DIAGNOSIS THROUGH ADVANCED DEEP LEARNING TECHNIQUES

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Abstract The LungCare AI system, tailored for X-ray and CT scan [3] image processing, employs diverse enhancement techniques to mitigate noise and enhance contrast. Following the pre-processing phase, a pre-trained Convolutional Neural Network (CNN) model is employed to analyze features like nodule shape, size, and distribution pattern. Cross-referencing with a comprehensive knowledge base ensures accurate identification, subject to verification by medical professionals, enabling prompt interventions to potentially avert disease progression. The proposed architecture streamlines appointment booking and image uploading, ensuring a secure workflow overseen by authorized personnel with a focus on prioritizing medical data confidentiality. Recent advances in deep learning have transformed medical image analysis, particularly in diagnosing lung diseases. Inspired by the brain’s structure, this sub-field of machine learning[2] excels in identifying patterns without hand-designed features. The transformative impact of the ”LungCare AI” application, harmonizing innovative technology and user-centric design, signifies a positive shift towards improved respiratory health outcomes.

Index Terms CNN, Deep Learning, Chest X-Ray, CT Scan

I. INTRODUCTION

In the contemporary healthcare environment, the urgency to address respiratory challenges has reached unprecedented levels, necessitating a profound examination of transformative technologies. The work meticulously explores the escalating need for advancements, with a specific focus on the early detection and management of diseases affecting lungs. Leading this technological revolution are advanced Deep Learning (DL) models [10], distinguished for their proficiency in deciphering subtle patterns indicative of respiratory conditions. The paper endeavors to illuminate the pivotal role played by these advancements in reshaping the entire landscape of respiratory healthcare.

Beyond the realms of diagnostics, the work recognizes that comprehensive care demands a holistic approach. To this end, it underscores the imperative integration of features such as appointment booking and direct chat communication with healthcare professionals. In an era where patient engagement and proactive management stand as paramount objectives, the incorporation of these user-centric elements becomes crucial. By shedding light on the symbiotic relationship between advanced DL technology and patient-oriented functionalities, the work envisions not only improved healthcare outcomes but also a heightened quality of life for individuals navigating the intricate challenges posed by respiratory health issues. This holistic perspective lays the groundwork for a transformative paradigm, fostering collaborative and informed relationships between patients and healthcare providers, ultimately contributing to an elevated standard of care and well-being.

II. LITERATURE SURVEY

A. CXR-NET MODEL

The approach[11] focuses on enhancing disease classification accuracy through image preprocessing, employing the U-Net model for lung segmentation. This model's architecture facilitates more precise segmentation by concatenating encoder and decoder features, optimizing with a hybrid loss function.

For image enhancement, Contrast Limited Adaptive Histogram Equalization (CLAHE) is utilized to address low contrast in Chest X-ray (CXR) images, crucial for analysis, avoiding noise amplification seen with traditional histogram equalization methods.

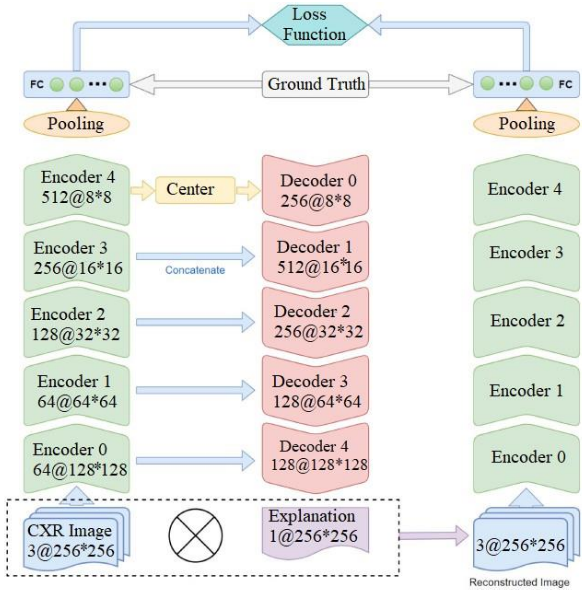

Fig. 1: The architecture of the proposed classification and explanation model, CXR-Net.

The CXR-Net model combines disease classification and pixel-level visual explanation, utilizing an Encoder-Decoder-Encoder structure. Two encoders and one decoder are employed, with shared weights, extracting features for disease identification and reconstructing heat-maps. This facilitates highlighting influential areas for classification.

Utilizing two encoders, the model extracts features from both input and reconstructed images for disease type identification, transforming them through average pooling and fully connected layers. Classifier architecture can adapt from established CNN models.

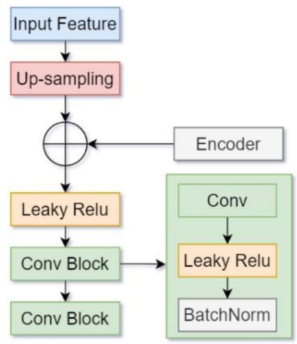

Fig. 2: The structure of the decoder in the model.

Dataset comprises 6499 CXR images [4], categorized into Healthy, Bacterial Pneumonia, and Viral Pneumonia, including COVID-19 cases. Lung segmentation improves COVID-19 diagnosis, with deeper ResNet models enhancing performance.

The model, compatible with various computing platforms, demonstrates efficient performance, making it suitable for deployment in healthcare settings. It excels in visual explanation, providing sharp heatmaps aiding in COVID-19 pneumonia diagnosis.

B. MULTI VIEW - KNOWLEDGE BASED COLLABORATIVE MODEL

The study [12] conducts the classification of lung nodules as either benign or malignant on chest CT scans[7]. It employs a multi-view approach, decomposing each three-dimensional lung nodule image into 9 fixed plane views, and utilizing a knowledge-based collaborative strategy. Three ResNet-50 neural networks are utilized to analyze three fundamental properties of a nodule: Appearance, Shape, and Voxel heterogeneity. Additionally, a penalty loss function is employed to regulate the balance between false negatives and false positives.

The methodology of the algorithm encompasses four major steps: extraction of two-dimensional nodule slices from the nine view planes, extraction of patches representing the overall appearance, heterogeneity in voxel values, and shapes on two-dimensional nodule slices, construction of nine submodels, and training each of them using the extracted patches from each plane view, followed by the construction and training of the model for classification. The model's performance is evaluated using the LIDC-IDRI database, demonstrating superior accuracy compared to state- of-the-art approaches. Moreover, the study compares the model's performance with other deep learning methods and traditional CADs, illustrating the effectiveness of the multi-view learning approach. In summary, the MV-KBC model integrates a multi-view approach and a penalty loss function to accurately segregate lung nodules [5] as either non-cancerous or cancerous, highlighting the potential of deep learning in medical imaging and contributing to early lung cancer detection.

1) Multi-View Slice Extraction: The method involves decomposing three-dimensional lung nodules into nine fixed view planes, including coronal, axial, sagittal, and six diagonal planes. Two-dimensional nodule slices are extracted from these views, and patches representing overall appearance, voxel value heterogeneity, and shapes are further extracted. Each submodel, fine-tuned to characterize specific nodule features, aims to leverage complementary information from different perspectives, thereby improving classification accuracy. Illustrated in Fig. 3.

2) OA, HVV and HS Patches Extraction: The approach involves decomposing 3D lung nodules into nine fixed view planes and extracting 2D nodule slices from each view. Each submodel utilizes pre-trained ResNet-50 networks to characterize overall appearance (OA), voxel value heterogeneity (HVV), and shape features (HS). The method aims to enhance accuracy by leveraging information from different perspectives, and data augmentation is applied to mitigate overfitting.

3) KBC Submodel: The proposed submodel describes lung nodules from various perspectives, utilizing pre-trained ResNet-50 networks fine-tuned to capture specific nodule characteristics. Patches representing overall appearance, voxel value heterogeneity, and shapes are extracted from two-dimensional nodule slices on each view plane, and the outputs from the networks are

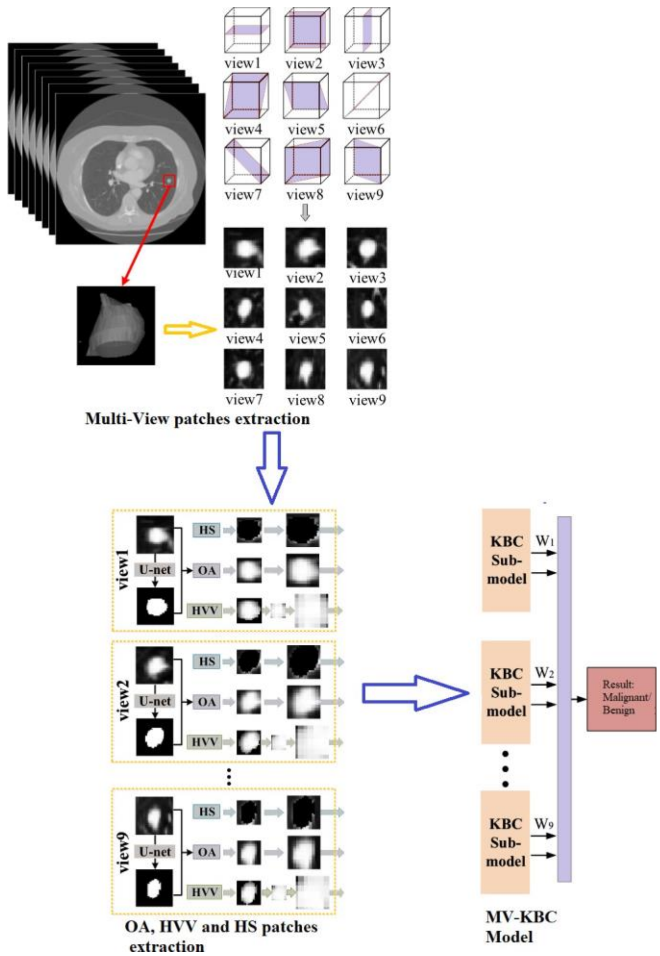

Fig. 3: Framework of the proposed algorithm

combined for classification. The KBC submodel aims to enhance accuracy by leveraging complementary features captured by ResNet-50 networks. The submodel's architecture is illustrated in Fig 4.

After feature extraction, the outputs from the three networks are passed through fully connected (Fc) layers and then integrated in a collaborative unit (U), which combines the features to make a final classification decision.

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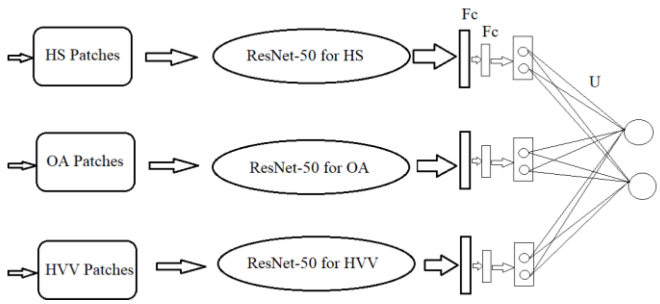

Fig. 4: Architecture of a submodel for a specific view

4) MV-KBC Model: The complete model comprises nine KBC sub-models, featuring a unique architecture with a penalty cross-entropy loss to address potential cost imbalances in misclassifications. The model has demonstrated promising accuracy, sensitivity, precision, and F1 score, particularly in distinguishing nodules within each Median Malignancy Level subgroup. However, the study acknowledges the risk of overfitting due to limited training data.

5) Performance Analysis: The MV-KBC algorithm proposed here has achieved 91.60% Accuracy, 86.52% Sensitivity, and 87.75% Precision in classifying lung nodules. It also received an F1 score of 87.13% and thus have proved to be a viable tool in the domain.

C. DETRAC DEEP-CNN MODEL[1]

The dataset utilized in the research [1] comprises chest X-ray (CXR) images sourced from multiple hospitals and institutions, encompassing normal cases, COVID-19 cases, and severe acute respiratory syndrome (SARS) cases. However, the dataset presents challenges due to inconsistencies in image intensity and irregularities in data distribution. Specifically, the dataset employed in the experiments includes 80 samples of normal CXR images from the Japanese Society of Radiological Technology (JSRT), with dimensions of 4020 × 4892 pixels. Additionally, CXR images of COVID-19 and SARS cases from another undisclosed source are included, comprising 105 samples of COVID-19 cases and 11 samples of SARS cases, with dimensions of 4248 × 3480 pixels.

The methodology employed in the study revolves around the DeTraC (Decompose, Transfer, and Compose) architecture, which consists of three phases. Initially, the backbone pre-trained Convolutional Neural Network (CNN) model of DeTraC is trained to extract deep local features from each image. Subsequently, the class-decomposition layer simplifies the local structure of the data distribution, followed by training using a sophisticated gradient descent optimization method. Finally, a class-composition layer refines the final classification of the images. This process involves partitioning each class within the image dataset into sub-classes using k-means clustering, which aids in simplifying the data distribution and enhancing classification performance. The obtained sub-classes are then assembled back to produce the final predictions based on the original image dataset.

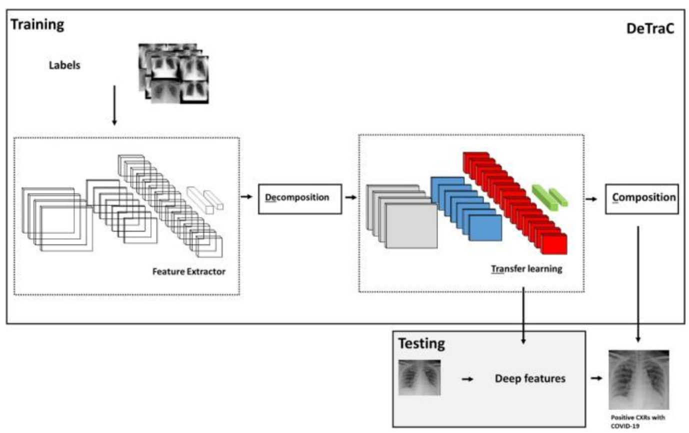

Fig. 5: Decompose, Transfer, and Compose (DeTraC) model for the detection of COVID-19 from CXR images

Transfer learning is a crucial aspect of the methodology, where pre-trained CNN models [8] are adapted to the new task of COVID-19 classification using the collected CXR image dataset. This approach capitalizes on the learned knowledge from the pre-trained models, facilitating faster and more efficient training. Several ImageNet pre-trained models are tested and compared in both

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shallow and deep-tuning modes to optimize the transfer learning process, considering the limited availability of training data and the potential for overfitting due to stochastic gradient descent (SGD) fluctuations in the objective/loss function.

Some advantages of using this advanced DeTraC method for identifying CoViD-19 infected lung images from normal healthy lungs are namely effective classification of the lung images, limited annotated data, and robustness.

While also some disadvantages exist like the lack of comparative analysis with a wide variety of custom CNN models.

Title	Technique Used	Advantages	Disadvantages
CXR-Net: A Multitask Deep Learning Network for Explainable and Accurate Diagnosis of COVID-19 Pneumonia From Chest X-Ray Images[5]	CLAHE and CXR-Net	Pixel-Level Explainability	Computational Complexity with large Kernel Sizes
Knowledge-based Collaborative Deep Learning for Benign-Malignant Lung Nodule Classification on Chest CT[2]	MV-KBC approach	Multi-view learning, Collaborative submodels	Nodule segmentation accuracy affect classification
Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network[11]	DeTraC DeepCNN	Can handle Data Irregularities	Multi-stage processing results in decrement in efficiency of the overall system

Table 1: Comparative Study of the reference papers

III. PROPOSED SYSTEM

The proposed LungCare AI system is tailored for processing X-Ray or CT scan images of the lungs.The doctor's schedule provides accessible consultation times, allowing patients to schedule appointments. The doctor is authorized to upload the patient's medical image, which undergoes pre-processing for model input. The system generates prediction results and a report, aiding in disease diagnosis. The doctor exclusively forwards medical images to the admin for result generation from the model, with the report comprising prediction details. This process ensures a streamlined and secure workflow, maintaining the confidentiality of medical data.

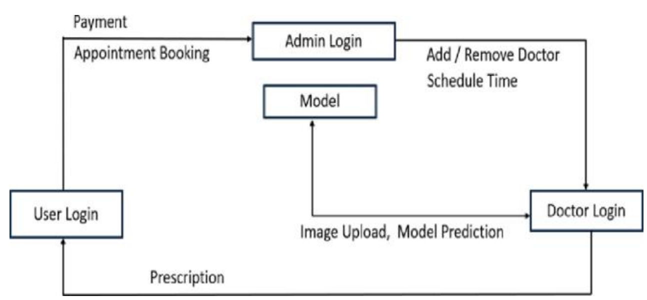

Fig. 6: Proposed Architecture

A. Process Overview

1. Dataset creation and Splitting:

The datasets are obtained from Kaggle and contains diverse lung images. The dataset included 2000 X-Ray images each of the four diseases excluding the Lung cancers, and the Lung Cancers (both malignant and benign) were trained using CT scan images, 250 images for each cancer type. The Dataset division is fundamental to prevent overfitting, a scenario where the model excessively fits to the training data, thereby compromising its ability to accurately predict on unseen data.

2. Preprocessing of the acquired images:

This ensures uniformity and helps in efficient model training. The standardization procedure includes Resizing, Rescaling, Shear transformation, Flipping and Zooming

3. Extract relevant features from the Preprocessed images:

Features like Texture patterns , Lesion Characteristics , nodules are crucial for detecting and classifying different types of lung diseases

4. Model Training:

The extracted features are used as input to the model. The model is Custom made CNN model is implemented using Tensorflow library of Python. The layers are stacked sequentially to define the architecture. This process of training the CNN model on the dataset is represented in Algorithm 1.

5. Use the trained CNN to predict the disease:

The system is capable of providing the predicted lung disease for each image that is being uploaded.The class with the highest probability is typically considered the prediction.

6. Evaluate the performance and Save the Trained model:

Once the CNN model is trained, its performance is evaluated using the validation set. This is typically done by computing metrics such as accuracy, precision, recall, and F1 score. If the performance of the model is not satisfactory, the hyperparameters can be tuned to improve its performance.

Algorithm 1 CNN Model Training

```
I ←set of input images
Split Dataset : Training, Validation
for each batch in Training: do
    shear, zoom, rescale, flip(batch)
end for
for each batch in Validation: do
    rescale(batch)
end for
model.compile()
model.fit(Training,Validation)
model.save()
evaluate(model)
```

IV. Experimental Analysis and Results

The CNN model was trained on both X-Ray images and CT images. The model after training for around 50 epochs yielded the ability to identify medical images of six different diseases (namely, Malignant Lung cancer, Benign lung cancer, Tuberculosis [9], CoViD-19, Viral Pneumonia and Bacterial Pneumonia) with a sufficient enough accuracy of 97.49%. The model classifies input test images into one of eight classes (six diseases, one normal healthy lung class in X-Ray image, and another normal healthy lung class in CT image). A delay of not more than 3 seconds is observed between the upload of a test image and disease prediction.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$TP = TruePositive$$

$$TN = TrueNegative$$

$$FP = FalsePositive$$

$$FN = FalseNegative$$

The accuracies of the proposed system in comparison to those studied in the litertature survey is cited in Table 2.

Method	Accuracy (%)
X. Zhang et al [11]	87.90
Y. Xie et al [12]	91.60
Asmaa Abbas et al [1]	97.35
Proposed System	97.49

Table 2: Comparison of accuracy

Training-validation accuracy curve of the proposed model is shown in Fig. 7.

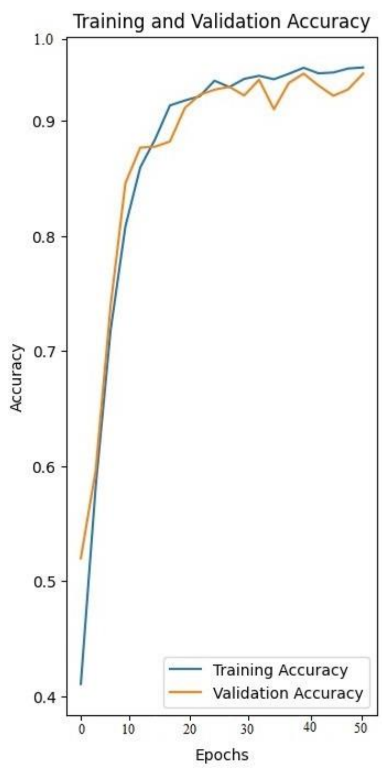

Fig. 7: Training-Validation Accuracy curve

The graph shown in Fig. 8 gives a comparative idea of the proposed system with those referenced.

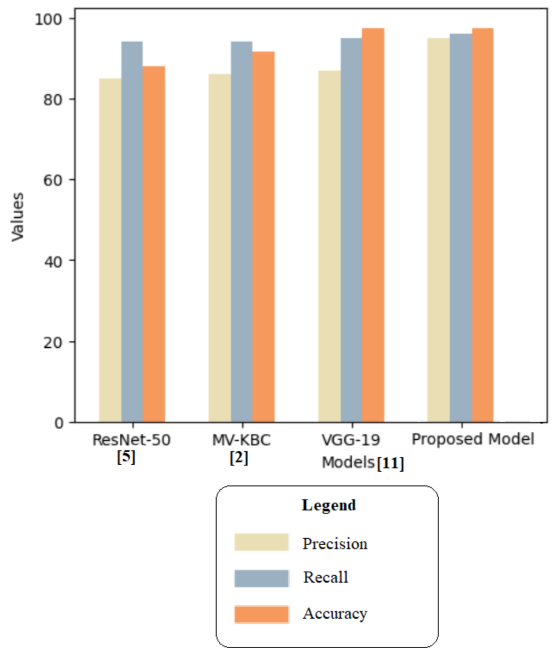

Fig. 8: Comparison with related works

The confusion matrix in Fig. 9 illustrates the performance of a classification model in predicting various lung conditions based on medical images. Each cell indicates the number of instances where the actual class (true label) corresponds to the predicted class, highlighting the model's accuracy and any misclassifications across different categories such as bacterial, viral, COVID-19 [6], and more.

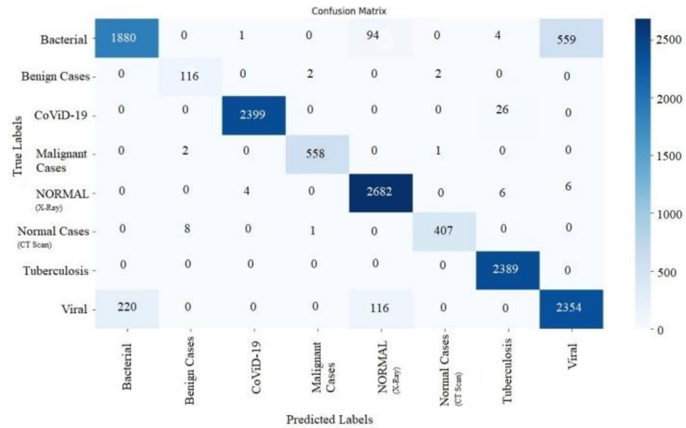

Fig. 9: Confusion Matrix of the Model

V. Conclusion

In conclusion, this approach examines the ”Lung Care AI” application, highlighting its pivotal role in revolutionizing respiratory healthcare. Through the strategic fusion of innovative technology and user-centric design, the mobile health solution utilizes deep learning algorithms to swiftly and accurately predict lung diseases. The integration of features like appointment booking and direct communication with healthcare professionals enhances the user experience. With robust report generation capabilities, the application becomes a valuable tool for users and healthcare providers. As a beacon of progress in mobile health, ”Lung Care AI” signifies a positive shift towards improved respiratory health outcomes, showcasing the transformative impact of artificial intelligence in healthcare diagnostics.

References

[1] Abbas, Asmaa & Abdelsamea, Mohammed & Gaber, Mohamed. (2021). Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. Applied Intelligence. 51. 1-11. 10.1007/s10489-020-01829-7

[2] E. A. A. Alaoui, S. C. K. Tekouabou, S. Hartini, Z. Rustam, H. Silkan and S. Agoujil, ”Improvement in automated diagnosis of soft tissues tumors using machine learning,” in Big Data Mining and Analytics, vol. 4, no. 1, pp. 33-46, March 2021, doi: 10.26599/BDMA.2020.9020023

[3] M. A. Alzubaidi, M. Otoom and H. Jaradat, ”Comprehensive and Comparative Global and Local Feature Extraction Framework for Lung Cancer Detection Using CT Scan Images,” in IEEE Access, vol. 9, pp. 158140-158154, 2021, doi: 10.1109/ACCESS.2021.3129597

[4] Malik H, Anees T, Din M, Naeem A. CDC-Net: multi-classification convolutional neural network model for detection of COVID- 19, pneumothorax, pneumonia, lung Cancer, and tuberculosis using chest X-rays. Multimed Tools Appl. 2023;82(9):13855-13880. doi: 10.1007/s11042-022-13843-7

[5] M. Obayya, M. A. Arasi, N. Alruwais, R. Alsini, A. Mohamed and I. Yaseen, ”Biomedical Image Analysis for Colon and Lung Cancer Detection Using Tuna Swarm Algorithm With Deep Learning Model,” in IEEE Access, vol. 11, pp. 94705-94712, 2023, doi: 10.1109/ACCESS.2023.3309711

[6] Punn NS, Agarwal S. Automated diagnosis of COVID-19 with limited posteroanterior chest X-ray images using fine-tuned deep neural networks. Appl Intell (Dordr). 2021;51(5):2689-2702. doi: 10.1007/s10489-020-01900-3

[7] P. Yadav, N. Menon, V. Ravi and S. Vishvanathan, ”Lung-GANs: Unsupervised Representation Learning for Lung Disease Classification Using Chest CT and X-Ray Images,” in IEEE Transactions on Engineering Management, vol. 70, no. 8, pp. 2774-2786, Aug. 2023, doi: 10.1109/TEM.2021.3103334

[8] S. Shirsat and S. V. Kedar, ”Lungs Diseases Prediction based on Convolutional Neural Net- work,” 2021 International Conference on Computing, Communication and Green Engineer- ing (CCGE), Pune, India, 2021, pp. 1-5, doi: 10.1109/CCGE50943.2021.9776371

[9] S. Urooj, S. Suchitra, L. Krishnasamy, N. Sharma and N. Pathak, ”Stochastic Learning-Based Artificial Neural Network Model for an Automatic Tuberculosis Detection System Using Chest X-Ray Images,” in IEEE Access, vol. 10, pp. 103632-103643, 2022, doi: 10.1109/AC CESS.2022.3208882.

[10] S. Z. Y. Zaidi, M. U. Akram, A. Jameel and N. S. Alghamdi, ”Lung Segmentation-Based Pulmonary Disease Classification Using Deep Neural Networks,” in IEEE Access, vol. 9, pp. 125202-125214, 2021, doi: 10.1109/ACCESS.2021.3110904.

[11] X. Zhang et al., ”CXR-Net: A Multitask Deep Learning Network for Explainable and Accurate Diagnosis of COVID-19 Pneumonia From Chest X-Ray Images,” in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 2, pp. 980-991, Feb. 2023, doi: 10.1109/JBHI.2022.3220813

[12] Y. Xie et al., ”Knowledge-based Collaborative Deep Learning for Benign-Malignant Lung Nodule Classification on Chest CT,” in IEEE Transactions on Medical Imaging, vol. 38, no. 4, pp. 991-1004, April 2019, doi: 10.1109/TMI.2018.2876510.