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ADVANCES IN AI FOR PULMONARY DISEASE DIAGNOSIS USING LUNG X-RAY SCAN AND CHEST MULTI-SLICE CT SCAN

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ABSTRACT

Worldwide, lung cancer, pneumonia, chronic obstructive pulmonary disease, and interstitial lung disease continue to endanger people's health. Conventional methods of diagnosing issues in the lungs often rely on chest x-rays as well as CT and ultra sound scans which need human interpretation . One area that is often taken too slowly and can at times lead to mistakes. This article looks into the most recent developments in deep learning automation systems designed for the diagnosis of chest abnormalities due to pulmonary diseases. Determining the effect of deep learning, namely convolutional neural networks, on the precision and effectiveness of clinical disease detection is the study's goal. Multiple stride deep learning models aimed at automatic recognition of pulmonary diseases will be captured with an emphasis on competition between various architectures of controlled neural nets and their algorithms. Also considered are other problems at the interface of deep learning and large medical datasets such as lack of properly labeled data, justification of model based predictions, and design of clinical decision support systems with user-hoping intelligence. Additionally, it analyzes the pioneering AI-enhanced pulmonary diagnostics and what public health outcomes can be achieved with improved timeliness and accuracy in clinical diagnosis. Afterward, we suggest critical issues that need to be addressed, such as the model verification assumptions and ethical implications regarding the use of global medical data and imaging.
Keywords— Pulmonary diseases, deep learning, chest imaging, diagnostic accuracy, medical AI

1. INTRODUCTION

Respiratory illnesses such as interstitial lung disease (ILD), pneumonia, COPD, and lung cancer are a worldwide concern that contributes greatly to morbidity and mortality across the globe. These diseases have a great impact on healthcare systems and take a toll on millions of people each year. An accurate diagnosis is critical for these conditions. However, unlike current practices, which rely on physicians assessing chest x rays and computed tomography (CT) scans, there are some discrepancy and inefficiency. The growing amount of medical imaging data has complicated the matter further. It has become increasingly important to have dependable automated diagnostic systems. Deep learning, a subset of artificial intelligence AI, has excelled in medical imaging, particularly through convolutional neural networks, best known for their application in image classification and recognition. These models can change the way pulmonary disease is diagnosed by enabling automated chest imaging – something that has been proven to provide consistent, prompt, and tremendously accurate medical image reading.

With regards to X-rays, these are regularly employed as the first point of imaging for screening for most lung diseases, primarily because they are affordable and readily available. However, with these chest X-rays, the two dimensional perspective and comparatively low resolution can sometimes miss critical lesions. On the other hand, CT scans of the chest provide insight using high resolution images in 3D, which is helpful in evaluating the lungs and any abnormalities in great detail. The use of deep learning approaches along with these imaging techniques increase the efficiency of the diagnosis process by

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automatically detecting and classifying abnormalities, thus assisting radiologists and enhancing clinical decisions. The merits of integrating deep learning technologies in chest imaging are significant. These models are capable of processing vast amounts of clinical information in less time without skimping on the quality of work, hence increasing the number of patients diagnosed. In addition, these models are able to detect disease processes at much earlier times through the recognition of microscopic details which clinicians are unable to and thus are a big shift for aiding patient intervention and management. Deep learning will enable observers to remove subjectivity off diagnostic criteria set which will help reduce intra-observer differences and ensure stricter conformity to the set standards of criteria.

This paper comprehensively reviews the development achieved so far in applying deep learning to the diagnosis of lung diseases, using chest X-rays and CT scans. It analyzes the progress in the development of models, evaluates their accuracy and explores their implementation in clinical practice. The review also defines the most important results, present problems, and prospects of efforts in this dynamically developing area of science. While examining the influence of artificial intelligence on the diagnosis of pulmonary diseases, this research aims to harness the power of AI in improving healthcare and patient services. The obstacles of deep learning in chest imaging are numerous and diverse, hence they pose the greatest challenges. These include a requirement for large, well annotated datasets of diverse populations to facilitate the building of comprehensive models, AI algorithms which consider varying imaging technologies, and the integration of AI tools into the existing clinical workflows. In addition, ethical issues such as preserving the privacy of the patients and eliminating biases in AI algorithms ought to be taken into account when devising ways for the application of these technologies in the healthcare domain.

2. LITERATURE SURVEY

The use of neural network algorithms for lung disease classification was explored in [1]. This study utilized the ChestX-ray14 dataset which comprises various lung diseases. The analysis was performed using a variant of the MobileLungNetV2 model. In order to improve the quality of the images, the chest X-rays in the dataset were first enhanced using the CLAHE method, and were subsequently filtered with a Gaussian filter. In addition, model generalization was increased by the use of augmentation. Transfer learning was applied with a remarkable success rate of 91.6% accuracy in diagnosing from chest X-ray images. The ChestX-ray14 dataset is arguably the most important dataset for frontal chest radiography, containing 112,120 bilateral chest X ray images of 30,805 patients for whom 14 diseases and a normal class were recorded. The class No finding corresponds to a case when no abnormal pathological changes are observed.

The research [2] focuses on two-dimensional segmentation and three-dimensional reconstruction of lung CT scans for COVID-19 patients using image processing techniques. The study proposes a methodology that includes pre-processing steps such as contrast stretching, adaptive histogram equalization, and non-linear filtering to enhance CT scan images. The segmentation process employs active contour modeling (Chan-Vese method) and threshold-based segmentation to isolate lung regions and ground-glass opacities (GGO). Morphological operations refine the segmentation results, followed by three-dimensional reconstruction using the marching cubes algorithm and point cloud plotting. The dataset used comprises COVID-19 patients' CT scans from the Harvard Dataverse. The reconstructed lung models were validated using a confusion matrix and intersection over union (IoU), achieving segmentation accuracy values of 92%, 96%, and 97% for different patients, with IoU similarity indices of 42%, 67%, and 77%. The study successfully visualized infected lung regions in three dimensions, aiding in clinical interpretation and potential 3D printing applications for medical diagnosis and patient education.

The study [3] focuses on enhancing early lung cancer detection by integrating Artificial Intelligence (AI) technology with Spiral Computed Tomography (SCT). Given the challenges of traditional screening methods, such as misdiagnosis and difficulty in identifying small nodules, the research explores AI-driven solutions to improve accuracy and efficiency. The approach involves pre-processing CT scan images using techniques like contrast stretching, histogram equalization, and windowing to enhance visibility and highlight critical details. Advanced AI models, including deep learning algorithms, are employed to automatically detect and classify pulmonary nodules as benign or malignant. Multi-slice SCT enables high-resolution imaging, while 3D reconstruction techniques like Volume of Interest (VOI) and Multiplanar Reconstruction (MPR) provide clearer visualization of lung abnormalities.

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The study demonstrates that AI-assisted SCT significantly reduces missed diagnoses, enhances radiologists' interpretation of lung scans, and improves early detection rates. However, challenges remain, such as ensuring AI model consistency across different datasets and validating its effectiveness on a larger scale. Overall, integrating AI with SCT shows great promise in improving lung cancer screening and patient outcomes.

This model was validated with the LIDC-IDRI and LUNA-16 datasets which demonstrated better results during lung cancer detection.Lung cancer takes the lives of many people and remains one of the foremost causes of death worldwide. The likelihood of survival is greatly increased when a case is diagnosed early, and the stage of cancer is accurately assessed. To address the complicated issues related to the diagnosis of lung cancer, the authors of [4] utilized image processing, biomarker-based methods, and automated machine learning techniques. Also, they analyzed and processed CT scan images through Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI). A hybrid neural network model CCDCHNN was developed that integrates Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) to provide more precise cancer diagnosis by fusion of the two models. The diagnostic accuracy is improved by performing final classification with the aid of both networks' outputs. In another study in [5], the focus was on the detection of malignant lung nodules on CT scans and image-based lung cancer classification. Cancerous nodules were detected using deep learning algorithms by the authors. Confidentiality and safety of the patients' identity during the transfer of data from one hospital to enable the use of DL models poses one of the greatest challenges for the deployment of DL models across the globe.

The solution was to implement a blockchain based Federated Learning (FL) model that enables collaboration of multiple hospitals without compromising on security. Local classification was done using CapsNets, and the evaluation was done on lung cancer datasets like LUNA16, CIA, and data from the local hospital.Lung cancer ranks among the most aggressive diseases, as early diagnosis is vital in improving its prognosis. While CT scans can prove useful, manual interpretation can be slow and inefficient as human error is always a possibility. To improve accuracy, the authors [6] used a transfer learning approach leveraging EfficientNet architecture, which was modified to be an automatic lung cancer classifier, Lung-EffNet. The supplementary layer modification tested on the "IQ-OTH/NCCD" dataset yielded greater accuracy and efficiency, which exceeded other CNN models. In another work, the authors [7] applied pre-trained Convolutional Neural Networks (CNNs) to recognize the different lung pathology CT scans associated with COVID-19, pneumonia, pneumothorax, tuberculosis, and normal. Their implementation was also twofold: First, a CNN model was trained, then the diseases were classified using the trained network. They surpassed previously proposed classification methods using eight architectures: AlexNet, Darknet-19, GoogLeNet, and others. Further, the authors [8] newly proposed the detection of lung cancer based on the fusion of PCA and t-SNE methods of feature extraction.

The research systematically reviews the application of deep learning (DL) techniques for diagnosing pulmonary Mycobacterium tuberculosis (PTB) using computed tomography (CT) imaging. The study follows PRISMA guidelines to evaluate diagnostic accuracy, searching databases such as PubMed and Web of Science. Various DL methodologies, including Convolutional Neural Networks (CNN), Multi-Scale Attention Residual Network (MAResNet), U-Net, 3D CNN, and Support Vector Machines (SVM), were examined for their role in image segmentation, classification, and lesion progression analysis. Key algorithms applied include Generative Adversarial Networks (GAN) for data augmentation, Transfer Learning with pre-trained models like VGG16, and Grad-CAM for model interpretability. Performance metrics such as accuracy, sensitivity, specificity, and AUC values were assessed, with models achieving high diagnostic accuracy, such as MAResNet with 94% accuracy and a U-Net-based classifier with an AUC of 0.980. The findings highlight challenges like data scarcity, model generalization, and ethical concerns while emphasizing the need for robust, interpretable models with clinical validation for improved TB diagnosis [10].

Deep learning models have shown great promise in the identification and categorization of lung conditions. The authors [11] used a pre-trained VGG19 model to diagnose lung cancer, pneumonia, lung opacity, and COVID-19 from chest x-rays. Those experiments using VGG19 and the CNN showed better results than the previous methods, aiding healthcare professionals in the assessment and control of the diseases.

The writers in [12] employed transfer learning involving EfficientNet-B4 architecture for lung disease classification. They also applied explainable AI (XAI) methods such as Grad-CAM which boosted model transparency by providing the rationale of why certain features led to a diagnosis.

The system achieved an outstanding accuracy of 96% on classification which enhanced disease diagnosis and patient management. In the paper, the authors [13] reviewed deep learning algorithms used in the classification of lung disease from chest X-ray photographs. They studied various pre-trained CNN models especially ResNet, VGG, and DenseNet, emphasizing the value of these models in sensitivity and diagnostic accuracy. Additionally, they studied the effectiveness of deep learning models coupled with other machine learning classifiers and the degree of improvement in performance. The authors in [14] devised a multi-class lung disease classification approach based on the hybridization of Support Vector Machine and CNN. After augmenting the enhanced VGG16 model with a two-layer CNN, Softmax and SVM classifiers were used. The research objective was to evaluate the effectiveness of some deep learning architectures like DenseNet201, VGG16, and InceptionV3 for the classification of lung diseases.

The implementation of automated screening through chest CT imaging driven by deep learning was developed by [15] with the aim of improving COVID-19 detection. Their model alleviated clinical workload alongside MobileNetV2 and DarkNet19- pre-trained networks enhancement in diagnosis. The model validation for CT scan dataset confirmed its applicability for COVID-19 screening. The authors proposed a hybrid model for prediction of lung diseases [16] which permits the combination of Bi-Directional Long Short Term Memory Neural Network (BiDLSTM) and Mask Region Based Convolutional Neural Network (Mask R-CNN). To aid in clinical decision-making, testing was conducted using three publicly available datasets: The NIH chest x-ray dataset, the TB chest x-ray database, and the COVID-19 radiography dataset. In another study [17] presented PulDi-COVID, a novel CNN model for estimating COVID-19 and other lung disorders from chest X-rays. It was shown to classify eight conditions of the lung, including pneumonia and pneumothorax, using the SSE algorithm. The research showed effectiveness for early detection and clinical management of COVID-19 and other disorders.

The application of CNNs and quantum classifiers in the identification of respiratory lung illnesses was examined in one of the first studies [18]. The combination of quantum classifiers and other deep learning techniques achieved higher accuracy while using less memory, showcasing the potential of quantum computing in medical diagnosis. The authors [19] implemented hybrid deep learning models which integrated CNNs with STN and VGG networks for the lung disease diagnosis. Their VDSnet implementation achieved lower training times and validation accuracy than the other models which makes it a suitable candidate for efficient diagnosis of lung diseases. In another study [20] the authors focused on the automatic detection of cancerous lung cells by using CNN, VGG-16, and InceptionV3 models of deep learning. The authors analyzed lymph nodes for cancer by using histopathological slides and CT scans and successfully achieved better detection rates with the combination of histopathologic evaluation and deep learning models.

The analysis of medical images has benefited from the new developments in deep learning technologies. The authors [21] described the implementation of CNNs, convolutional autoencoders, and graph convolutional networks for lung disease diagnosis through X-ray, CT, and MRI scans. They also evaluated available datasets and new approaches in deep learning in regard to pulmonary disease diagnosis. The authors [22] researched the application of deep learning techniques for classification of respiratory disorders based on audio samples. Their review covering the years 2015 to 2021 focused on the application of DL in physician-led diagnosis of respiratory illnesses with a view of broadening the scope of diagnosis by medical practitioners. Finally, the authors [23] proposed a weakly supervised deep learning model for lesion localization in chest X-rays with the lung disease. The model used max-min pooling and multi-map transfer for assisting in the automatic classification of lung diseases through lesion location identification. The authors [24] discussed the latest trends in detection and analysis of Chronic Obstructive Pulmonary Disease (COPD) with the aid of deep learning and training on CT images. This research was an attempt to describe in detail the signs, causes, and therapies of COPD, so as to improve some aspects of the care, management of infection, and treatment of the patient.

Tablei: Comparison Of Models And Output

Study	Dataset/Method	Focus/Objective	ML/DL Technique	Accuracy/Performance
[1]	ChestX-ray14 Dataset, MobileLungNetV2	Lung illness detection, X-ray image analysis	MobileLungNetV2, Transfer Learning	91.6% accuracy
[2]	COVID-19 patient CT scans from Harvard Dataverse, image processing (contrast stretching, adaptive histogram equalization, non-linear filtering)	2D segmentation and 3D reconstruction of lung CT scans for COVID-19 diagnosis	Active contour modeling (Chan-Vese), threshold-based segmentation, marching cubes algorithm, point cloud plotting	Segmentation accuracy: 92%, 96%, 97%; IoU similarity indices: 42%, 67%, 77%
[3]	Spiral Computed Tomography (SCT) images	AI-assisted early lung cancer detection to reduce misdiagnosis and improve accuracy	Deep learning models, feature extraction techniques, 3D reconstruction (VOI, MPR)	Enhanced nodule detection, reduced false positives, improved early detection rates
[4]	LIDC-IDRI, Hybrid CNN and RNN	Lung cancer detection, Hybrid CNN and RNN	Hybrid CNN and RNN	Improved classification with hybrid model
[5]	Federated Learning, Blockchain, CapsNets	Global lung cancer prediction, Federated Learning	Federated Learning, CapsNets	Improved global model prediction
[6]	Lung-EffNet, EfficientNet-B4	Lung cancer categorization, EfficientNet-based model	EfficientNet, Transfer Learning	EfficientNet-B4 outperforms CNNs
[7]	Pre-trained CNN models, 8 datasets	Lung disease classification, CNN models comparison	CNNs, 8 pre-trained models	Improved classification accuracy
[8]	PCA, t-SNE, BF-SSA, HR-DEL	Lung cancer prediction, Feature selection, HR-DEL	HR-DEL, BF-SSA	Superior feature selection and HR-DEL
[9]	Kaggle Chest CT-scan, DenseNet201	Lung cancer types classification, DenseNet201	DenseNet201, Feature Selection	Enhanced accuracy with DenseNet201
[10]	Literature review (PRISMA), datasets from PubMed, Web of Science	Application of DL in diagnosing Mycobacterium tuberculosis (PTB) using CT imaging	CNN, MAResNet, U-Net, 3D CNN, SVM, GAN (data augmentation), Transfer Learning (VGG16), Grad-CAM (interpretability)	MAResNet accuracy: 94%, U-Net classifier AUC: 0.980
[11]	VGG19, CNN, 3615 COVID-19 and pneumonia images	Lung disease classification, VGG19 + CNN	VGG19 + CNN, Fully Connected Network	Outperformed previous methods in accuracy
[12]	EfficientNet-B4, Grad-CAM	Lung cancer categorization, Transfer learning	EfficientNet-B4, Transfer Learning	96% reliability, improved classification
[13]	Transfer Learning, XAI, Grad-CAM	Lung disease detection, Explainable AI	XAI, Grad-CAM	Enhanced model interpretability with Grad-CAM
[14]	VGG16-CNN, SVM, DenseNet201, VGG16, InceptionV3	Multi-class lung disease classification, SVM and CNN	CNN, SVM, DenseNet201	Best performance with SVM + CNN
	COVID-19 Screening, MobileNetV2, DarkNet19	Automated COVID-19 detection, MobileNetV2 and DarkNet19	MobileNetV2, DarkNet19	Improved COVID-19 detection with MobileNetV2
[15]	BiDLSTM, Mask-RCNN, 3 public datasets	Lung disease detection, BiDLSTM and Mask-RCNN	BiDLSTM, Mask-RCNN	Enhanced disease detection with BiDLSTM
[16]	PulDi-COVID, SSE Algorithm, Chest X-ray Dataset	COVID-19 and lung disease classification, SSE algorithm	PulDi-COVID, SSE Algorithm	Improved COVID-19 prediction accuracy
[17]	Quantum CNN, Quantum ML, Respiratory Illnesses	Respiratory illness detection, Quantum and	Quantum Classifiers, CNN	Hybrid quantum-classical model outperforms

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		classical ML		
[18]	CNN, STN, VGG, Data Augmentation	Lung disease diagnosis, CNN and STN	CNN, Spatial Transformer Network, VGG	Faster diagnosis with CNN + STN
[19]	Lymph Node Involvement, CNN, Histopathological Slides	Cancer detection in lungs, Histopathology analysis	CNN, Histopathology	Improved detection with histopathology analysis
[20]	CNN, Autoencoders, Graph CNN	Lung illness diagnosis, CNN, autoencoders, and graph CNN	CNN, Autoencoders, Graph CNN	Improved accuracy with CNN, Autoencoders
[21]	Audio Samples, DL models	Respiratory disorders, Audio-based classification	Audio Samples, DL models	Audio-based prediction improved accuracy
[22]	Weakly Supervised Deep Learning, Max-Min Pooling	Thoracic illness detection, Max-Min pooling and ML	Max-Min Pooling, Deep Learning	Improved lesion detection and classification
[23]	COPD, Deep CNN, CT Image Analysis	COPD, Deep CNN, CT Image Analysis	Deep CNN	Improved accuracy in COPD diagnosis

3. DEEP LEARNING MODELS FOR PULMONARY ILLNESS DETECTION

The dataset discussed includes lung CT scans from the COVID-19 CT Segmentation dataset, which consists of chest CT images from COVID-19 patients exhibiting various lung abnormalities. The scans span different stages of the illness, and each image is annotated to highlight areas affected by COVID-19. These annotations are essential for creating machine learning models capable of detecting and evaluating the affected regions. The dataset can be accessed here: https://github.com/UCSD-AI4H/COVID-CT.

The collection encompasses chest CT scans of COVID-19 patients, illustrating a variety of lung conditions that evolve throughout the course of the illness. Each scan is meticulously annotated to delineate regions of the lung impacted by the virus. These detailed markings are vital for training models aimed at detecting and analyzing affected lung regions. The dataset for lung X-rays used in the study is ChestX-ray8, a large-scale collection of over 100,000 annotated chest X-ray images that cover 14 significant thoracic disorders, including lung-related diseases. It can be accessed here: https://arxiv.org/abs/1705.02315.

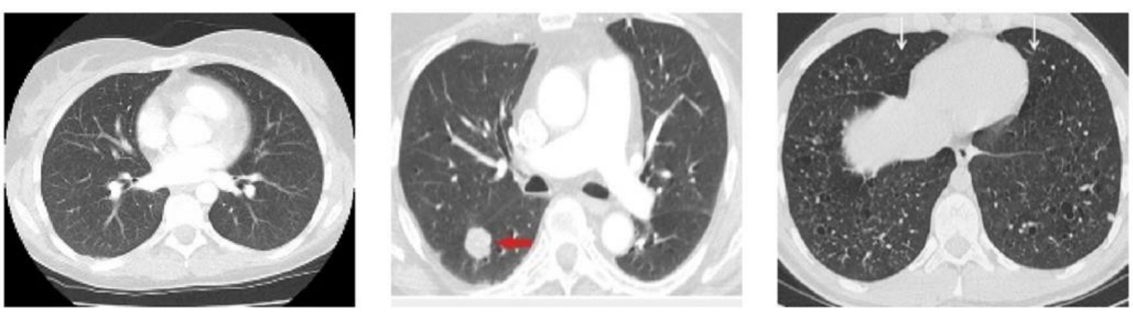

Fig. 1. Sample Lung CT Images from the Dataset

Fig. 2. Sample Chest X-ray Images from the Dataset

This dataset includes images labeled for 14 common thoracic diseases. An individual X-ray image can carry multiple labels, reflecting the presence of one or more diseases. Convolutional neural networks (CNNs) and other machine learning models are utilized to classify these images into categories corresponding to the specific pathologies present.

4. METHODOLOGY OVERVIEW

The structure of the proposed model is depicted in Figure 3. Initially, the dataset undergoes a pre-processing stage before being divided into training and testing subsets. The classification is performed using different data split ratios of [60:40, 70:30, 80:20], with results recorded for each case accordingly.

The method starts with the collection of chest X-ray pictures and lung CT scans, which serve as the main dataset for this study. These images are sourced from COVID-19 patients and are used to identify various lung-related abnormalities. The subsequent step involves pre-processing, where irrelevant or noisy data is eliminated to enhance image quality. Additionally, the images are resized to a standard dimension to ensure compatibility across deep learning models. The pixel values are then scaled to a range between 0 and 1 after normalization. This stage guarantees stability during training and improves the models' learning process.The dataset is divided into two subsets following pre-processing: one for testing and one for training. The models use the training dataset to identify trends and extract valuable characteristics, while the testing dataset evaluates the models' effectiveness. The data division follows different ratios, such as 60:40, 70:30, and 80:20, indicating the proportion of data allocated for training versus testing.

The process starts with obtaining chest X-ray and lung CT scan pictures, which serve as the main dataset for this study. These images are sourced from COVID-19 patients and are used to identify various lung-related abnormalities. The subsequent step involves pre-processing, where irrelevant or noisy data is eliminated to enhance image quality. Additionally, the images are resized to a standard dimension to ensure compatibility across deep learning models.The dataset is pre-processed and then divided into two subsets: one for testing and one for training. The models use the training dataset to identify patterns and extract useful features, and the testing dataset assesses how well the models work.The training dataset is utilized to help the models recognize patterns and extract meaningful features, while the testing dataset evaluates the models' effectiveness. The data division follows different ratios indicating the proportion of data allocated for training versus testing.

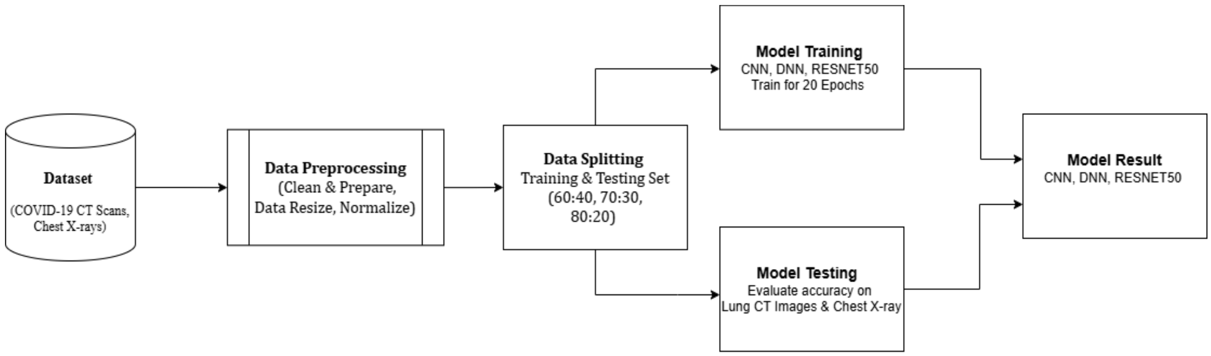

Fig. 3. Workflow of the Proposed Model

This study employs Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), and RESNET50, a CNN variant that incorporates residual learning for enhanced performance. These models undergo training for 20 epochs, where each epoch represents a full pass through the training dataset. During this iterative process, the models continuously adjust their internal parameters to optimize their performance and learning capability. The models are tested using lung CT and chest X-ray images from the specified testing dataset after the training phase is finished. The accuracy of each model is calculated to assess its capacity to classify lung diseases based on the input images, and these accuracy scores offer important information about how well each model detects and classifies pulmonary conditions.The results obtained from this study demonstrate the potential of deep learning models in real-world diagnostic applications.

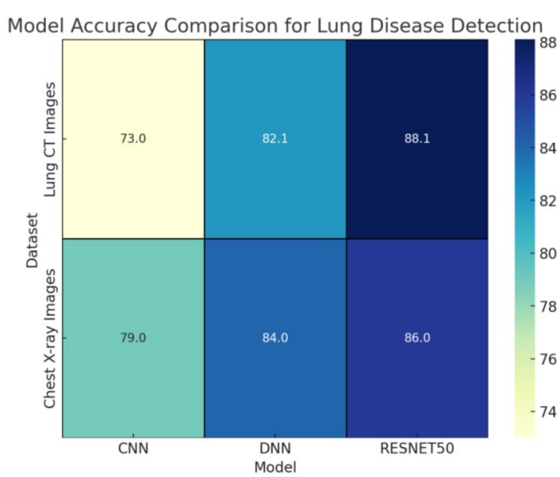

Fig. 4. Heatmap for Model Accuracy

The heatmap visually presents the accuracy of three deep learning models—CNN, DNN, and RESNET50—when applied to two different lung disease detection datasets: Lung CT Images and Chest X-ray Images. Each row of the heatmap represents one of the datasets, while the columns correspond to the models being evaluated. The intensity of the color in each cell reflects the accuracy of the models, with darker blue shades indicating higher accuracy and lighter blue shades indicating lower accuracy. For the Lung CT Images dataset, RESNET50 achieved the highest accuracy of 88.1%, followed by DNN with 82.1% and CNN with 73%. This suggests that RESNET50 was the most effective in detecting lung diseases from CT scan images, outperforming both DNN and CNN. A comparable pattern was seen on the dataset of chest x-ray images, where RESNET50 achieved an accuracy of 86%, DNN scoring 84%, and CNN attaining 79%. Although the accuracy for Chest X-ray Images was slightly lower compared to the Lung CT Images dataset, RESNET50 still demonstrated the best performance.

3. CONCLUSION

This paper demonstrates the potential effectiveness that deep learning models can bring towards the diagnosis of pulmonary disease from CT and X-ray scans of the chest. CNNs and their more sophisticated variants have been found to excel in the detection of pulmonary malignancies - lung cancer, pneumonia, ILD, or interstitial lung disease, and COPD, or chronic obstructive pulmonary disease. This study highlights the use of deep learning technology improves accuracy, efficiency, and reliability of diagnosis which helps healthcare providers to provide faster and more accurate diagnosis to patients. While these improvements are encouraging, some obstacles still remain. The most stringent of these is the insufficient availability of quality annotated datasets required to train effective deep learning models. Another major challenge is to make sure these models will generalize well across different demographics and imaging modalities. In addition, the seamless incorporation of AI diagnostic tools into the current clinical workflow is essential for their use by healthcare professionals. Furthermore, ethical concerns such as protecting patients' privacy and ensuring there is minimal discrimination bias in the AI algorithms need to be addressed adequately to ensure safe practice in medicine. The findings of this study show how much the diagnosis of pulmonary disease will change with the use of deep learning technology. The progress of AI technologies can profoundly help healthcare systems in terms of early diagnosis, improving patient outcomes, and optimizing services. Still, additional work needs to be done to realize these benefits, which include enhancing model resilience, addressing ethical issues, and encouraging international collaborative dataset development. By tackling these problems, AI-powered pulmonary diagnostics can be made ultra-accurate and ultra-accessible, completely transforming the field of medical imaging.

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