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A Comparative Study of Artificial Intelligence and eXplainable AI Techniques for Pulmonary Disease Detection and Its Severity Classification

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***Abstract*—As respiratory diseases like tuberculosis, pneumonia, COVID-19, and cancer become more common, the need for accurate and efficient diagnostic tools is growing. This paper provides an overview of the use of artificial intelligence (AI) and explainable AI techniques for pulmonary disease detection and severity classification. Using AI, especially deep learning (DL) algorithms, has shown promise in automating the process of detecting pulmonary diseases from chest radiographs. This study looks at different AI methodologies, such as deep learning architectures and preprocessing techniques, and uses explainable AI (XAI) to improve pulmonary disease detection and severity classification mechanisms. It also addresses the restrictions and challenges associated with AI-based disease detection, offering insights into possible future directions. To group cutting-edge techniques according to image types, DL algorithms, XAI techniques, and targeted pulmonary diseases, a taxonomy is put out. By helping researchers organize their work and contributions, this taxonomy eventually improves the efficiency of AI-assisted pulmonary disease detection and severity classification systems.**

Keywords- Chest Radiograph, Feature Extraction, Deep Learning, Severity Check, eXplainable AI

I. Introduction

Diseases of the airways and other lung's structures are referred to as pulmonary diseases, or respiratory disorders. Pneumonia, tuberculosis, asthma, and Coronavirus Disease 2019 (COVID-19) are a few pulmonary diseases. The Forum of International Respiratory Societies estimates that 334 million people worldwide suffer from asthma, 1.4 million die from tuberculosis, 1.6 million die from lung cancer, and millions more die from pneumonia annually. Global effects of the COVID-19 pandemic include millions of infections and strain on the healthcare system [1]. One of the main reasons for death and frailty globally is pulmonary disease. Improving long-term survival rates and improving the likelihood of recovery depend heavily on early detection. Conventionally, tests for skin, blood, sputum samples, and chest radiographs can be used to identify pulmonary disease. Now artificial intelligence (AI), in particular machine learning (ML) and deep learning (DL), has revolutionized medical diagnostics in recent years by analyzing clinical data and complex patterns in medical images to produce automated, extremely accurate assessments. By learning features directly from data, deep learning, which emulates the structure and function of the human brain, performs better in pulmonary disease detection and severity classification, improving diagnostic performance [2]. This study will focus on the precise evaluation of severity, as it will impact treatment decisions, patient care, and results, allowing for individualized attention and prompt interventions. Again, the "black box" character of many deep learning models, however, emphasizes the necessity of Explainable AI (XAI), which offers clear, comprehensible insights into AI predictions, promoting clinician confidence and successful AI integration with human expertise. XAI integration is still crucial for clinical adoption and trust-building as deep learning progresses.

A. Role of Medical Imaging

Using a variety of methods, medical imaging is essential for identifying and diagnosing pulmonary diseases. Different types of chest radiographs are mentioned below [3]:

X-rays: Provide 2D pictures for the detection of anomalies such as fractures, tumours, and lung conditions like pneumonia, tuberculosis, and COVID-19.

CT Scans: Provide in-depth 3D and cross-sectional images, identifying abnormalities or tiny nodules that are invisible on X-rays. They are helpful in the diagnosis of pulmonary embolism, fibrosis, and lung cancer, frequently identifying problems before symptoms manifest.

3. MRI: Less popular for lung imaging because of difficulties in breathing and moving the lungs, but helpful for fine-grained pictures of anomalies in the chest wall or lung nodules.

PET scans: When paired with CT scans, PET scans can identify metabolic activity in lung tissue, which helps with cancer staging and appraisal of metastasis.

In order to identify lung anomalies, AI and ML systems commonly use X-rays and CT scans as inputs. Since each imaging technique has distinct advantages and disadvantages, combinations are frequently employed to provide precise diagnosis.

II. BACKGROUND STUDY

In pulmonary disease detection, artificial intelligence (AI) plays an important role. AI helps healthcare practitioners predict the disease. Machine learning (ML) and deep learning (DL) provide the best results. Any AIML model goes through 3 phases: image preprocessing, feature extraction, and classification. Each phase has been explained in detail below. Figure 1 shows the general pipeline of the pulmonary disease detection model.

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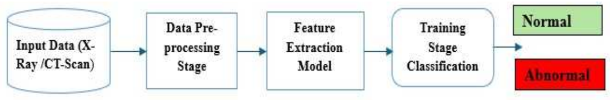

Fig. 1. General Pipeline of Lung Disease Detection Model

A. Preprocessing

Preprocessing medical images is essential to improving the accuracy, reliability, and efficiency of disease detection systems, particularly in AI-assisted diagnostic tools. Optimizing clinical data and medical images for AI models involves several preprocessing methods, such as The standardization of pixel values in images by image normalization (0 to 1 or -1 to 1) enables faster model convergence. Similarly, data augmentation techniques, such as rotation, scaling, flipping, shearing, shifting, and zooming, artificially enlarge datasets and enhance generalization. Gaussian smoothing is one type of noise reduction technique that improves the appearance of essential features. By narrowing down on pertinent regions of the image, segmentation or ROI extraction helps the model detect problems more accurately. Techniques like SMOTE and oversampling are used to address class imbalance. Common preprocessing procedures in feature engineering for medical data include scaling, one-hot encoding, and missing value imputation. All these techniques are mentioned in Table I. Image preprocessing, which can significantly impact accuracy and prediction, entails balancing an image's component parts in accordance with the requirements of the suggested model [4]. Z. Lutowski [5] explores six distinct image preprocessing techniques in Figure 2, which are aimed at enhancing chest radiograph images for machine learning-based diagnosis.

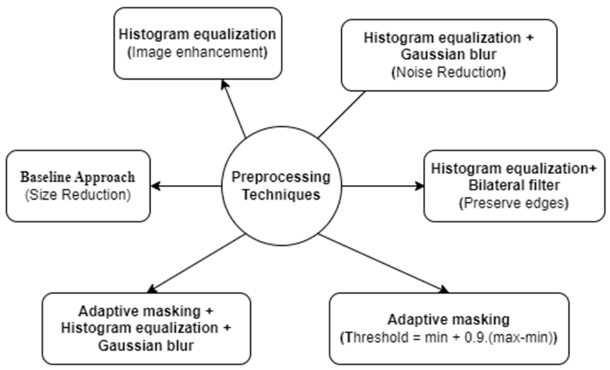

Fig. 2. Pre-Processing Techniques used for pulmonary disese detection

B. Feature Extraction

In the domain of medical imaging, feature extraction techniques encompass a variety of methods that aim to analyze and extract relevant information from medical images for diagnostic, prognostic, and research purposes. Here in Figure 3, several techniques are mentioned that are used in AI for medical image feature extraction. These AI-driven techniques in medical imaging play a pivotal role in aiding healthcare professionals by automating image analysis, assisting in early disease detection, and providing quantitative insights from complex medical images. The choice of technique depends on the specific imaging modality, the clinical application, and the desired outcome [6].

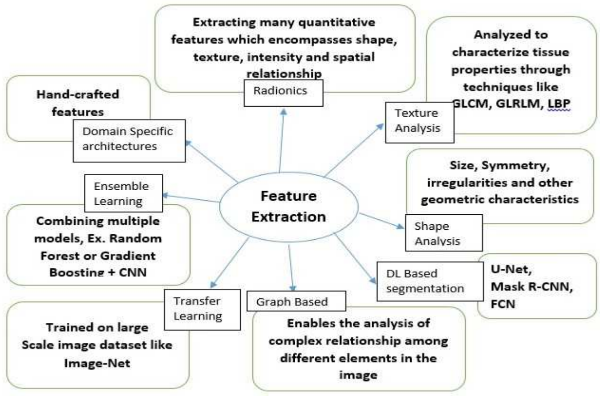

Fig. 3. Image Feature Extraction Techniques

C. Classification

Convolutional neural networks (CNNs) serve as powerful tools in image classification, mimicking human-like accuracy in recognizing diverse images. CNNs can extract radiographic patterns on chest X-ray images and have the ability to provide useful data in healthcare. The architecture of a CNN comprises interconnected convolution layers, activated by rectified linear units, alongside pooling layers, and batch normalization operations. This structure is inspired by the connectivity pattern of neurons in the visual cortex, reflecting how individual neurons respond to stimuli within specific receptive fields. As these fields overlap, they collectively cover the entire visual area. The hierarchical arrangement of CNNs results in high-level feature extraction, reduced computational complexity, and enhanced generalization capabilities. Leveraging these advantages, CNNs have found extensive applications in various domains of image processing [7].

III. METHODOLOGIES

Various methods were used in the image classification process for deep learning and AI/ML-based models for the identification of pulmonary diseases. The dimensionality of the dataset and the adjustment of hyperparameters are important aspects of model optimization. Here are several essential methods and factors to consider about:

Deep Learning-Based Models: As deep learning is a subset of AI and ML, it gives better accuracy than machine learning. According to the experimentation, machine learning classifiers are inferior to deep learning classifiers [8]. Furthermore, DL-based classification techniques generate outcomes nearly five times more quickly than machine learning classifiers. Thus, they are utilized in various fields. Among radiographs, the CXRs are chosen over CT's as they support quick triaging in correspondence to virus-related scanning while being easily available because of their versatility; targeting other regions is very simple. Although the radiographs produced can significantly increase the process, it requires some form of computerization. For disease detection, X-rays are a commonly used input dataset, but some researchers have used CT- scans for lung segmentation. Various deep learning algorithms, including CNNs and hybrid models [9], have demonstrated high performance in detecting diseases like COVID-19, pneumonia, and TB. Techniques such as transfer learning, image preprocessing, and model enhancements like adding dropout layers or combining different architectures have significantly improved accuracy, sensitivity, and specificity in medical diagnoses. Advanced models like Unet [10], BDCNet [11] exhibit exceptional performance metrics, often surpassing conventional methods and even expert radiologists in accuracy and reliability. Table I, which summarizes the outcome of the disease detection method and the preprocessing techniques on the applied dataset, is a survey of deep learning techniques.

A. Dataset

The model performance and generalizability in AI-driven pulmonary disease research are strongly influenced by the dimensions of the datasets used. Medical imaging modalities, including computed tomography (CT) scans and chest X-rays (CXR), are typically included in these datasets. One of the most important factors is the size of the dataset; bigger datasets (such as the NIH ChestX-ray14, which has over 100,000 CXR images) are usually preferred, but smaller datasets (such as the LIDC-IDRI, which contains about 1,000 CT scans) are also employed because of availability issues. Class distribution needs to be taken into account since model performance might be impacted by imbalances between common and uncommon conditions. For CT scans, the image resolution (512x512 pixels) affects detail capture and processing requirements, which are critical for precise severity categorization. Furthermore, evaluating model bias requires the use of a data split ratio as (80:10:10 or 70:15:15 or 60:20:20) training, validation, and testing split [9-24].

B. Hyperparameter Tuning

Optimizing hyperparameters is essential for enhancing AI models in the identification of pulmonary diseases. The learning rate (0.001 to 0.0001), which regulates the model's learning speed, and the batch size (16 to 128), which strikes a balance between computing efficiency and gradient noise, are important parameters. To avoid overfitting, models are trained over several epochs (25 to 200), frequently with an early stop. Weight updates are handled by optimizers such as Adam and SGD, with Adam being a popular choice due to its adaptable learning rates. CNNs like ResNet and U-Net are common architectures, while regularization strategies like batch normalization and dropout (0.3–0.5) help avoid overfitting. Loss functions differ depending on the task: MSE/MAE for regression and cross-entropy for classification [9-24].

After examining Table I, there are certain areas where current techniques could be improved, namely in deep learning models, simple structures result in underfitting, which produces low accuracy on both training and testing datasets, whereas complex structures lead to overfitting, which produces excellent training accuracy but poor performance on untested data. Severity analysis, interpretability, and generalizations are some of the methodologies, limitations that must be addressed to attain higher levels of precision.

TABLE I. DEEP LEARNING TECHNIQUES ANALYSIS

Dataset Used	Pre-Processing Technique	Feature Extraction Algorithm	Result
The LIDC-IDRI from The Cancer imaging Archive (TCIA) Ct-Scan	Normalization using spline interpolation Data Augementation [9]	Hybrid neuro-probabilistic reasoning algorithm (1..Bayesian network 2.A graph convolutional network)	Accuracy:95.36% AUC: 96.54%
Beijing Hospital Ct-Scan	Image Resizing[10]	UNet(ResNet+ Spatial attention mechanism network)	Accuracy: 74.20% Sensitivity:60.37%, Specificity: 89.36%
GitHub,SIRM,TCIA,Kaggle, NIH, Radiological Society of North America (RSNA), ,Mendeley X-ray+ Ct-Scan	Data Normalization [11]	BDCNet(VGG-19 + CNN)	Accuracy:99.10% Precision:99.9% Recall:98.31% F1-score: 99.09%
Public curated dataset (X-Ray)	Image Augementation [12]	CNN(Xception, VGG19,VGG16) Transfer Learnin with Fine Tuning	Accuracy :98%
Kaggle C19RD CXIP X-Ray	Optimal Filtering and Contrast Adjustment Techniques[13]	HDLA- DNN Robust 2D CNN Pretrained Resnet-50	Accuracy:98.35%, Precision:97.43% Recall:98.87% Specificity:97.67%
LCTSC from TCIA CT	Anisotropic Diffuse Filtering[14]	Model-free algorithm Guided filtering	Intersection over Union(IoU):92.36%±02.90 (mean±std) Dice Coefficient: 96.01%±01.58
Kaggle CT-Scan	Histrogram Equilization[16]	ResUnet-based segmentation model	Intersection over Union (IoU) : 94.1% Dice coefficient::97.6%.
Signal Processing Grand Challange(SPGC) CT-Scan	Data Augmentation [17]	Residual C-NiN model	Slice-level classification accuracy :93.54%, Patient-level accuracy :86.59%,
GuangzhouWomen's and children's medical center CT+X-Ray	Matrix Normalization [18]	COVID-RDNet (Residual +Dense Block)	Accuracy:99% Sensitivity :99.9% Specificity: 99.5% AUC: 99.98%
1.Public Dataset 2.Xiangya Hospital 3.Wuhan Red Cross Hospital; Ct-Scan	Nomalization [19]	Dynamic 3D radiomics approach	Accuracy: 90% Macro-average AUC: 97.5%.
Public Dataset X-Ray	Min-Max Normalization [20]	NASNet(Neural Architecture Search Network)	Accuracy:97.35% Precision:97% Recall: 98% F1- Score:97.49%
Kaggle X-Ray	Image Resizing[21]	CheXImageNet ,CNN	Accuracy: 100% Sensitivity: 100% Specificity: 100%
CheXpert X-Ray	Data Augementation [22]	DenseNet 121 CNN Bayesian Network	AUC: 82.9% F1-score:75.9%
Kaggle X-ray	Image Resizing[23]	Enhanced Restricted Boltzmann Machine ERBM)	Accuracy :98.56% Precision: 98.97% Recall: 98.78% Specificity:98.86%
Public dataset Ct-Scan	Image enhancement technique [24]	Fuzzy histogram equalization(fuzzy expected value)	Accuracy: 94.6%, Specificity: 92.5%, Sensitivity: 84.1%, Precision: 96.7%

C. Performance Evaluation Matrics

Evaluation of Confusion Matrix: Different qualitative parameters are represented by a confusion matrix. For proper classification, the true positive and true negative rates should ideally be very near to 100%. To lessen the likelihood of an incorrect detection, the false positive and false negative rates should also be as near to 0% as feasible [12]. The above terms are defined below:

True Positives (TP): These are images for which the class (normal or abnormal) was predicted, and they truly fall within the expected class.

True Negatives (TN): We believed that neither the class nor the images' length would correspond to them.

False Positives (FP): Commonly referred to as "Type I errors," these occur when we predict a class, but images do not truly belong in that class.

False Negatives (FN): This is commonly known as a "Type II error," as it is believed the images were in a class even if they were not.

The system's performance is calculated using the aforementioned parameters, such as [13]:

Accuracy: The following equation(1) represents accuracy, which is the number of data instances properly identified over the total number of data instances.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} * 100 \quad (1)$$

Precision: According to equation (2), precision is the ratio of all expected positive cases to all accurately detected positive cases.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} * 100 \quad (2)$$

Recall: These metrics indicate the proportion of cases that are accurately classified as positive cases relative to all actual positive cases, also called sensitivity.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} * 100 \quad (3)$$

Specificity: It is the total number of accurate labels present in the class.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} * 100 \quad (4)$$

F1-score: The F1 metric, which is superior to accuracy, equation (5) is the harmonic mean of accuracy and recall:

$$\text{F1-Score/(DSC)} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Recall}} * 100 \quad (5)$$

Dice similarity coefficient (DSC): It is calculated by dividing the sum of the segmentation mask volumes by the intersection of the mask volumes twice [14]:

$$\text{DSC} = \frac{2|A \cap B|}{|A|+|B|} \quad (6)$$

Intersection over Union (IOU): It is the ratio of the intersection and union of the segmentation mask defined by the algorithm (A) and the manual labelling (B) [14]:

$$\text{IOU (A. B)} = \frac{|A \cap B|}{|A \cup B|} \quad (7)$$

OR

$$\text{IOU} = \frac{\text{TP}}{\text{TP+FP+FN}} * 100 \quad (8)$$

A. Belay [15] states that the training time, extraction time, and test time have all been assessed in addition to the assessment parameters.

IV. SEVERITY CLASSIFICATION

Tobacco use and air pollution severely harm lung health, particularly affecting the elderly, young, and those with preexisting conditions like diabetes or asthma [25, 26]. The act of assessing the degree or seriousness of a lung ailment is known as severity classification in pulmonary disease. This information can be used to guide therapy choices, forecast results, and efficiently manage patient care. It entails rating the illness according to clinical factors, imaging results, and additional diagnostic standards. Classifying diseases according to severity is crucial for tailoring treatment plans. Identifying the appropriate interventions based on the severity of the disease. Forecasting the path and outcome of a disease is known as prognostication. Allocating resources to ensure that patients receive the appropriate level of care, which may involve hospitalization in cases of severe severity. Monitoring and Follow-Up: Tracking the progression of the disease and the efficiency of the prescribed course of care over time. By automating the examination of complicated medical data, the severity classification process can benefit from the integration of AI and deep learning, which can improve accuracy and efficiency and improve patient outcomes. Figure 4 shows that RCNN achieved the best result (99.5%) when CT scan data was classified into four severity levels. Following are some techniques used for severity classification by researchers in Table II.

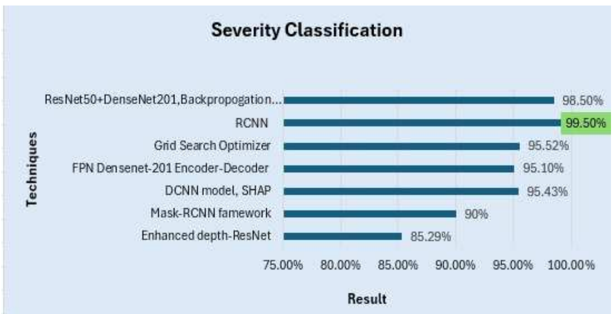

Fig. 4. Techniques used for Severity classification and its Result

After studying Table II, significant gaps have been observed. One-versus-all method can be explored for severity classification of pulmonary disease. Severity classification can be mapped to confidence scores to detect the levels. An experiment into improving Mask-RCNN learning using bounding box annotations for precise area localization in lung images. Integrating responsible AI for risk mitigation and data protection into the system.

TABLE II. SEVERITY CLASSIFICATION APPROACHES

Dataset	Technique Used	Result	Classification
GE healthcare, USA CT-Scan	Automatic radiomics, texture statistical features, Random Forest classifier [27]	Normal Stage Accuracy:96.25% Progressive stage Accuravcy:100%,	Normal, Early, Progressive Peak, Absorption
Image CLEF2018 on TB CT-Scan	Enhanced depth-ResNet, SVM classifier [28]	Accuracy:85.29%	Severer, Non-severer
Kaggle RSNA X-Ray	Mask-RCNN, pixel-level analysis, segmentation `mask prediction [29]	Mean average precision(mAP) Train set: 90% Test set: 89%	Low, High
Taichung Vieteran General Hospital (TCVGH) NIH-U.S.Human Health and Services Vindr-Vietanam X-Ray	Interpretable deep convolutional neural network (DCNN) model, SHAP [30]	DCNN with TCVGH +VinDr, Accuracy: 92.14% AUC :93.57% Ttransfer learning Accuracy:93.29% AUC :95.43%.	Normal, Slight, Moderate, Severe
Kaggle CT-Scan	FPN Densenet-201 Encoder-Decoder CNN [31]	Lession Segementation DSC:94.13% IOU:95.10% Sensitivity:99.64 %	Mild, Moderate, Severer, Critical
Kaggle X-ray	CNN tuned with Grid Serch Optimizer [32]	Average Accuracy:95.52%	Mild, Moderate, Severer, Critical
KUAH hospital in Jordan CT-Scan	RCNN (Region CNN) VGG, EfficientNet, Transformer model [33]	Accuracy: 99.5%	Normal, Mild, Moderate, Severe
Covid Ct-Scan Dataset SARS-CoV-2 CT-scan dataset	ResNet50+Dense Net201, Backpr-opagation Neural Network [34]	Accuracy:98.5% Sensitivity:98.58 % Average Accuracy:87.84%	Low, Medium, High
Publicly available COVID-19 Indian datasets	XGBoost; LIME, SHAP [35]	Accuracy:86.9%, F1-Score :85.9% Precision:87.7% Recall: 84.2%	Mild, Moderate, High
GE healthcare, USA CT-Scan	Automatic radiomics, texture statistical features, Random Forest classifier [27]	Normal Stage Accuracy:96.25% Progressive stage Accuravcy:100%,	Normal, Early, Progressive Peak, Absorption

V. EXPLAINABLE AI IN HEALTHCARE

The goal of XAI is to create explainable methods that enable end users to effectively understand, trust, and operate the next breed of AI systems. The necessity for explanations can be traced back to the initial studies on expert systems and Bayesian networks. On the other hand, deep learning (DL) has led to the flourishing of XAI research [36]. Explainable AI (XAI) in healthcare refers to the incorporation of transparency and interpretability into AI models used in medical applications. As AI systems become more prevalent in healthcare for tasks such as diagnosis, treatment planning, and prognosis prediction, it becomes crucial to understand and trust the decisions made by these systems. So, for effective treatment planning, we should know the reason behind predictions made by the model. The T. Evans et al. [43] study proposes two avenues for advancing explainable AI (XAI) to balance usability and fidelity in representing AI decision-making. First is the parallel approach, which proposes xAI elements telling AI decision-making factors parallel to users' methods. This method supports statistical accuracy while aligning with human understanding. Second is the orthogonal approach, which suggests xAI elements based on AI decision-making components that depart from human reasoning. However, this approach risks separating users and may require additional user training and acclimation to appreciate the differences. Both approaches aim to adopt reliable and more realistic hopes in human-AI collaboration. The orthogonal approach emphasizes the uniqueness of AI. Table III shows XAI technologies used for pulmonary disease detection.

TABLE III. SURVEY OF EXPLAINABLE AI TECHNIQUES

Dataset	Technique Used	Accuracy	Research Gap/Future Scope
Kaggle X-Rays Covid 19=2896 Normal= 1341	CNN Model with LIME(XA), Quadrant Approach [37]	99.6%	Severity Classification
Kaggle X-ray Lungs Diseasse Covid:2510 Pneumoni:2561 TB =2509 Normal=2507	Inception3, EfficientNet B0, and LeNet Shap, Lime, GradCAM GradCAM++ [38]	99.20%	Generalizability,incorporating advanced XAI methods will improve the model's interpretability,
Lung Disease -X-rays Bacterial Pnemonia:2009 Corona :2031 Normal:2013 TB:2034 Viral Pnemonia:1208	CNN, hybrid models, Ensembles, Transformers , and Big Transfer Lime, Grad CAM, Xception [39]	96.21%	Integrating imaging modalities, hybrid models, image segmentation and SHAP to enhance accuracy and robustness.
Kaggle X-Rays Covid19: 3611 Other:9849	UNet and UNet+, GradCAM [40]	97.45%	More Generalized Dataset can be used for training
X-rays COVID:3,616 Normal:10,192, Lung opacity:6,012	Custom CNN (LRP)-based method Deep Taylor Decomposition [41]	85.24%	Can apply on more robust metrics to gain a deeper understanding
X-Rays Total:6650 COVID-19 , Pneumonia NIAID: TB, NIH:Fibrosis	Multi-Scale CNN, SHAP and Grad-CAM[42]	96.05%	Devised to expand the number of disease classes.

Here are some XAI techniques shown in Figure 5. Each technique has its strengths and limitations, and the choice often depends on the specific AI model, the domain, and the intended audience for the explanations. Figure 6 shows the best XAI method applied on respective datasets in terms of achieved accuracy.

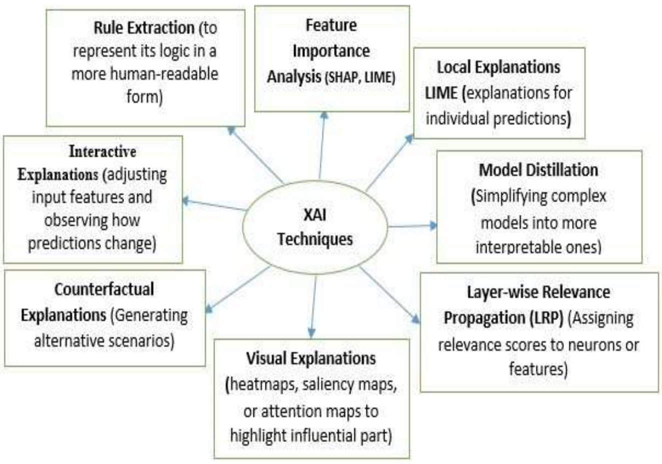

Fig. 5. Explainable AI techniques

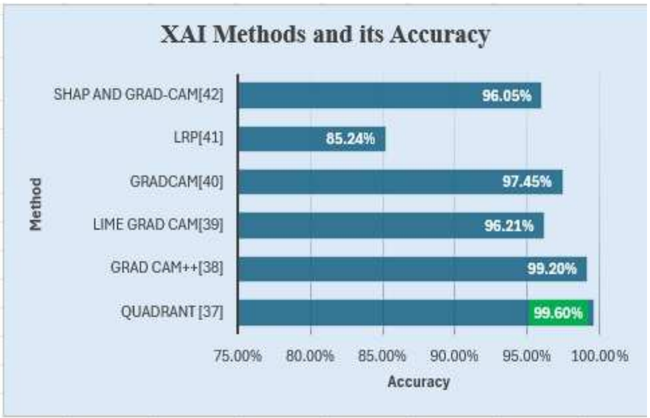

Fig. 6. XAI Methods and its Accuracy

VI. Result and Discussion

Numerous studies have shown encouraging outcomes when applying deep learning (DL) models for the diagnosis and severity grading of pulmonary diseases. Large datasets, like NIH ChestX-ray 14, have allowed models to be trained with excellent accuracy, frequently outperforming conventional diagnostic techniques, in the detection of common lung illnesses such as pneumonia, tuberculosis, and lung nodules. For example, cutting-edge convolutional neural networks (CNNs) have demonstrated disease identification accuracy of 70% to 100%; models such as ResNet and DenseNet are especially successful because of their capacity to recognize complex patterns in medical images. Similar to this, although performance varies, DL models have proved successful in identifying lung cancer and its severity in smaller datasets like LIDC-IDRI by examining the size, shape, and spread of lung nodules in CT scans. Again, this research emphasizes the explainable AI-based models such as LIME, SHAP, and GRADCAM used for detection of pulmonary disease and demonstrated accuracy of 85% to 99%. Even though with advances in medical imaging and diagnostic techniques, the various and frequently overlapping clinical manifestations of these diseases make accurate diagnosis and severity classification difficult.

VII. CHALLANGES

After studying all existing AIML-based pulmonary disease detection, severity classification methods, and explainable AI models from different researchers' studies, the following are challenges and future scope.

The need for a universally applicable model across age groups' datasets and validation in diverse geographical areas underscores a barrier for researchers in developing robust diagnostic tools from medical imaging data. Currently, existing methods typically lack the granularity, making it challenging to effectively categorize disease severity, necessitating the accurate differentiation between levels of severity. Improving the model's interpretability even more and investigating developments in explainable AI methods to increase decision-making transparency is necessary. This may include input data and the underlying computation of the learning model. From a computational standpoint, this issue is implicitly related to accountability and explainability in the learning model's decision-making process. An external entity in an AI-based ecosystem may want to know which data points influence the final choice in a learning model. Poor Region of Interest (ROI) estimation during the pre-processing stage. Deep learning models with complex structures tend to overfit, which produces good training accuracy but deficient performance on unknown data. On training and testing datasets, underfitting from basic structures leads to low accuracy.

VIII. CONCLUSION

The development of an automated pulmonary disease detection and severity classification model with explainable AI is the primary objective of this study, aiming to surpass the limitations of existing AI-based machine learning and deep learning techniques. In conclusion, this survey paper has provided a comprehensive overview of the current state-of-the-art in pulmonary disease detection. Through an extensive examination of the literature, we have identified key trends, methodologies, challenges, and future directions in the field. Our analysis highlights the significance of generalizability, severity classification with explainability, and transparency in pulmonary disease detection. It is evident from this survey that AI in healthcare is a dynamic and rapidly evolving field with immense potential for further exploration and innovation.

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