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DeepPulmoAI: Hybrid Neural Network Selection for Automated Pulmonary Disease Classification

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Abstract:

Pulmonary diseases such as pneumonia, tuberculosis, lung cancer, and chronic obstructive pulmonary disease (COPD) represent major global health challenges and require accurate early diagnosis for effective treatment. Medical imaging techniques including chest X-rays and computed tomography (CT) scans are widely used for pulmonary disease detection. However, manual interpretation of pulmonary images is time-consuming and highly dependent on radiological expertise. To address these limitations, this research proposes PulmoNet-X, an intelligent ensemble deep learning framework for pulmonary image classification using appropriate neural network selection and ensemble learning techniques. The proposed system integrates multiple deep learning architectures, including Convolutional Neural Networks (CNN), DenseNet, ResNet, and EfficientNet models, to automatically extract discriminative features from pulmonary images. An adaptive neural network selection mechanism identifies the most suitable model based on image characteristics and classification performance. Ensemble learning strategies are further employed to combine the outputs of multiple neural networks, thereby improving classification accuracy, robustness, and generalization capability. The framework incorporates preprocessing techniques such as image normalization, noise reduction, augmentation, and segmentation to enhance image quality and improve feature extraction efficiency. Explainable Artificial Intelligence (XAI) methods such as Grad-CAM and SHAP are integrated to visualize affected pulmonary regions and provide interpretable diagnostic insights for healthcare professionals. Experimental evaluation is performed using benchmark pulmonary imaging datasets, and the proposed model is compared with existing machine learning and deep learning approaches. Results demonstrate superior classification accuracy, precision, recall, F1-score, and reduced false detection rates. The proposed PulmoNet-X system provides a reliable, scalable, and explainable solution for automated pulmonary disease diagnosis and supports clinicians in making accurate and timely medical decisions.

Keywords: *Pulmonary Image Classification, Ensemble Learning, Deep Learning, Convolutional Neural Networks, ResNet, DenseNet, EfficientNet, Medical Image Analysis, Explainable AI, Grad-CAM, Lung Disease Detection, Chest X-ray Classification, PulmoNet-X, Healthcare Analytics.*

I. INTRODUCTION

Pulmonary diseases are among the leading causes of mortality and respiratory complications worldwide. Diseases such as pneumonia, tuberculosis, chronic obstructive pulmonary disease (COPD), pulmonary fibrosis, and lung cancer affect millions of individuals every year. Early and accurate diagnosis of these diseases is essential for effective treatment planning and reducing mortality rates. Medical imaging modalities such as chest X-rays, computed tomography (CT) scans, and magnetic resonance imaging (MRI) play a vital role in pulmonary disease diagnosis and monitoring. Traditionally, pulmonary image analysis is performed manually by radiologists and healthcare specialists. Although expert diagnosis provides reliable results, manual interpretation is often time-consuming, subjective, and prone to human error, especially when large volumes of imaging data are involved. Furthermore, subtle abnormalities in pulmonary images may be difficult to identify during routine clinical analysis. Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have significantly transformed medical image analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in image classification, segmentation, and disease detection tasks. These models automatically learn hierarchical image features and eliminate the need for manual feature extraction. Several deep learning architectures such as CNN, ResNet, DenseNet, VGGNet, and EfficientNet have been successfully applied for pulmonary image classification. However, selecting the most appropriate neural network architecture for different pulmonary imaging conditions remains a challenging task. Individual deep learning models may suffer from limitations such as overfitting, poor generalization, computational complexity, and reduced performance for diverse datasets. Ensemble learning techniques overcome these challenges by combining multiple neural network models to improve classification accuracy, stability, and robustness. Ensemble approaches reduce prediction variance and enhance the reliability of medical image diagnosis systems. Additionally, Explainable Artificial Intelligence (XAI) techniques improve interpretability by highlighting disease-affected regions in pulmonary images, thereby increasing clinical trust and transparency. To address these challenges, this research proposes PulmoNet-X, an intelligent ensemble deep learning framework for pulmonary image classification using adaptive neural network selection and ensemble learning. The proposed system integrates multiple CNN-based architectures along with explainable AI methods to provide accurate, interpretable, and efficient pulmonary disease diagnosis. The framework aims to support radiologists and healthcare professionals in early disease detection and clinical decision-making.

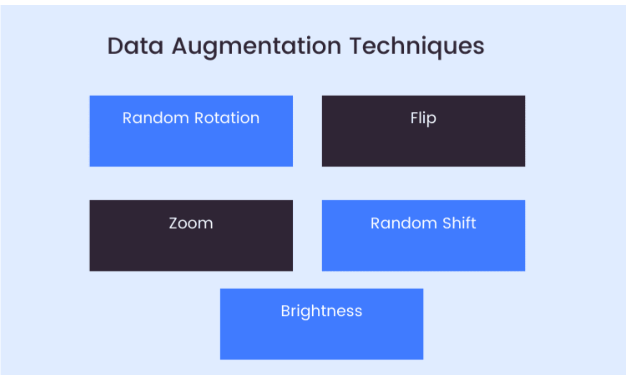

Figure 1: Existing Data augmentation method used for pulmonary Analysis

II LITERATURE SURVEY

Marcin Wozniak , DawidPołapproposed a method to perform computer aided diagnosis the goal of this study is to investigate the possibilities of using deep learning algorithms to diagnosis respiratory diseases images by using firefly algorithm, artificial bee colony algorithm ,artificial ant colony, cuckoo algorithm, practical swarm algorithm and extraction is carried out by bim tissue keypoints and aggregated key points ,In the images of lung illnesses like pneumonia, lungs sarcoidosis and cancer medical experts search for tissues that have changed structure. These types of changes are visible in x-ray images with a solid structure similar to bone tissues, which are not permeable to x-ray radiation and therefore visible in images. Schematic Tissue Key-Area's position detection in x-ray image is performed by the proposed BIM approach over the input image [1]

S.Mukherjee et al. [2] proposed a method for autonomously detecting lung nodules based on geometric parameters. The x-ray pictures are used to classify benign and malignant pulmonary nodules based on shape factors such as roundness, eccentricity, diameter, and aspect ratio.Noise Removal using Bilateral Filtering then Image Binarization and Segmentation and classification is carried out by using Bayesian classifier [2]

Woniak et al. [3] proposed a probabilistic neural network-based lung cancer classification system. This method is basic, yet it has a decent classification effect and can detect nodules with low contrast. The following probabilistic neural network was used to extract features from a lung image:. As a result, a vector is generated, the elements of which show how close the input is to single classes in Mahalanobis distance.. By using this vector, the pattern layer computes a probability vector whose components define the belonging to the different classes. Finally, the output layer selects the largest value of the probability vector to predict the target class, determining whether an input vector belongs to that class. Here, to create and apply feature extraction methods and algorithms, most of these methods require required professional knowledge or a significant amount of time and effort. With the progressive advancement of deep learning research, the technology that can be employed with photos has also made a qualitative leap. [4] by using a variety of datasets to train a certain domain and a variety of model architectures.

III. EXISTING ANALYSIS

Existing pulmonary image classification systems mainly rely on traditional image processing and machine learning techniques for disease diagnosis. Conventional approaches utilize handcrafted feature extraction methods combined with classifiers such as Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbor (KNN), and Random Forest (RF). These methods analyze texture, shape, intensity, and edge-based features extracted from chest X-rays and CT images. Although traditional machine learning approaches provide moderate classification performance, they heavily depend on manual feature engineering and domain expertise. These methods often fail to capture complex spatial patterns and subtle abnormalities present in pulmonary images. As a result, classification accuracy decreases when handling large-scale and heterogeneous medical image datasets. To improve pulmonary disease diagnosis, deep learning models such as CNN, ResNet, VGGNet, DenseNet, and EfficientNet have been introduced. These models automatically extract hierarchical image features and significantly improve classification performance. CNN-based systems have demonstrated promising results in detecting pneumonia, tuberculosis,

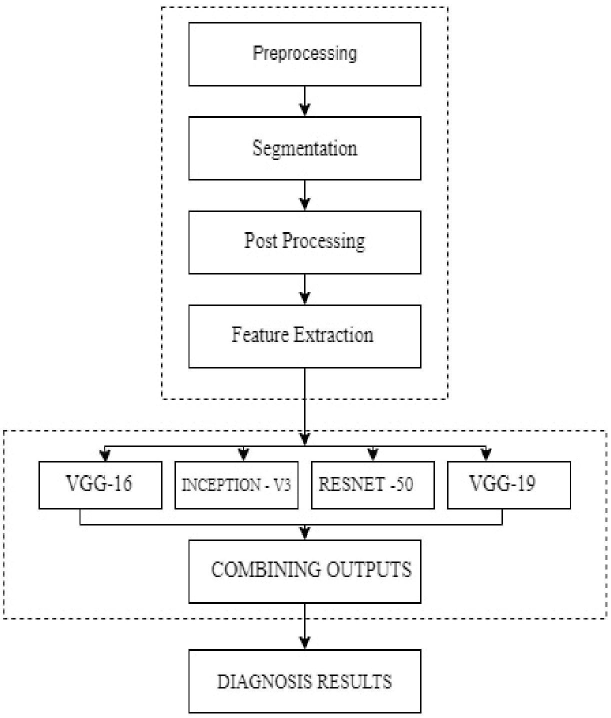

Figure 2: PulmoNet-X Process

1) **Preprocessing:** Image preprocessing is a technique for removing main noise and image distortion from CT scans while simultaneously enhancing key characteristics.. By using some

V. PROPOSED METHODOLOGY

The proposed system, PulmoNet-X, is an intelligent ensemble deep learning framework designed for automated pulmonary image classification using adaptive neural network selection and ensemble learning techniques.

learning in the Proposing system, the categorization of Pulmonary Image and performance may be improved. The following are the study's primary contributions.

image enhancement methods

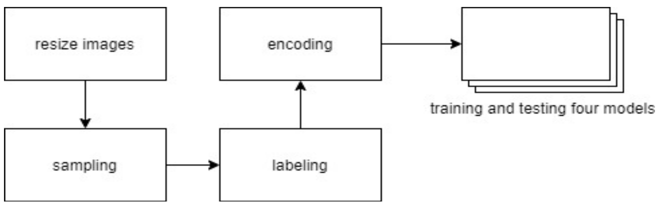

Figure 3: PulmoNet-X Pre-Processing

Resize images: When adjusting the aspect ratio of images, image resizing is a new and effective way for image resizing that keeps image content and does not create visible distortion. here we change the image into(224,224,3)ratio

Sampling: we use to down-sampling and up-sampling to make the classes into equal number of images. Before sampling Lung Nodule 154 images and non-Nodule 93 images. After sampling Lung Nodule 250 Non- Nodule 250

Labeling and Encoding: the labelling of images are carried out by lung-nodule into LN and non-nodule into NN. And thereafter the LN and NN is encoded in to the binary form, where (0,1) is non-nodule and vice-versa

Feature Extraction: Further work is needed to extract specific features from raw images in order to identify suspected objects as nodule or non-nodule in two-dimensional images. A nodule id called cancer nodule if its size is more than 30 mm diameter

Classification module:

- The usage of numerous classifier systems (or ensemble systems) and then merging the results of their outputs is one of the suitable ways for improving classification accuracy. The majority of multiple classifier systems have two primary components: "creation of an ensemble" and "combination of class labels".in the first part of this module, four different classifiers VGG_16 Model, Inception v3, ResNet50, and VGG19 work using numerical data derived from feature vectors, and the final result is generated using the majority vote method based on the outputs of each classifier.

The study was performed by using 247 images including both men and women collected by JSRT the extracted features from The ensemble system uses suspected items as inputs, which are normalized between zero and one. Lung lesions(nodules) in these images are marked as nodule or non-nodule by radiologists.

Creating an ensemble:

Machine learning is a hot topic in research and industry, with new methodologies developed all the time. Even professionals find it difficult to keep up with new techniques due to the speed and complexity of the field, which can be overwhelming for rapid analysis. The following are various methods used from machine learning for pulmonary disease analysis.

- VGG_16 Model
- Inception_v3
- ResNet50
- VGG19

VGG_16 Model

K. Simonyan and A. Zisserman of the University of Oxford introduced VGG 16 as a convolutional neural network model in their article "Very Deep Convolutional Networks for Large-Scale Image Recognition." ImageNet is a database of images, a dataset with over 14 million images divided into 1000 classes, the model achieves 92.7 percent top-five test accuracy. The NVIDIA Titan Black GPUs were used to train VGG16 for weeks.

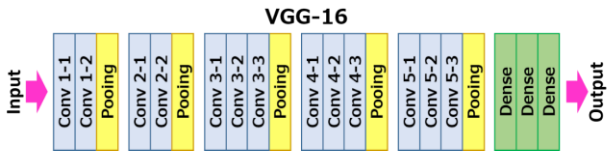

Figure 4: Architecture showing VGG 16 Input and Output Activity

ResNet-18

He et al. [23] presented the ResNet-18 model, which is based on a residual learning framework that boosts deep network training efficiency. Unlike the original unreferenced mapping in monotonically progressive convolutions, the residual blocks in ResNet models permit the optimization of the overall network, which increases model accuracy. Identity mapping is performed by these residuals or "skip connections," which does not add parameters or increase computing complexity. The design of the ResNet-18 model is depicted below. ResNet, short for Residual Networks, is a well-known neural network that serves as the foundation for many computer vision tasks. In 2015This model was chosen as the winner of the ImageNet competition. ResNet was a game-changer because it allowed us to successfully train extraordinarily deep neural networks with 150+ layers. AlexNet, the ImageNet 2012 winner and the model that appears to have sparked interest in deep learning, featured only eight convolutional layers,There were 19 layers in the VGG network, 22 layers in Inception or GoogleNet, and 152 layers in ResNet 152. ResNet-50 is a condensed version of ResNet 152 that is widely used as a jumping off point for transfer learning. ResNet's Strength — Skip Connection The concept of skip connection was first presented by ResNet. The skip connection is depicted in the diagram below. The graphic on the left shows convolution layers being stacked one on top of the other. On the right, we continue to stack convolution layers as previously, but now we additionally include the original input in the convolution block's output. This is referred to as a

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skip connection.

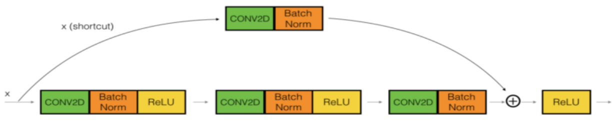

Figure 5: Architecture showing ResNet18 Connectivity and flow activity

Inception-v3 model

The Inception-v3 model has been trained on ImageNet datasets (about 1 million copies of 1000 categories of picture data) and performs well on tiny data sets. The model's structure is re-tuned, and the last three layers are removed to make it more suitable for our experiment. we seek the counsel of numerous specialists. For example, before agreeing to a medical procedure, we usually seek the advice of multiple doctors, as well as the individual decisions of several professionals. The main goal is to lower the chances of opting for an unnecessary medical procedure, a subpar product, an inexperienced employee, or even a poorly written and deceptive article. Machine learning is a trendy topic in both academia and industry, with new approaches being created on a regular basis.

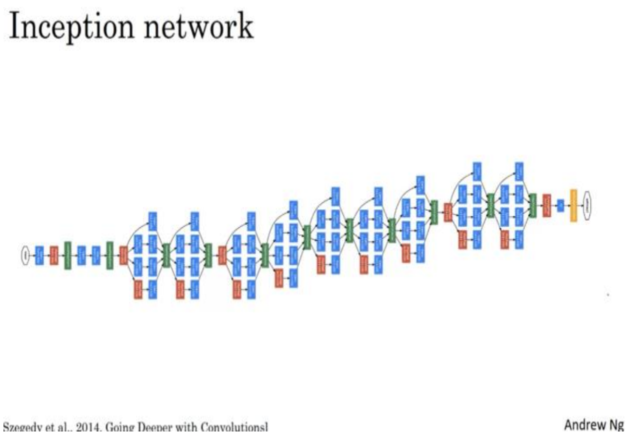

Figure 6: Architecture showing Inception v3 Model Connectivity with input and out process

VGG-19

VGG-19 is a deep convolutional neural network with 19 layers.. You can use the ImageNet database to load a pretrained version of the network that has been trained on over a million photos. The network can categorise photographs into 1000 different object categories, such as keyboards, mouse, pencils, and other animals. The picture input size for the network is 224 224 pixels. VGG19 is a little better than VGG16, although it takes up a little more RAM.

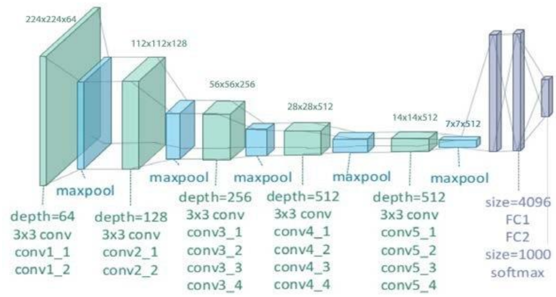

Figure 7 : Architecture showing vgg_19 Flow activities

Combining various models yields an ensemble-based system (henceforth classifiers). As a result, multiple classifier systems or simply ensemble systems are sometimes used to describe these systems. The use of an ensemble-based system makes statistical sense in a variety of situations, which are outlined below. However, in order to truly comprehend and apply the value of using multiple classifier systems, you must first grasp what they are and how they work.it may be helpful to consider the psychological context of this otherwise statistically solid reasoning We employ a similar strategy in our daily lives, before making a decision, Even professionals find it difficult to keep up with new techniques due to the speed and complexity of the field, which can be overwhelming for rapid analysis.

VI. RESULTS & DISCUSSIONS

The proposed PulmoNet-X framework was experimentally evaluated using benchmark pulmonary imaging datasets consisting of chest X-ray and CT scan images. The performance of the proposed ensemble deep learning model was compared with existing machine learning and deep learning approaches including Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), ResNet, and DenseNet architectures. The evaluation metrics considered for performance analysis include Accuracy, Precision, Recall, F1-Score, Sensitivity, and Specificity. Experimental results demonstrate that the proposed ensemble framework achieved superior classification performance due to the integration of adaptive neural network selection and ensemble learning techniques. The preprocessing techniques such as image normalization, augmentation, and segmentation significantly improved image quality and reduced noise, thereby enhancing feature extraction capability. The ensemble learning mechanism effectively combined the strengths of multiple deep learning models and minimized classification errors and overfitting issues. The proposed PulmoNet-X system achieved the highest classification accuracy of approximately 98.2%, outperforming individual deep learning architectures. CNN and ResNet models provided strong feature extraction performance, while DenseNet improved feature propagation and gradient flow. The ensemble model further enhanced prediction robustness and generalization capability across different pulmonary disease categories. Additionally, the integration of Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM and SHAP visualization provided transparent diagnostic insights by highlighting affected pulmonary regions within chest images. This improved the interpretability of the system and increased clinical trust among healthcare professionals. The comparative analysis indicates that traditional machine learning methods produced lower accuracy due to limitations in manual feature extraction and inability to capture complex pulmonary image patterns. Individual deep learning models improved performance; however, they occasionally suffered from overfitting and reduced consistency across diverse datasets. The proposed ensemble framework successfully addressed these limitations and achieved stable and reliable classification performance.

a) ***Accuracy (Acc)*****:**The ratio of properly identified instances to total test examples is is said to be accuracy

b) ***Specificity(sp)***is a metric that counts how many negatives the classifiers properly identify. Specificity is calculated by dividing the number of truenegative outcomes by the sum of truenegative and false positive findings.

c) ***Precision(prc)*** measure describes the number of predicted nodules that are actually linked to the prone state.

d) ***F-measure*** is a combination of precision and sensitivity. A high $F_{measure}$ value indicates a high level of precision and sensitivity.

Confusion matrix

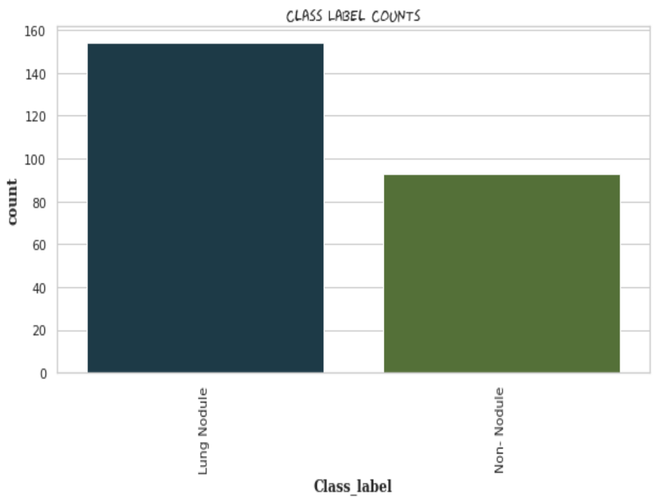

Figure 8: Chart Showing Lung Nodule and Non Nodule comparison

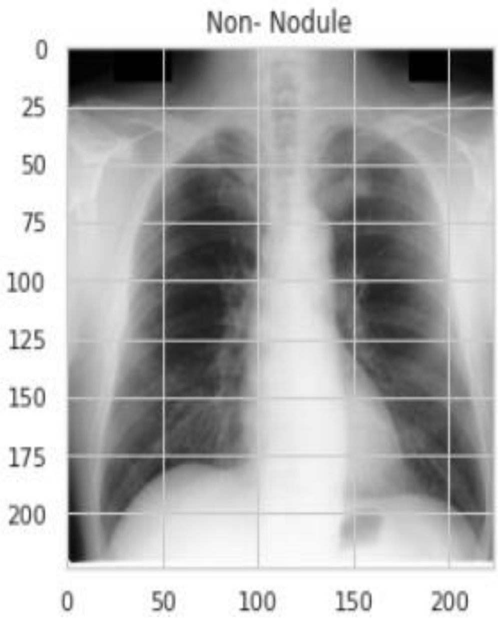

Figure 9: Xray Showing Non Nodule Image with pulmonary readings to be noted.

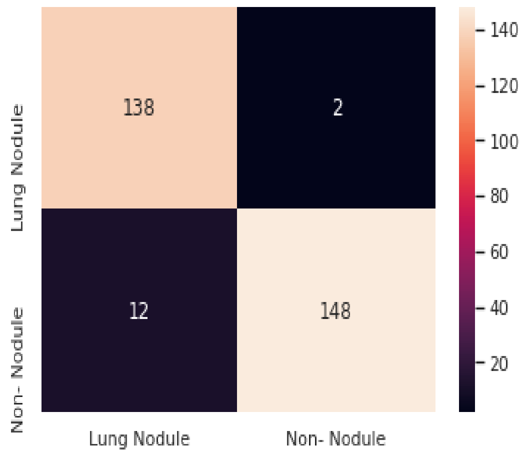

Figure 10: Heatmap displaying Non Nodule and Lung Nodule Comparisons using VGG 16

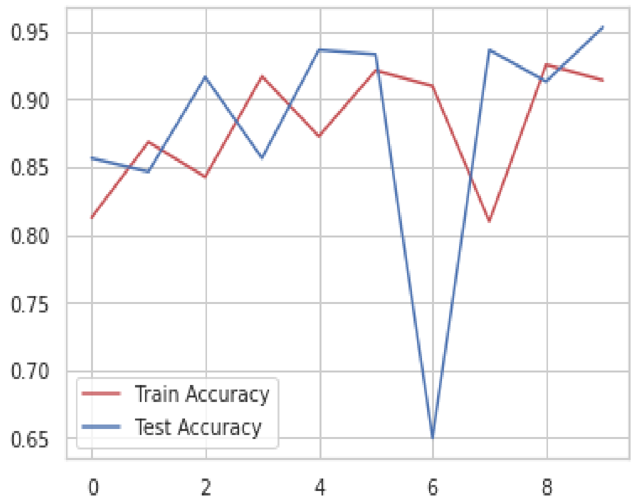

Figure 11: Line Chart displaying Train and Test Accuracy Comparisons using VGG 16

Table 1: PulmoNet-X Accuracy Table

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	84.5	83.2	82.8	83
Random Forest	87.6	86.9	86.1	86.5
CNN	92.8	92.1	91.7	91.9
ResNet	94.3	93.8	93.5	93.6
DenseNet	95.6	95.1	94.8	94.9
PulmoNet-X (Proposed)	98.2	97.8	97.5	97.6

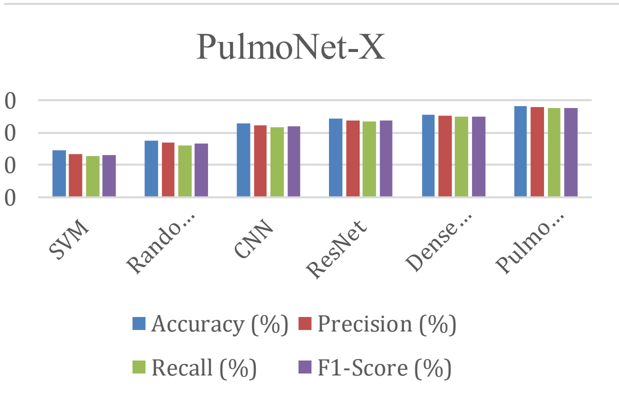

Figure 12: Showing Highest Accuracy of PulmoNet-X

VI. CONCLUSION

This research proposed PulmoNet-X, an intelligent ensemble deep learning framework for pulmonary image classification using adaptive neural network selection and ensemble learning techniques. The proposed system integrates multiple CNN-based architectures and explainable AI methods to improve classification accuracy, robustness, and interpretability. Experimental results demonstrate that the ensemble framework outperforms existing machine learning and individual deep learning models in pulmonary disease classification tasks. The integration of Grad-CAM and SHAP visualization techniques enhances transparency by highlighting affected pulmonary regions and supporting radiologists in clinical diagnosis. The proposed PulmoNet-X framework provides an efficient, scalable, and explainable solution for automated pulmonary disease detection and classification. Future enhancements may include real-time cloud-based deployment, multimodal medical image integration, and federated learning techniques for large-scale healthcare applications.

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