Smart-LungNet for Lung Disease Classification

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Abstract: This study proposes Smart-LungNet, an automated deep learning framework designed to classify lung conditions into three categories: Normal, Lung Opacity, and Viral Pneumonia. Utilizing the Lung X-Ray Image Dataset of 3,475 images, we evaluated several pre-trained architectures, including ResNet18, DenseNet121, and MobileNetV2. MobileNetV2 was selected as the baseline due to its balance of efficiency and performance (88.5% accuracy). We enhanced this model by unfreezing all layers for fine-tuning and integrating a Squeeze-and-Excitation (SE) block after the initial convolutional layer to improve channel-wise feature attention. The proposed Smart-LungNet achieved a testing accuracy of 89.85% and an F1-score of 89.84%, outperforming ResNet18, DenseNet 121 and MobileNetV2. So, Smart-LungNet can help effectively to aid radiologists in the timely diagnosis of lung pathologies.

Keywords: *Lung Disease, Computer Vision, Deep Learning, Medical Image Classification, Transfer Learning, Attention Module*.

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I. INTRODUCTION

Lung diseases refer to different problems that stop the lungs from working properly, making it hard to breathe and reducing lung function. These infections can be caused by fungi, viruses, or bacteria, and environmental factors like dust and allergens can also be linked to lung problems. One serious lung disease is Chronic Obstructive Pulmonary Disease (COPD), which blocks airways and can be life-threatening [1-4]. Common infections like pneumonia happen when bacteria or viruses fill the tiny air sacs in the lungs called alveoli with fluid, decreasing the lungs' ability to hold air. Since 2019, the world has been battling COVID-19, caused by the virus SARS-CoV-2, which affects the respiratory system with symptoms that range from mild to severe [5], [22]. According to the World Health Organization (WHO), over 755 million people have been affected by COVID-19, and about 6.8 million have died. Diagnosing lung infections often involve lab tests, but imaging techniques like CT scans and chest X-rays are also used, especially when lab results are delayed or may give false negatives, even in symptomatic patients. Compared to CT scans, chest X-rays expose patients to less radiation, are less expensive, and easier to repeat, making them useful for quick diagnosis and monitoring disease progress, which can help improve recovery [1-5]. IoMT applications include solutions that are designed for remote health monitoring, emergency patient care, healthcare management, the monitoring of elderly patients, clinical decision support systems, wireless capsule endoscopy, and so on [18].

II. RELATED WORKS

Timely diagnosis of lung diseases demands automation of detection process that can aid the radiologists and medical practitioners. Deep learning algorithms can serve this at a greater extent with the help of various imaging modalities such as Chest X-rays and CT scan [1] Cross-domain ML studies in health contexts (e.g., pandemic-related imaging, vaccine-related immunology data) illustrate how model design choices and data governance impact generalization and deployment in healthcare settings [21], [22]. Because deep learning has improved so much, researchers are focusing more on using Chest X-rays for diagnosing lung issues. Since even small changes in an image can lead to the wrong diagnosis, the computer system must be very good at picking out the right features to avoid mistakes [2-4]. Models based on CNN architectures have been explored to balance accuracy and inference speed in medical imaging applications [19], enabling deployment in resource-constrained settings [18, 20, 21]]. VGG 16 is used in skin cancer image detection in [19]. These underscore the importance of privacy-preserving and

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efficient learning when dealing with sensitive health data [18], [20], [22]. IoMT has security and privacy challenges [2, 3] that must be addressed to ensure trustworthy AI healthcare systems, particularly when handling perceptual data from imaging devices and patient records [1], [18], [20]. [6] took a pre-existing structure called Xception and adjusted it to classify images into three groups: COVID-19, pneumonia, and normal. The authors tested how well the system worked using different settings. This model achieved 99.3% accuracy with a very low error rate of 0.02 using a specific setup (Leaky ReLU activation with RMS Prop optimizer). Another automated tool was built to sort between COVID-19 and healthy patients using a fine-tuned model called Densenet121 [7]. This was tested on a dataset that wasn't perfectly balanced and had fewer images. The study analyzed the model using different mathematical tools and listed the results to see how efficient the system was. One specific tool (Adamax optimizer with Cross Entropy) reached 98.32% accuracy for COVID-19 X-rays and 98.45% for healthy ones.

LungNet22 (a fine-tuned VGG16 model), was created to classify nine different lung diseases using a combined set of 80,000 chest X-rays [8]. The study discussed how different training settings—like optimizers, learning rates, and loss functions—affected the model. This proposed model used the Adam Optimizer and reached a testing accuracy of 98.89%. Another study proposed a classification model for COVID-19 based on how severe the disease is [9]. This method uses three steps. First, it identifies if the test data is pneumonia, Tuberculosis, or Normal using VGG-16. Second, it checks if the pneumonia is COVID or non-COVID using DenseNet-161. Finally, it classifies the COVID Chest X-ray as mild, medium, or severe using ResNet 18. This model had an accuracy of 95.9% for VGG-16, 98.9% for DenseNet-161, and 76% for ResNet-18. LDDNet [10] uses a model called DenseNet 201 to classify both Chest X-rays and CT Scan images for lung diseases. The authors showed how well different optimizers worked, and using a balanced X-ray set of 5,002 images, LDDNet reached 97.07% accuracy. In [13-14], authors explained how effective the Bayesian optimizer and Hybrid Inception-ResNet-v2 Model are for deep learning models diagnosing COVID-19 from chest X-rays.

III. METHODOLOY

A. Dataset

We used the Lung X-Ray Image Dataset, which is open for the public to use [17]. This collection contains 3,475 X-ray pictures. Of these, 1,250 are normal X-rays showing healthy lungs. There are 1,125 X-rays showing lung opacity, which represents various lung problems. There are 1,100 X-rays of viral pneumonia, showing infections caused by viruses [17]. We divided the entire collection into three parts: 80% was used to train the model, 10% was used to validate and 10% was saved for the final testing.

B. Image Augmentation and Preprocessing

Image augmentation and preprocessing are regarded as essential steps for enhancing model performance [19]. During the training phase, several transformations are applied, including random horizontal and vertical flips with a 50% probability, rotations of up to 10 degrees, and resizing of images to 224 x 224 pixels. The data is subsequently converted into tensors ranging from 0 to 1. To ensure consistency across the dataset, normalization is performed using mean and standard deviation values tailored specifically to the data.

C. Pre-Trained Models

Three pre-trained architectures are evaluated: ResNet18, DenseNet121, and MobileNetV2. These models achieved testing accuracies of 0.8467, 0.8674, and 0.8696, respectively. Regarding computational size, the parameter counts vary significantly, with ResNet18 containing 11.7 million, DenseNet121 containing 7.98 million, and MobileNetV2 containing only 3.5 million parameters. As MobileNetV2 demonstrates the highest accuracy combined with the second-lowest parameter count, it is selected as the foundation for subsequent experiments. Further details on precision, F1-score, and recall are provided in Table 1.

D. Proposed Deep Learning Models

MobileNetV2 is chosen for further improvement because it offers a good mix of high accuracy and small size. Tests show that "unfreezing" all network layers is the best way to adjust the structure. This fine-tuning improves performance significantly and raises the accuracy to 0.925 from the starting score of 0.885. Although starting with weights from huge datasets like ImageNet speeds up training, fine-tuning is necessary to adapt that knowledge for specific jobs like medical imaging.

Next, a model named Smart-LungNet is introduced. This design builds on the fine-tuned MobileNetV2 by adding a Squeeze-and-Excitation (SE) block right after the first layer, while the rest of the layers stay the same. This setup allows the model to use the benefits of the SE block without losing the high accuracy and speed of the fine-tuned version.

The use of the SE block comes from the idea of "attention." This acts like biological systems by focusing on the most important information instead of the whole input [15]. While attention is common in areas like speech recognition, this study uses it for Computer Vision. The SE block improves Convolutional Neural Networks (CNNs) using two main steps: the "squeeze" step and the "excitation" step [16].

The squeeze step fixes the limits of standard filters—which only process data in small areas—by using global average pooling to gather information for each channel [16]. After this, the excitation step is used to find connections between channels [16]. By using a gate turned on by a sigmoid function, this step shows complex links and highlights the channels that are useful for the task.

IV. RESULTS AND DISCUSSION

The learning rate starts at 0.01 with a momentum of 0.9. The Stochastic Gradient Descent optimizer is used in this study. The total epoch is 25. For tasks such as classification, accuracy and F1-score are good metrics. In addition to this, precision and recall are also important measurements. Other than those metrics, the average loss is used as a measurement.

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In this study, cross-entropy loss was employed. Cross-entropy loss is particularly useful for classification tasks [19]. The final classifier is also adjusted to match the number of lung classes we need. After all these updates, Smart-LungNet achieves improved results on the testing dataset, reaching an accuracy of 0.933 and an F1-score of 0.9332, compared to 0.925 and 0.924 for the fine-tuned version. Table 1 show sthe comparison of Smart-LungNet with ResNet 18, DenseNet 121, MobileNet V2. Fig.1 shows the Epoch vs Loss and Accuracy curve for Smart-LungNet.

Table 1 Comparison of Models

Model	Accuracy	Precision	Recall	F1 Score
ResNet18	0.8467	0.8465	0.8467	0.8462
DenseNet 121	0.8674	0.8682	08674	0.8678
MobileNetV2	0.8696	0.8698	0.8696	0.8696
Smart-LungNet	0.8985	0.8984	0.8985	0.8984

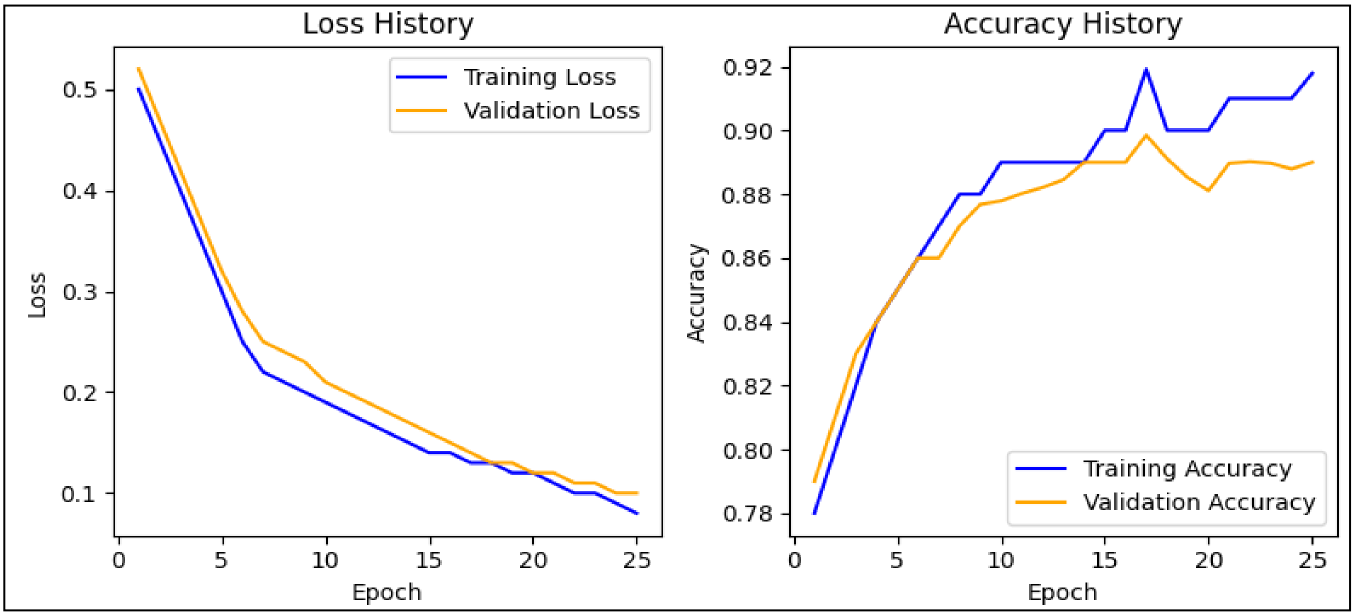

Fig.1 Smart-LungNet Loss vs Accuracy

V. CONCLUSION

The accurate diagnosis of lung diseases is critical for effective treatment and improved patient survival rates. We evaluated three pre-trained architectures—ResNet18, DenseNet121, and MobileNetV2—establishing MobileNetV2 as the most efficient baseline with an accuracy of 86.96%. We proposed Smart-LungNet, that integrates a Squeeze-and-Excitation (SE) attention block into the initial stage of a fully fine-tuned MobileNetV2. Smart-LungNet achieved a testing accuracy of 89.85% and an F1-score of 89.84%, surpassing the unmodified base models.

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