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Optimizing the Powerhouse: Fine-Tuning CNNs for Superior Lung Disorder Detection

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***Abstract*— Present work involves the use of deep learning models, in particular, Convolutional Neural Networks, to detect critical diseases of the lungs such as pneumonia, tuberculosis, and lung cancer through the analysis of chest X-ray and CT scan images. CNN has emerged as a robust tool for the analysis of medical images due to their natural ability to automatically extract hierarchical features, hence making them ideal for complicated tasks such as disease detection. Well-known architectures in this work are VGG16 and VGG19; they are combined with specially designed sequential and functional models to solve this task of recognizing those diseases. These models are trained on open-source data that will provide the model with real-world medical images for it to learn from diverse cases of lung abnormalities. One important enhancement in pursuit of model performance and robustness in this work is the employment of augmentation techniques. Since, in most cases, labeled medical data comes in a limited amount, augmentation is an important way of artificially increasing the effective size of the training set to allow the models to generalize better on unseen data. The images were rescaled, shear transformed, and flipped horizontally to simulate different orientations and variations that can arise during real-world X-ray and CT scans. This will also make the models less sensitive to changes in orientation, scale, or noise of an image and enhance their capability of detecting diseases more precisely in different datasets. The results of the study show that early detection by deep learning models has improved a lot by incorporating advanced CNN architectures and augmentation strategies. Those customized sequential and functional models performed very well, especially in the classification of lung diseases with very high precision. This is indeed important for early diagnosis because early identification of diseases like pneumonia, tuberculosis, and lung cancer can lead to better treatment plans and improved patient outcomes. Moreover, the study highlights how deep learning models may represent the most viable tool in clinical practice to provide not only accurate but timely diagnostic information that would support medical professionals most proficiently.**

Keywords—CNN; VGG19; VGG16; Functionalmodel; Sequential Model.

I. INTRODUCTION

The lungs are very important organs of the respiratory system, which contribute to exchanging oxygen and carbon dioxide. However, the lungs are susceptible to a number of diseases which may impair their function. Such respiratory diseases may range from the common cold and influenza, which are relatively mild conditions causing temporary discomforts, to life-threatening conditions like pneumonia, tuberculosis. The global burden of respiratory disease is enormous. According to estimation through the Worldwide Conference of Respiratory Societies, in any particular year, an approximate 10.4 million people suffer from tuberculosis worldwide, accounting for the death toll of 1.4 million annually [1]. Lung cancer is also such a killer disease; more than 1.6 million deaths take place in a year due to this disease alone worldwide. Moreover, pneumonia was solely responsible, especially in infants, for over 1.23 million deaths of the children under five years of age, according to a study published by the Bloomberg School of Public Health at John Hopkins.

The only method of dealing with such diseases is early detection, and this assists in increased survival rates and a reduction in the death rates. Some of the most utilized medical imaging for diagnosis include X-ray scans of the chest and CT scan images. These images require interpretation from skilled radiologists. The number of health care providers, such as doctors, may be low with regard to rural areas; for example, in certain places-CHCs-76.1 percent of doctors are lacking there.

Recent advances in AI, and more so deep learning in the previous years, have achieved a lot in automating and improving the accuracy in the analysis of medical images. CNNs are one of the deep learning models that have indeed shown outstanding results for the class of the image classification task, hence aptly. The different pre-trained deep learning models, such as CNN, VGG16, and VGG19 used in this work, are applied for the detection and classification of lung diseases by taking chest X-ray and CT scan images. In this work, publicly available data have been used, and augmentation has been performed to increase the strength of these models and generalize their capability. The performances of the custom sequential and functional models that show high potential in clinical settings are compared. Indeed, the results obtained from this study did prove that deep learning models do stand a chance of being helpful in early lung diseases detection, with the purpose of assisting healthcare professionals in making timely and early precise diagnosis. This work adds to the accumulation of evidence on AI integration into medical practice in general and radiology in particular. [1]

Fig .1. Lung Disorder

Fig-1 is the image based on focusing on the detection of lung diseases with deep learning technology. The image focuses on highlighting the lungs with an X-ray and CT scans with digital analytic elements that symbolize the detection process. Based on the research here are some of the Contributions below:

- The datasets used here are Pneumonia Chest X-ray Dataset and Chest CT-Scan for the detection of lung diseases, which may be pneumonia or COVID-19.
- The Deep Learning models were used in the research: CNN models-VGG16, VGG19, and our sequential and functional models for classification.
- Sequential and functional models have been designed, optimized, and tested in order to see which one of the two does a better job regarding the detection of lung diseases.
- The augmented image techniques involved the flipping, rotation, and scaling of images to make them larger and robust.
- The fine-tuned VGG16 and VGG19 models, sequential models, and functional models on medical imaging datasets for early disease diagnosis.
- On carrying out the performance evaluation, it came out that the models evaluated the accuracy, precision, recall, and F1-score, where VGG19 and the functional models were among the best.

II. RELATED WORK

Liu et al. [1] models of tuberculosis detection using CNN-SVM. However, issues arose in terms of low accuracy. Jaiswal et al. extracted X-ray features using Mask RCNN, which was a pretty heavy computation. Elshennawy and Ibrahim developed pneumonia detection models involving CNNs and pre-trained models like ResNet152v2 and MobileNetV2. However, the challenges they encountered were computational complexity. Li et al. [2] that Random Forest Regression and Gradient Boosting are the best methods for air quality prediction. Rajaselvi et al. used CNN and transfer learning in the diagnosis of lung diseases. Agarwal et al. presented a comparison done with several machine learning models, from which it was obtained that the best performance in the classification of lung cancer was achieved using Random Forest, outperforming other algorithms such as Support Vector Machines. Xie et al.[3] used deep learning to classify CT images into benign and malignant nodules. Wu and Zhao used EDM AI for differentiating early small cell lung cancer. Anifah et al. used Gray-Level Co-occurrence Matrices in detecting lung cancer and achieved a moderate level of accuracy. Deshpande used SVM and image fusion to enhance the detection performance. Bhukya et al. [4](2023) propose advanced CNNs for the classification of lung diseases, mainly COVID-19, pneumonia, tuberculosis, and normal cases. The classification accuracy [5] obtained in this study is 94%, using large datasets and CNN architecture to improve diagnosis, hence highlighting the potential in the improvement of medical image analysisRaju et al. [6] present the prediction of lung diseases from chest X-ray images using a CNN-based deep learning model. It highlights the use of machine learning in support of the diagnosis of diseases such as COVID-19, pneumonia, and tuberculosis with an accuracy of 91%, showing how important CNN would be for diagnostics. Some works have used CNNs for the detection of lung diseases, which seem promising-include ResNet, Dense Net, and VGG19. Previous works focused on the classification of single diseases based on medical images, particularly pneumonia, tuberculosis, and lung cancer, using X-rays and computed tomography scans [7]. However, in most of these studies, the datasets were either too small or imbalanced, which, eventually, showed up in the accuracy and generalization aspect . [8] author explains in detail the integrated approach to the prediction of air quality by determining the seriousness of the lung disease through image-based AQI analysis. Techniques involved in the system are Neural Network, KNN, and SVC models, out of which very high accuracy was observed during testing.[9] covers early prediction of lung diseases by applying machine learning and deep learning techniques, including CNN and Capsule Networks on [15]X-ray data to improve early detection accuracy for conditions such as asthma, COPD, and lung rapid rise in the incidence of lung diseases, including COPD, asthma, and pneumonia caused by environmental changes, pollution, and smoking requires the design [11][12]and development of diagnostic systems with efficiency. Large datasets, such as chest X-rays, therefore, are increasingly subjected to the application of ML and DL methods for lung disease prediction[13][14] The application of Machine learning in classifying disease based on lung sounds produces good performance but still needs a wider scope of studies[16]. learning improves the rate of automation, interprets non-structured information and performs with greater precision AI related tasks and forecasts [17] chest X-ray-based lung disease detectors using several types of deep learning and optimization techniques[10][18].

III. PRELIMINARIES

A. Convolutional Neural Network Model

A CNN is a type of deep learning model that is mostly used in the fields of classification and image recognition**.** It makes use of convolutional layers to achieve feature hierarchies in space in an automatic manner using filters with backpropagation. Fully connected, pooling, and convolutional layers make to a CNN's general architecture. It does exceptionally well in the processing tasks of images and videos because it effectively catches the features of an object in space.

B. Functional Model

Another important feature of deep learning frameworks like Keras is the Functional API, which allows more flexibility than a Sequential model. This could be used to make complex architectures such as multi-input models, multi-output models, shared-weight layers, or even residual connections. Unlike in Sequential, where layers can only be stacked linearly, the Functional API allows for directed acyclic graph-like structures, making for more complex models.

C. Sequential Model

The 'Sequential' model represents a simpler way of building a model wherein layers are added to each other in continuum. In this model, every layer has only one input and one output; hence, it is quite handy for uncomplicated models like CNN. There isn't any multiple input or even branching layers in this architecture. However, that makes it less flexible since, compared to the Functional API, for complicated architectures, this probably is not what one would want to use.

D. VGG16

Oxford's Visual Geometry Group created the 16-layer deep Convolutional Neural Network known as VGG16. Thirteen convolutional layers and three fully linked layers utilizing tiny 3x3 filters made up this model. A nice thing about this concept is that, since it uses identical filter sizes all over, this concept makes it easy for user understanding and implementation. VGG16 is widely used for image classification tasks and has achieved high performance in benchmarks like ImageNet; though, it comes rather expensively due to depth and the number of parameters.

E. VGG19

VGG19 is the extension of VGG16, comprising in total 19 layers: 16 convolutional and 3 fully connected. While VGG19 operates with the same characteristics as VGG16-it also uses small 3x3 filters-the presence of more convolutional layers makes it much deeper, hence much more capable of learning complex features from images. Accordingly, the computational burden and memory significantly rise with the fact that this network has become much deeper compared to VGG16. VGG19 has found extensive use in image classification, transfer learning, and feature extraction.

IV. PROPOSED METHODOLOGY

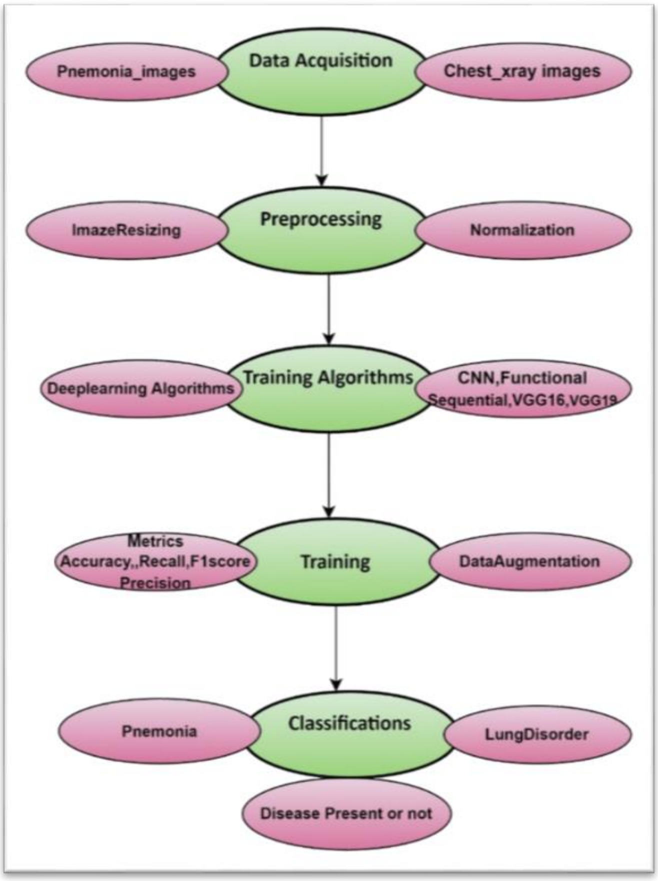

Fig. 2. Deep learning workflow for Lung Disorder Detection

Fig 2 describes the procedure for diagnosing pneumonia and lung diseases using deep learning: from the acquisition of data to the classification outcome Below is the explanation of diagram

A . Data Acquisition

Pneumonia Images and Chest X-ray Images: Data is obtained by the system from chest X-ray images. These images are taken from the datasets [17][18]. Such data would be crucial for lung diseases like pneumonia, tuberculosis, and lung cancer. Data gathered becomes the input to train the model. The datasets are prepared in such a way that they include great variation in patient demographics, disease stages, and image quality to support the model in generalizing well. These, after proper labeling, form the input for training the model in finding and classifying abnormalities in the lungs.

B. Preprocessing

Resizing will be standardization of size dimensions of images to decrease computation and keep vital attributes for coherence with VGG16/VGG19 architectures. Normalizing pixel values to scale between 0-1 accelerates convergence speeds and avoids model bias that could occur due to differing pixel intensities or dimension, thus improving models during preprocessing.

C. Training Algorithms

- Convolutional Neural Networks: CNNs perform feature extraction and can learn from the medical images possessing patterns that will be informative in classification tasks.
- Pre-Trained Models: Pre-trained VGG16 and VGG19 models on large image datasets such as ImageNet. Transfer learning makes use of the weights learned for the detection of lung diseases.
- Convolutional Neural Networks: These are a category of deep neural networks designed to operate upon image data, making them quite suitable for medical imagery regarding different types of lung diseases.
- The sequential model is a deep learning model architecture that stacks layers linearly. This, in turn, makes its implementation very easy. It is perfect for cases where the model should go in a straightforward, linear direction-the VGG16 and VGG19 among others.
- Functional Model in Keras: This model gives one more liberty when one wants to build some very complex neural networks with branch-out and merging layers. An example could be an architecture where there isn't a strictly linear relationship between layers.

F. Training

- Metrics During training, accuracy, recall, F1-score, and precision are used as metrics for performance tracking. These metrics represent the capability of this model to learn and generalize on unseen data.
- Data Augmentation The augmentations performed are flipping, rotation, and shearing. This is to avoid overfitting, and it hopefully will make the model robust. Data augmentation artificially increases the size of a training dataset by adding variability in training data, simulating different view angles and conditions.

E. Classifications

The model was used to classify or differentiate between healthy lungs, pneumonia-affected, and other lung disorders. The system output assists the physician in diagnosing at an early stage through a clinical decision support system. It can indicate the presence or absence of disease.
VGG16: slightly faster with fewer parameters, it generalized better on smaller-sized datasets.
VGG19: While the deeper model was generalizing better in the case of larger datasets, still it requires more careful tuning of the learning rate and regularization techniques, such as dropout.

V. RESULTS AND DISCUSSIONS

A. Description of Dataset

TABLE I. PNEMONIA_DATASET [17]

Attribute	Details
Dataset Name	Pneumonia Dataset - Chest X-ray
Source	Kaggle (Paul Mooney)
Total Images	5,856
Class Distribution	Normal: 1,583 Pneumonia: 4273
Subcategories	Bacterial and Viral
Resolution	Variable (Standardized during pre-processing)
Pre-processing	Resizing, Normalization
Ages	Pediatric and adult cases
Diversity	Broad age range and geographic diversity

Table-I describes the Pneumonia Chest X-ray dataset, class distribution, resolution, and also preprocessing methods used.

TABLE II. CHEST_XRAY DATASET [18]

Attribute	Details
Dataset Name	Chest CT-Scan Images Dataset
Source	Kaggle (Mohamed Hany)
Total Images	907
Class Distribution	COVID-19, Viral Pneumonia, Normal
Subcategories	None
Resolution	Standard CT scan resolution
Pre-processing	Segmented for disease detection
Ages	Not specified
Diversity	Includes various lung disease images

Table-II describes the Chest X-ray dataset, class distribution, resolution, and also preprocessing methods used.

B. Performance of Metric[1]

1)Accuracy: It is the proportion of correct predictions, both positive and negative.

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

2) Precision: It will measure the proportion of correct positive predictions from all the predicted positives.

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

3)Recall: Recall measures the ability to spot all actual positive cases.

$$Recall = \frac{TP}{TP+FP} \quad (3)$$

4)F1-Score: This F1 score is the harmonic mean of precision and recall, balancing their trade-offs.

$$F1=2\times \frac{Precision\times Recall}{Precision+Recall} \quad (4)$$

TABLE III. PNEMONIA_DATASET METRICS

Dataset	Techniques	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Pneumonia dataset	CNN	93.0	89.0	90.0	92.0
	Sequential model	98.7	92.0	87.5	91.0
	Functional model	98.9	89.0	90.0	87.5
	VGG16	92.0	85.5	87.0	90.0
	VGG19	99.4	99.1	99.0	98.0

Table-III is a comparison table of different deep learning techniques on the Pneumonia dataset in terms of accuracy, precision, recall, and F1-score.

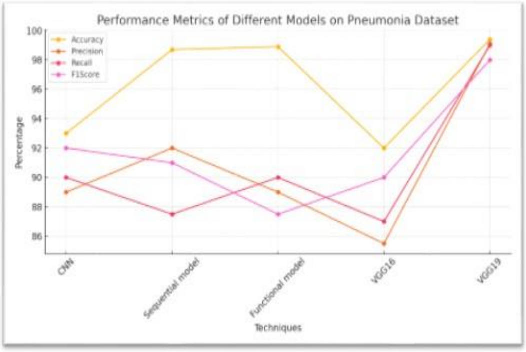

Fig. 3. Performance of metrics in Pnemonia_dataset

Fig. 3 and Fig. 4 show the performance metrics (accuracy, precision, recall, and F1 score) of different models: CNN, Sequential, Functional, VGG16 and VGG19 on the pneumonia dataset. Fig. 3 demonstrates these metrics in the format of a line graph where every metric for the models is shown in a different color to point out the differences across various models. Fig. 4, a bar chart for the same metrics, where each of them is depicted in a different color, and provides a comparative view, where in which model performance can be judged on the accuracy, precision, recall, F1-score.

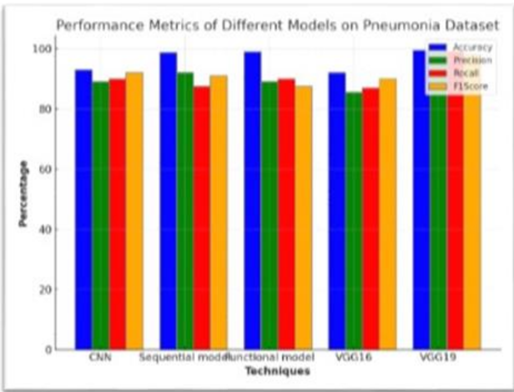

Fig. 4. Performance of metrics in bargraph

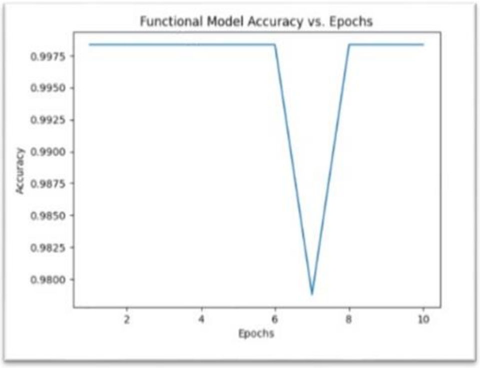

Fig 5. Functional model accuracy vs epoch

Fig5 is the plot of a line graph that reads Functional Model Accuracy vs. Epochs, showing fluctuations in accuracy over 10 epochs with a dip around epoch 5.

Fig.6 is a bar chart comparing the accuracy of the two models, namely, SequentialModel and Functional Model. Interestingly, the bars for both appear almost of the same height, which means their accuracy levels are somewhat equal or very close to each other.

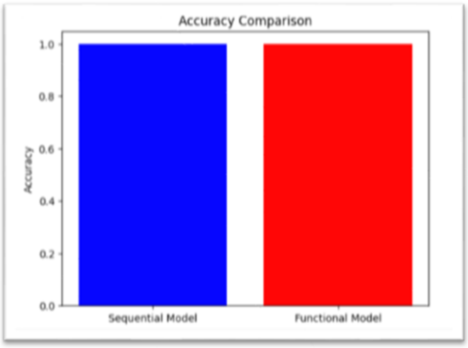

Fig. 6. Accuracy comparison

TABLE IV. CHEST_XRAY_DATASET METRICS

Dataset	Techniques	Accuracy	Precision	Recall	F1Score
Chest x-ray dataset	CNN	89	77	80	85
	Sequential Model	98.2	91	85.6	88
	Functional Model	99.1	90	89	90
	VGG16	85	80	79	80
	VGG19	99.3	92	91	93.5

Table-IV is a comparison table of different deep learning techniques on the Chest_xray dataset in terms of accuracy, precision, recall, and F1-score.

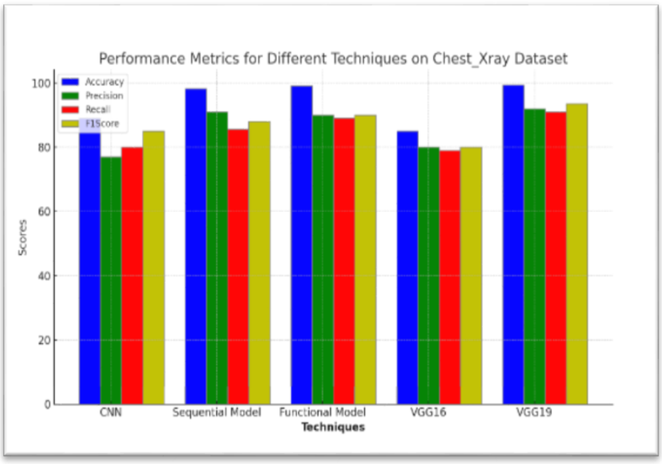

Fig.7. performance metrics on Chest_xray dataset

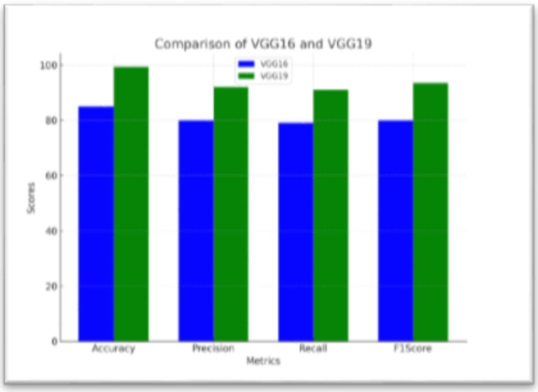

Fig. 8. Comparison of VGG16 and VGG19

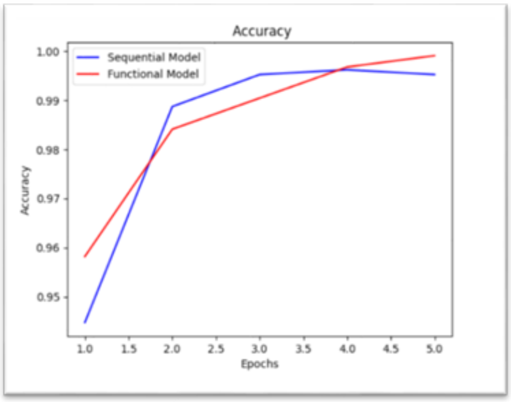

Fig. 9. Sequential model vs functional

VI. CONCLUSION

VGG19 pneumonia dataset achieves an accuracy of 99.4% and a F1-score of 98 with a fair trade-off between precision, which is 99.1%, and recall of 99%. That is, VGG19 prevents both false positives and negatives, making it very reliable in giving a valid conclusion about the actual case of pneumonia. While the Functional Model, with accuracy 98.9%, has a relatively low F1 score, which is 87.5, this does indicate a certain tradeoff between precision and recall, not best suited in the medical field due to equal importance of both. CNN and VGG16 are accurate at 93% and 92%, respectively. However, the F1-scores obtained for them are relatively lower than those of VGG19.

Overall, VGG19 is the best predictive model of pneumonia since it very well balances precision with accuracy and recall, thus making it the most dependable for real application in hospitals. Its sensitivity and specificity are high and will ensure a good prediction of pneumonia with errors that are the least in the clinic.

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