Lung Disease Detection From Chest X-ray Images Using Hybrid Machine Learning Model

Mrs. Lis Jose
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
lisjose@amaljyothi.ac.in

Akhil Lorence
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
akhillorence2024@cs.ajce.in

Akhil Manohar
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
akhilmanohar2024@cs.ajce.in

Amal Jose Chacko
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
amaljosechacko2024@cs.ajce.in

Arjun J
Dept. of Computer Science
Amal Jyothi College of Engineering
Kottayam, India
arjunj2024@cs.ajce.in

***Abstract*—Lots of people die due to lung diseases in India alone. The human lungs is a complicated system where different disease occur at different parts of this system. Some diseases, such as asthma, affect the airways of the lungs causing inflammation which results in shortness of breath. Diseases such as pneumonia, tuberculosis, and lung cancer affect the air sacs inside the lungs, which are called alveoli. The Covid-19 corona virus has significantly disrupted the global economy, culture, and health systems. Since the corona virus usually first causes symptoms in the lungs of patients, chest X-ray images can be useful in accurately diagnosing a patient.The rapid advancement in deep learning techniques has significantly impacted the field of medical imaging, particularly in diagnosing lung diseases. The proposed system aims to develop a hybrid machine learning model using InceptionV3 and DenseNet for the detection of lung diseases from chest X-ray images. Our work highlights the potential of machine learning models in automating the detection of lung diseases, providing insights into their comparative strengths and suggesting new pathways for future research.**

***Index Terms*—DenseNet, InceptionV3, Deep learning**

I. Introduction

One of the biggest challenges in the medical industry is the timely and precise detection of lung disorders, such as pneumonia, TB, and COVID-19, and differentiating them from healthy lung states. Pneumonia is an acute respiratory infection that affects the lungs. The lungs are made up ofsmall sacs called alveoli, which fill with air when a person breathes. When a person has pneumonia, the alveoli gets filled with pus and fluid, which makes breathing painful and limits the oxygen intake. Pulmonary tuberculosis is causedby the bacterium mycobacterium tuberculosis. Tuberculosis is contagious, which means, the bacteria may spread from an infected person to another person. They can be spread through coughing or sneezing from an infected person. The infectious disease COVID-19 is brought on by the corona virus thatwas most recently identified. Prior to the outbreak that started in Wuhan, China, in December 2019, nothing was known about this novel virus or illness. The most typical COVID-19 symptoms include fever, exhaustion, and dry cough. Ithas an impact on the infected person's immune system. The emergence of deep learning technology holds great promise for improving radiology diagnostic techniques, especially in the area of picture identification. A subclass of deep neural networks called convolutional neural networks, or CNNs, have demonstrated remarkable skills in the interpretation and classification of medical pictures, such as chest X-ray scans. These developments have the potential to improve patient outcomes by increasing diagnosis precision and cutting down on the amount of time between screening and action.

One of the most popular radiological examinations is the chest X-ray, which is essential for the diagnosis and treatment of many thoracic disorders. On the other hand, radiologists' skill is crucial for the sophisticated interpretation of theseimages. The necessity for automated systems that can correctlyinterpret X-ray images is highlighted by the enormous demandand sheer volume of X-ray imaging, which is made worseby global health emergencies like the COVID-19 pandemic. This will lessen the burden on medical workers and mini-mize human mistake. Powerful models like InceptionV3 and DenseNet, which have set new standards in image classifica- tion tasks, are the result of recent advances in deep learning. These models are perfect for medical image analysis sincethey can extract subtle information from images and havebeen trained on large datasets. Nonetheless, every model possesses distinct advantages and drawbacks, which has led tothe investigation of hybrid models that integrate the optimal features of many architectures to enhance diagnostic precision.In the proposed system, we provide a novel hybrid deep learning model for the categorization of chest X-ray pic- tures into four categories: pneumonia, COVID-19, healthy,and tuberculosis. The model utilizes the advantages of both InceptionV3 and DenseNet121. Our method seeks to maximizethese models' complementing feature extraction powers in order to improve the model's overall performance. We want to increase the precision of automated lung disease detection by integrating these designs, providing radiologists with a useful tool to help them diagnose patients more quickly.

II. Related Works

Adem Tekerek et al. [1] proposed a novel method intended to increase the prediction accuracy of lung disorders using DenseNet and MobileNet. For the diagnosis of lung cancer, pneumonia, and tuberculosis, among other respiratory diseases, chest X-ray images were used. In the suggested approach to improve their quality and get rid of any noise or artifacts that can impede the analysis process, the chest X-ray images first go through preprocessing. The DenseNet and MobileNet architectures are used to extract features from the chest X-ray images after preprocessing. DenseNet is renowned for its densely connected layers, which makeit possible to reuse features and learn more effectively. However, MobileNet is made to be computationally efficient and lightweight, which makes it appropriate for contexts with limited resources like cloud-based apps or mobile devices. The suggested approach seeks to improve the model's predictive performance by extracting a complete set of features from the chest X-ray pictures through the use of both DenseNet and MobileNet. These extracted features are fedinto a classifier, which is trained using the learned features to differentiate between various lung disease states. DenseNet and MobileNet together provide increases in accuracy and computing efficiency over previous approaches, making it a useful tool for automated lung disease diagnosis.

M. Jasmine Pemeena Priyadarsini et al. [2] in their study focuses on chest X-ray pictures and investigates the use of several deep learning algorithms for the identification of lung disorders utilizing medical imaging. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variations, such as ResNet, VGG, LSTM, and GRU,are among the deep learning architectures that are examinedby them. Because of their distinct qualities and advantages, each architecture is suited for a certain area of medical picture processing. The research technique includes applying the selected deep learning algorithms for feature extraction after preprocessing the chest X-ray pictures to improve their quality and eliminate noise. These algorithms are trained using a dataset of labeled chest X-ray pictures, where each picture is linked to a particular diagnosis of lung illness. Metrics like accuracy, sensitivity, specificity, and area under the curve (AUC) of the receiver operating characteristic (ROC) curve are used to assess the performance of the deep learning models. These measures shed light on how well the algorithms categorize lung disorders and differentiate between various ailments.

Abobaker Mohammed Qasem Farhan et al. [3] presenta unique method for automatically diagnosing lungillnesses from chest X-ray pictures. The strengths of various architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and perhaps other types of networks, are combined in the suggested hybrid deep learning method. By utilizing each architecture's special strengths—for example, CNNs' capacity to capture spatial information and RNNs' expertise in managing sequential data—this hybrid strategy seeks to maximize its benefits. Preprocessing the chest X-ray pictures to improve their quality and eliminate noise is part of the practice. The hybrid deep learning algorithm is then trained on a tagged dataset of chest X-ray pictures linked to certain diagnosisof lung diseases. Standard measures including accuracy, sensitivity, specificity, and area under the curve (AUC) ofthe receiver operating characteristic (ROC) curve are usedto assess the algorithm's performance. These measurements shed light on the algorithm's capacity to accurately categorize lung disorders and differentiate between various ailments. The goal of the study is to show how well the hybrid deep learning system performs autonomous lung disease classification through experimentation and comparative analysis. The project intends to increase the precision andefficacy of diagnostic systems by utilizing a hybrid deep learning algorithm, which could improve patient outcomesand healthcare delivery.

Goram Mufarah M. Alshmrani et al. [4] offer a deep learning architecture designed to use chest X-ray (CXR) images for the multi-class classification of lung illnesses. The suggested architecture is made expressly to address the difficulties involved in identifying various lung conditions from CXR pictures. Convolutional neural networks (CNNs) are used for feature extraction, and fully linked layers are used for classification, among other essential components. To improve performance, the architecture could include extra methods like data augmentation and transfer learning. Preprocessing CXR photos is part of the technique to enhance quality and reduce noise. The deep learning architecture is then trained ona dataset of tagged CXR images linked to different diagnosis of lung diseases. The study attempts to show how well the deep learning architecture performs in multi-class lung disease categorization through experimentation and analysis. Furthermore, the study might investigate how the model's performance is affected by variables like the quantity of the dataset, the quality of the images, and the preprocessing methods used.

Lingzhi Kong et al. [5] present a technique that uses a combination of characteristics taken from the DenseNet and VGG16 architectures to classify and detect COVID-19 from X-ray pictures. There are multiple crucial steps in the suggested process. X-ray pictures are first preprocessedto improve quality and eliminate noise. Next, featuresfrom the VGG16 and DenseNet designs are retrieved independently. While VGG16 emphasizes hierarchical feature extraction, DenseNet concentrates on densely connected feature representations, capturing multiple characteristics of the X-ray pictures. Through the use of a fusion technique,the derived features from both architectures are combined,allowing for the merging of complimentary data for enhanced detection and classification performance. The accuracy of the model's ability to differentiate between COVID-19-positive and negative X-ray pictures is improved by this fusion step. The project intends to show the efficacy of feature fusion from DenseNet and VGG16 architectures in COVID-19 diagnosis from X-ray pictures through testing and comparative analysis. Furthermore, the study might investigate how the model's performance is affected by variables like the quantity of the dataset, the quality of the images, and the preprocessing methods used. Overall, by developing a technique that uses feature fusion from the DenseNet and VGG16 architectures for precise COVID-19 classification and detection from X-ray pictures, the paper advances the field of medical image analysis. The suggested method seeks to enhance diagnostic precision and facilitate the effective screening of COVID-19 cases by merging the advantages of both architectures, ultimately leading to improved patient outcomes and public health initiatives.

III. Proposed Methodology

A. Model Architecture

We present a novel hybrid deep learning framework (shown in Fig. 1) that leverages the best features of two power- ful convolutional neural networks (CNNs), InceptionV3 and DenseNet121. The following process is used to coordinate the integration of various models:

Feature Extraction: To take advantage of the rich feature

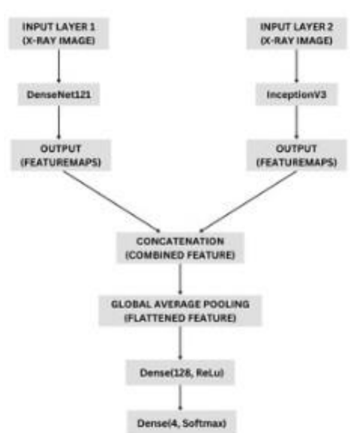

Fig. 1. The model architecture

representations acquired from a sizable and varied dataset, DenseNet121 and InceptionV3 were both started with pre-trained ImageNet weights. We modified the architecture of these models to suit our particular objective by eliminating their upper layers in order to adapt them for feature extraction.

Hybridization: Each model's Global Average Pooling 2D layer outputs were concatenated to provide a comprehensive feature map that captured the unique advantages of DenseNet121 and InceptionV3.

Classification Layer: To learn the intricate patterns unique to our assignment, a dense layer of 1024 neurons with ReLU activation was added after the hybrid feature extraction. Four neurons, one for each of the four classes, make up the final output layer. Softmax activation is used to enable multi-class classification.

B. Dataset and Pre-processing

A large collection of carefully assembled chest X-ray pictures was used in our study, and it was kept on Google Drive for easy accessibility and integration. A sample of the datasetused in each classification is shown in Fig. 2. The dataset consists of pictures classified into four different classes: COVID-19, pneumonia, tuberculosis, and healthy lungs. We used a number of pre-processing techniques to ensure that the dataset was homogeneous across all photos before beginning training. Among these actions were resizing the photos to224 by 224 pixels and standardizing the pixel values to fall between 0 and 1. Furthermore, data augmentation methodslike horizontal flipping, zooming, and shear transformation were used to increase the diversity of the dataset, which improved the model's generalization skills.

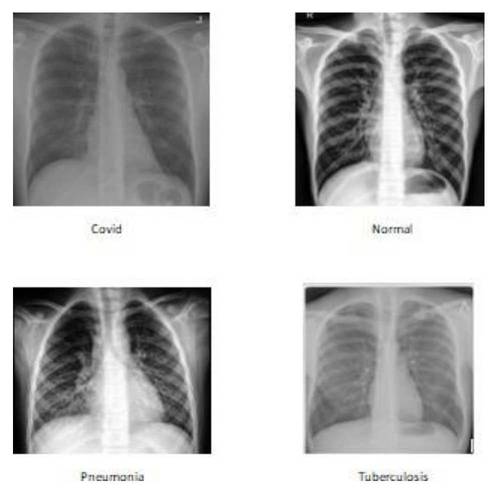

Fig. 2. Sample Dataset

C. Training

Because of its efficacy in multi-class classification tasks, the Adam optimizer and categorical crossentropy loss function were used in the compilation of the model. Using the enlarged dataset, we trained the model for ten epochs with a batch size of 32 images. The goal of this training program was to strike a balance between high model accuracy and computational economy. The dataset was divided into training and validation segments of 80% and 20%, respectively, to guarantee that the model was assessed on a neutral set of photos.

D. Metrics for Evaluation

The major criterion used to evaluate the performance of the model was accuracy. This selection demonstrates how evenly distributed our dataset is among the four classifications. A clear-cut and understandable indicator of the model's aptitude for accurately classifying unseen images is its accuracy.

ISSN:2230-9993

IV. Result and Discussion

The development and assessment of our hybrid deep learning model, which combines the DenseNet121 and InceptionV3 architectures, showed encouraging outcomes in the classification of chest X-ray pictures into four different groups: COVID-19, pneumonia, tuberculosis, and healthy. A large dataset was used for training and validation of the model, and data augmentation techniques were employed to guarantee the model's robustness and generalizability under a variety of imaging settings. After 10 epochs, the model's final training accuracy was 94.13%, and its validation accuracy was 88.52% as shown in Fig. 3. These results demonstrate the model's capacity to understand intricate patterns and perform well when applied to new data. The accuracy gradually increasing across epochs demonstrates how well the hybrid design captures the subtle elements required for precise categorization. The

Fig. 3.

hybrid technique was found to be superior when compared to standalone InceptionV3 and DenseNet121 models. The validation accuracy of DenseNet121 and InceptionV3 alone was 85.19% and 84.94%, respectively. Our hypothesis that combining the capabilities of both architectures will resultin improved diagnostic accuracy is validated by the hybrid model's superior performance, as shown by its validation accuracy of 88.52%.

Conclusion

In this work, we introduced a novel hybrid deep learn-ing model for the categorization of chest X-ray pictures into COVID-19, pneumonia, healthy, and tuberculosis cate- gories. This model combines the strengths of InceptionV3 and DenseNet121. The architecture of the model was created with the goal of improving diagnostic accuracy in the identifica- tion of lung disorders from X-ray pictures by utilizing the complementing features extracted by each base model. With a validation accuracy of 88.52%, the model demonstrated its efficacy in precisely categorizing lung illnesses. These findings highlight the potential of hybrid deep learning techniques for medical image processing, providing radiologists with a useful tool to aid in diagnosis and speed up the procedure. Although our approach represents a big step forward in the automated classification of lung diseases, there are still some unexplored research areas. The diagnostic capabilities of the model could be further enhanced by including multi-modal imaging data and expanding the dataset to encompass a wider spectrum of lung disorders. Furthermore, rather simply freezing the weights of the base models, investigating the effect of fine- tuning them on the attributes unique to the dataset may improve the performance of the models. Integrating clinical data—such as patient history and symptoms—with imaging data is another exciting field of study. Personalized medicine may be made possible by this multifaceted approach, which could improve the model's diagnostic accuracy and offer a more comprehensive picture of the patient's condition. In summary, our research adds to the expanding collection of knowledge on artificial intelligence in healthcare by emphasizing the potential of hybrid deep learning models to improve lung disease diagnosis precision. We are getting closer to realizing these technologies' full promise in helping healthcare professionals and enhancing patient outcomes as we continue to improve them.

References

[1] A Novel Approach for Prediction of Lung Disease Using Chest X-ray Images Based on DenseNetAdem Tekerek , Ismael Abdullah Mohammed Al-Rawe and MobileNet

[2] Lung Diseases Detection Using Various Deep Learning AlgorithmsAuthors: Meimei Yang, Ji-Jiang YANG, Qin yan Zhang, Yu Niu, Jianqiang Li

[3] Automatic lung disease classification from the chest X-ray images using hybrid deep learning algorithm-Authors:Abobaker Mohammed Qasem Farhan and Shangming Yang

[4] A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images- Author: Goram Mufarah M.Alshmrani , Qiang Ni , Richard Jiang , Haris Pervaiz , Nada M. Elshennawy

[5] Classification and detection of COVID-19 X- Ray images based on DenseNet and VGG16 feature fusion- Author:Lingzhi Kong , Jinyong Cheng

[6] Classification of COVID-19 X-ray images using transfer learning with visual geometrical groups and novel sequential convolutional neuralnet-works- Author:Sunil Kumar , Harish Kumar

[7] Artificial intelligence in diagnosis of obstructive lung disease: current status and future potential- Authors:Das, Nilakash, Topalovic, Marko; Janssens, Wim

[8] Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learningDeep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning- Authors:Shervin Minaee,Rahele Kafieh, Milan Sonka, Shakib Yazdani, and Ghazaleh Jamalipour Soufie

[9] High-precision multiclass classification of lung disease through customized MobileNetV2 from chest X-ray images- Authors: FM Javed Mehedi Shamrat , Sami Azam , Asif Karim , Kawsar Ahmed , Francis M. Bui , Friso De Boer

[10] Detection and classification of lung abnormali- ties by use of convolutional neural network (CNN) and regions with CNN features (R-CNN)- Authors: Shoji Kido, Yasusi Hirano, Noriaki Hashimoto