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DeepLungNet: An Optimized Deep Learning Framework for Automated Lung Disease Detection

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***Abstract**: Lung diseases provide considerable difficulties for diagnosis and therapy, frequently necessitating accurate and prompt identification for efficient care. Deep learning models have become extremely effective tools in recent years for automating the diagnosis of lung diseases by analyzing data from medical imaging tests, especially CT and X-rays. To improve diagnosis accuracy and efficiency, this research focuses on creating a sophisticated deep learning framework for feature extraction and categorization of lung disorders. We are using different CNN models in this project: VGG16, VGG19, and DenseNet121. We aim to compare the models to determine which one performs well in feature extraction and classification of lung disease. In general, this initiative advances automated lung disease identification through the use of deep learning methods to classify and extract features. The suggested approach may help medical practitioners make fast and accurate decisions. Diagnosis eventually leads to better patient outcomes and less strain on medical systems.*

***Keywords:** VGG16, VGG19, DenseNet121, Pneumonia Detection, Tuberculosis Detection Classification, Normal detection, Medical Image Analysis, Transfer Learning, Computer-Aided Diagnosis (CAD), Image Preprocessing, Disease Classification Model.*

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I. Introduction

Lung conditions like TB and pneumonia pose a critical threat to world health. Obstacles significantly raise the incidence of illness and death in certain groups globally. If these illnesses are not identified and treated right away, they may have dangerous implications. For efficient patient management, an early and precise diagnosis is essential, as well as therapy scheduling. Conventional techniques for lung disease diagnosis frequently depend on visual examination and interpretation of X-rays and other medical imaging. However, this procedure can be laborious and prone to human error, which could cause delays in the start of treatment and even lead to a false positive. These difficulties may also be made worse by the fact that access to qualified. Radiologists may be limited in low-resource environments.

Medical image analysis has seen a revolutionary change in recent years, thanks to the Development of deep learning techniques, specifically convolutional neural networks (CNNs). CNNs are specialized neural networks that are ideal for tasks like image classification, segmentation, and detection since they are built to automatically learn hierarchical representations of input. CNN-based computer-aided diagnosis systems have demonstrated encouraging outcomes in automating the interpretation of medical images, such as X-rays of the lungs. Large datasets of labeled images are used to train CNN models, which enable these systems to recognize patterns and characteristics that are suggestive of particular lung diseases, such as tuberculosis and pneumonia infiltrates. The creation of precise and effective CNN-based diagnostic models has the potential to revolutionize clinical practice by giving medical professionals useful instruments for decision assistance. By helping radiologists and physicians analyze medical pictures more quickly and precisely, these models can help identify lung disorders early and improve patient outcomes. The objective of this research is to create computer-aided diagnosis tools for the automatic classification of lung X-ray pictures by utilizing deep learning techniques. In particular, we will investigate how CNN architectures—like VGG16, VGG19, and DenseNet121—can be used to categorize X-ray pictures into groups that correspond to pneumonia, tuberculosis, and normal lung morphology. Our goal is to improve patient care by increasing the effectiveness and precision of lung disease diagnosis by utilizing CNNs.

II. literature survey

1. Development of Pneumonia Disease Detection Model Based on Deep Learning Algorithm

The authors of this study are Dalya S. Al-Dulaimi, Sayf A. Majeed, Ahmed Alkhayyat, Nadia Moqbel Hassan, and Aseel Ghazi Mahmoud. The CNN models VGG16 and ResNet 50 are employed in this study. The precision, recall, F1-score, and accuracy statistics are98%, 98%, 97%, and 99.82%, respectively.

2. Deep-Pneumonia Framework Using Deep Learning Models Based on Chest X-Ray Images

The authors of this study are Dina M. Ibrahim and Nada M. Elshennawy developed a deep learning architecture using four different CNN models to classify pneumonias. ResNet152V2, MobileNetV2, CNN, and LSTM-CNN are the models. The accuracy, precision, F1-score, recall, and AUC of our deep learning framework were evaluated, and the results for our model were 99.22%, 99.43%, 99.44%, 99.44%, and 99.77%, in that order. . It appears that the ResNet152V2 model outperforms the others.

3. Lung Diseases Detection Using Various Deep Learning Algorithms

The authors of this study are M. Jasmine Pemeena Priyadarsini, Ketan Kotecha, G.K. Rajini, K. Hariharan, K. Utkarsh Raj, K. Bhargav Ram, V. Indragandhi, V. Subramaniyaswamy, and Sharnil Pandya. This research paper has been published on the detection of lung diseases such as pneumonia, COVID-19, and tuberculosis using the VGG16 model from CNN.

4. Automated Pneumonia-Based Lung Diseases Classification with Robust Technique Based on a Customized Deep Learning Approach

The authors of this study are Yaman Akbulut. This study reports on the use of an algorithm based on a newly designed deep learning model (ACL model) for the detection of lung diseases, such as pneumonia and COVID-19. The ACL model was trained simultaneously with the attention and LSTM models, utilizing CNN models.

5. Deep MLP-CNN Model Using Mixed-Data to Distinguish between COVID-19 and non-COVID-19 Patients

The authors of this study are Md Manjurul Ahsan, Tasfiq E. Alam, Theodore Trafalis, and Pedro Huebner. In this work, they introduced an MLP-CNN-based model that takes into account mixed input data, namely image data (chest X-ray pictures) and numerical/categorical data (age, gender, and temperature) for the early detection of patients with COVID-19 symptoms 96.30% of the time.

6. Efficient ensemble for image-based identification of Pneumonia utilizing deep CNN and SGD with warm restarts

The authors of this study are G. Vrbančič and V. Podgorelec. The authors of this research presented a novel ensemble approach for identifying childhood pneumonia from chest X-ray pictures called SGDRE, which is based on stochastic gradient descent with a warm restart mechanism. The method is especially suitable for medical imaging applications.

7. A novel approach for the detection of COVID-19 and Pneumonia using only binary classification from chest CT scans

The authors of this study are S. Hasija, P. Akash, M. Bhargav Hemanth, A. Kumar, and S. Sharma. The suggested approach is trained in two stages: the first stage uses the DenseNet-201 architecture to classify CT slices as NON-COVID and COVID; the accuracy was 98.39%; the second stage uses the InceptionV3 architecture to classify CT slices as Normal and Pneumonia; the accuracy was 99.98%. A total of 98.38% accuracy is achieved.

8. Comparison of deep learning approaches to predict COVID-19 infection

The authors of this study are Talha Burak Alakus and Ibrahim Turkoglu. Six distinct deep learning models were employed in this work to predict COVID-19.ANN, CNN, CNLSTM, CNRNN, LSTM, and RNN are them. LSTM deep learning model has an accuracy of 86.66%, a recall of 99.42%, and an AUC score of 62.50%, which suggests that it performs better than the other models.

9. Multi-Channel Based Image Processing Scheme for Pneumonia Identification.

The authors of this study are G. U. Nneji, J. Cai, J. Deng, H. N. Monday, E. C. James, and C. C. Ukwuoma. This work presents a weighted fusion-based pneumonia diagnosis algorithm that can process simultaneously LBP, CLAHE, and CECED CXR images. Shallow CNN, MobileNet-V3, and Inception-V3 are the models that are employed. 98.3% accuracy, 98.9% sensitivity, 99.2% specificity, 98.8% precision, and 99.0% F1-score.

10. Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray

The authors of this study are T. Rahman, M. E. H. Chowdhury, A. Khandakar et al. In this work, a deep-CNN-based transfer learning method for the automatic diagnosis of pneumonia and related disorders is presented. Using chest x-ray pictures, four common CNN-based deep learning algorithms were utilized to categorize patients as normal and as pneumonia patients. The models AlesNet, ResNet18, DenseNet201, and SqueezeNet are employed. It appears that the DenseNet201 model outperforms the others.

III. Methodology

The methodology of this project involves a systematic flow designed to automate the detection and classification of lung diseases using deep learning techniques. The process is broken down into several key steps:

3.1 Data Collection: A publicly available dataset of chest X-ray images is used, consisting of images categorized into three classes:

- **Normal**
- **Pneumonia**
- **Tuberculosis**

The dataset is split into training, validation, and test sets.

3.2 Data Preprocessing:

- **Image resizing**: All images are resized to a uniform dimension (e.g., 224x224 pixels) to fit the CNN input requirements.
- **Normalization**: Pixel values are normalized to improve training performance.
- **Noise reduction**: Image denoising techniques are applied to enhance image quality.
- **Data augmentation**: Techniques such as rotation, flipping, and zooming are used to increase dataset diversity and reduce overfitting.

3.3 Model Selection and Architecture:

The following pre-trained CNN models selected for comparison:

- **VGG16**
- **VGG19**
- **DenseNet121**

These models are used with transfer learning, where the last few layers are fine-tuned on our specific dataset while keeping the earlier layers frozen.

3.4 Feature Extraction

CNN layers automatically extract hierarchical image features such as edges, textures, and patterns relevant to identifying lung diseases.

These features are passed through fully connected layers for classification.

3.5 Model Training

Each CNN model is trained using the categorical cross-entropy loss function and Adam optimizer.

Training is performed over multiple epochs with batch processing.

Performance is monitored using validation accuracy and loss.

3.6. Evaluation Metrics

The performance of each model is evaluated using:

- Accuracy
- Precision
- Recall
- F1 Score

These metrics help identify the most reliable model for practical use.

3.7 Deployment

The final model is deployed as a web application using Flask.

Users (e.g., lab technicians or doctors) can upload chest X-rays images and get instant predictions.

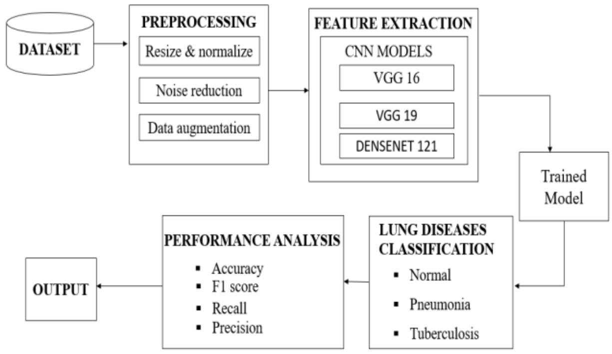

Figure 1: System Architecture

The system architecture represents a deep learning-based pipeline for the automated classification of lung diseases, specifically targeting normal lungs, pneumonia, and tuberculosis. The process starts with a dataset of lung images, which undergoes a preprocessing phase to ensure consistency and quality. During this phase, all images are resized and normalized to standard dimensions and pixel ranges suitable for input into convolutional neural networks (CNNs). Noise reduction techniques are employed to remove irrelevant distortions in the images, while data augmentation methods, such as rotation, flipping, and zooming, are applied to increase the diversity of training data and enhance the model's ability to generalize.

Once preprocessing is complete, the images proceed to the feature extraction stage, where deep CNN models like VGG16, VGG19, and DenseNet121 are used to automatically learn and extract meaningful features from the images. These features are then used to classify the lung condition into one of three categories: normal, pneumonia, or tuberculosis. The trained model, once optimized, is used to predict outcomes on new data.

To assess its effectiveness, the system conducts a performance analysis using evaluation metrics such as accuracy, precision, recall, and F1 score. The final output consists of both the classification results and the corresponding performance metrics, making the system a valuable tool for assisting in clinical diagnosis and decision-making.

Proposed Methodology Workflow:

The overall workflow of the proposed system for lung disease classification is illustrated in Figure 2. The methodology involves several sequential stages, each contributing to the effective training and deployment of deep learning models. The steps are as follows:

1. Read:
The dataset comprising normal, pneumonia, and tuberculosis-affected chest X-ray images is read into the system after being downloaded from relevant sources.

2. Pre-process:
Image pre-processing is carried out to enhance the quality and consistency of input data. This includes resizing the images and applying data augmentation techniques to improve model generalization and reduce overfitting.

3. Develop:
In this phase, deep learning models are developed using pre-trained Convolutional Neural Network (CNN) architectures, specifically VGG16, VGG19, and DenseNet121. These models are chosen for their proven performance in image classification tasks.

4. Compile:
The CNN models are compiled using the Adam optimizer, and appropriate evaluation metrics are specified (such as accuracy, precision, and recall) to monitor the model's performance during training.

5. Train & Validate:
The compiled models are trained and validated using the labeled dataset containing normal, pneumonia-affected, and tuberculosis-affected lung images. This step ensures that the model learns meaningful features for accurate classification.

6.Test/Predict:
After training, the model is evaluated using a separate test dataset to predict the class labels of previously unseen lung images. This step helps assess the model's generalization capability.

7. Compare:
The performance of the trained models is compared by analyzing training and testing accuracies. The comparison helps in selecting the best-performing model for deployment.

8. Web Application:
Finally, best-performing model is integrated into a web-based application. This allows end users (e.g., medical

practitioners) to upload lung images and receive disease classification results in real-time.

IV. Implementation:

In this paper, deep learning-based Convolutional Neural Networks (CNNs) such as VGG16, VGG19, and DenseNet121 are employed for the dual tasks of feature extraction and classification of lung diseases (Pneumonia, Tuberculosis, and Normal lungs) from chest X-ray images. Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for processing image data. In your lung disease classification project, CNNs are used to automatically learn and extract important spatial features from chest X-ray images without the need for manual feature engineering. The architecture of a CNN typically includes convolutional layers, activation functions (like ReLU), pooling layers (e.g., max pooling), and fully connected layers.

In the implementation, pre-trained CNN models such as VGG16, VGG19, and DenseNet121 are used with transfer learning. These models have already learned generic image features from the large ImageNet dataset and are fine-tuned on your specific lung disease dataset. The convolutional layers in these networks act as feature extractors they detect edges, textures, and patterns relevant to lung conditions. As the image passes through deeper layers, the network captures increasingly complex features like lung opacities or cavity formations (common in pneumonia or tuberculosis). After the convolution and pooling stages, extracted feature are flattened and passed through fully connected layers to perform classification, predicting whether the image shows a normal lung, pneumonia, or tuberculosis. By using CNNs, your project achieves. High accuracy and automation in medical image diagnosis, reducing the need for expert radiologists in initial screening. Moreover, the integration of transfer learning not only accelerates the training process but also enhances the model's performance by leveraging the learned representations from vast datasets. This significantly reduces the requirement for large amounts of labeled medical data, which is often scarce. To further improve generalization and prevent overfitting, techniques such as data augmentation.

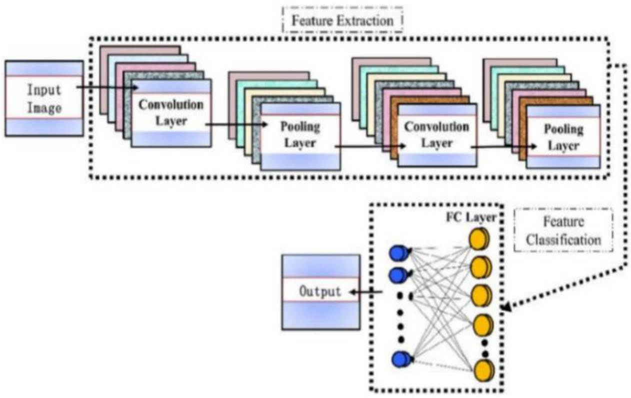

Figure 2: Convolutional Neural Networks

i. VGG16 and VGG19:

VGG16 and VGG19 are popular deep CNN architectures introduced by the Visual Geometry Group at the University of Oxford. They are known for their simplicity and depth. VGG16 contains 16 layers (13 convolutional + 3 fully connected), while VGG19 contains 19 layers (16 convolutional + 3 fully connected). These networks use small 3×3 filters throughout the convolution layers and are pre-trained on large datasets like ImageNet. In this project, these models are used with transfer learning, where the pre-trained weights are used to extract robust and abstract features from the input X-ray images. The final dense layers are retrained on your lung disease dataset to classify the images into the correct disease category.

ii. DenseNet121:

DenseNet121 is a more advanced CNN architecture that uses dense connections between layers. Unlike traditional models, where each layer passes output only to the next one, DenseNet connects each layer to every other layer in a feed-forward fashion. This improves feature propagation, encourages feature reuse, and significantly reduces the number of parameters. In your implementation, DenseNet121 captures more discriminative and deeper features from chest X-ray images, making it especially effective in handling subtle differences between lung diseases like pneumonia and tuberculosis.

All models are trained and tested using labeled X-ray image datasets. Feature extraction is automatically performed by the convolutional layers of these networks. The classification is done using the final fully connected layers, followed by a softmax activation function that predicts the probability of each class.

Performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, showing how well each model performs in real-world diagnosis.

V. Result And Analysis

5.1 Bacterial Pneumonia

In the "Lungs Disease Prediction" web application interface, where a chest X-ray has been uploaded and analyzed to yield the prediction result: "Bacterial Pneumonia." This diagnosis is prominently displayed in red text above the X-ray image. As with the previous instances, the interface includes a file selection option, an "Upload & Predict" button, and a brief explanation that the tool utilizes a deep learning model to detect lung conditions such as pneumonia, tuberculosis, and COVID-19. The background continues to showcase a vibrant, anatomically inspired visualization of lungs and blood vessels, emphasizing the medical and diagnostic focus of the application.

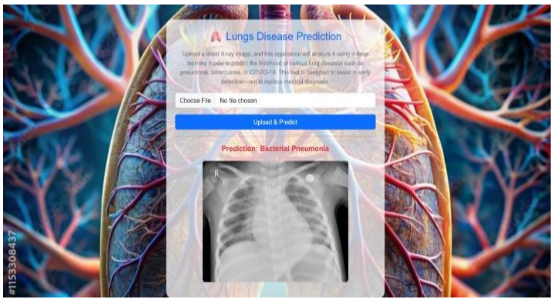

Figure 5.1 Bacterial Pneumonia

The model detected features commonly associated with bacterial pneumonia, such as:

- Patchy or lobar consolidation
- Increased lung opacity
- Possible air bronchograms

These findings are indicative of an acute lung infection, typically caused by bacteria such as Streptococcus pneumoniae. The deep learning algorithm has matched this X-ray with training examples showing classic signs of bacterial pneumonia, pointing to a likely active infection.

5.2 Tuberculosis

The system has analyzed the X-ray and produced a prediction result labeled "Tuberculosis,". The interface includes a file upload button and a prominent "Upload & Predict" button, with a short description explaining that the tool uses deep learning to identify lung diseases like pneumonia, tuberculosis, or COVID-19. The background consists of a highly detailed anatomical illustration of lungs, reinforcing the medical theme.

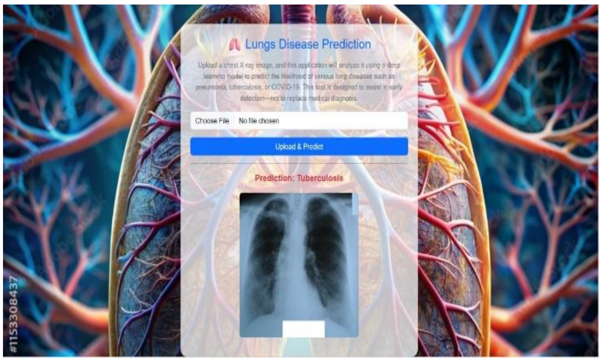

Figure 5.2 Tuberculosis

The deep learning model identified radiographic abnormalities consistent with pulmonary tuberculosis. This typically includes signs such as:

- Upper lobe infiltrates
- Cavitary lesions
- Nodular opacities

These features suggest a potential chronic infectious process, commonly caused by Mycobacterium tuberculosis. The model's prediction indicates that the uploaded X-ray closely matches patterns seen in training data labeled as tuberculosis cases.

5.3 Normal

This time, the system has returned a prediction of "Normal," indicating no signs of lung disease were detected in the X-ray. The layout remains consistent, with the same upload controls and descriptive text at the top. The diagnostic result is presented in maroon text, and the background retains the vivid, vascular lung illustration, creating a cohesive and visually engaging user experience.

Figure 5.3 Normal

The chest X-ray was analyzed and classified as normal, meaning:

- No signs of infection, inflammation, or abnormal lung structure
- Lung fields appear clear
- No masses, fluid buildup, or other radiographic anomalies were detected

This suggests healthy lung function and anatomy based on the model's trained criteria. The prediction implies no immediate signs of pneumonia, tuberculosis, or COVID-19 in this X-ray.

VI. Conclusion

In conclusion, the creation of deep learning models for lung X-ray image categorization is an important development in the field of medical diagnostics, especially for the early identification of illnesses like tuberculosis and pneumonia. By applying transfer learning techniques and convolutional neural networks (CNNs), we have shown that it is possible to automate the categorization process and so enable timely and precise diagnosis of lung ailments. VGG16, VGG19, and DenseNet121 are among the trained models that have demonstrated encouraging outcomes in correctly classifying lung X-ray pictures into three categories: tuberculosis, pneumonia, and normal. Through the utilization of deep learning, we have attained elevated degrees of precision and responsiveness, thus enabling the timely identification and management of lung conditions. Enormous potential exists for bettering healthcare outcomes from the successful implementation of these diagnostic models, especially in areas where access to board-certified radiologists may be scarce. To improve patient care, lower diagnostic errors, and eventually save lives, we provide medical personnel with trustworthy tools for diagnosing lung diseases. The models must be further improved, their performance optimized, and their efficacy confirmed on a wider range of datasets in the future. The seamless adoption of these models by healthcare professionals, their integration into healthcare systems, and ethical issues about patient privacy and data security should all be prioritized. In addition, further research and development are required to investigate further uses of deep learning in the field of medical imaging and to broaden the scope of disease identification to include disorders other than tuberculosis and pneumonia in the lung. Essentially, a major step in bettering patient outcomes and healthcare diagnostics is the creation of deep learning models for lung disease classification. We are well-positioned to make significant progress in the early diagnosis and treatment of lung disorders by utilizing the capabilities of artificial intelligence and machine learning, which will ultimately improve global health.

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