A *CONV-RFDNN* Model for the Classification and Detection of Lung Diseases on Chest X-Rays Using Transfer Learning

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Abstract: ***Identifying and categorizing lung diseases involves the application of advanced techniques such as Computer Vision (CV) and Machine Learning (ML). These methodologies play a crucial role in recognizing and classifying ailments affecting lung health. By employing Computer Vision and Machine Learning, medical professionals can swiftly identify and manage lung diseases, contributing to enhanced healthcare outcomes. This utilization of technology mirrors its role in healthcare, where these methods assist medical professionals in identifying and managing lung diseases to ensure effective diagnoses and treatment strategies. Deep Learning (DL), a subset of Artificial Intelligence (AI), has proven successful in automating the detection and classification of lung diseases. This research leverages the CONV-RFDNN model for the Automatic Detection and Classification of Lung Diseases. The process begins with a pre-processing stage, involving tasks such as image resizing and the application of a Bilateral filter to enhance image quality. Feature extraction is then performed using a neural network architecture like VGG-19. Finally, the extracted features are input into a classification model, such as Random Forest (RF), to differentiate between various lung disease types. A thorough analysis of experimental results reveals that the CONV-RFDNN model outperforms recent approaches, demonstrating superior performance in lung disease detection and classification.***

Keywords: Computer Vision, Machine Learning, Deep Learning, VGG-19, Random Forest, Transfer Learning

1. Introduction

Respiratory conditions are widespread globally, encompassing a range of issues such as chronic obstructive pulmonary disease, COVID-19, pneumonia, asthma, tuberculosis, and fibrosis. The timely identification of these lung diseases is crucial, given their increasing impact on health due to environmental changes, climate variations, lifestyle choices, and other contributing factors. Developing and low-middle-income countries face heightened risk, with millions grappling with poverty and exposure to air pollution. According to the World Health Organization, over 4 million premature deaths annually are linked to diseases resulting from household air pollution, including asthma and pneumonia [1]. Addressing this challenge requires collaborative efforts to reduce air pollution and carbon emissions. Equally important is the implementation of effective diagnostic systems for the early detection of lung diseases, significantly mitigating their life-threatening potential and enhancing the quality of life for affected individuals [2].

In contemporary medical imaging, diagnostic tools like chest X-ray radiography (CXR) and computed tomography (CT) provide invaluable insights into internal bodily structures without invasive procedures. Radiologists predominantly use CXR images for lung disease detection due to their convenience and non-invasiveness, making them suitable for comprehensive chest assessments [3] and follow-up examinations. However, the inherent complexity of the chest's anatomical structure may lead to human errors, underscoring the need for computer-aided diagnostic systems (CADs). These systems, leveraging machine learning and deep learning architectures, enable precise diagnoses, reducing the risk of misinterpretations.

Recent advancements in CAD frameworks have seen the incorporation of graphical processing units (GPUs) for rapid, automated diagnosis through medical image processing. Machine learning (ML) and deep learning (DL) have played pivotal roles in various medical imaging applications, with convolutional neural networks (CNNs) particularly showing promise for radiological image classification [4].

This study presents a novel approach to the detection and classification of lung diseases, focusing on pneumonia, utilizing an effective deep learning (DL) model named the ***CONV-RFDNN*** model. The selection of the ***CONV-RFDNN*** model is justified by its capability to address challenges such as the vanishing-gradient problem, enhance feature propagation, promote feature reuse, and significantly reduce the parameter count. The proposed model encompasses essential stages, including pre-processing, feature extraction based on VGG-19, and classification based on Random Forest. The integration of deep features extracted from the VGG-19 model is conducted to evaluate the effectiveness of these features.

The subsequent sections of this study are organized as follows: Section 2 provides a concise overview of related works in the field of lung disease detection and classification. Section 3 introduces the model developed for detecting and classifying lung diseases, with a focus on pneumonia. Section 4 details the validation process employed to assess the proposed model's performance, and Section 5 concludes the study, summarizing key findings and potential implications for lung disease detection and classification tasks.

2. Related Works

In their research [6], the authors proposed an innovative framework for predicting lung diseases by combining Bidirectional Long Short-Term Memory (BiLSTM) and Mask Region-Based Convolutional Neural Network (Mask-RCNN). They utilized the Crystal technique to enhance the convergence and scalability of the Mask-RCNN method. The BiDLSTM component played a crucial role in capturing long-term dependencies for predicting pulmonary diseases, seamlessly integrated with the Fully Connected (FC) layer of the Mask-RCNN approach.

Another study [7] introduced a Deep Learning (DL) technique with Transfer Learning (TL) to classify lung diseases in chest X-ray (CXR) images. This approach aimed to enhance the accuracy and efficiency of Computer-Aided Diagnosis (CAD) by directly inputting raw CXR images into a DL model (EfficientNet v2-M) for extracting meaningful features and identifying various disease classes.

In a different approach [8], a multi-channel deep learning method for lung disease detection using chest X-rays was developed. Pre-trained EfficientNet models (B2, B0, B1) were employed, and their features were merged and processed through non-linear Fully Connected (FC) layers. A stacked ensemble classifier, initially employing SVM and RF, followed by LR, achieved effective lung disease detection. Another contribution [9] introduced CXR-Ultranet, a method for identifying and classifying 13 thoracic lung diseases from chest X-rays. This approach utilized an EfficientNet baseline and a multi-class cross-entropy loss function with a compound scaling structure. Furthermore, in a separate study [10], researchers designed a multi-scale adaptive Recurrent Neural Network (MARnet) for the identification of pulmonary ailments in CXR images.

3. The Proposed CONV-RFDNN Model

The **CONV-RFDNN** technique follows a comprehensive workflow, as depicted in Fig 1. The initial step involves pre-processing to enhance image quality. The VGG-19 model is then employed for feature extraction, and finally, the is used for image classification into distinct class labels. The details of each stage are elaborated in the subsequent sections.

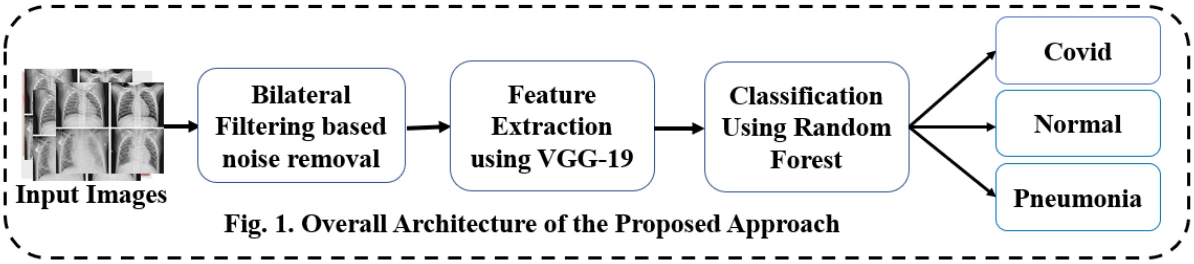

Fig. 1. Overall Architecture of the Proposed Approach

3.1. Bilateral Filtering

Bilateral filtering emerges as a valuable technique in image processing, particularly in the context of lung disease detection and classification tasks, for its effectiveness in noise elimination while preserving the edges of medical images. In the domain of lung disease detection, the application of bilateral-based noise removal plays a crucial role in refining image quality, making them more conducive to accurate classification. This significance arises from the recognition that noise in medical images can compromise the performance of machine learning models, affecting their ability to precisely identify and classify lung diseases.

The bilateral filtering approach takes into account both spatial and intensity information during the image-smoothing process. This consideration allows the filter to distinguish between noise and genuine edges, preserving the structural details within the lung images. In lung disease detection and classification, this preservation is essential for capturing the intricacies of lung structures, crucial for accurate disease identification. Bilateral filtering demonstrates efficacy in reducing various types of noise, including salt-and-pepper noise and Gaussian noise. By smoothing the lung images while safeguarding edges, the bilateral filter facilitates the creation of cleaner images. This, in turn, simplifies the task for machine learning models, enabling them to focus on relevant features for disease classification [11].

The bilateral filter is typically defined using the following equation:

Bilateral(I)=Wp1∑q∈Ωexp(−2σs2∥p−q∥2)exp(−2σr2∥I(p)−I(q)∥2)I(q)

Where:
I is the input image.
p and q are pixel coordinates.
Ω is the neighborhood of pixels.
σ_s controls the spatial decay of the filter.
σ_r controls the intensity decay of the filter.
W_p is a normalization factor.

In the realm of lung disease detection and classification, the bilateral filter is applied to medical images to reduce noise while preserving critical structural details. The denoised images obtained through this process serve as input for machine learning models, improving their accuracy in identifying and classifying lung diseases based on distinctive features present in the lung images.

3.2. Feature Extraction Using VGG-19

The VGG-19 architecture plays a crucial role in the concept of lung disease detection and classification by serving as a powerful feature extractor in deep learning models.VGG-19 is a deep convolutional neural network (CNN) architecture with 19 layers, which enables it to automatically learn hierarchical features from input images. In the case of lung disease detection, the deep layers of VGG-19 can capture intricate patterns, textures, and features in chest X-ray images associated with various lung conditions.VGG-19 has been pre-trained on large-scale image datasets like ImageNet. Leveraging pre-trained models for feature extraction is particularly valuable in medical imaging where labeled datasets are often limited. Transfer learning allows the model to inherit knowledge gained from general image recognition tasks, enhancing its ability to recognize relevant features in lung disease images as shown in Fig 2.

The features extracted by VGG-19 serve as a rich representation of the input images. These features encapsulate the essential characteristics of the lung images, which are crucial for distinguishing between different lung diseases. The features can be used as input to subsequent layers or models for classification, providing a foundation for making informed predictions.VGG-19's layer-by-layer architecture aids in creating interpretable features. This interpretability is essential in medical applications, allowing researchers and healthcare professionals to understand which patterns the model is utilizing for disease detection and classification [12].

Interpretable features enhance the transparency and trustworthiness of the model, facilitating its acceptance in clinical settings. The lung's anatomical structure is intricate, and VGG-19's depth allows it to capture complex structures and subtle abnormalities present in chest X-ray images. The ability to handle complex structures is vital for accurate disease identification and classification, especially in the context of lung diseases with diverse manifestations.

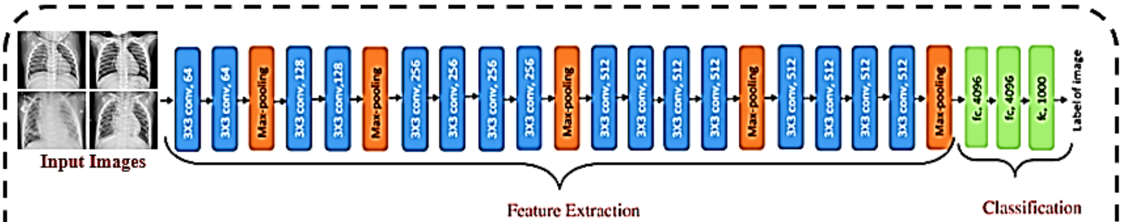

Fig. 2. Feature Extraction using VGG-19

3.3. Classification Using Random Forest

Random Forest is a machine learning algorithm that plays a significant role in the concept of lung disease detection and classification, particularly when dealing with three classes: COVID-19, normal, and pneumonia. Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. Each tree in the forest contributes to the final decision through a voting mechanism. In the context of lung disease classification, ensemble learning helps improve the robustness and generalization of the model by aggregating predictions from multiple decision trees. Lung disease classification often involves intricate relationships and interactions among various features in medical images. Random Forest is capable of capturing complex non-linear relationships between input features and output classes. It can handle a variety of input features, making it suitable for scenarios where the relationships between different aspects of lung images contribute to the classification task. Random Forest provides a measure of feature importance, indicating the contribution of each feature in making predictions as depicted in Fig 3.

In lung disease detection, understanding which features (e.g., pixel intensity patterns, texture details) are most relevant for distinguishing between COVID, normal, and pneumonia cases can provide insights into the diagnostic criteria. Random Forest is inherently robust to overfitting, a common challenge in medical image classification tasks where the model may learn noise rather than meaningful patterns [13].This robustness helps ensure that the model generalizes well to new, unseen data, which is crucial for reliable lung disease detection and classification. Medical datasets, including those for lung disease, often suffer from class imbalance, where certain classes have fewer instances than others. Random Forest can handle imbalanced datasets and still produce reliable predictions.

In the case of lung disease classification, where the prevalence of certain conditions may be uneven, Random Forest can provide accurate predictions across different classes. Random Forest models are relatively easy to interpret compared to more complex deep learning models. The decision trees in the ensemble can be visualized, providing insights into the decision-making process. Interpretability is crucial in medical applications, allowing healthcare professionals to understand and trust the model's predictions.

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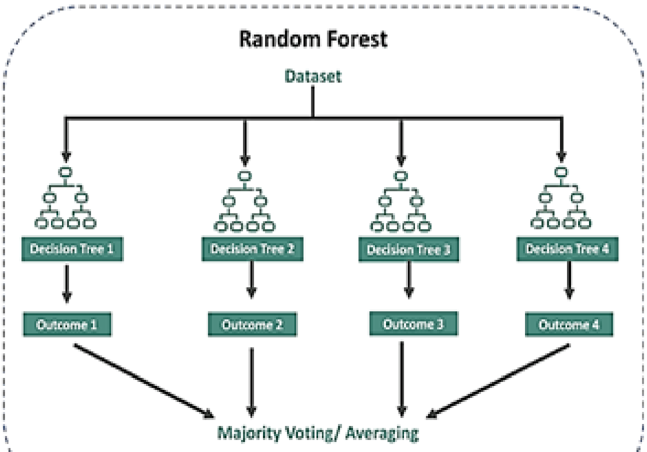

Fig. 3. Classification using Random Forest

4. Performance Validation

4.1. Implementation Setup

In this section, we conducted experimental validation of the CONV-RFDNN technique for lung disease detection and classification on chest X-ray images, considering various factors. The simulations were executed using Python 3.6.5 on a PC equipped with an i5-8600K processor, 250GB SSD, GeForce 1050Ti 4GB GPU, 16GB RAM, and a 1TB HDD. The performance evaluation of the CONV-RFDNN model was measured using key metrics such as Sensitivity, Specificity, Precision, Accuracy, and F-score. The validation process utilized a benchmark Kaggle dataset comprising chest X-ray images [14]. Sample test images representing each class are illustrated in Fig4 , and the corresponding number of samples is detailed in Table 1.

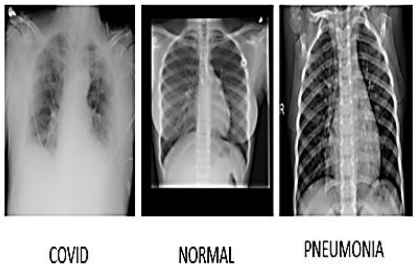

Fig. 4. Sample Images

Table 1. Dataset Description

Class	No.of.Samples
Covid	500
Normal	100
Pneumonia	400
Total	**1000**

4.2. Results and Discussion

In Fig. 5, the confusion matrix, is presented, showcasing the CONV-RFDNN model's accurate classifications across different classes during its execution. The performance assessment of the CONV-RFDNN model, as illustrated in Table 2 and Fig. 6, highlights its efficacy in classifying chest X-ray images for Pneumonia detection. Here 70% is used for training and 30% is used for testing. Notably, the model exhibits outstanding performance in identifying Pneumonia disease, achieving maximum sensitivity, specificity, precision, and accuracy, and an F-score of 93.16%, an impressive overall accuracy of 95.67%, and a substantial F-score of 87.59%.

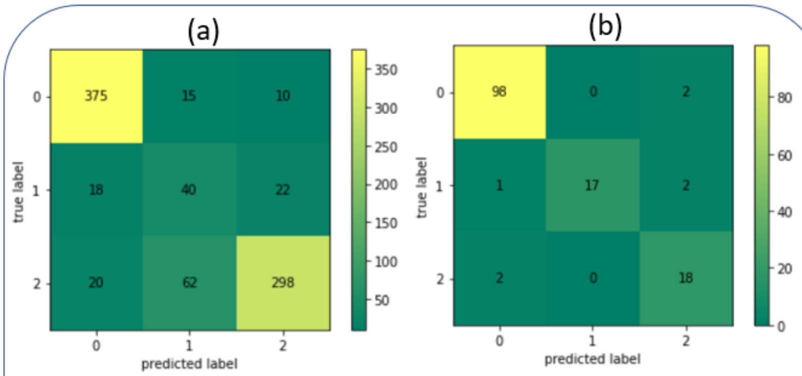

Fig. 5. (a) Confusion Matrix based on TR set (b) Confusion Matrix based on TS set

Table 2: Performance Evaluation of test images on the proposed CONV-RFDNN Model

Labels	Accuracy	Sensitivity	Specificity	F Score	MCC
TR set (70%)					
Pneumonia	93.79	77.87	97.30	81.91	78.33
Normal	95.43	66.29	99.59	78.38	77.53
Average	**93.86**	**80.90**	**91.72**	**85.00**	**79.23**
TS set (30%)					
Pneumonia	95.00	85.12	97.49	87.29	84.22
Normal	94.67	67.09	100.00	8030	79.94
Average	**95.67**	**83.74**	**93.16**	**87.59**	**83.07**

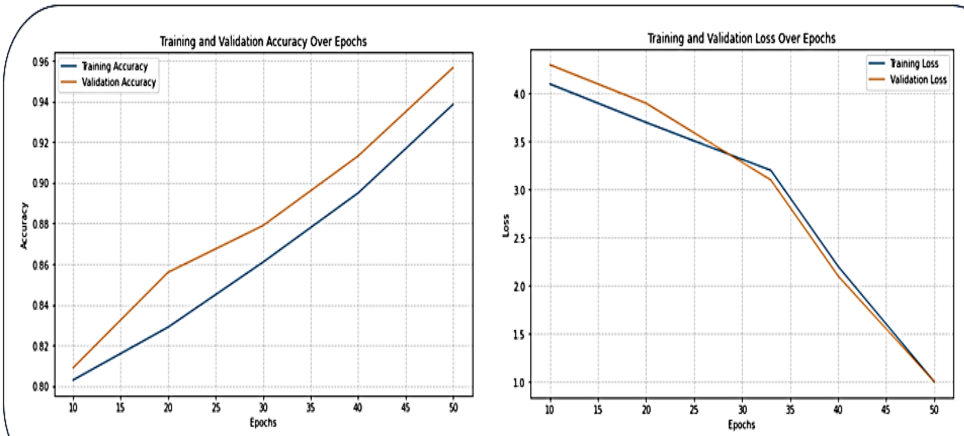

Fig. 6. Accuracy & Loss graph based on TR and TS set

Table 3 presents an accuracy analysis for the CONV-RFDNN model in the context of lung disease detection and classification, specifically focusing on Covid and Pneumonia compares it to previously employed methods [15]. Notably, the CONV-RFDNN approach surpasses all other methods, achieving an impressive accuracy rate of 95.67%. These empirical results affirm the robust detection and classification capabilities of the CONV-RFDNN model, which is meticulously designed for covid and Pneumonia disease detection and classification in chest X-ray images. The elevated performance can be attributed to the inherent strengths derived from the pre-trained VGG-19 model. Consequently, the proposed model stands out as a compelling solution for real-time diagnosis of lung diseases, offering crucial support to medical professionals and contributing to advancements in healthcare outcomes.

Table 3: Comparative Outcome of Kaggle Dataset with Existing Systems

Method	Accuracy	Precision	Sensitivity	Specificity	F-Score
CONV-RFDNN	**95.67**	**83.74**	**93.16**	**87.59**	**83.07**
Non-optimization	90.22	82.10	92.89	86.68	82.71
Genetic Algorithm	94.89	81.31	92.80	82.43	85.09
Pattern search	94.82	82.43	93.02	83.62	82.51
Simulated Annealing	95.24	82.76	92.11	82.62	82.62
PSO Algorithm	95.16	82.76	92.70	85.22	82.13

5. Conclusion

This research is centered around the creation of automated models for the detection and classification of lung diseases in chest X-ray (CXR) images. The development of the CONV-RFDNN technique is an automated lung disease detection and classification model for CXR images. To assess the performance of this model, the CXR image dataset from the Kaggle repository, comprising 500 covid, 100 normal, and 400 pneumonia samples, are utilized. The experimental results affirm the efficacy of the proposed model in accurately identifying COVID and Pneumonia cases in CXR images. This interpretability serves as a valuable tool for radiologists and clinicians, instilling confidence in model predictions and aiding in making more informed clinical decisions. Future endeavors could explore various deep-learning techniques or employ ensemble methods to enhance the overall performance and robustness of lung diseases identification models. Additionally, integrating multi-modal data such as medical reports and laboratory outcomes has the potential to improve the diagnostic capabilities of deep learning algorithms, allowing for a more comprehensive understanding of a patient's condition.

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