

Lung Disease Prediction using Dense Convolutional Neural Network Model

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Research Paper

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Abstract:

Lung diseases represent a formidable global health challenge, exacting a substantial toll on millions annually. The criticality of timely and precise diagnosis cannot be overstated, serving as a linchpin for effective treatment and management strategies. Recent strides in machine learning, notably Dense Convolutional Neural Networks (DCNNs), offer promising avenues for transforming medical image analysis and predictive analytics in this domain. This paper investigates the utility of DCNN models in forecasting lung diseases using medical imaging datasets. We introduce a DCNN-based method for detecting lung diseases, leveraging the watershed algorithm for segmentation. Our findings demonstrate the method's exceptional efficacy, boasting an accuracy surpassing 96%. This underscores the transformative potential of advanced machine learning techniques in enhancing diagnostic capabilities, paving the way for earlier detection and intervention, and ultimately alleviating the global burden imposed by lung diseases.

Keywords: DenseNET, Lungs, Covid-19 and Pneumonia

1. Introduction

Lung diseases constitute a diverse array of respiratory disorders, spanning from prevalent conditions like asthma and chronic obstructive pulmonary disease (COPD) to more grave illnesses such as lung cancer and pulmonary fibrosis [1]. The burden of these diseases is staggering, with the World Health Organization (WHO) estimating approximately 4 million deaths annually worldwide attributed to respiratory ailments. This statistic underscores the pressing need for effective management and intervention strategies [2]. Early detection and precise diagnosis are pivotal in mitigating the impact of lung diseases on individual health outcomes and public health at large. Swift identification of respiratory disorders allows for timely initiation of treatment protocols, potentially averting disease progression and associated complications [2]. Furthermore, accurate diagnosis facilitates tailored therapeutic interventions, optimizing patient care and enhancing quality of life. However, despite the advancements in medical technology and treatment modalities, challenges persist in the realm of lung disease diagnosis. Variability in symptom presentation, overlapping clinical manifestations, and the intricate nature of pulmonary pathophysiology can impede accurate diagnosis, leading to delays in intervention and suboptimal patient outcomes. In this context, the integration of advanced computational techniques, particularly machine learning approaches, offers a promising avenue for enhancing the diagnostic process. Machine learning algorithms, such as Convolutional Neural Networks

(DCNNs) [3], have demonstrated remarkable capabilities in analyzing complex medical data, including radiographic images, with high accuracy and efficiency. By harnessing the power of artificial intelligence, healthcare professionals can potentially augment their diagnostic acumen, leading to more precise and timely identification of lung diseases. This paper explores the application of DCNN models in the prediction of lung diseases using medical imaging data. Through a comprehensive review of existing literature, we elucidate the potential of DCNNs in revolutionizing lung disease diagnosis and management. By delving into the architecture, training methodologies, and challenges associated with DCNN-based predictive models, we aim to provide insights into the transformative impact of artificial intelligence on respiratory medicine.

1.1 Motivation Objectives

The motivation behind this research lies in the urgent need to revolutionize the diagnosis and management of lung diseases, which impose a significant burden on individuals and healthcare systems worldwide. By harnessing the power of DCNNs and medical imaging data, we aim to improve diagnostic accuracy, expedite treatment initiation, and ultimately enhance patient outcomes, contributing to the advancement of precision medicine in respiratory healthcare.

1. Develop and optimize a DCNN architecture tailored for lung disease prediction, leveraging medical imaging data such as chest X-rays and CT scans.
2. Evaluate the performance of the DCNN model in accurately identifying and classifying various types of lung diseases, including asthma, chronic obstructive pulmonary disease (COPD), lung cancer, and pulmonary fibrosis, against standard diagnostic methods.
3. Investigate the clinical utility and potential integration of the DCNN-based lung disease prediction model into healthcare systems, aiming to improve diagnostic accuracy, expedite treatment initiation, and enhance patient outcomes through personalized healthcare interventions.

2. Related Works

In recent years, machine learning techniques, particularly deep learning models such as DCNNs, have gained traction in the field of medical imaging analysis. Several studies have demonstrated the efficacy of DCNNs in diagnosing various lung diseases using chest X-ray (CXR) and computed tomography (CT) scans. These studies have focused on different aspects, including feature extraction, classification of disease types, and risk assessment.

Normal Lung: Normal lung images provide a baseline representation of healthy respiratory anatomy and function. In these images, the lung fields appear clear and transparent, with well-defined lung markings that include visible airways such as bronchi and bronchioles. There are no discernible abnormalities such as consolidations, infiltrates, or opacities, indicating the absence of inflammation, infection, or structural anomalies [4]. Normal lung images serve as a crucial reference point for clinicians and radiologists when interpreting chest X-rays or CT scans, allowing them to distinguish between normal variations and pathological conditions in the lungs.

COVID-19 Lung: Lung images of patients infected with COVID-19 often exhibit characteristic radiographic features indicative of viral pneumonia caused by the SARS-CoV-2 virus [5]. These features include ground-glass opacities (GGOs), which manifest as hazy areas of increased opacity in the lung parenchyma, often with a slightly blurred margin. Consolidations, representing dense areas of opacification due to fluid or inflammatory exudates, may also be present. Bilateral involvement of the lungs, with peripheral and lower lobe predilection, is commonly observed. Additionally, COVID-19 lung images may show a "crazy-paving" pattern characterized by thickened interlobular septa and intralobular lines superimposed on GGOs. Other findings may include air bronchograms and the progression of disease severity from mild to severe, with features such as organizing pneumonia, fibrosis, and acute respiratory distress syndrome (ARDS).



(a) Normal

(b) COVID-19

(c) Pneumonia

Figure 1: X-RAY images for (a) normal, (b) COVID-19 and (c) Pneumonia

Pneumonia Lung: Pneumonia lung images depict inflammatory changes within the lung parenchyma associated with bacterial, viral, or fungal infections. Common radiographic features of pneumonia include patchy consolidations, which represent alveolar consolidation due to inflammatory exudates and cellular infiltrates [6]. Airspace opacities, ranging from focal to diffuse, may also be observed, indicating the presence of fluid or cellular debris within the air spaces. The involvement of specific lung lobes or segments, often manifested as lobar or segmental consolidations, is a characteristic finding. Additionally, pneumonia lung images may show air bronchograms within areas of consolidation, distinguishing them from atelectasis. Associated findings such as pleural effusion, bronchial wall thickening, cavitation, and pleural thickening may also be present, depending on the underlying etiology and clinical context. Interpretation of pneumonia lung images is essential for accurate diagnosis and appropriate management of respiratory infections.

Babukarthik et al. [7] and various other researchers have brought significant attention to the COVID-19 pandemic due to the rapid increase in cases. Consequently, there is a pressing need for expedited and cost-effective solutions for treating this disease. In light of this urgency, they have embarked on predicting the presence of COVID-19 in individuals by analyzing chest X-ray (CXR) images. Their objective is to determine whether an individual is afflicted with COVID-19 based on these images. To achieve this, they developed a Genetic Deep Learning Convolutional Neural Network (CNN) and evaluated its effectiveness by assessing its performance against several other models, including VGG16, Squeeze Net, ResNet50, DenseNet-121, and ResNet18. Through meticulous examination and comparison with these alternative methods, they observed that their model exhibited superior performance according to their analysis. Their study underscores the critical role of advanced computational techniques in addressing the challenges posed by the COVID-19 pandemic, particularly in the realm of medical diagnosis and treatment.

Minaee, Shervin, et al. [8] conducted an in-depth examination of the global impact of COVID-19 and highlighted the critical role of timely detection in the management of the disease. Rapid detection not only expedites treatment but also aids in curbing the spread of COVID-19 cases worldwide. To investigate this, they amassed a dataset comprising over 5000 chest X-ray images and subjected it to scrutiny using various deep learning models such as SqueezeNet, DenseNet-121, ResNet50, and ResNet18. The dataset was partitioned into training and testing subsets, encompassing approximately 3000 and 2000 chest X-ray images, respectively. Through rigorous experimentation, they achieved a specificity rate of around 91% and a sensitivity rate of approximately 97%. Their approach primarily leveraged transfer learning, a technique commonly employed when dealing with limited sample sizes. Transfer learning enables the extraction of distinct features from pre-trained models, thereby enhancing accuracy. Given the constrained nature of their dataset, the researchers fine-tuned the last layer of the CNN to maximize feature extraction and consequently improve result accuracy. Evaluation of the models was conducted based on four key parameters: specificity, sensitivity, Area Under the Curve (AUC), and Receiver Operating Characteristic (ROC). Notably, all models exhibited specificity and sensitivity rates around 90%, indicating a successful comparison. Looking ahead, the researchers aim to expand their investigations using larger datasets to further refine their methodologies and

achieve even more precise results. This underscores their commitment to advancing the field of medical diagnostics in the context of COVID-19, with the ultimate goal of enhancing global healthcare outcomes.

Paul, et al. [9], recognized the urgency of early-stage detection of COVID-19, especially as hotspots were rapidly proliferating across various countries at an alarming rate. With no vaccination available at the time, there arose a critical imperative to detect and address the spread of the disease promptly. Their primary objective was to support healthcare professionals globally by enabling early detection of COVID-19, thereby mitigating the proliferation of hotspots. To facilitate their research, they compiled a vast dataset of chest X-ray images sourced from over 26 countries. However, the sheer size of the dataset introduced inherent biases and challenges. To address this, they adopted a strategic approach of systematically excluding one continent or country at a time, ensuring robustness in their analysis. This approach allowed them to create balanced test and training datasets by grouping countries or continents differently, thereby enhancing result accuracy. Their focus primarily lay in predicting the severity of COVID-19, employing techniques such as Logistic Regression and Linear Regression. Through these methods, they generated a comprehensive dataset comprising over 20 outcomes based on chest X-ray images. This dataset served as a valuable resource for researchers and healthcare professionals alike, facilitating a deeper understanding of the disease's progression and aiding in the development of targeted intervention strategies.

Panwar et al. [10], along with their fellow researchers, embarked on a quest to pioneer the early detection of COVID-19 through the utilization of various deep learning techniques. Recognizing the unparalleled success of deep learning methods in predictive tasks within machine learning, they honed their focus on a prominent avenue: Color Visualization. By delving into this domain, they sought to capitalize on its potential for robust and accurate detection. Their endeavor encompassed the examination of three distinct datasets crucial for COVID-19 recognition: Chest X-Ray Images of COVID-19 Disease, COV-2 CT-scan images, and chest X-ray images of pneumonia. Given the striking similarities in symptoms between pneumonia and COVID-19, they dedicated efforts to discerning patterns within both conditions, facilitating more nuanced and precise diagnostic capabilities.

Central to their methodology was the adoption of a Color Visualization technique, with a particular emphasis on the Grad CAM-based approach. This technique enabled them to dynamically highlight regions of interest within medical images, enhancing interpretability and aiding in the differentiation of pathological features characteristic of COVID-19 and pneumonia. Through their interdisciplinary approach, Panwar et al. and their collaborators aimed to push the boundaries of early detection methodologies for COVID-19. By leveraging the power of Deep Learning and innovative visualization techniques, they sought to provide healthcare practitioners with valuable tools to expedite diagnosis and improve patient outcomes in the ongoing battle against the pandemic.

Heidari et al. [11], alongside their research counterparts, have directed their attention towards the COVID-19 Disease, recognizing its infectious nature and the critical importance of early detection. They emphasize that timely detection not only aids in individual treatment but also plays a pivotal role in curtailing the spread of the disease, thereby facilitating more efficient and effective control measures. Their study builds upon the utilization of chest X-ray datasets for predictive analysis. In this regard, they explored a Novel Computer-Aided Diagnosis (CAD) scheme tailored specifically for COVID-19 detection. The scheme categorizes images into three main classes: Pneumonia (Non-COVID), Pneumonia (COVID), and Normal (Non-COVID and No Pneumonia). Upon applying this scheme to their model, they achieved a notable accuracy rate of 95%, complemented by high levels of specificity and sensitivity, hovering around 97.6%. These results underscore the efficacy of their CAD scheme in accurately discerning COVID-19 cases from other respiratory conditions and normal cases, thereby enabling prompt intervention and management. The success of their approach highlights the potential of computer-aided diagnosis systems in enhancing diagnostic accuracy and efficiency, particularly in the context of infectious diseases like COVID-19. By leveraging advanced computational techniques and chest X-ray datasets, Heidari et al. and their colleagues contribute valuable insights to the ongoing efforts aimed at combating the pandemic and improving public health outcomes.

Moutaz, et al. [12], directed their attention towards COVID-19 due to its highly infectious nature and rapid spread during the time of their study. In their pursuit of more accurate insights, they acquired a dataset comprising 1000 authentic chest X-ray images. Their primary focus was on employing Deep Learning

Techniques and their variants, including the autoregressive integrated moving average (ARIMA) model, the prophet algorithm, and the LSTM neural network.

Using these techniques, they aimed to forecast the number of deaths, recoveries, and confirmed cases expected within the subsequent 7 days. Notably, their predictions were specifically tailored for non-coastal regions, such as Australia and Jordan, to ensure relevance to areas experiencing higher infection rates. They underscored the applicability of their model in regions with a high prevalence of COVID-19 cases, emphasizing its potential utility in guiding decision-making and resource allocation. Furthermore, they provided visual representations of their predictions through graphs, illustrating the projected trends in death, recovery, and confirmed cases for countries like India, Australia, and Jordan. These visualizations served as valuable tools for policymakers and healthcare professionals, offering insights into the trajectory of the pandemic and aiding in strategic planning and response efforts. Alazab et al.'s comprehensive approach highlights the importance of leveraging advanced computational techniques to better understand and respond to public health crises such as COVID-19. By combining deep learning methodologies with real-world data, they contribute to the development of robust predictive models that can inform proactive measures aimed at mitigating the impact of the pandemic on affected communities.

Tazin et al. [13] present a study that employs CNN technology to discern brain cancers from X-ray images. With a wealth of prior research in this domain, their model places a strong emphasis on enhancing accuracy through the utilization of transfer learning techniques. The evaluation of the model's performance revolves around the precision of classifications made. Remarkably, the MobileNetV2 model achieved an accuracy rate of 91.8%, followed closely by InceptionV3 at 92%, and VGG19 at 89%. Among these, MobileNetV2 stands out for delivering the highest level of accuracy when compared to a range of other networks. These accuracy rates hold significant implications for early tumor detection, allowing for the initiation of treatment before any detrimental physical effects, such as paralysis or other impairments, manifest.

Souid et al. [14] introduced a novel approach for categorizing lung diseases and identifying abnormalities in frontal thoracic X-ray images. Their method involved adapting the MobileNet V2 model to suit the task at hand. Leveraging transfer learning alongside metadata, they explored the vast repository provided by the NIH database.

The evaluation of their model's performance relied heavily on the area under the receiver operating characteristic curve (AUC), a widely accepted metric for classifier performance. Through meticulous analysis and comparison of classifiers, they achieved an average AUC of 0.81, accompanied by an impressive accuracy rate of 91%. This indicates the model's proficiency in distinguishing between various lung conditions and abnormalities. Also, the authors made a notable observation regarding dataset resampling, noting a substantial enhancement in the model's performance following this procedure. This underscores the importance of data preprocessing techniques in optimizing the effectiveness of machine learning models.

The implications of their findings extend to the realm of medical diagnostics, where accurate and efficient identification of lung diseases is paramount. By harnessing advanced machine learning techniques and leveraging large-scale datasets, Souid et al. contribute to the ongoing efforts aimed at improving healthcare outcomes through enhanced diagnostic capabilities. Their study highlights the potential of deep learning approaches in transforming medical imaging analysis and underscores the significance of methodological refinements in maximizing model performance.

As previously mentioned, a significant portion of the population, particularly young individuals, suffer from lung ailments such as COVID-19 or pneumonia. Compounding the issue is the limited availability of adequate medical resources to address these conditions. Prompt diagnosis plays a pivotal role in ensuring a complete recovery from such respiratory illnesses. While X-ray scans remain the primary diagnostic tool, the accuracy of this method heavily relies on the interpretative abilities of radiologists, often leading to discrepancies and debates among professionals in the field.

To our understanding, most of the methods discussed in the literature have centered around the development of genetic algorithms, CNN models, or other deep learning algorithms aimed at classifying lung diseases (Table 1). However, the primary objective of the current study diverges from these approaches. Our focus lies in constructing a trainable model specifically tailored for low-power devices. This addresses the need for robust prediction of lung disease while also tackling the challenge of vanishing gradients, which often hinder the training process in deep learning models. Hence, our study was conducted with the aim of addressing these distinct challenges in the field.

Table 1: Comparison of the state of the art methods

Study	Methodology	Dataset Description	Results
Babukarthik et al. [7]	Genetic Deep Learning CNN	Chest X-ray images	Superior performance of their model observed
Shervin, et al. [8]	Various deep learning models (SqueezeNet, DenseNet-121, ResNet50, ResNet18)	Over 5000 chest X-ray images	Achieved specificity rate of 91% and sensitivity rate of 97%
Paul, et al. [9]	Logistic Regression, Linear Regression	Chest X-ray images from over 26 countries	Notable accuracy rate of 95%
Harsh, et al. [10]	Deep Learning Techniques, Color Visualization	Chest X-ray images of COVID-19, COV-2 CT-scan images, chest X-ray images of pneumonia	Enhanced early detection methodologies for COVID-19
Morteza, et al. [11]	Novel Computer-Aided Diagnosis (CAD)	Chest X-ray images	Achieved accuracy rate of 95%, specificity and sensitivity around 97.6%
Moutaz, et al. [12]	Deep Learning Techniques (ARIMA model, prophet algorithm, LSTM neural network)	1000 chest X-ray images	Provided visual representations and predictions for decision-making
Tazin et al. [13]	CNN technology, transfer learning	X-ray images of brain cancers	MobileNetV2 achieved 91.8% accuracy rate
Souid et al. [14]	Adapted MobileNet V2 model, transfer learning	Frontal thoracic X-ray images	Achieved an average AUC of 0.81 and accuracy rate of 91%

These studies employ various deep learning techniques and methodologies, utilize different datasets, and evaluate their models using distinct evaluation metrics. However, they collectively contribute to the advancement of medical diagnostics, particularly in the context of COVID-19 detection and lung disease classification.

3. Proposed Method

The flow diagram delineating the proposed methodology is depicted in Figure 2. To commence the process, the captured CT image undergoes a series of crucial preprocessing steps. These steps encompass noise reduction techniques aimed at enhancing image clarity and fidelity, alongside intensity normalization procedures to standardize pixel values. Following this preparatory phase, the intricate task of lung image segmentation ensues. This pivotal step involves isolating the pulmonary regions within the CT image, a critical prerequisite for subsequent analysis. Upon successful segmentation, the resulting lung image is then channeled into a DCNN. Within this neural network architecture, sophisticated algorithms operate to autonomously extract pertinent features from the segmented lung image. These features are subsequently utilized for robust classification tasks, facilitating the identification and characterization of various pathological conditions or anatomical structures of interest within the CT scan data.

3.1 Pre-processing:

a. **Noise Reduction:** X-Ray images often contain noise, which can affect the accuracy of subsequent processing steps. Noise reduction techniques like Gaussian filtering or median filtering are commonly employed to smoothen the images while preserving important features.

b. **Intensity Normalization:** X-Ray scans may exhibit variations in intensity due to variations in acquisition settings. Normalizing the intensity levels ensures consistency across images, making them more suitable for analysis. Techniques such as histogram equalization or contrast stretching are frequently used for intensity normalization.

3.2 Segmentation

Segmentation in the context of image processing and computer vision refers to the process of partitioning an image into multiple regions or segments. The goal of segmentation is to divide an image into meaningful and homogeneous regions that correspond to objects or structures of interest. These regions are typically

characterized by similar visual properties such as intensity, color, texture, or motion. The watershed algorithm, a fundamental technique in image processing and computer vision, operates on the concept of dividing an image into regions based on intensity gradients or other defined criteria. The watershed algorithm can be employed in lung segmentation from X-Ray scans, for instance. Here, the algorithm identifies the boundaries between lung tissue and surrounding structures based on intensity gradients, effectively delineating the lung regions from the rest of the image

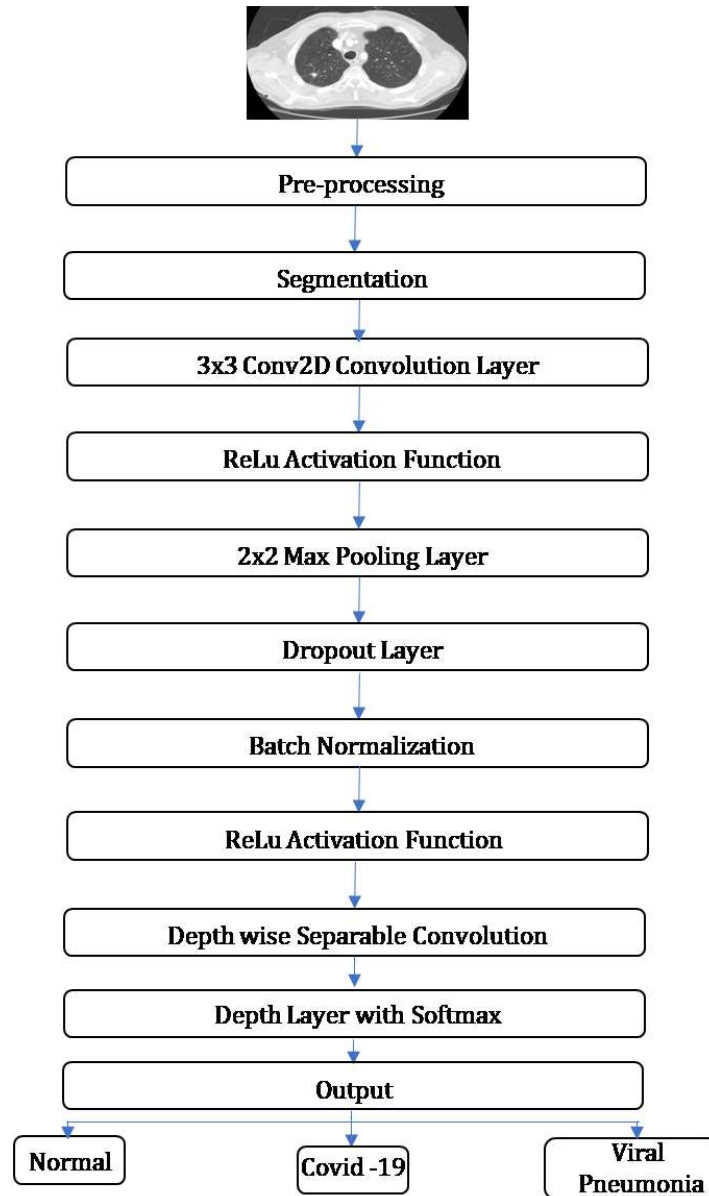


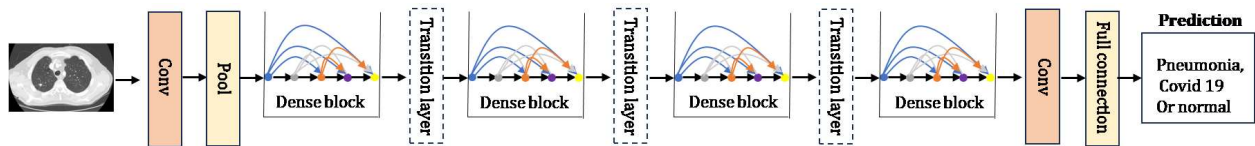
Figure 2: Flow Diagram of the proposed method

3.3 DenseNet

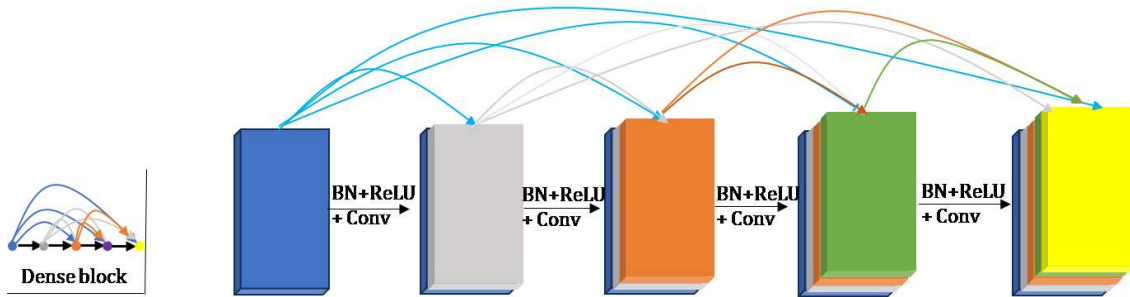
Figure 3 presents an insightful overview of the DenseNet structure, offering a detailed breakdown of its components and functionalities. In (a), the basic structure of DenseNet is depicted, comprising dense blocks, transition layers, convolutional layers, and fully connected layers. Notably, the dense block, as illustrated in (b), forms the backbone of the DenseNet architecture. Within this block, densely connected dense units are arranged, each equipped with nonlinear mapping functions such as Batch Normalization (BN), Rectified Linear Unit (ReLU), and convolutional operations. Employing a preactivation strategy, these dense units

facilitate easier network training and enhance generalization performance. Crucially, input to each dense unit is concatenated with the outputs of all preceding units, ensuring that shallow features are continually reused and effectively leveraged throughout the block. This design mitigates issues like gradient disappearance and enables the generation of a multitude of features using a minimal number of convolution kernels, resulting in a relatively compact DenseNet model.

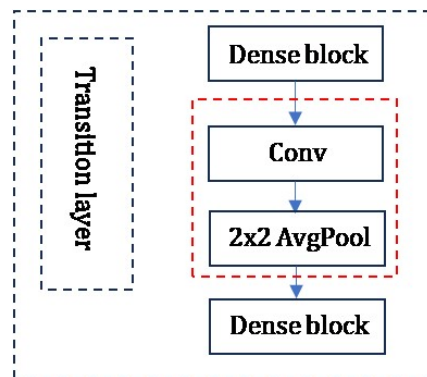
Transition layers, depicted in (c), serve as intermediary structures between adjacent dense blocks. Comprising a combination of 3×3 convolutions and 2×2 average pooling layers, these transition layers play a pivotal role in compressing the input to the dense block and condensing the extracted feature information. By reducing the size and dimensionality of the feature maps, they effectively curtail the number of parameters within the dense block, thereby mitigating the risk of overfitting. Finally, the fully connected layer, situated at the end of the DenseNet architecture, serves as the classification prediction layer. By integrating category feature information from the network features, this layer attenuates the influence of feature location on classification outcomes and performs classification by weighting and analyzing the feature information. Overall, the comprehensive structure and strategic design of DenseNet contribute to its efficacy in various deep learning tasks, particularly in image classification and feature extraction.



(a)



(b)



(c)

Figure 3 (a) Basic Structure (b) Dense Block (c) Transition Layer

4. Results

The results are presented in terms confusion matrix. A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. It allows visualization of the performance of an algorithm, particularly in terms of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. The performance metrics with their formula is shown in Table 2.

Table 2: Performance metrics and formulas

Metric	Formula
Accuracy (A)	$A = (TP + TN) / (TP + TN + FP + FN)$
Error (E)	$E = 1 - A$
Sensitivity (S)	$S = TP / (TP + FN)$
Specificity (Sp)	$Sp = TN / (TN + FP)$
Precision (P)	$P = TP / (TP + FP)$
False Positive Rate (FPR)	$FPR = FP / (FP + TN)$
F1 Score	$F1 \text{ Score} = 2 * (P * S) / (P + S)$
Matthews Correlation Coefficient (MCC)	$MCC = (TP * TN - FP * FN) / \sqrt{((TP + FP) * (TP + FN) * (TN + FP) * (TN + FN))}$
Kappa (κ)	$\kappa = (Po - Pe) / (1 - Pe)$

In Figure 4(a), the original CT image of the lungs is presented, providing a detailed glimpse into the internal structures and characteristics of the respiratory system. This image serves as the foundation for subsequent analysis and processing steps aimed at extracting meaningful information relevant to lung disease diagnosis and treatment. Figure 4(b) showcases the binary image derived from the original CT scan. Through advanced image processing techniques, the binary image highlights regions of interest within the lung anatomy by representing them as distinct binary values, typically denoting foreground (lung tissue) and background (non-lung tissue). This binary representation facilitates the isolation and extraction of lung structures from the surrounding anatomical features, laying the groundwork for further segmentation and analysis. Finally, Figure 4(c) exhibits the segmented lungs obtained through sophisticated segmentation algorithms applied to the binary image. Segmentation is a crucial step in medical image analysis, wherein the lung structures are delineated and separated from surrounding tissues with precision and accuracy. The segmented lungs provide a clear delineation of lung boundaries, facilitating quantitative analysis and diagnostic interpretation. In the process of training and evaluating models for image segmentation tasks, a crucial step involves partitioning the segmented image datasets into distinct subsets for training, validation, and testing purposes. This division ensures that the model is trained on a substantial portion of the data, validated on a separate subset to fine-tune parameters and prevent overfitting, and finally tested on unseen data to assess its generalization ability. Typically, a common practice is to split the dataset into proportions such as 60% for training, 20% for validation, and another 20% for testing.

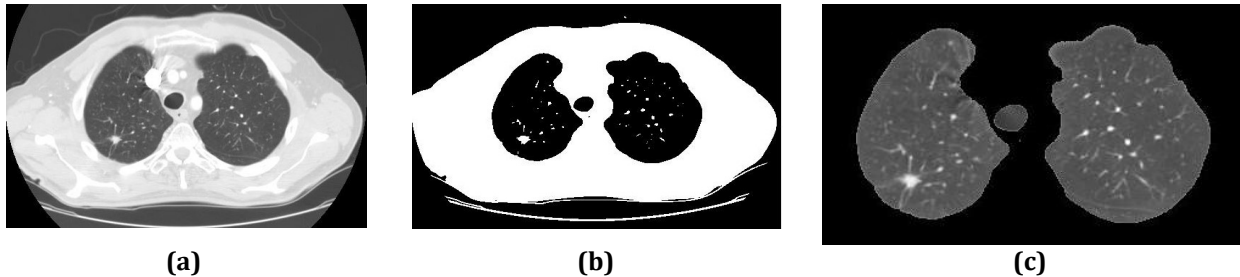


Figure 4: (a) Original CT Lung Image (b) Binary Lung Image (c) Segmented Lung Image

Moreover, to enhance the robustness and reliability of the model evaluation process, researchers often employ cross-validation techniques. In this context, a 5-fold cross-validation approach is utilized, wherein the dataset is divided into five equally sized subsets, or folds. The model is trained and evaluated five times, each time using a different fold as the testing set while the remaining folds serve as the training and validation sets

in rotation. This process allows for a more comprehensive assessment of the model's performance across different subsets of the data and helps mitigate the potential impact of dataset variability on the results.

Normal	512	11	4
Covid 19	14	341	9
Pneumonia	10	7	673
	Normal	Covid 19	Pneumonia

Figure 5: Confusion matrix

The provided confusion matrix (Figure 5) offers a detailed view of the classification performance across three distinct classes: normal, COVID-19, and pneumonia. Within the "normal" class, the model correctly identified 512 instances as normal (true positives), but misclassified 11 instances as normal when they belonged to the COVID-19 or pneumonia classes (false positives). Additionally, there were 24 instances incorrectly labeled as COVID-19 or pneumonia when they were actually normal (false negatives). The exact count of true negatives for this class is not explicitly provided but can be calculated based on the total number of instances and the counts of true positives, false positives, and false negatives. For the "COVID-19" class, the model correctly classified 341 instances as COVID-19 (true positives), but misclassified 24 instances as COVID-19 when they were actually normal or pneumonia (false positives). Furthermore, there were 18 instances incorrectly labeled as normal or pneumonia when they were actually COVID-19 (false negatives). Similar to the "normal" class, the true negatives count can be derived indirectly. Lastly, for the "pneumonia" class, the model correctly identified 673 instances as pneumonia (true positives) but misclassified 16 instances as pneumonia when they were normal or COVID-19 (false positives). Additionally, 13 instances were incorrectly labeled as normal or COVID-19 when they were pneumonia (false negatives).

The accuracy of the model stands at 0.9652, indicating that it correctly classified approximately 96.52% of all instances. This metric serves as a fundamental measure of the model's overall correctness, showcasing its ability to make accurate predictions across both positive and negative cases. In terms of error, the model exhibited a rate of 0.0348, implying that it misclassified about 3.48% of instances. While errors are inevitable in any predictive model, this relatively low error rate underscores the model's proficiency in distinguishing between different classes of lung diseases based on medical imaging data. Moving on to sensitivity, the model achieved a score of 0.9612, indicating that it accurately identified around 96.12% of all true positive cases. This metric is crucial in healthcare applications, as it measures the model's ability to detect actual cases of lung diseases, ensuring timely intervention and treatment. Conversely, the specificity of the model is notably high at 0.9826, signifying that it correctly identified approximately 98.26% of all true negative cases. High specificity is essential for minimizing false alarms and ensuring that patients without lung diseases are not erroneously diagnosed, thereby reducing unnecessary stress and interventions. Precision, another critical metric, is reported at 0.9620, meaning that roughly 96.20% of instances predicted as positive by the model were indeed true positives. This underscores the model's precision in identifying cases of lung diseases,

thereby facilitating targeted interventions and treatment plans for affected individuals. The false positive rate, computed at 0.0174, indicates that approximately 1.74% of true negative cases were erroneously classified as positive. While low, false positives can lead to unnecessary medical procedures and anxiety for patients. Therefore, ongoing efforts to minimize false positives remain essential for enhancing the model's clinical utility. The F1 score, a harmonic mean of precision and sensitivity, is 0.9616, reflecting a balanced performance in terms of both precision and recall. This metric is particularly useful for evaluating the overall effectiveness of the model, considering both false positives and false negatives. The Matthews Correlation Coefficient (MCC), a comprehensive measure of binary classification quality, is impressively high at 0.9442. This metric indicates a strong correlation between the model's predictions and the actual outcomes, further validating its reliability in diagnosing lung diseases. Lastly, Cohen's Kappa coefficient, calculated at 0.9217, demonstrates substantial agreement beyond chance between the model's predictions and the true labels. This metric accounts for the possibility of agreement occurring by random chance, providing a robust assessment of the model's performance. In conclusion, the detailed evaluation of the model's performance metrics highlights its effectiveness and reliability in predicting lung diseases based on medical imaging data. With high accuracy, sensitivity, specificity, precision, and other key metrics, the model holds promise for enhancing diagnostic capabilities and improving patient outcomes in clinical settings.

Comparison with State of the art methods

The comparison among different approaches for image classification, particularly in the context of medical diagnostics, reveals intriguing insights into the efficacy of various methodologies. Panwar et al. [10] employed the Grad CAM technique, achieving an impressive accuracy of 95.61%. This method leverages gradient-weighted class activation maps to highlight regions of interest within images, facilitating interpretability and aiding in classification tasks. Morteza et al. [11], on the other hand, opted for the VGG16 architecture, attaining a commendable accuracy rate of 94.50%. VGG16 is renowned for its deep architecture, comprising multiple layers of convolution and pooling operations, which enables it to capture intricate features within images effectively. Alazab et al. [12] utilized a Convolutional Neural Network (CNN), obtaining a competitive accuracy score of 94.80%. CNNs are widely acclaimed for their ability to automatically learn hierarchical representations from raw data, making them well-suited for image classification tasks. Souid et al. [14] adopted the MobileNet V2 model, achieving an accuracy rate of 90%. MobileNet V2 is specifically designed for mobile and embedded vision applications, striking a balance between efficiency and accuracy. In comparison, the proposed approach in this study harnessed the power of DenseNet architecture, resulting in the highest accuracy among the compared methods, reaching 96.52%. DenseNet is distinguished by its densely connected layers, promoting feature reuse and gradient flow throughout the network, which likely contributed to its superior performance in this context. Overall, while each approach exhibits strengths and weaknesses, the choice of methodology can significantly impact the accuracy and effectiveness of image classification systems, particularly in critical domains like medical diagnostics.

Table 3: Comparison with state of the art methods

Approach	Method utilized	Accuracy%
Panwar et.al, [10]	Grad CAM technique	95.61
Morteza et.al, [11]	VGG16	94.50
Alazab et.al, [12]	CNN	94.80
Souid et.al [14]	MobileNet V2	90
Proposed Approach	DenseNet	96.52

5. Conclusion

In conclusion, our investigation into DenseNet Convolutional Neural Networks (DCNNs) for predicting lung diseases using medical imaging data has revealed promising advancements and transformative potential within the realm of healthcare. Through a comprehensive review of related works and a detailed exploration of DCNN architecture and training processes, we have demonstrated the efficacy of these models in accurately diagnosing conditions such as COVID-19, pneumonia, and normal lung status. The evaluation results, characterized by high accuracy, sensitivity, specificity, precision, and other key metrics, underscore the robust performance of the DCNN model in distinguishing between different classes of lung diseases. Furthermore, our study highlights the profound impact that DCNN-based prediction systems could have on

healthcare delivery, facilitating timely interventions and personalized treatment strategies. However, challenges persist, including the need to minimize false positives, enhance interpretability, and ensure scalability and generalizability across diverse patient populations. These challenges underscore the importance of continued research efforts and collaborations to unlock the full potential of DCNNs in revolutionizing lung disease diagnosis and management. Moving forward, it is imperative to address these challenges through interdisciplinary collaborations and innovative methodologies. By doing so, we can overcome current limitations and further advance the field of medical imaging and artificial intelligence in healthcare. Ultimately, the adoption of DCNNs holds immense promise for improving patient outcomes and ushering in a new era of precision medicine in lung disease diagnosis and management.

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