**DEEP-LEARNING-BASED-CNN ALGORITHMIC TOOL DIAGNOSING DIVERSE LUNG DISEASES IN**

**A CHEST X-RAY IMAGE**

**ABSTRACT**

The global public health concern of lung diseases is substantial due to the rise in morbidity and mortality rates. The emergence of the COVID-19 pandemic in late 2019 has brought even greater urgency for early and accurate diagnosis and management of these diseases. Although chest X-rays play a crucial role in identifying and monitoring these conditions, accurately interpreting the images remains challenging—as the task relies on the expertise and experience of radiologists—making the process time-consuming for large datasets and susceptible to human error when detecting subtle signs or early stages of the diseases. Considering the issue, our paper presents a state-of-the-art deep-learning-based CNN algorithm that enables the development of an automated AI tool capable of accurately and independently identifying various abnormalities and detecting diverse lung diseases in a Chest X-ray Image.

**Keywords:** Convolution Neural Network (CNN), Chest X-Ray (CXR), Deep-learning (DL), Densely Connected Convolutional Network (DenseNet), Lung Diseases

1. **INTRODUCTION**

Lung diseases are medical conditions that affect the lungs and respiratory system. These conditions develop from various causes such as infections, genetic factors, or environmental factors like smoking, pollution, or chemical exposure. Lung diseases manifest in several types, from acute conditions like pneumonia and bronchitis to chronic conditions such as asthma, lung cancer, and COPD. These diseases often exhibit diverse symptoms, including coughing, shortness of breath, wheezing, chest pain, and fatigue [1], [2]. Consequently, lung diseases have become a substantial cause of morbidity and mortality globally, leading to millions of deaths annually—particularly in low and middle-income countries [3], [4].

The outbreak of the COVID-19 pandemic in late 2019 has emphasized the critical importance of diagnosing and managing lung conditions: not only to prevent infection in individuals with pre-existing lung diseases but also to reduce the risk of severe illness to those already infected [5], [6]. While chest X-rays are a fast, cost-effective, and non-invasive imaging tool that provides valuable and relevant information for diagnosing lung diseases, accurately interpreting the images remains challenging for subtle abnormalities or early-stage diseases. The process relies on the expertise and experience of radiologists, making it expensive, time-consuming, and prone to human errors —resulting in missed or incorrect diagnoses [7]–[10].

In recent years, Artificial Intelligence (AI) has established itself as a dominant and potent technology in medical imaging [11], [12]. By automatically and objectively analyzing images, AI can achieve improved levels of accuracy. Hence, incorporating AI into the analysis of Chest X-ray images can aid in reducing subjectivity interpretation by radiologists [13]. However, earlier studies have suggested that the top traditional machine learning AI algorithms, including support vector machines (SVMs) and decision trees, have certain drawbacks. Specifically, they are subjective due to their dependence on expert domain knowledge and manual feature engineering. Additionally, these techniques are not well-suited for handling large unstructured datasets and can be time-consuming [14], [15].

The capability of Deep learning (DL) to mimic human brain behavior in solving intricate problems—by training artificial neural networks in multiple computational layers: has exhibited immense potential in medical imaging analysis [16]–[18]. As a result, DL has emerged as breathtaking AI innovation in Chest X-ray imaging [19]. With the help of the CNN algorithm, it is now viable to effectively analyze and categorize high-dimensional Chest X-ray images [20] —as the algorithm extracts relevant patterns and structures from numerous data, regardless of their variation in qualities—without explicitly feature engineering. Hence, it computes faster and achieves accurate results at a low cost [21]–[23].

In this study, we showcase an AI algorithmic tool that diagnoses lung diseases and detects several lung abnormalities from a chest X-ray image—by employing deep learning Convolutional Neural Networks (CNNs) algorithm. The paper is structured as follows: Section I provides background information; Section II outlines the materials used and justifies the proposed methods; Section III presents the experimental setup and results obtained; Section IV interprets and analyses the study findings; and Section V concludes the paper and explores future research opportunities.

1. **MATERIALS AND METHODS**

This section provides a comprehensive description of the materials and methods used. It includes the datasets (ChestX-ray14), proposed methodology (DenseNet-121), and model design: to ensure the reproducibility and validity of our findings.

* 1. **Datasets**

We use the ChestX-ray14 dataset from the National Institutes of Health Clinical Center (NIH), which is publicly available and has privacy and security measures in place. The dataset contains 112,120 front-view chest X-ray images with 14 different thoracic pathologies labeled by a panel of four expert radiologists. These images come from 30,805 unique patients [24].

**Data Preprocessing:** The datasets were labeled with 0 for absence and 1 for presence of 14 different thoracic pathologies, including Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Consolidation, Edema, Emphysema, Fibrosis, Pleural Thickening, and Hernia. To ensure compatibility and computational efficiency with the DenseNet architecture—which was trained on pre-trained ImageNet [25], [26]—the images were resized to 224 x 224 pixels and the values were normalized to a mean of 0 and a standard deviation of 1. The dataset were split in a ratio of 80:10:10 for training, validation, and testing respectively. To increase the data diversity, data augmentation techniques (rotations and flips) were employed.

**Addressing Class imbalance:**

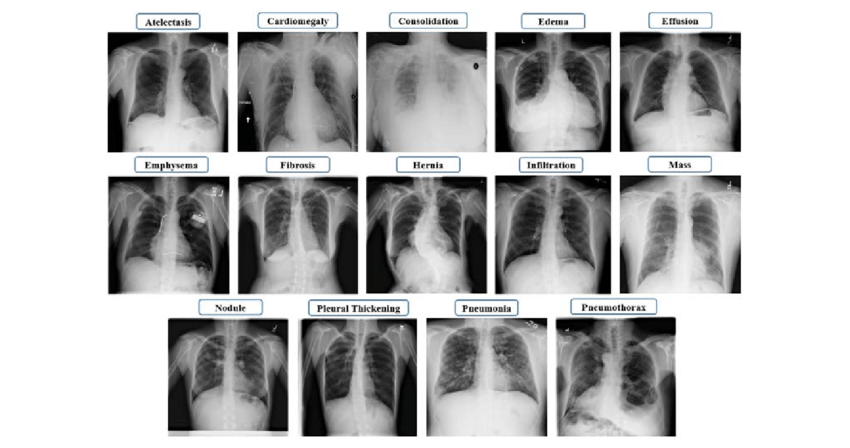


Figure 1: A Visual DenseNet Architecture representation: A Simplified Overview

* 1. **DenseNet 121 Architecture**

The DenseNet, or Densely Connected Convolutional Network, is a robust CNN architecture that has transformed the computer vision field in medical imaging. The architecture achieves a state-of-the-art performance by connecting each layer to all subsequent layers in a feed-forward manner to maintain feature maps while using fewer parameters. With this attribute, DenseNet has outperformed traditional CNNs: in addressing issues such as vanishing gradients, overfitting, and information loss—whenever large datasets are available for training [27].

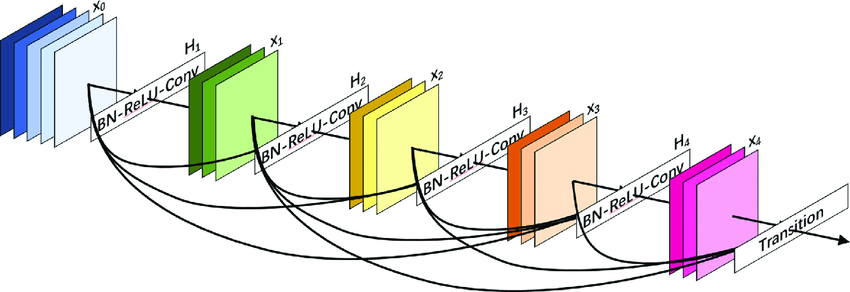


Figure 2: A Visual DenseNet Architecture representation: A Simplified Overview

The DenseNet architecture consists of initial convolutional layers, followed by a sequence of densely connected convolutional layers (Dense blocks)interposed with several transition layers. It concludes with a Global Average Pooling (GAP) layer and a fully-connected layer (FC). In this design, the input RGB image with a height (H) and width (W) undergoes initial feature extraction via a Convolutional layer with 'k' filters. Each dense block concatenates feature maps—instead of summing them—to maintain constant dimensions for feature reuse and information flow.

This operation is viable through Batch normalization (BN), Rectified Linear Unit (ReLU) activation, and a 3x3 Convolutional layer (Conv)—however, this concatenation increases the number of parameters in the network. To reduce dimensionality and control network growth, transition layers between the blocks use Batch Normalization, a 1x1 Conv layer, and a 2x2 average pooling layer. Finally, the GAP layer generates a single feature vector from the feature maps. This vector is fed into an FC layer with Softmax activation to produce the final output [28], [29]. Figure 2 above illustrates that the layer of the network concatenates the feature-maps of preceding layers as a tensor [, , ..., ], using the composite function H, mathematically represented as = ([, , ..., ]).

In this study, we propose the DenseNet-121 architecture. Compared to other DenseNet architectures, the design is preferred for medical image analysis due to its well-balanced, versatile, and lightweight architecture—making it easy to train, achieving high accuracy at high speed, and deploying on devices with limited resources. DenseNet-121 architecture comprises 121 layers: 117 Convolutional, 3 pooling, and 1 Fully-connected layers.

It includes (4) dense blocks with a growth rate of 32, (3) transition layers, (1) global average pooling (GAP) layer, and (1) a fully connected layer. Since there are L (L+1)/2 direct connections for 'L' layers, DenseNet-121 has 159 connections—with approximately 8 million learnable parameters.

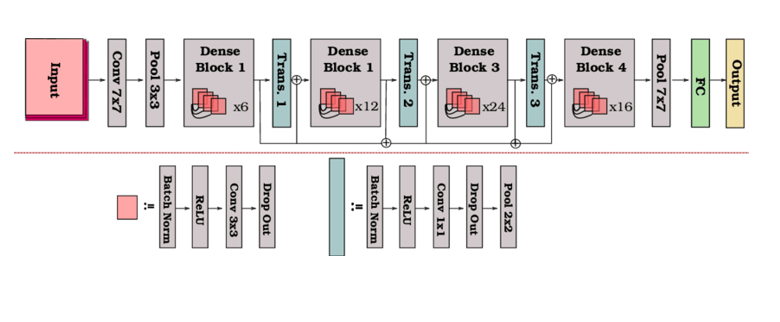


Figure 2: An In-Depth Analysis of Blocks and Layers of DenseNet-121

We use the ChestX-ray14 dataset from the National Institutes of Health Clinical Center (NIH), which is publicly available and has privacy and security measures in place. The dataset contains 112,120 front-view chest X-ray images with 14 different thoracic pathologies labeled by a panel of four expert radiologists. These images come from 30,805 unique patients. atients.

Data prepressing: We labelled the data as zero for absence, and 1 for present diseases for the 14 pathologies include Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Consolidation, Edema, Emphysema, Fibrosis, Pleural Thickening, and Hernia. As DenseNet trained on pre-trained ImageNet architecture, we resized the images to 224 x 224 pixels to ensure the compatibility and computational efficiency. We normalize the values to have a mean of 0 and standard deviation of 1, and split the data in the ratio of 80:10:10 for training, validation and test sets respectively. We also increased the diversity of data through data augmentation techniques like rotations and flips.

The datasets were labeled with 0 for absence and 1 for presence of 14 different thoracic pathologies, including Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Consolidation, Edema, Emphysema, Fibrosis, Pleural Thickening, and Hernia. To ensure compatibility and computational efficiency with the DenseNet architecture—which was trained on pre-trained ImageNet—the images were resized to 224 x 224 pixels. The image values were also normalized to have a mean of 0 and a standard deviation of 1. The dataset was split in a ratio of 80:10:10 for training, validation, and testing respectively. To increase the diversity of the dataset, data augmentation techniques such as rotations and flips were employed.

We resized all images to 224x224 pixels and normalized their pixel values to have a mean of 0 and a standard deviation of 1. We also split the dataset into training, validation, and testing sets with a ratio of 80:10:10.

Each image in the dataset has been labeled by a panel of four expert radiologists, and the labels have been aggregated to produce the final ground truth. The dataset also includes associated radiology reports, which provide additional information about the patients and their conditions.

The images in the ChestX-ray14 dataset were collected from two sources: the National Institutes of Health Clinical Center (NIH) and the Guangzhou Women and Children's Medical Center (GZ). The NIH dataset consists of 112,120 frontal-view X-ray images from 30,805 unique patients, while the GZ dataset consists of 5,232 X-ray images from 2,800 unique patients.

The ChestX-ray14 dataset is available for download from the NIH Clinical Center website and can be used for non-commercial research purposes.

Dataset Challenges:

One of the main challenges associated with the ChestX-ray14 dataset is the imbalanced class distribution. Some pathologies, such as Atelectasis and Infiltration, are much more prevalent in the dataset than others, such as Hernia and Pleural Thickening. This can make it difficult to train models that accurately detect the less prevalent pathologies.

Another challenge associated with the ChestX-ray14 dataset is the presence of confounding factors, such as patient age, gender, and medical history, which can affect the appearance of the X-ray images and complicate the interpretation of the results.

Conclusion:

However, researchers should be aware of the imbalanced class distribution and potential confounding factors when using this dataset for medical image analysis tasks.

Top of Form

The input to the DenseNet-121 architecture is typically 224x224 pixels because this is the input size used for the ImageNet dataset, which was used to pretrain the model. The ImageNet dataset consists of millions of images with a resolution of 224x224 pixels, and this resolution has become a standard input size for many deep learning models trained on image recognition tasks. The choice of input size also affects the computational complexity of the model, and 224x224 has been found to be a good balance between model performance and computational efficiency for DenseNet-121.

1. The role and benefits of dense connectivity: DenseNet-121 employs dense connectivity, where each layer in a block is connected to all subsequent layers. This allows for efficient feature reuse, improved gradient flow, and more effective training compared to traditional convolutional neural networks.
2. The number of layers and their configurations: DenseNet-121 has a total of 121 layers, with each dense block containing a specific number of convolutional layers and growth rate. Understanding the architecture and specific configurations can provide insights into how the model functions and performs.
3. Transfer learning and pre-training: DenseNet-121 has been pre-trained on the ImageNet dataset, which allows for transfer learning and adaptation to various image classification tasks. Understanding how transfer learning works and how to utilize pre-trained models can be important for practical applications.
4. Applications in medical imaging: DenseNet-121 has shown promising results in various medical imaging tasks, including chest X-ray and mammography. Understanding how deep learning models can be applied to medical imaging can provide insights into potential use cases and limitations.
5. Hyperparameters and tuning: DenseNet-121 has various hyperparameters that can be adjusted to improve performance, including learning rate, batch size, and regularization. Understanding how to properly tune these hyperparameters can be crucial for achieving optimal results.

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