Lung Disease Classification using DenseNet-121: A Deep Learning Approach for Early Diagnosis

Athulya Bhaskar
Department of Computer Applications
MES College Marampally, Aluva, Kerala, India

Jaseena K.U.
Department of Computer Applications
MES College Marampally, Aluva, Kerala, India

Leena C. Sekhar
Department of Computer Science
MES College Nedumkandam, Kerala, India

ABSTRACT
The intricate mechanism of our lungs involves frequent expansion and contraction throughout the day, facilitating the essential exchange of oxygen and carbon dioxide. Any damage to the respiratory system can lead to the development of lung diseases, which are prevalent worldwide. This category encompasses chronic obstructive pulmonary disease (COPD), asthma, tuberculosis (TB), cancer, and other prevalent conditions. Notably, lung cancer stands as a primary cause of global mortality, underscoring the critical importance of timely detection. Predominantly stemming from factors such as smoking, infections, and genetic predispositions, the majority of lung disorders pose significant health risks. Diagnostic procedures typically involve examining CT/X-Ray images of the patient's lungs, a process known for its time-consuming nature. To streamline and enhance this process, deep learning-based technologies have proven effective. In the current era of big data, traditional computational models fall short in accurately detecting lung diseases. Therefore, the integration of deep learning techniques becomes imperative, enabling the processing of image datasets for more efficient learning and predictive capabilities. In this study, Dense Net architecture is employed to classify lung diseases, and an accuracy of 86% is achieved. The simulation results demonstrate the effectiveness of the proposed model over other baseline models used for comparison.

General Terms
Machine Learning, Image Processing

Keywords
Deep learning, Lung disease detection, Convolutional neural networks, Dense Net

1. INTRODUCTION
Lung illness encompasses a wide range of diseases and disorders that impair the lungs' ability to function normally. Respiratory function, or the capacity to breathe, and pulmonary function, or how effectively the lungs perform, can both be affected by lung illness. Lung infections like bacterial, viral, and fungal infections, cause a variety of disorders. Other lung disorders, such as asthma and lung cancer, are linked to environmental causes.

A condition in which a person's airways become inflamed, narrow, swell, and produce extra mucus, which makes it difficult to breathe. Asthma can be minor or it can interfere with daily activities. Sometimes it may lead to a life-threatening attack. It causes difficulty breathing, chest pain, cough and wheezing. Asthma can usually be managed with inhalers. Pneumonia is an anther lung infection that causes difficulty in breathing and fluid in the lungs and also various viruses, bacteria, and fungi can cause pneumonia. The condition that affects the lungs is the overgrowth of cells in the lung that can form tumors. Lung cancer is the second most common form of cancer, as well as the leading cause of cancer death. The use of tobacco is the overall leading cause of lung cancer. Individuals with a less immune system have the chance to get pneumonia easily. As a result, 50–70% of persons with lung cancer get significant lung infections throughout their disease, such as pneumonia.

This paper delves into the application of deep learning techniques, with a particular focus on the utilization of advanced models like DenseNet-121, in the detection of various lung diseases. The prevalence of these conditions, coupled with the challenges associated with traditional diagnostic methods, underscores the pressing need for innovative and efficient solutions. This study aims to contribute to the evolving landscape of medical diagnostics by evaluating the efficacy of deep learning in accurately identifying and classifying lung diseases.

The study explores the limitations of conventional diagnostic approaches, such as the time-consuming nature of manual examination by healthcare professionals and the inherent constraints in processing complex medical images. The proposed deep learning-based system offers a potential breakthrough, providing a cost-effective and time-efficient means of detecting lung diseases through the classification of medical images. This manuscript not only reviews the current state of the art in deep learning for lung disease detection but also presents original research findings, including the application of DenseNet-121 and its comparative accuracy with other models.

The subsequent sections of this paper are structured as follows: Section 2 conducts a review of related works, providing an overview of existing literature in the field. Following this, Section 3 details the proposed methodology employed in this study. Section 4 is dedicated to the presentation of results and subsequent discussions. Lastly, Section 5 brings the paper to a conclusion, offering summaries of key findings and outlining potential avenues for future research.

2. LITERATURE REVIEW
Some of the publications relevant to lung illnesses are evaluated in this section. Kalaivani et al. [1] used a densely connected convolutional neural network (DenseNet) and an adaptive boosting method to detect and classify lung cancer in CT scan pictures. A dataset of 201 lung images is used for training and testing purposes. Experimental results showed that the proposed method achieved an accuracy of 90.85%.

Table I. Comparison of various models

Reference	Methods employed	Accuracy (%)	Remarks
[1]	DenseNet, adaptive boosting algorithm	90.85	Images are pre-processed and feature selection and testing & The algorithm determines if the input lung picture is normal or pathological or not
[2]	Neural systems ,GLSM and SVMs	92.50	GLSM is employed to extract the various features of image and which takes less time for generating the result
[3]	ANN,KNN,SVM,LSTM &RNN	94.31	It has been found that the proposed model provides better accuracy with low computational efforts
[4]	Genetic Algorithm combined with K-Nearest Neighbor	90	The proposed GKNN classifier is applied for classification using GA to obtain high accuracy
[5]	ACACM,SIM	96	The proposed methodology can be used as a tool in CT screening and tool to help pulmonary diagnosis
[6]	VGG Data STN with CNN (VDSNet)	73	VDSNet requires much lower training time at the expense of a slightly lower validation accuracy
[7]	ROC Analysis	82	A potential approach in deep learning analysis of CXR pictures attain better results.
[8]	VGG16, ResNet-50, and InceptionV3	94	InceptionV3 based model almost tied with the best performing solution
[9]	CNN	93.3	The next step in the early diagnosis of IPF is to create a CAD that can be used on any computer station and is accessible to non-academic centers.
[10]	DCNN	96.09	The proposed DCNN model performed exceptionally well by attaining the training accuracy of 98.02%, and the validation accuracy of 96.09%.

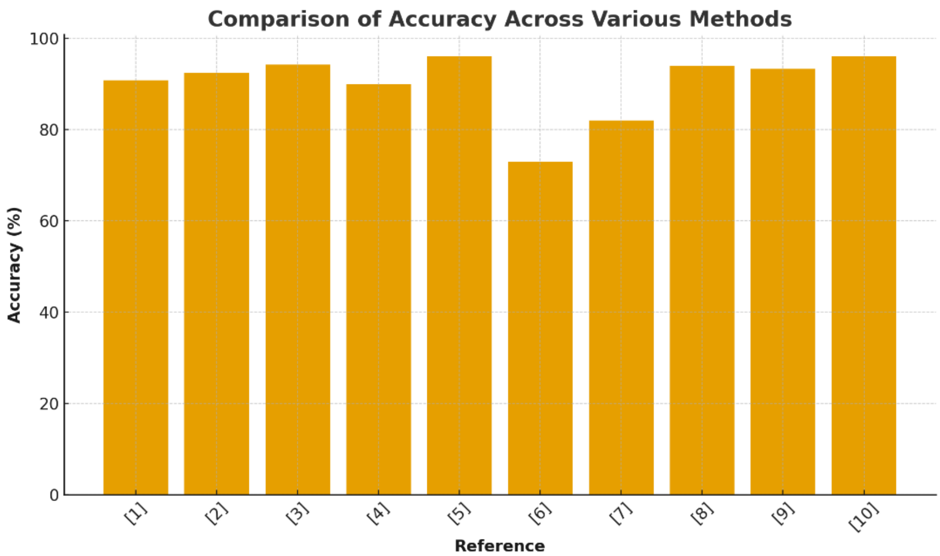

Fig 1: Comparison of performance of the models

Shivani Kasar et al. [2] proposed lung disease prediction using image processing and CNN algorithms in X-beam midsection movies, CT, and MRI. Shimpy Goya and Rajiv Singh [3] suggested a new paradigm for predicting lung diseases including pneumonia and Covid-19 from patients' chest X-ray scans. Proposed a framework consisting of dataset acquisition, picture quality enhancement, adaptive and accurate area of interest (ROI) estimate, features extraction, and illness anticipation. They used two publicly accessible chest X-ray image datasets to detect and classify illnesses, and they developed a robust approach. Artificial neural networks (ANN), support vector machines (SVM), K-nearest neighbor (KNN), ensemble classifiers, and deep learning classifiers are among the soft computing approaches used for classification. Deep learning architecture based on recurrent neural networks (RNN) with large short-term memory has been proposed for accurate lung disease diagnosis (LSTM)

Bhuvaneswari and Brintha Therese [4] employed the Genetic K-Nearest Neighbor Algorithm, a non-parametric approach for detection. This approach enables clinicians to detect nodules in CT lung pictures hence detecting lung cancer at an early stage. The genetic Algorithm approach is paired with the K-Nearest Neighbor (K-NN) algorithm to swiftly and accurately categorize the cancer pictures. 50-100 samples are picked for each iteration in this suggested technique, which uses a Genetic Algorithm to achieve a classification accuracy of 90 percent. Geraldo Luis Bezerra Ramalho et al. [5] used CT images for the detection of lung diseases. They used ACACM for lung structure segmentation and proposed a novel method for lung disease detection based on feature extraction of ACACM segmented images within the co-occurrence statistics framework (SIM) synthesizes the structural information of lung image structures in terms of three attributes. Finally, a classification experiment on this set of attributes to discriminate between two types of lung diseases and healthy lungs and evaluated the discrimination ability of the proposed lung image descriptors using an Extreme Learning Machine Neural Network comprising 4-10 neurons in the hidden layer and 3 neurons in the output layer to map each pulmonary condition. This network was trained and validated by applying a holdout procedure. The experiment gives 96% accuracy

Subrato Bharati et al. [6] propose a new hybrid deep learning framework for examining the X-ray images by combining VGG, data augmentation, and spatial transformer network (STN) with CNN. This new hybrid method is termed here as VGG Data STN with CNN (VDSNet). For the full dataset, VDSNet exhibits a validation accuracy of 73%, while vanilla gray, vanilla RGB, hybrid CNN and VGG, and modified capsule network have accuracy values of 67.8%, 69%, 69.5%, and 63.8%, respectively. Becker et al. [7] proposed Detection of tuberculosis patterns in digital photographs of chest X-ray images using Deep Learning, the images were stratified by pathological patterns into classes: cavity, consolidation, effusion, interstitial changes, military pattern or normal examination. Image analysis was performed with commercially available Deep Learning software in two steps. Pathological areas were first localized; detected areas were then classified. Detection was assessed using receiver operating characteristics (ROC) analysis, and classification using a confusion matrix. Matthew Zak and Adam Krzyzak [8] classified the lung diseases by examining the chest X-ray. They implemented three deep convolutional neural networks (VGG16, ResNet-50, and InceptionV3) pre-trained on the ImageNet dataset and assessed them in lung disease classification tasks using a transfer learning approach. Their method was able to reach the same level of accuracy as the best-performing models trained on the Montgomery dataset. Ana Adriana Trusculescu [9] presented a study based on Interstitial lung diseases and used CNN for the classification. Rong Yi1 et al. [10] analyzed chest X-ray images using a deep convolutional neural network (DCNN). Table I depicts the comparison of various models used for lung disease detection.

In summary, this literature review not only consolidates existing knowledge but also sheds light on the promising advancements and diverse methodologies employed in the detection and classification of lung diseases using deep learning techniques. As the field continues to evolve, these insights provide a valuable foundation for further research aimed at refining and advancing diagnostic capabilities for improved patient outcomes. Figure 1 compares the performance of the various models discussed in the literature. From the figure, it can be observed that CNN-based models produced better accuracy in lung disease prediction.

3. PROPOSED METHODOLOGY

3.1 Datasets

The dataset used in this study is collected from the following website which is publicly available at "https://www.kaggle.com/datasets/omkarmanohardalvi/lungs-disease-datase t-4-types". It consists of the X-RAY images of lungs with diseases; Viral Pneumonia, Bacterial Pneumonia, COVID-19, and Tuberculosis, and also has images of Normal lungs. In this dataset, there are a total of 6025 images, which is normal-sized with 64 x 4 resolution and for testing about 2025 images are taken. Figure 2 shows the screenshot of affected and normal lung images.

3.2 Methods Employed

3.2.1 DenseNet-121

In this study, for the training and testing of lung images, DnseNet-121 is employed. A convolutional neural network called DenseNet-121 (Dense Convolutional Network) is composed of 120 convolutional and 4 AvgPool in a feed-forward manner.

Each layer in a DenseNet design is linked to every other layer, thus the term Densely Connected Convolutional Network. There are L(L+1)/2 direct connections for L layers. The feature maps of all previous layers are utilized as inputs for each layer, and its feature maps are used as input for each following layer. The architecture of DenseNet is shown in Figure 3.

DenseNets connects every layer to every other layer. This is the core concept, and it is quite strong. A layer's input in DenseNet is the concatenation of feature maps from preceding layers.

The dense connectivity can be represented as given in equation (1):

$$X_l = H_l\left(\left[X_{0,} X_{1,}, \ldots \ldots, X_{l-1,}\right]\right) \tag{1}$$

3.2.1.1 DenseBlocks

When the size of feature maps varies, the concatenation method cannot be used. However, a critical component of CNNs is layer downsampling, which minimizes the size of feature maps through dimensionality reduction to achieve faster computation rates.

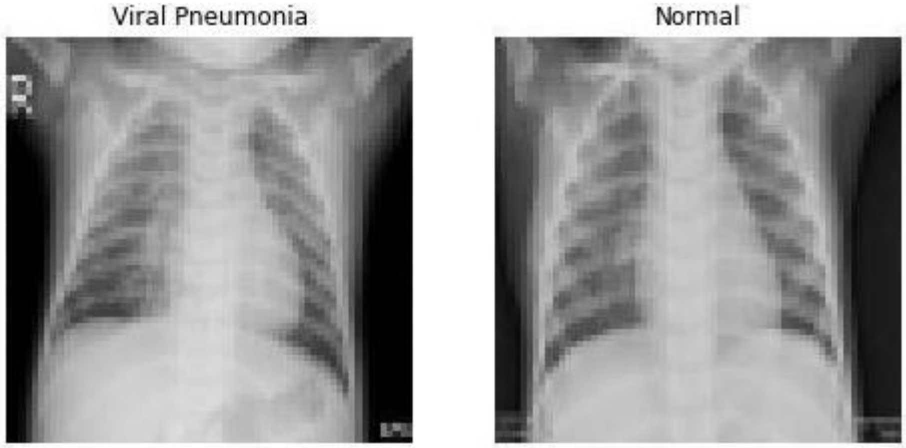

Fig 2: Sample image for affected and normal lung

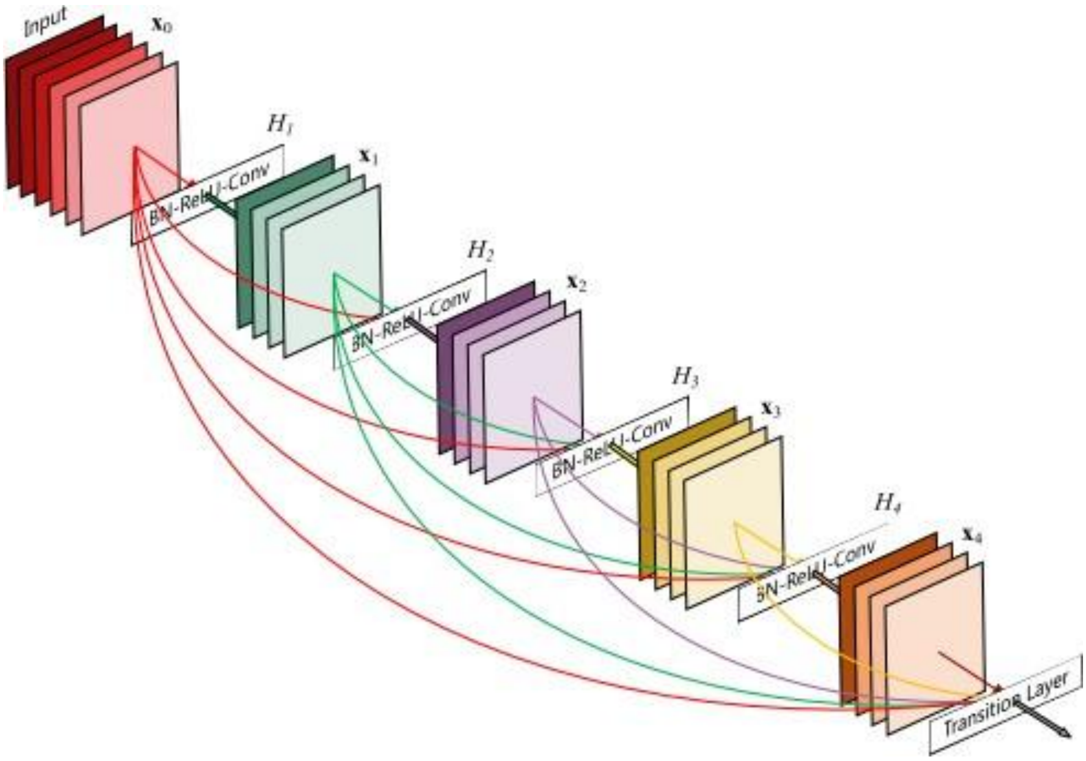

Fig 3: DenseNet121 Architecture

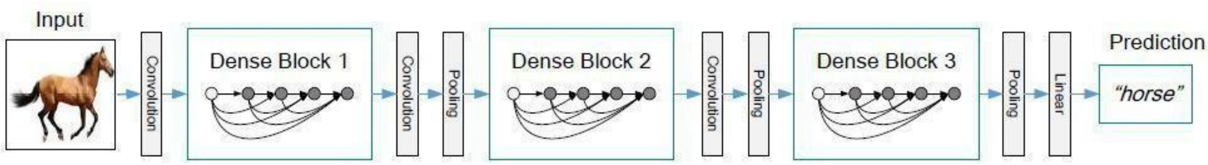

Fig 4: A deep DenseNet with three dense blocks

DenseNets are divided into DenseBlocks to facilitate this, with the size of the feature maps remaining constant inside a block but the number of filters between them changing. Transition Layers are the layers between the blocks that limit the number of channels to half of the present channels.

Hi is defined as a composite function that applies three sequential operations for each layer in the equation above: batch normalization (BN), a rectified linear unit (ReLU), and a convolution (Conv).

Figure 4 depicts a deep DenseNet with three dense blocks. Transition layers perform downsampling (i.e. change the size of the feature maps) via convolution and pooling operations between two adjacent blocks, however, inside the dense block the size of the feature maps is the same to permit feature concatenation.

3.2.1.2 Growth Rate

Consider the characteristics to be the network's overall condition. After passing through each thick layer, the size of the feature map rises, with each layer adding 'K' features on top of the global state (existing features). This parameter 'K' is referred to as the network's growth rate, and is defined in equation (2). It controls the quantity of information added to each layer of the network. If each function Hl generates k feature maps, the lth layer, input feature-maps, where k0 is the number of input layer channels DenseNets, unlike conventional network topologies, may have incredibly narrow layers.

$$k_l = k_0 + k * (l - 1) \qquad (2)$$

3.2.1.3 Bottleneck layers

Although each layer only generates k output feature maps, the number of inputs can be fairly large, particularly for subsequent levels. To increase the efficiency and speed of calculations, a 1x1 convolution layer can be included as a bottleneck layer before each 3x3 convolution. DenseNet-121, in summary, has 120 Convolutions and 4 AvgPool. All layers, even those within the same dense block and transition layers, dis-tribute their weights over numerous inputs, allowing deeper layers to lever-age characteristics collected earlier in the process. Because transition layers produce numerous duplicated features, the layers in the second and third dense blocks provide the least weight to the transition layers' output. Furthermore, even if the end layers employ the weights of the entire dense block, there may be more high-level features created deeper into the model due to a higher concentration towards final feature mappings in trials.

3.3 Proposed Framework

The proposed framework employs the DenseNet-121 architecture for training and testing lung disease images. DenseNet-121 is a convolutional neural network where each layer is directly connected to all subsequent layers, forming dense connections. This design enables maximum feature reuse, mitigates the vanishing gradient problem, and significantly improves information flow across the network. For example, the first convolutional layer connects not only to the second layer but also to the third, fourth, and subsequent layers. Similarly, the second layer connects to all layers that appear after it. This dense connectivity allows the model to learn deeper feature representations efficiently with reduced computational cost.

The proposed framework is depicted in Figure 5. The overall system pipeline consists of four major stages: Data Preprocessing, Feature Extraction, DenseNet-121 Model Training, and Testing.

During preprocessing, all medical images are standardized and resized to a uniform dimension. Noise removal, normalization, and enhancement operations are applied to eliminate irrelevant pixel information and improve image clarity. Feature extraction is inherently performed by the DenseNet architecture, where the network automatically learns hierarchical and discriminative features from the input images without manual feature engineering.

For model development, the dataset is divided into two parts: 80% of the images are used for training the network, and the remaining 20% are used for testing and validation of model performance.

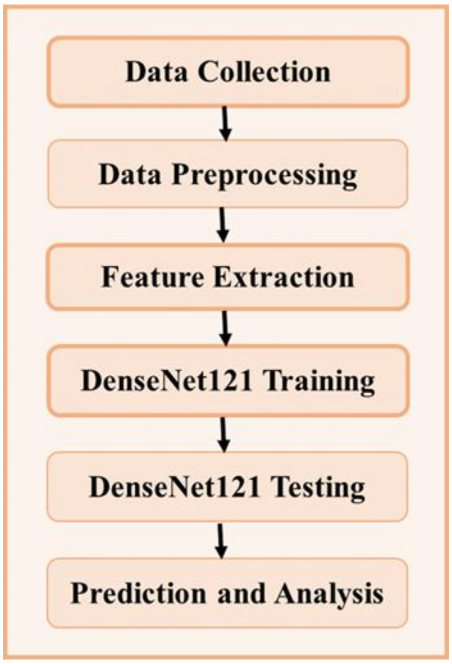

Fig 5: Proposed Model

The DenseNet-121 structure begins with an initial convolution and pooling layer, followed by multiple Dense Blocks interconnected through Transition Layers. Each Dense Block consists of repeated sequences of Batch Normalization, ReLU activation, and 2D convolution layers. Transition layers reduce spatial dimensions and the number of feature maps using convolution and pooling operations, making the architecture both deep and computationally efficient. A fully connected classification layer is placed at the end of the network to predict the type of lung disease based on the learned feature representations.

This framework enables robust classification of lung diseases from medical imaging, improving diagnostic efficiency and supporting clinical decision-making.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the proposed DenseNet-121 architecture is evaluated using standard classification metrics such as Precision, Recall, F1-score, and Accuracy. Table 2 presents the detailed class-wise evaluation results of the DenseNet model for lung disease classification. The model demonstrated an overall classification accuracy of 0.86. The per-class analysis indicates that classes 1, 2, and 3 achieved superior F1-scores (0.96, 0.95, and 0.97 respectively), reflecting strong prediction capability for these disease categories. However, Class 0 and Class 4 yielded slightly lower performance, with Class 4 showing the lowest F1-score (0.67). This may be attributed to image distortions, insufficient samples, or class imbalance within those categories.

In addition, micro average and weighted average values are also computed to provide a more comprehensive evaluation of the model performance. The micro average F1 score of 0.86 and weighted average score of 0.86 indicate that the model maintains consistent performance across the entire dataset.

Table 2. Performance Overview of DenseNet

	Precision	Recall	F1-Score
0	0.70	0.84	0.77
1	0.93	0.99	0.96
2	0.95	0.95	0.95
3	1.00	0.95	0.97
4	0.77	0.59	0.67
accuracy			0.86
micro_avg	0.87	0.87	0.86
weighted_avg	0.87	0.86	0.86

To assess the robustness of the proposed model, DenseNet-121 is compared against traditional CNN, SVM, and other popular deep learning architectures such as VGG and ResNet. Table 3 illustrates the comparative analysis across all models. From the results, it is evident that the DenseNet-121 model significantly outperformed the other architectures in terms of overall classification performance. Specifically, the DenseNet model achieved the highest precision (0.863), recall (0.863), F1-score (0.863), and accuracy (0.86). The higher performance demonstrates the advantage of dense connections which support efficient feature propagation, improved gradient flow, and better feature reuse, thus leading to superior classification capability.

The experimental findings confirm that DenseNet-121 provides more reliable and accurate results for automated lung disease classification compared to conventional CNN, SVM and standard deep learning architectures such as VGG and ResNet. This validates the effectiveness of the proposed approach in supporting medical image-based diagnostic applications.

Table 3. Comparison of results

Model	Precision	Recall	F1-score	Accuracy
DenseNet	0.863	0.863	0.863	0.860
VGG	0.729	0.729	0.729	0.720
ResNet	0.690	0.690	0.690	0.680
CNN	0.689	0.689	0.689	0.690
SVM	0.660	0.660	0.660	0.630

5. CONCLUSION

Lung diseases are prevalent worldwide, encompassing chronic obstructive pulmonary disease, asthma, tuberculosis, cancer, and other related conditions. Notably, lung cancer stands as a leading cause of global mortality, emphasizing the critical need for timely detection to enhance survival rates. Early detection significantly improves the chances of survival, yet the conventional method of relying on medical professionals to examine and anticipate abnormalities in medical photos proves both time-consuming and costly. To address this, the proposed system offers a cost-effective approach by employing machine learning to classify medical images and identify affected areas efficiently. The system utilizes DenseNet-121, comparing its classification accuracy with other models. Notably, DenseNet-121 achieves an accuracy rate of 86%, showcasing promising results. These technologies encounter limitations when processing blurry and slanted images. Overcoming these challenges through hybrid methods presents a potential avenue for future advancements in lung disease detection.

6. REFERENCES

[1] Kalaivani1, Manimaran, Sophia & D Devi D. 2020. Deep Learning Based Lung Cancer Detection and Classification, IOP Publishing IOP Conf. Series: Materials Science and Engineering 994 (2020) 012026 doi:10.1088/1757-899X/994/1/012026.

[2] Shivani Kasar, Darshan Hujband, Abhijeet Ahire, Jyoti Rahade. 2020. “Lung Diseases Prediction Using Image Processing and CNN Algorithm”, International Research Journal of Engineering and Technology (IRJET),07 Issue: 03 | Mar 2020.

[3] Shimpy Goyal, Rajiv Singh. 2023. “Detection and classification of lung diseases for pneumonia and Covid-19 using machine and deep learning techniques”, Journal of Ambient Intelligence and Humanized Computing,https://doi.org/10.1007/s12652-021-03464-7.

[4] Bhuvaneswari, Brintha Therese. 2014. Detection of Cancer in Lung With K-NN Classification Using Genetic Algorithm, Elsevier Ltd, 2nd International Conference on Nanomaterials and Technologies (CNT 2014).

[5] Geraldo Luis Bezerra Ramalho, Pedro Pedrosa Rebouças Filho, Fátima Nelsizeuma Sombra de Medeiros, Paulo César Cortez. 2014. “Lung Disease Detection Using Feature Extraction and Extreme Learning Machine”, Brazilian Journal of Biomedical Engineering, December 2014, DOI: 10.1590/rbeb.2014.019.

[6] Subrato Bharati, Prajoy Podder, M. Rubaiyat Hossain Mondal. 2020. Hybrid deep learning for detecting lung diseases from X-ray images, Informatics in Medicine Unlocked 20 (2020) 100391.

[7] Becker, A.S., Blüthgen, C., Sekaggya-Wiltshire, C., Castelnuovo, B., Kambugu, A., Fehr, J. and Frauenfelder, T., 2018. Detection of tuberculosis patterns in digital photographs of chest X-ray images using Deep Learning: feasibility study. The International Journal of Tuberculosis and Lung Disease, 22(3), pp.328-335. http://dx.doi.org/10.5588/ijtld.17.0520.

[8] Matthew Zak and Adam Krzy˙zak. 2020. Springer Nature Switzerland AG 2020 ICCS 2020, LNCS 12139, pp. 621–634, 2020, https://doi.org/10.1007/978-3-030-50420-5_47.

[9] Ana Adriana Trusculescu, Diana Manolescu, Emanuela Tudorache,& Cristian Oancea. 2020. “Deep learning in interstitial lung disease—how long until daily practice” Published online: 14 June 2020, European Radiology (2020) 30:6285–6292,https://doi.org/10.1007/s00330-020-06986-4.

[10] Rong Yi, Lanying Tang, Yuqiu Tian, Jie Liu, Zhihui Wu. 2023. “Identification and classification of pneumonia disease using a deep learning-based intelligent computational framework”, Neural Computing and Applications, https://doi.org/10.1007/s00521-021-06102-7(0123456789()., -volV)(0123456789,-().volV).