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Evaluation Of 3dcnn Architecture For Classification Of Lung Diseases.

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ABSTRACT

Globally, infectious disease-related illnesses have long been a problem. Lung Cancer, COVID-19 and pneumonia (bacterial and viral pneumonia), all impact the lungs and result in millions of fatalities annually. In every situation, opportunities for improved care can be created by early identification and diagnosis. Computerized Tomography (CT) is utilized, nevertheless, to identify lung disease and identify symptoms. Even for doctors, using various imaging modalities is a challenging and time-consuming activity that is subject to varying opinions from different observers. Thus, there is considerable interest in creating algorithms that can automatically distinguish between people with lung disease and those who are healthy. Our research compares different 3DCNN architecture to accurately detect a subset of lung disorders using patient respiratory images, with the goal of improving the diagnostic accuracy of respiratory ailments. We demonstrated that 3D-VoxResNet produces superior outcomes when compared to other frameworks like 3D-VGG16,3D-AlexNet,3D-GoogleNet..

Keywords: *3DCNN,3D-VGG16, 3D-AlexNet, 3D-GoogleNet, 3D-VoxResNet.*

INTRODUCTION

Lung illnesses constitute a considerable worldwide health burden, with a high morbidity and mortality associated with ailments including lung cancer, interstitial lung disease (ILD), and different infections. Improved patient outcomes and efficacious therapy depend on an early and precise diagnosis. The area of medical diagnostics has undergone a revolution with the introduction of improved imaging technologies, namely computed tomography (CT). With the help of comprehensive cross-sectional images provided by CT imaging, structures and abnormalities that are not visible with traditional radiography may be seen. This capacity is especially helpful for tracking the development of lung disorders, assessing the effectiveness of treatment, and diagnosing them early on.

Machine learning (ML) modules specifically designed for CT image interpretation are being developed as a result of the growing availability of large-scale medical imaging datasets. The aim of these algorithms is to enhance radiologists' diagnostic abilities by automating the identification, categorization, and measurement of lung irregularities. The main objective is to improve the consistency and accuracy of diagnoses by minimizing the subjectivity and unpredictability that come with human interpretation. Deep learning-based machine learning models in particular have shown impressive results in the identification and classification of lung illnesses using CT scans. The capacity of convolutional neural networks (CNNs), a family of deep learning models, to learn hierarchical feature representations from raw pixel input makes them especially well-suited for image processing.

Machine learning algorithms will be trained to identify numerous pathological signs in the context of classifying lung diseases. For example, these models can detect and distinguish between benign and malignant nodules in lung cancer based on their size, texture, and form. Similar to this, deep learning algorithms can segment and quantify various lesions, such as honeycombing and ground-glass opacities, which are symptomatic of the severity and development of interstitial lung disease. These automated devices are essential for illness staging, prognostication, and therapy planning in addition to helping with diagnosis.

A number of crucial processes, such as data preparation, feature extraction, model training, and validation, are involved in the integration of machine learning with CT imaging. The goal of data preprocessing is to improve image quality and balance out discrepancies caused by different equipment and acquisition techniques. This stage might include spatial normalization, contrast enhancement, and noise reduction. Finding pertinent patterns and structures in the photos that are suggestive of particular illnesses is known as feature extraction. Following that, labeled datasets—where each image's illness state is known—are used to train machine learning models. The models are able to correctly categorize new, unseen photos because they are trained to correlate particular visual attributes with different illness classifications.

An important step in evaluating the effectiveness of the trained algorithms is model validation. Usually, separate test sets and cross-validation methods are employed to make sure the models perform well when applied to a variety of patient demographics and imaging scenarios. The efficacy of these models is frequently assessed using performance measures including area under the receiver operating characteristic curve (AUC-ROC), sensitivity, specificity, and accuracy. By identifying questionable areas for additional examination, high-performance models can greatly lighten radiologists' workloads and speed up the diagnosis process.

The use of machine learning in CT-based lung disease categorization also include longitudinal research, the aim of which is to monitor the course of the illness over an extended period of time. These models provide important insights into the dynamics of the disease and the effectiveness of treatment by examining successive CT images and identifying minute alterations in lung tissue. This skill is especially crucial for chronic illnesses like ILD, where fast medical treatments might possibly improve patient outcomes by detecting exacerbations early on.

The categorization of lung diseases using CT imaging and machine learning has significant social implications. Through precise and prompt treatments, these technologies can enhance patient outcomes by improving diagnostic accuracy and consistency. By ensuring that patients receive the right therapy based on their unique condition, the decrease in diagnostic variability contributes to care standardization. Furthermore, more precise and quantitative monitoring of the course of the disease and the response to therapy can result in more individualized and successful therapeutic approaches.

By simplifying diagnostic workflows and lowering the need for invasive procedures, the broad use of these technologies can also lessen the strain on healthcare systems. This maximizes resource use within healthcare institutions while also improving patient comfort and safety. In the end, machine learning's incorporation into CT-based lung disease categorization marks a substantial breakthrough in medical diagnostics that might revolutionize clinical practice and enhance public health globally.

2 RELATED WORK

Lung diseases include illnesses affecting the lungs, which are the organs needed for breathing, and are among the most common medical ailments globally, especially in India. Using computed tomography (CT) scans and chest X-rays, some researches have used image processing and machine learning approaches to identify and categorize lung disorders in an effort to improve diagnosis accuracy and assist medical professionals in efficiently arranging treatments.

Lung disorders [1] including pleural effusion and normal lung states using moment invariants for feature extraction and evolutionary algorithms for feature selection. They used Naïve Bayes and Decision Tree classifiers for picture classification after applying preprocessing approaches to eliminate noise. They discovered that, in terms of accuracy, the Decision Tree classifier performed better than the Naïve Bayes classifier. This approach's primary benefit is its ability to extract and select features effectively, which results in a classification that is more accurate. But one drawback is the dependence on conventional classifiers like Naïve Bayes, which could struggle to handle intricate patterns. Researched machine learning techniques [2] for the classification of illnesses of the lungs, including pleural effusion, malignancy, bronchitis, emphysema, and normal lungs, using CT scans. In their method, features were extracted using the Gray Level Co-occurrence Matrix (GLCM), and then MLP, KNN, and SVM classifiers were used for classification. The study demonstrated how well the KNN classifier performed in terms of accuracy. This work's strength is its extensive feature extraction strategy and usage of numerous classifiers. The possible overfitting of models to certain datasets, which may result in poor generalization to other datasets, is the study's drawback. Applying deep learning and machine learning methods on chest X-ray images to detect and categorize lung illnesses [3], such as pneumonia and Covid-19. Within their framework, they employed median filtering and histogram equalization to improve the quality of the images. They then used classifiers like ANN, SVM, KNN, ensemble classification algorithms, and deep learning models like RNN with LSTM to estimate the region of interest (ROI), extract features, and predict diseases. When compared to more conventional approaches, the deep learning strategy performed reliably and effectively. This study's main benefit is its thorough approach, which incorporates deep learning, precise ROI extraction, and picture improvement. However, the intricacy and high computational demand of deep learning models may be considered disadvantages, necessitating substantial resources and knowledge.

A deep convolution neural network (CNN) with an efficient but streamlined design [4] for categorizing lung pictures from CT scans. Six external shape-based characteristics were integrated, including the histogram of orientated gradient (HOG), moment, solidity, circular economy, individual Fourier transformation of radial length function, and histogram of active contour picture. Recall and precision were averaged out, and the results showed that recall was relatively low while precision was high. A strong point of the work is how it incorporates external shape-based data into CNN to improve classification quality. The model's robustness might be limited, nevertheless, by the dependence on shape-based variables that might not fully capture all pertinent elements of lung illnesses. Emphysema in CT images is classified using a texton-based classification approach that combines raw pixel representation with a support vector machine (SVM) [5] and a radial basis function kernel. Their method outperformed popular approaches such as histogram values of filter outputs based on Gaussian derivatives when evaluated on annotated regions of interest. High accuracy was shown by the system, which was somewhat better than local binary pattern-based techniques. This study's unique application of texton-based categorization, which offers better accuracy, is its strongest point. But the emphasis on classifying emphysema may make it less applicable to other lung illnesses, requiring more research on a wider spectrum of ailments.

A hybrid deep learning method for lung nodule categorization and early prediction on CT scans [6]. Three essential components comprise the approach they use, Lung Nodule Detection and Classification with Hybrid Deep Learning (LNDC-HDL): segmenting lung nodules using the Chaotic Bird Swarm Optimization (CBSO) algorithm; extracting and selecting features using an improved Fish Bee (IFB) algorithm; and predicting and classifying tumors using a Hybrid Differential Evolution-based Neural Network (HDE-NN). Their study's usage of computed tomography showed improved sensitivity and fewer false positives, underscoring the practical value of merging statistical data with hybrid deep learning methods. However, real-time clinical deployment of the hybrid strategy may be difficult due to its processing needs and complexity. A complete deep convolutional neural network (CNN) classification method for interstitial lung disorders (ILD) using CT images [7]. By using the complete picture as input, their solution avoids the typical requirement for manual designation of areas of interest (ROIs), better matching with clinical processes. With excellent classification accuracy, this all-encompassing method worked well for categorizing ILD patterns. Notwithstanding its achievements, the problem still lies in handling the greater complexity of processing complete pictures in comparison to patch-based techniques, which can call for more advanced hardware and software solutions. the VGG19 network's combined segmentation and classification of lung nodules in CT images [8]. For nodule identification and deep learning-based classification, their approach incorporates VGG-SegNet. It is then improved by concatenating deep features with manually created features like Pyramid Histogram of Oriented Gradients (PHOG), Local Binary Pattern (LBP), and Grey Level Co-Occurrence Matrix (GLCM). To attain better accuracy, this hybrid technique makes use of both handmade and deep features. Its applicability to diverse clinical contexts may be constrained, nevertheless, by its dependence on two datasets (LIDC-IDRI and Lung-PET-CT-Dx) and the difficulty of merging disparate feature types.

A system for automatically classifying lung diseases [9] that makes use of a hybrid deep learning algorithm (HDLA) and chest X-ray pictures. Their approach entails pre-processing photos to improve their quality, then classifying the images using a variety of machine learning techniques, including AdaBoost, SVM, Random Forest, Backpropagation Neural Network, and Deep Neural Network, and extracting features using a 2D CNN model. With its enhanced accuracy and decreased computing complexity, the HDLA framework is a viable solution for contexts with limited resources. However, the method's inability to be uniformly applied to various imaging settings may be hindered by its dependence on pre-processing stages and the requirement for ideal filtering. examined the use of radiomics and deep learning algorithms for the histological categorization of lung cancer from CT images [10]. In patients with non-small cell lung cancer (NSCLC), they sought to differentiate between adenocarcinoma (AC) and squamous cell carcinoma (SCC). They used four alternative approaches in their study: a mixture of CNN and long short-term memory (LSTM) relationships, radiomics with kNN and SVM classifiers, transfer learning using four CNNs (AlexNet, ResNet101, Inceptionv3, and InceptionResNetv2), and combinatorial models (LSTM + CNN + radiomics). The LSTM + Inception model performed better than professional radiologists and produced the best results. This method simplifies the categorization procedure because it does not call for a thorough segmentation of the tumor. Nevertheless, combining many cutting-edge approaches might make the system more complicated and need a lot of processing power.

A new kind of fusion model that uses the median absolute deviation (MAD) method to merge information from Walsh Hadamard [11] transform and Gabor filter. Three steps comprise their methodology: decision tree, k-nearest-neighbor (KNN), and multilayered perceptron neural network (MLP-NN) classifiers for classification; picture preprocessing and feature extraction; and feature selection via a genetic approach. The 400 CT scans in the collection included pictures of normal lungs, pleural effusion, bronchitis, and emphysema. Despite the excellent classification accuracy of their method, its adaptation to new data sources may be limited due to its reliance on handmade characteristics. Regarding the categorization of lung cancer by a traditional features fusion technique based on contrast-stretching. Using gamma correction [12], multiple texture, point, and geometrical feature extraction, and serial canonical correlation-based fusion are the techniques they use to improve the contrast of CT images. Before being fed into an ensemble classifier, the most discriminative features were chosen using a weighted local component analysis (NCA) and an entropy-based methodology. They validated their strategy using the Lungs Data Science Bowl 2017 dataset, and the results showed exceptional accuracy. Nevertheless, the intricacy of the feature extraction and selection procedure may impede its immediate implementation.

Designed a multimodal framework [13] that uses lung sound and cough samples in addition to CT scans for the early diagnosis and categorization of chronic obstructive pulmonary disease (COPD). Mel-Frequency Cepstral Coefficients (MFCCs), chroma, texture, histogram intensity, and Gaussian scale space characteristics were all retrieved using this thorough method. Public respiratory datasets and data from the All India Institute of Medical Sciences (AIIMS) were utilized for validation. Their approach to early COPD patient categorization and severity evaluation showed potential. However, the inclusion of audio data may complicate the process of acquiring and processing data. Enhancing the classification criteria for COVID-19 diagnosis from CT images with the use of Dep learning-based techniques [14]. They classified COVID-19 and non-COVID-19 cases, as well as COVID-19 pneumonia and other forms of pneumonia, using a 24-layer convolutional neural network (CNN) architecture. The study used 4320 and 3801 CT images for the respective classifications to examine the effectiveness of many pipeline techniques, such as local binary pattern (LBP) and dual-tree complex wavelet transform (DT-CWT). Their approach was successful in classification overall and had excellent sensitivity and specificity. Nonetheless, the deep learning methodology necessitates substantial processing power and extensive annotated datasets, which may be a constraint in settings with limited resources. The use of convolutional neural networks (CNNs) for the identification and categorization of lung illnesses in humans [15]. Their study used a similar dataset and approach to [14] work, which also addressed classifications relating to COVID-19. High classification performance and automatic feature extraction were made possible by the usage of CNNs. However, there are still issues that must be resolved, such as the need on sizable datasets with labels for training and the possibility of overfitting on particular data distributions. The heterogeneous character of lung disease diagnosis is reflected in the variations in methodology utilized in these investigations. Audio-based analysis [16], highlighting the significance of careful feature assessment and noise reduction. used ensemble techniques [17], combining many deep learning models to improve accuracy. Deep Learning Models for Classification of Tuberculosis Chest X-Ray Images [18], Features are extracted based on first order statistics and second-order statistics which is used to analyse images as a texture. Classification was performed by GLCM, GLRLM and NGTDM methods. Convolutional neural networks are used for lesion segmentation [19], and feature selection is done using quantitative analysis. Enhanced image classification efficiency by combining CNN and ViT [20]; presented a theoretical and practical summary of deep learning [21] methods in medical imaging.

Deep learning techniques for Multi-level Classification of COVID-19 from Tuberculosis and Pneumonia [22], highlights the feature extraction technique namely “Fusion of Handcrafted and Deep features” (FHD). To enhance the feature extraction “Modified Moth Flame Optimization” (MMFO) algorithm is used and utilized for multi-level classification of lung diseases.

3. METHODOLOGY OVERVIEW

3.1 Key Differences Between 2D CNN and 3D CNN in Medical Imaging

2D Convolutional Neural Networks (2D CNNs) and 3D Convolutional Neural Networks (3D CNNs) represent distinct methodologies for processing imaging data, with significant implications for lung disease classification in medical imaging. 2D CNNs operate on individual 2D slices of medical images, such as chest X-rays, focusing on extracting features from the spatial dimensions of the images—width and height. This makes them efficient for tasks involving single-plane imaging where the depth information is relatively sparse. However, their primary limitation lies in their inability to capture the spatial correlations along the depth axis, which is crucial for tasks like lung disease detection were understanding the 3D nature of structures like normal and abnormalities can enhance classification accuracy.

On the other hand, 3D CNNs are designed to handle volumetric data by processing entire 3D volumes of medical images, such as CT scans. These networks leverage the additional depth information available in these scans, allowing them to capture more comprehensive spatial dependencies across multiple planes simultaneously. This is particularly beneficial in medical imaging for lung diseases, where depth-aware features are critical for accurate diagnosis and classification. Despite the increased computational complexity associated with 3D CNNs—requiring more resources and memory. They generally provide superior performance compared to their 2D counterparts in tasks involving volumetric data, such as identifying and classifying lung abnormalities from CT scans.

For lung disease classification, the additional depth processing capabilities of 3D CNNs make them more appropriate, enabling them to extract richer, more informative features from volumetric data, thereby improving diagnostic accuracy and aiding medical practitioners in more reliable and effective decision-making. Fig1(a) shows that the overall architecture of the framework and Fig1(b) shows the multilevel classification of lung diseases.

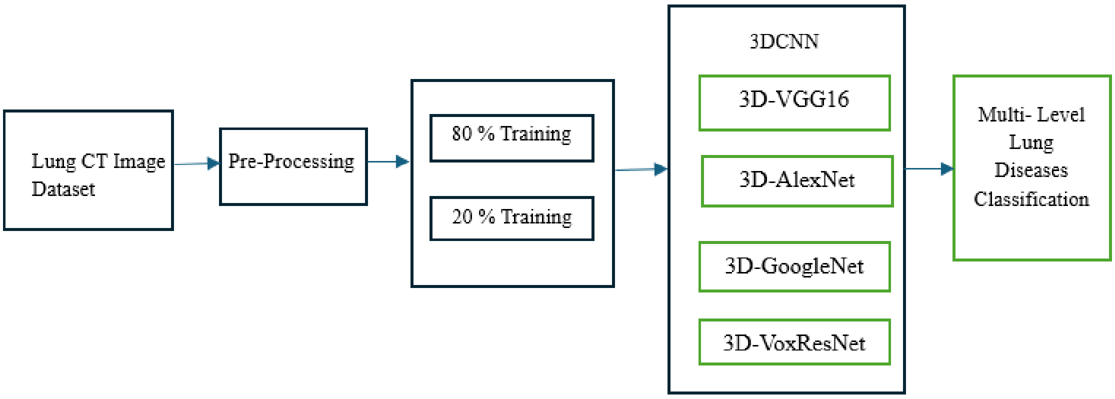

Figure 1(a). Overall architecture of the framework

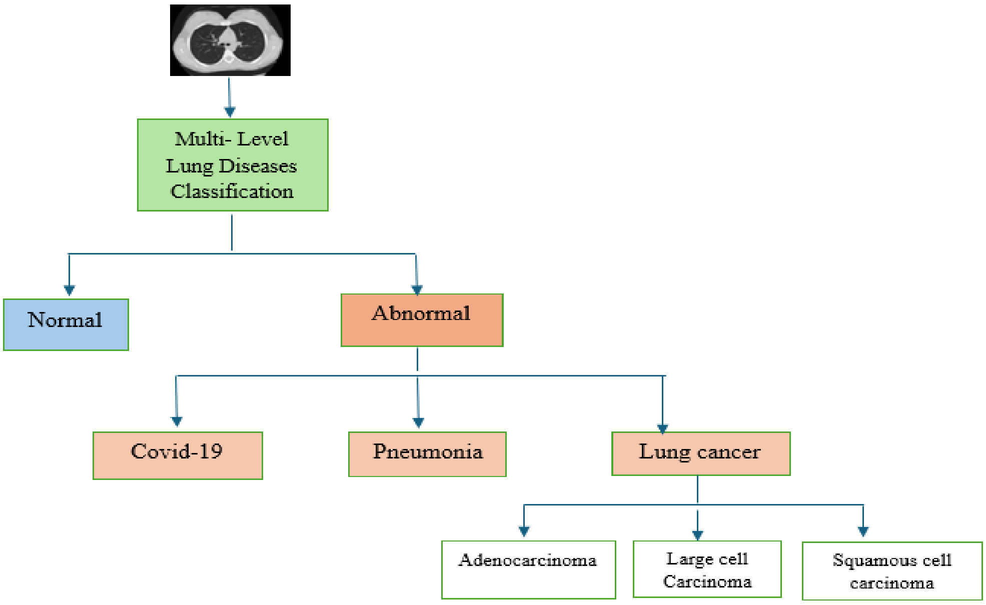

Figure 1(b). Multi-level Lung Diseases classification

The overall architecture of the work is depicted in figure 1. To settle the issue of lung disease classification, we require a proficient technique that rapidly and precisely classifies CRIs utilizing prepared 3D Convolutional Neural Network (3DCNNs). This review offers a proficient and robotized technique for arranging lung disease that guides in the early diagnose of lung sickness.

3.1 3D-VGG16

The VGG model is known for its simplicity while maintaining substantial depth. The 3D-VGG16 [23] architecture was selected due to its lightweight nature, which enables faster training. All network layers utilize 3×3×3 filters, with max pooling applied using a 2×2×2 window, a stride of 1, and a padding size of 1. The structural representation of the 3D-VGG16 model is depicted in Figure 2, illustrating its 16-layer composition. This includes thirteen convolutional layers with ReLu activation, along with five max-pooling layers placed between them to down sample input features. Following the convolutional layers, a sequence of three fully connected (FC) layers is employed, with the SoftMax layer consisting of 4096, 4096, and 1000 channels, respectively. The final fully connected layer, integrated with a SoftMax activation, is specifically adapted for binary classification, as the objective is to differentiate between various lung diseases.

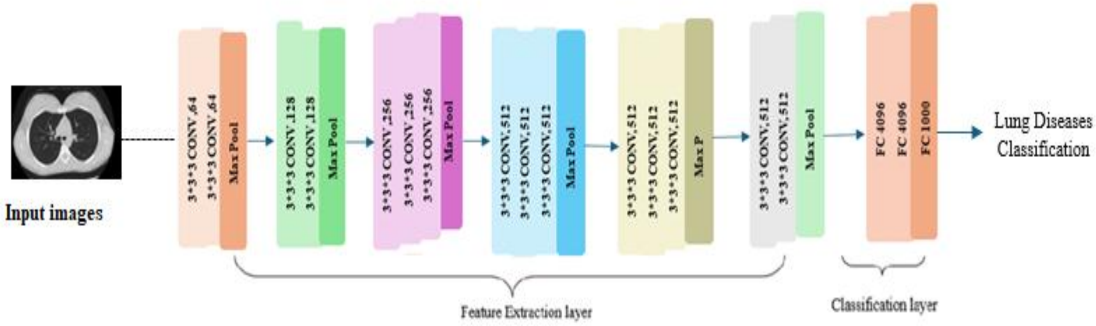

Figure2. Architecture of 3D-VGG16.

3D-AlexNet

The 3D-AlexNet model [24] consists of five convolutional layers, five pooling layers, and three fully connected layers. The first convolutional layer employs 96 kernels of size 11×11×11, producing an output of 96×55×55×55, while subsequent layers utilize smaller kernels (3×3×3, 5×5×5). Max-pooling is applied after crucial convolutional layers to reduce dimensionality. The fully connected section comprises two layers with 4096 neurons each, followed by a SoftMax layer. The ReLu activation function is used to introduce non-linearity in both convolutional and fully connected layers. AlexNet's default classifier, SoftMax, is also employed. In this study, the batch size and learning rate are set to 32 and 0.01, respectively. Furthermore, Table 1 provides a detailed summary of the network's layers and the output dimensions of lung images during training.

Layer Type	Number of Kernels	Kernel Size	Output Size
Convolutional	96	$11 \times 11 \times 11$	$96 \times 55 \times 55 \times 55$
Max pooling		$3 \times 3 \times 3$	$96 \times 27 \times 27 \times 27$
Convolutional	256	$5 \times 5 \times 5$	$256 \times 27 \times 27 \times 27$
Max pooling		$3 \times 3 \times 3$	$256 \times 13 \times 13 \times 13$
Convolutional	384	$3 \times 3 \times 3$	$384 \times 13 \times 13 \times 13$
Convolutional	256	$3 \times 3 \times 3$	$256 \times 13 \times 13 \times 13$
Max pooling		$3 \times 3 \times 3$	$256 \times 6 \times 6 \times 6$
Fully connected			$4096 \times 1 \times 1 \times 1$
Fully connected			$4096 \times 1 \times 1 \times 1$
Fully connected with softmax			$2 \times 1 \times 1 \times 1$

Table 1. 3D-AlexNet architecture.

3.3 **3D-GoogleNet**

The 3D-GoogleNet [24] model is composed of three convolutional layers, two max-pooling layers, and nine inception modules. Each inception module integrates multiple convolutional layers along with a max-pooling layer. Several inception blocks (Inception 3a-5b) are specifically designed to extract multi-scale features by utilizing convolutional filters of different kernel sizes and pooling operations. The network employs SoftMax as its default classifier. Furthermore, the batch size and learning rate for 3D-GoogleNet are set at 32 and 0.01, respectively. A detailed summary of the architecture, including the layers and corresponding output sizes for lung image training, is presented in Table 2.

Layer Type	Number of Kernels	Kernel Size	Output Size
Convolutional	64	$7 \times 7 \times 7$	$64 \times 112 \times 112 \times 112$
Max pooling		$3 \times 3 \times 3$	$64 \times 56 \times 56 \times 56$
Convolutional	192	$3 \times 3 \times 3$	$192 \times 56 \times 56 \times 56$
Max pooling		$3 \times 3 \times 3$	$192 \times 28 \times 28 \times 28$
Inception 3(a)			$256 \times 28 \times 28 \times 28$
Inception 3(b)			$480 \times 28 \times 28 \times 28$
Max pooling		$3 \times 3 \times 3$	$480 \times 14 \times 14 \times 14$
Inception 4(a)			$512 \times 14 \times 14 \times 14$
Inception 4(b)			$512 \times 14 \times 14 \times 14$
Inception 4(c)			$512 \times 14 \times 14 \times 14$
Inception 4(d)			$528 \times 14 \times 14 \times 14$
Inception 4(e)			$832 \times 14 \times 14 \times 14$
Max pooling		$3 \times 3 \times 3$	$832 \times 7 \times 7 \times 7$
Inception 5(a)			$832 \times 7 \times 7 \times 7$
Inception 5(b)			$1024 \times 7 \times 7 \times 7$
Avg pooling		$7 \times 7 \times 7$	$1024 \times 1 \times 1 \times 1$
Fully connected			$1024 \times 1 \times 1 \times 1$
Fully connected with softmax			$2 \times 1 \times 1 \times 1$

Table 2. 3D-GoogleNet architecture.

3.4 3D-VoxResNet

The fourth approach we propose for lung disease classification is based on 3D-VoxResNet. To harness the strength of deep residual learning and efficiently handle high-dimensional volumetric images, we adapt 2D deep residual networks into a 3D framework and design the architecture accordingly. VoxResNet [25] extends deep residual learning to 3D volumetric data, enabling effective feature extraction. The architecture of our VoxResNet model for volumetric image classification is illustrated in Figure 4. The VoxRes module incorporates identity mapping through a skip connection, allowing input features to pass through a residual function. Instead of auxiliary classifiers, a fully connected layer is integrated into VoxResNet to perform the classification task.

Figure 3. Architecture of 3D-VoxResNet

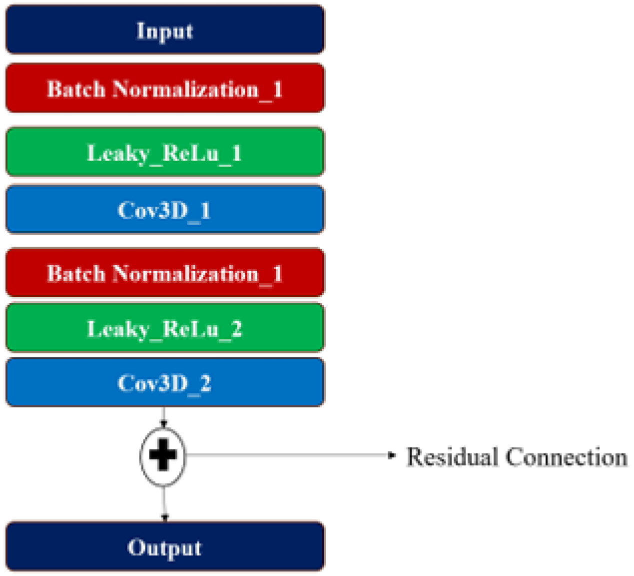

Figure 4. Architecture of VoxRes Module

To improve the learning of volumetric feature representation, VoxResNet implements all of its operations in three dimensions. The suggested network architecture can be seen in Figure 3. There are 32 filters in each of the first two convolutional layers. Each of the subsequent levels has 64 filters. To minimize the size of the feature map, a convolutional layer with stride 2 was inserted after every two VoxRes modules in place of the traditional pooling layer technique. Following each convolutional layer, a ReLu activation function and batch normalization are applied, with a kernel size of $3 \times 3 \times 3$. The 3D data from the previous feature map is preserved using a 64-unit 3D global-pooling layer. Subsequently, the leaky-ReLu activation function is introduced to a completely linked layer. To provide a smooth learning curve and avoid abrupt learning spikes, an L2-regularizer is also employed. The Keras/TensorFlow framework is used to implement the network.

4. RESULT AND ANALYSIS

4.1 Dataset Description

4.1.1 CT Dataset

A dataset named CT Dataset was created by merging CRIs from publicly available sources containing various lung conditions, including COVID-19, Pneumonia, Lung Cancer, and Normal cases. Since no single dataset comprehensively covers all these lung diseases, we combined images from two publicly available datasets to assess the effectiveness of our model. Specifically, COVID-19 and Pneumonia images were obtained from the "Large COVID-19 CT scan slice dataset" [26]. Additionally, images of adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal (non-cancerous) lung tissue were sourced from the "Lung Cancer CT Scan Dataset (4 types)" [27]. Table 3 presents detailed information about the dataset, while Figure 5 showcases some sample images.

Table 3. Details of the datasets used

Dataset	Training Images	Testing Images	Total Images
Dataset 1	13,683	3421	17,104
Dataset 2	613	315	928

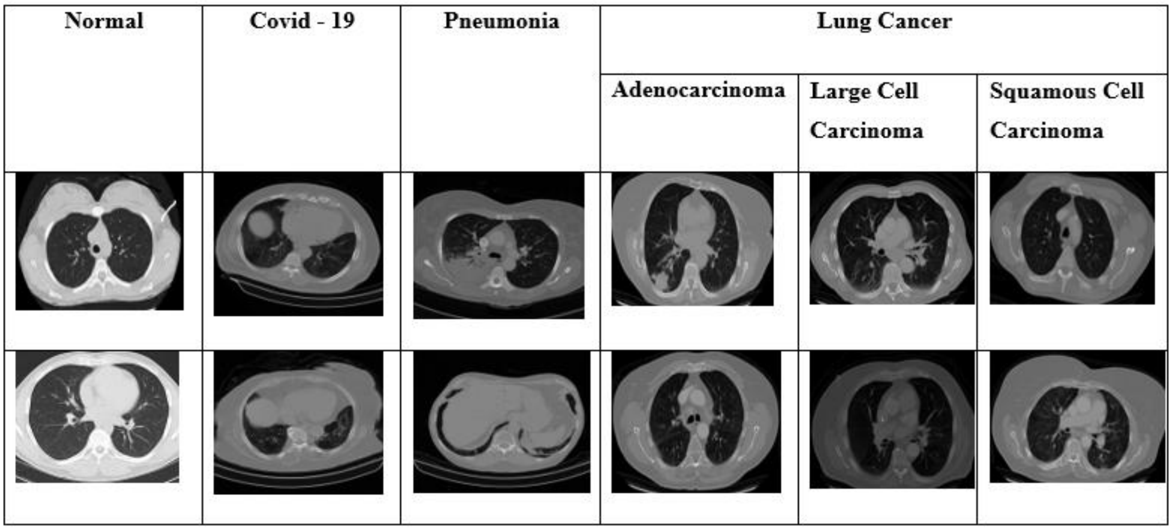

Figure 5. Sample CT dataset Images

4.2 Metrics

A. Accuracy

This demonstrates the general performance of the classified images. By comparing the percentage of accurate predictions to all cases, the model's performance is evaluated. Below is the accuracy calculation formula,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

B. Precision

The accuracy of identifying positive samples depends on the proportion of actual positive patterns that are correctly or incorrectly classified.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

C. F1_Score

The **F1 score** represents the harmonic mean between precision and recall, providing a balanced evaluation of a model's performance.

$$F1\_Score = \; 2 * \frac{Precision*Recall}{Precision+Recall} \quad (3)$$

D. Recall

Recall measures the percentage of actual positive patterns that are correctly classified, offering insight into the model's ability to detect relevant cases.

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

The 3D-VoxResNet [25] model yielded a higher accuracy 85% compared with other existing methods for CT Dataset. Table 4 shows the accuracy of different methods for CT Dataset.

Table 4. Accuracy comparison of various methods using CT Dataset

	Accuracy	Precision	Recall	F1Score
3D-VGG16	80%	0.80	0.81	0.82
3D-Alexnet	82%	0.82	0.83	0.84
3D-GoogleNet	84%	0.81	0.84	0.83

3D-VoxResNet	**85%**	**0.85**	**0.86**	**0.87**

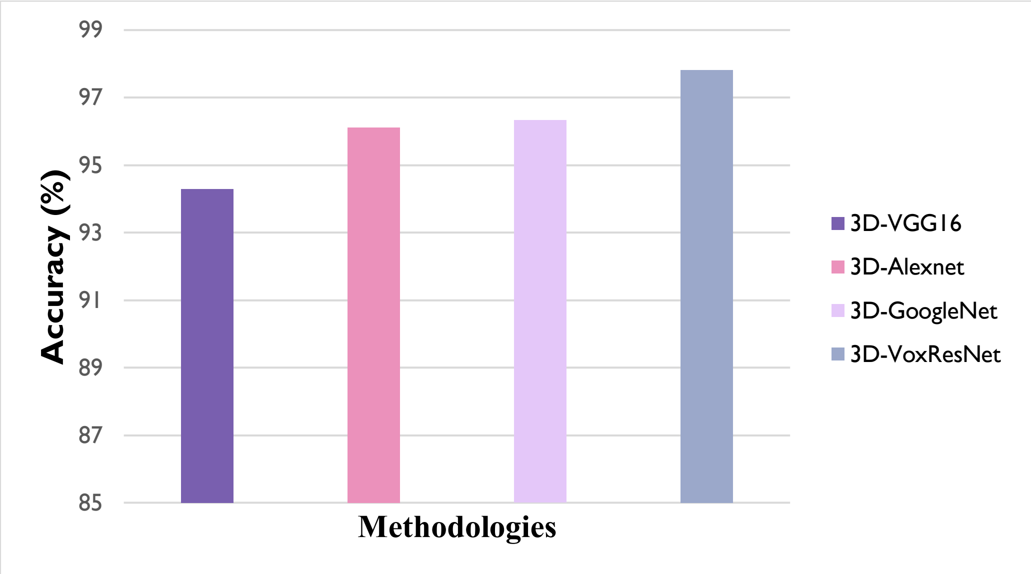

Figure 6. Accuracy comparison of CT Dataset

The graphical representation of Accuracy comparison of CT Dataset with Existing Methods is given in Figures 7. In terms of Accuracy 3D-VGG16 [23] gives 80% ,3D-Alexnet [24] gives 82%,3D-GoogleNet [24] gives 84%, and 3D-VoxResNet[25] gives 85%.

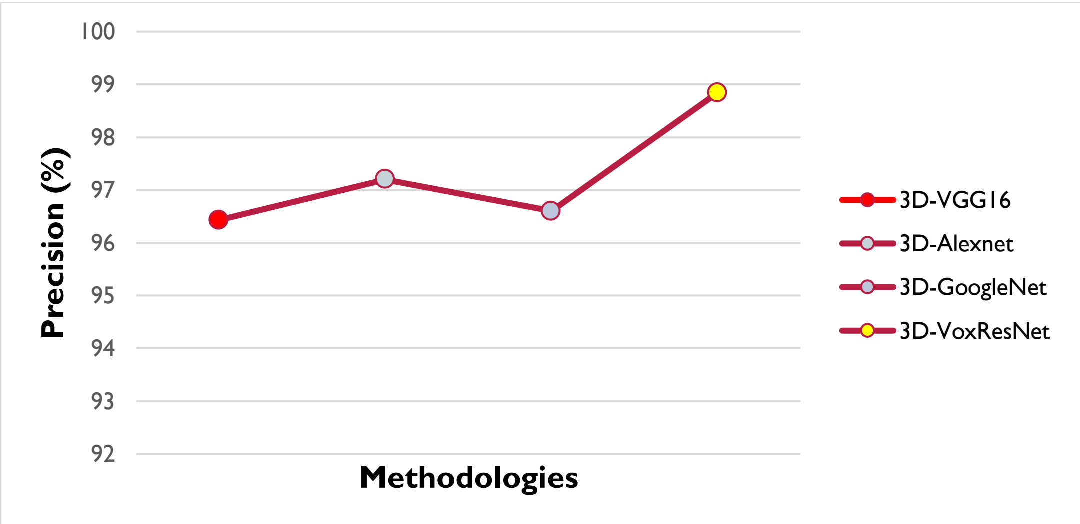

Figure 7. Precision comparison of CT Dataset

The graphical representation of Precision comparison of CT Dataset with Existing Methods is given in Figures 7. In terms of Precision, 3D-VGG16 [23] gives 0.80% ,3D_Alexnet [24] gives 0.82%,3D_GoogleNet [24] gives 0.81%, and 3D-VoxResNet[25] gives 0.85%.

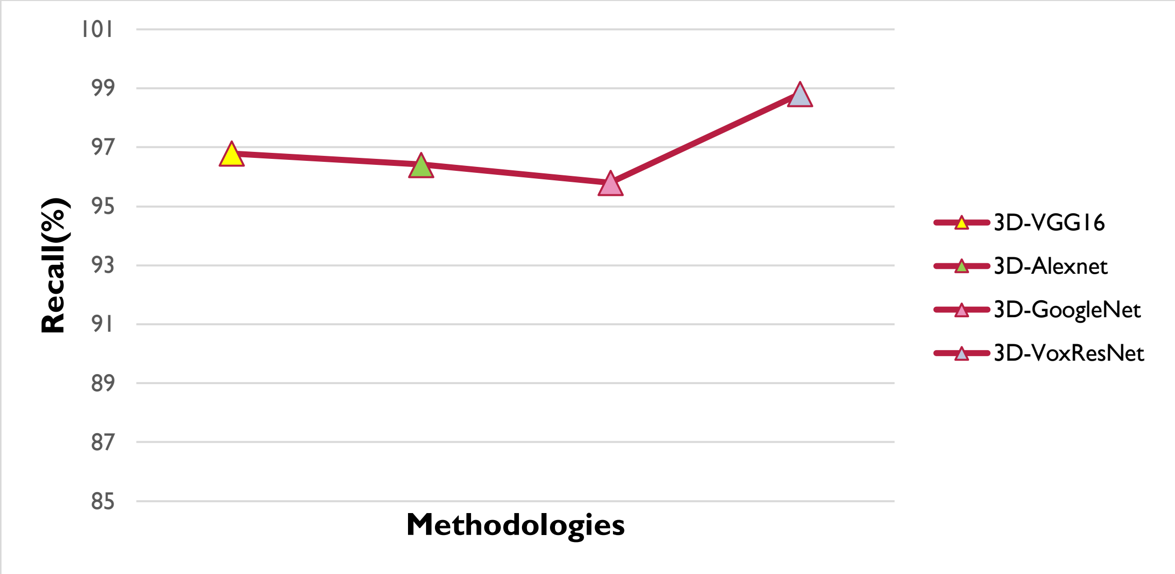

Figure 8. Recall comparison of CT Dataset

The graphical representation of Recall comparison of CT Dataset with Existing Methods is given in Figures 8. In terms of Recall, 3D-VGG16 [23] gives 0.81% ,3D_Alexnet [24] gives 0.83%,3D_GoogleNet [24] gives 0.84%, and 3D-VoxResNet [25] gives 0.86%.

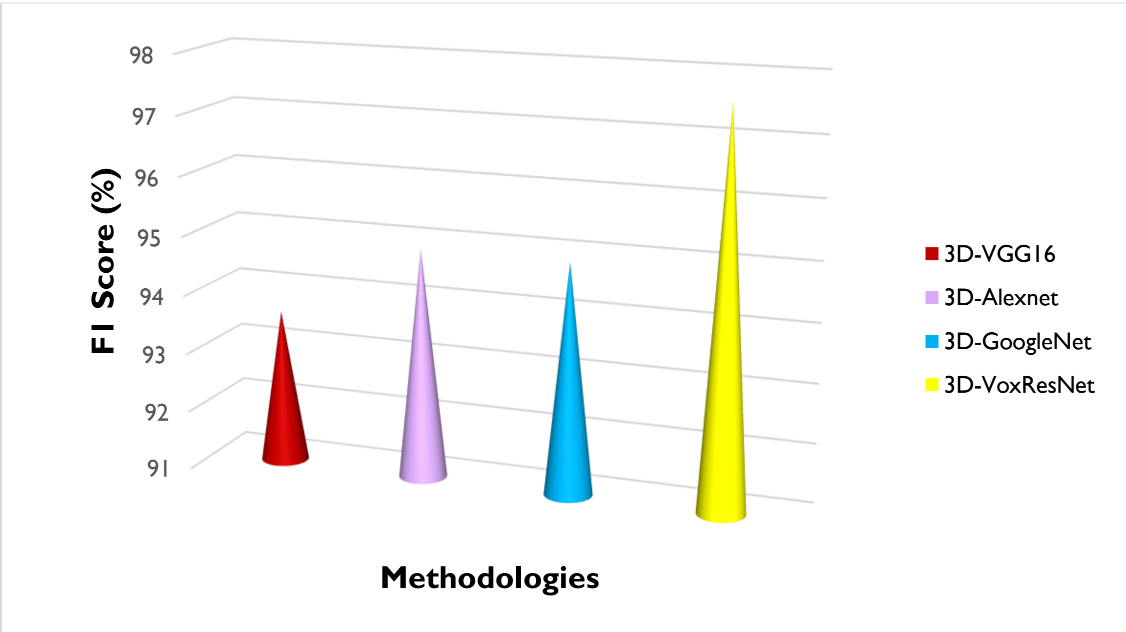

Figure 9. F1Score comparison of CT Dataset

The graphical representation of F1 Score comparison of CT Dataset with Existing Methods is given in Figures 9. In terms of F1 Score, 3D-VGG16 [23] gives 0.82% ,3D-Alexnet [24] gives 0.84%,3D-GoogleNet [24] gives 0.83%, and 3D-VoxResNet [25] gives 0.87%.

5. CONCLUSION

In order to lower mortality rates and support medical professionals, lung problems must be identified and detected early. A Deep Learning architecture-based multiclass classification of chest illnesses for COVID-19, pneumonia, Lung Cancer, and normal, is designed and tested in works. In order to determine which framework was best for classifying lung illnesses, we compared four of them. We demonstrated that 3D-VoxResNet performs better than the other three frameworks by comparing them for the diagnosis of lung diseases

The model uses volume-wise annotations without any further feature augmentation or meta-data inclusion. The implementation was carried out using python programming language on a system equipped with a GPU (Graphics Processing Unit) to handle the computationally intensive training of the 3D-VoxResNet model. In the CT dataset, 3D-VoxResNet performs better than all other existing works. It yields an accuracy of 85% in the CT dataset..

REFERENCES

1. Bhuvaneswari, C., Aruna, P., & Loganathan, D. (2014). Classification of lung diseases by image processing techniques using computed tomography images. International Journal of Advanced Computer Research, 4(1), 87.

2. Boban, B. M., & Megalingam, R. K. (2020, July). Lung diseases classification based on machine learning algorithms and performance evaluation. In 2020 international conference on communication and signal processing (ICCSP) (pp. 0315-0320). IEEE.

3. Goyal, S., & Singh, R. (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, 14(4), 3239-3259.

4. Srivastava, V., & Purwar, R. K. (2020). Classification of CT scan images of lungs using deep convolutional neural network with external shape-based features. Journal of digital imaging, 33(1), 252-261.

5. Gangeh, M. J., Sørensen, L., Shaker, S. B., Kamel, M. S., De Bruijne, M., & Loog, M. (2010). A texton-based approach for the classification of lung parenchyma in CT images. In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2010: 13th International Conference, Beijing, China, September 20-24, 2010, Proceedings, Part III 13 (pp. 595-602). Springer Berlin Heidelberg.

6. Gugulothu, V. K., & Balaji, S. (2024). An early prediction and classification of lung nodule diagnosis on CT images based on hybrid deep learning techniques. Multimedia Tools and Applications, 83(1), 1041-1061.

7. Gao, M., Bagci, U., Lu, L., Wu, A., Buty, M., Shin, H. C., ... & Mollura, D. J. (2018). Holistic classification of CT attenuation patterns for interstitial lung diseases via deep convolutional neural networks. Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 6(1), 1-6.

8. Khan, M. A., Rajinikanth, V., Satapathy, S. C., Taniar, D., Mohanty, J. R., Tariq, U., & Damaševičius, R. (2021). VGG19 network assisted joint segmentation and classification of lung nodules in CT images. Diagnostics, 11(12), 2208. https://doi.org/10.3390/diagnostics11122208

9. Farhan, A. M. Q., & Yang, S. (2023). Automatic lung disease classification from the chest X-ray images using hybrid deep learning algorithm. Multimedia Tools and applications, 82(25), 38561-38587.

10. Marentakis, P., Karaiskos, P., Kouloulias, V., Kelekis, N., Argentos, S., Oikonomopoulos, N., & Loukas, C. (2021). Lung cancer histology classification from CT images based on radiomics and deep learning models. Medical & biological engineering & computing, 59, 215-226.

11. Bhuvaneswari, C., Aruna, P., & Loganathan, D. (2014). A new fusion model for classification of the lung diseases using genetic algorithm. Egyptian Informatics Journal, 15(2), 69-77.

12. Khan, M. A., Rubab, S., Kashif, A., Sharif, M. I., Muhammad, N., Shah, J. H., ... & Satapathy, S. C. (2020). Lungs cancer classification from CT images: An integrated design of contrast based classical features fusion and selection. Pattern Recognition Letters, 129, 77-85.

13. Kumar, S., Bhagat, V., Sahu, P., Chaube, M. K., Behera, A. K., Guizani, M., ... & Alsamhi, S. H. (2024). A novel multimodal framework for early diagnosis and classification of COPD based on CT scan images and multivariate pulmonary respiratory diseases. Computer Methods and Programs in Biomedicine, 243, 107911.

14. Yasar, H., & Ceylan, M. (2024). Deep Learning–Based Approaches to Improve Classification Parameters for Diagnosing COVID-19 from CT Images. Cognitive Computation, 16(4), 1806-1833.

15. Vijay, P., Jena, A., & Gnanavel, S. (2024, July). Detection and classification of human lung diseases using convolutional neural networks. In AIP Conference Proceedings (Vol. 3075, No. 1). AIP Publishing.

16. Sabry, A. H., Bashi, O. I. D., Ali, N. N., & Al Kubaisi, Y. M. (2024). Lung disease recognition methods using audio-based analysis with machine learning. Heliyon.10(24), 2405-8440

17. Quasar, S. R., Sharma, R., Mittal, A., Sharma, M., Agarwal, D., & de La Torre Díez, I. (2024). Ensemble methods for computed tomography scan images to improve lung cancer detection and classification. Multimedia Tools and Applications, 83(17), 52867-52897.

18. D.Arul Suresh, J.Jude Moses Anto Devakanth, Dr.R.Balasubramanian (2022) A Novel Feature Extraction Technique for classification of Tuberculosis Chest X-Ray Images using Deep Learning Models. NeuroQuantology,

3733-3756

19. Lai, Y., Liu, X., Hou, F., Han, Z., Su, N., Du, D., ... & Wu, Y. (2024). Severity-stratification of interstitial lung disease by deep learning enabled assessment and quantification of lesion indicators from HRCT images. Journal of X-Ray Science and Technology, (Preprint), 1-16.

20. Pham, T. A., & Hoang, V. D. (2024). Chest X-ray image classification using transfer learning and hyperparameter customization for lung disease diagnosis. Journal of Information and Telecommunication, 1-15.

21. Pal, T., Goswami, B., & Barnwal, R. P. (2024). Handling Segmentation and Classification Problems in Deep Learning for Identification of Interstitial Lung Disease. In Machine Learning and Deep Learning Techniques for Medical Image Recognition (pp. 128-151). CRC Press.

22. J. Jude Moses Anto Devakanth, Dr. R. Balasubramanian, Arul Suresh(2023).A Modified Moth Flame Optimization Algorithm for Multi-level Classification of COVID-19 from Tuberculosis and Pneumonia Chest X Ray images using Deep learning. Journal of chemical health risk 13(3),177-1197

23. Sneha Balannolla et al “Detection and Classification of Lung Carcinoma using CT scans” Journal of Physics (2022). doi:10.1088/1742-6596/2286/1/012011.

24. Huseyin Polat and Homay Danaei Mehr “Classification of Pulmonary CT Images by Using Hybrid 3D-Deep Convolutional Neural Network Architecture” applied science (2019):9,940.

25. Ahmed, J. et al. (2020). COPD Classification in CT Images Using a 3D Convolutional Neural Network. In: Tolxdorff, T., Deserno, T., Handels, H., Maier, A., Maier-Hein, K., Palm, C. (eds) Bildverarbeitung für die Medizin 2020. Informatik aktuell. Springer Vieweg, Wiesbaden https://doi.org/10.1007/978-3-658-29267-6_8.

26. Large COVID-19 CT scan slice dataset Available online:

https://www.kaggle.com/datasets/maedemaftouni/large-covid19-ct-slice-dataset.

27. Lung Cancer Detection dataset available online: https://github.com/DorsaRoh/LungAI.

28. Hochreiter S, Schmidhuber J. Long short-term memory. Neural Comput. (1997) 9:1735–80.

29. H. Chen, Q. Dou, L. Yu, J. Qin, and P. Heng. Voxresnet: Deep voxelwise residual networks for brain segmentation from 3d mr images. NeuroImage, 170:446–455, 2018.

30. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. ImageNet Classification with Deep Convolutional Neural Networks. Adv. Neural Inf. Process. Syst. 2012, 60, 84–90.

31. Iandola, F.N.; Han, S.; Moskewicz, M.W.; Ashraf, K.; Dally, W.J.; Keutzer, K. SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5 MB model size. arXiv 2016, arXiv:1602.07360.

32. Zhang, X.; Zhou, X.; Lin, M.; Sun, J. ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices. arXiv 2017, arXiv:1707.01083v2.

33. Zhou, B.; Khosla, A.; Lapedriza, A.; Torralba, A.; Oliva, A. Places: An image database for ddeep scene understanding. arXiv 2016, arXiv:1610.02055. [CrossRef].

34. leUllah, N.; Marzougui, M.; Ahmad, I.; Chelloug, S.A. DeepLungNet: An Effective DL-Based Approach for Lung Disease Classification Using CRIs. Electronics 2023, 12, 1860.

35. Hussein, F.; Mughaid, A.; AlZu’bi, S.; El-Salhi, S.M.; Abuhaija, B.; Abualigah, L.; Gandomi, A.H. Hybrid clahe-cnn deep neural.

36. Avanzato R, Beritelli F, Lombardo A, Ricci C. Lung-DT: An AI-Powered Digital Twin Framework for Thoracic Health Monitoring and Diagnosis. Sensors (Basel). 2024 Feb 1;24(3):958. doi: 10.3390/s24030958. PMID: 38339678; PMCID: PMC10857717.

37. Uddin, Jia. "Attention-Based DenseNet for Lung Cancer Classification Using CT Scan and Histopathological Images." Designs 8.2 (2024): 27.

38. Zhang, Pinzhi, Alagappan Swaminathan, and Ahmed Abrar Uddin. "Pulmonary disease detection and classification in patient respiratory audio files using long short-term memory neural networks." Frontiers in Medicine 10 (2023): 1269784.

39. Hong Liu1 & Haichao Cao & Enmin “Multi-model Ensemble Learning Architecture Based on 3D CNN for Lung Nodule Malignancy Suspiciousness Classification.” Journal of Digital Imaging (2020). https://doi.org/10.1007/s10278-020-00372-8..