ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

COMPREHENSIVE SURVEY ON THE EFFICACY OF 3D CNNS FOR LUNG ABNORMALITY DETECTION IN MEDICAL IMAGING

T.Evangeline Dhivya[1], Dr.R.Balasubramanian[2]
[1]Research Scholar, [2]Professor
Department of Computer Science and Engineering,
Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli.
*Corresponding Author: evangelinedhivya94@gmail.com

Abstract- In medical imaging, precise and efficient detection of lung abnormalities is critical for early diagnosis and therapy. In recent years, three-dimensional convolutional neural networks (3D CNNs) have showed promise in enhancing the efficacy of lung anomaly detection. This thorough survey will give an in-depth review of the efficacy of 3D CNNs for detecting lung abnormalities in medical imaging. We discuss the most recent advances in 3D CNN designs, techniques, and applications designed exclusively for lung anomaly detection. We assess the performance metrics of several 3D CNN models in identifying lung abnormalities from computed tomography (CT) scans and X-ray pictures by reviewing a wide range of papers and experimental data, including accuracy, sensitivity, specificity, and area under the curve (AUC). Furthermore, we examine the benefits and limits of existing techniques, real-world implementation issues, and potential future possibilities for using 3D CNNs to identify lung abnormalities. This study offers useful information for medical imaging researchers, doctors, and practitioners, allowing for the development of more accurate and reliable diagnostic tools for early lung disease identification and management.

1. Introduction

The development of improved imaging technologies has substantially altered the landscape of medical diagnostics, with a growing dependence on non-invasive methods for early identification and diagnosis of numerous illnesses. In the field of pulmonary health, medical imaging, particularly computed tomography (CT) scans, has become critical for detecting and characterizing lung disorders. One significant achievement in this field is the use of three-dimensional Convolutional Neural Networks (3D CNNs), a complex family of deep learning models that excel in extracting complicated spatial properties from volumetric data. Lung abnormalities, such as nodules, tumours, and infections, provide special problems due to their complex and varied spatial patterns. This comprehensive review seeks to investigate and assess the efficacy of 3D CNNs in the context of lung anomaly detection, including a thorough evaluation of their application, techniques, strengths, and limits.

The relevance of this survey originates from the crucial need to improve the accuracy and efficiency of lung abnormality identification, taking into account the possible influence on patient outcomes and the whole healthcare system. The complexity of pulmonary structures needs cutting-edge techniques, and 3D CNNs have emerged as potential tools for detecting minor anomalies using volumetric information. Understanding the possibilities and challenges of 3D CNNs in lung anomaly identification is critical for medical practitioners and academics looking

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

to increase the sensitivity and specificity of diagnostic tools. This assessment will look at major research, methodology, and results, giving light on the present state of the field and setting the way for future advances in this vital area of medical imaging.

2. Motivation

The rising incidence of respiratory illnesses throughout the world (2.1) motivates researchers to investigate 3D CNN technology in the context of lung disease diagnosis. With the growth of lung illnesses such as pneumonia, TB, and lung cancer, better diagnostic techniques are crucial for early identification and management. Furthermore, fast advances in 3D CNN technology for medical image processing (2.2) provide a chance to improve the accuracy and efficiency of lung disease detection by extracting detailed three-dimensional characteristics from CT scans and X-rays. This combined purpose emphasizes the potential of 3D CNNs to change the area of respiratory health diagnosis.

2.1 Increasing prevalence of lung diseases.

The research evaluation begins by looking at chronic respiratory disorders (CRDs) from a worldwide viewpoint [1]. The study looks at trends in the prevalence and incidence of CRDs from 1990 to 2017, using data from the Global Burden of Diseases Study. The overall number of CRD cases has risen by 39.5%, indicating a major health risk. Despite this rise, age-standardized prevalence and incidence rates showed a downward trend. The study focuses on variations in CRD patterns, such as substantial discrepancies in the incidence rates of certain illnesses between men and women. Notably, chronic obstructive pulmonary disease (COPD) had lower age-standardized incidence rates in higher socio-demographic index (SDI) locations, but interstitial lung disease and pulmonary sarcoidosis had increased, particularly in high-SDI districts. This data gives a thorough picture of the evolving worldwide landscape of CRDs, offering insight on individual illnesses and their prevalence in various populations and areas. The study [2] examines the frequency of chronic pulmonary illnesses among Iraq and Afghanistan combat veterans. In contrast to previous research goals focused on traumatic brain injury and mental health issues, this study underlines the need of looking into respiratory ailments. The study found a substantial rise in chronic obstructive lung disease and asthma over time, implying a link with deployment-related exposures. The study investigates numerous sociodemographic, military, and clinical factors linked to chronic lung disorders, such as age, smoking, and traumatic brain damage. Importantly, it underscores the need for additional research to identify particular deployment-related exposures associated with chronic pulmonary disorders, therefore filling a significant gap in the current literature.

Important insights into the changing health environment among veterans, particularly respiratory health challenges. The prevalence of interstitial lung disorders (ILDs) in the general population [3]. Recognizing the lack of epidemiologic data on ILDs, the research sets up a population-based registry in Bernalillo County, New Mexico. The data show the frequency and incidence of ILDs, with an emphasis on pulmonary fibrosis and idiopathic pulmonary fibrosis. Notably, the study found a frequency of preclinical or undiagnosed ILDs, indicating that these

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

illnesses may be more frequent than previously thought based on specific groups. The study adds important knowledge concerning the prevalence of ILDs in the general community, underlining the possibility for underrecognition of these conditions. This work presents a core knowledge of ILD epidemiology, which will influence future research and healthcare interventions for these illnesses.

The works provided here add to our understanding of the rising prevalence of lung disorders, notably obstructive lung diseases, asthma, chronic bronchitis/emphysema, and fibrosing interstitial lung diseases. The study [4], performed in southern Sweden, stresses the growing frequency of obstructive lung disorders and respiratory symptoms. The research spans a wide demographic range, concentrating on persons aged 20 to 59, and employs a postal survey with a customized questionnaire. Notably, the study indicates disparities in incidence across geographical regions, implying possible regional gradients. The research emphasizes the importance of family history in determining the prevalence of asthma and chronic bronchitis/emphysema. This research [5] looked at temporal changes in the prevalence rates of respiratory symptoms/diseases across a 25-year period. The study uses a large general population sample obtained through a series of cross-sectional surveys. The data show a steady rise in the incidence of respiratory symptoms and disorders such as asthma, allergic rhinitis, and Chronic Obstructive Pulmonary Disease (COPD). The study also investigates the relationships between respiratory diseases and numerous risk factors. The long-term view enriches our understanding of the changing environment of respiratory health. To fibrosing interstitial [6] lung diseases (ILDs) other than idiopathic pulmonary fibrosis, stressing the development of a progressive clinical pattern. This systematic review and physician survey-based study investigates the prevalence of fibrosing ILDs and its progressive forms. The data synthesis from many sources yields estimates of ILD prevalence in Europe and the United States. Notably, a significant number of ILDs have been recognized as evolving to a fibrosing phenotype, adding to the total frequency of progressive fibrosing ILDs. This research stresses the complexity of ILDs and the unmet need for these chronic respiratory illnesses.

2.2 Advancements in 3D CNN technology for medical image analysis

The rapid progress of machine learning, along with advances in graphics processing capabilities and the availability of large medical imaging datasets, has resulted in a rise in the use of deep learning models in the medical sector. Notably, after AlexNet's breakthrough in 2012, convolutional neural network (CNN) designs have grown in popularity in medical image analysis to improve human physicians' diagnostic capabilities. In recent years, there has been a noticeable movement toward three-dimensional (3D) CNNs in medical image analysis, notably for classification, segmentation, detection, and localization.

The development and implementation of 3D CNNs in medical imaging [7]. The study follows the historical growth of 3D CNNs from their machine learning foundations, providing a concise mathematical explanation and explaining the methods required to preprocess medical pictures before feeding them into 3D CNNs. The authors dive into major studies in the discipline, emphasizing applicability in a variety of medical settings. The emphasis is on classification,

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

segmentation, detection, and localization, which demonstrate the adaptability of 3D CNNs. The research continues by exploring the obstacles connected with the application of 3D CNNs in medical imaging and offering predictions for future advances in the area. Deep learning-based approaches to medical image analysis and clinical applications [8]. The report recognizes the substantial progress of artificial intelligence (AI), namely deep learning, in medical research. They focus on convolutional neural network-based strategies for the neurological, cardiovascular, digestive, and skeletal systems. Notably, the authors highlight the effectiveness of deep learning models in medical picture interpretation while raising concerns regarding algorithms based on small-scale medical datasets. The System recommends future directions, such as federated learning, benchmark dataset collection, and the use of domain topic knowledge as priors.
Contribute important insights into medical image processing with deep convolutional neural networks (CNNs), emphasizing the importance of computer-aided detection or diagnosis (CAD) [9] in improving diagnostic and treatment procedures. The research emphasizes the difficulties in data analysis with the rapid growth of science and technology in contemporary CAD systems. The authors focus on CNN applications, including breast cancer therapy, lung nodule detection, and prostate cancer localization. They emphasize the importance of large-scale annotated datasets in image recognition and go over three main strategies for using CNNs in medical image classification: training from scratch, using pre-trained CNN features off the shelf, and performing unattended pre-training with supervised fine-tuning. Transfer learning is recognized as an important strategy for fine-tuning pre-trained CNN models from natural image datasets to medical imaging problems. Significant advances in 3D CNN technology for medical image analysis, notably in the context of lung disease detection and picture segmentation. In the present landscape of computer-aided medical image analysis, CNNs are preferred for image segmentation [10]. The authors emphasize the growing popularity of 3D deep learning approaches, which are being driven by advances in 3D imaging technologies as well as robust hardware and software support for handling massive amounts of data. The article conducts a thorough analysis of recently suggested 3D deep learning approaches for medical picture segmentation, emphasizing its potential for expert clinical diagnosis and treatment planning. This leads to a better understanding of the paradigm change in medical image analysis [11] caused by deep learning. The authors notably mention the rise in interest in the Medical Imaging Community, which led to a specialized conference on "Medical Imaging with Deep Learning" in 2018. The research organizes the examined literature according to pattern recognition tasks and human anatomy, stressing the absence of correctly annotated large-scale datasets as a major difficulty in the area. The insights gained from adjacent research domains provide viable avenues for the Medical Imaging Community to fully realize the promise of deep learning in the future. In medical image analysis, convolutional neural networks (CNNs) are recognized as one of the most typical deep learning models [12]. This article discusses frequently used CNNs in medical image processing and gives an overview of its applications in picture classification, segmentation, detection, and other tasks across a variety of medical diagnosis fields. The authors examine the current state of the art, comparisons, improvements, and future directions for CNNs in medical picture processing. They also highlight outstanding obstacles and recommend potential future research options.

An examination of deep learning applications in medical image processing [13], including

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

a historical review and descriptions of developments from the subcellular to organ levels. The authors thoroughly examine deep learning models, with a particular emphasis on CNNs, describing their architecture, learning methods, and real-world applications. The article also discusses the biological applications of deep learning, which include a variety of tools and methodologies for studying the morphology and physiology of the human body. Finally, we'll look at field-specific difficulties and potential solutions.

3. Identifying Lung Diseases in CT and X-ray Images

CNN-based identification is crucial for the field of health imaging since it may identify anomalies in the lungs on X-rays and CT images. Convolutional Neural Networks (CNNs) are able to precisely recognize small patterns suggestive of lung illnesses because they are skilled at automatically learning hierarchical characteristics from images. CNNs are excellent at catching minute details that are essential for precise identification because they make use of the spatial hierarchies present in the data. This strategy makes it possible to automate the identification process in a reliable and effective manner, which advances the field of respiratory health diagnostics. A CT scan works by using X-rays and computer technology to create detailed images of the inside of the body and to determine the exact size of three-dimensional objects. The identification of lung illnesses in CT scans is a crucial field of medical imaging, which is being investigated using approaches such as 3D CNNs and regular CNNs particularly intended for lung abnormality detection. The use of 3D CNNs in lung disease diagnosis demonstrates advances in three-dimensional image processing. This technique has major real-world consequences since it assists medical practitioners in accurate clinical diagnosis and treatment planning, highlighting the critical role of cutting-edge technology in improving the efficiency and precision of lung disease detection using CT scans.

3.1 3D CNN

Three-dimensional Convolutional Neural Networks (3D CNNs) are a strong class of neural network designs created primarily for processing volumetric data, making them ideal for use in medical image analysis and video processing. Unlike their 2D predecessors, 3D CNNs use three-dimensional input tensors to capture both spatial connections and temporal dynamics. In the case of medical imaging, such as CT scans, where information is spread over numerous slices, 3D CNNs excel at extracting complex characteristics from the entire volume, providing a comprehensive comprehension of the data. This feature is particularly useful for activities such as finding and diagnosing anomalies in organs or tissues, which need contextual information in the third dimension.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

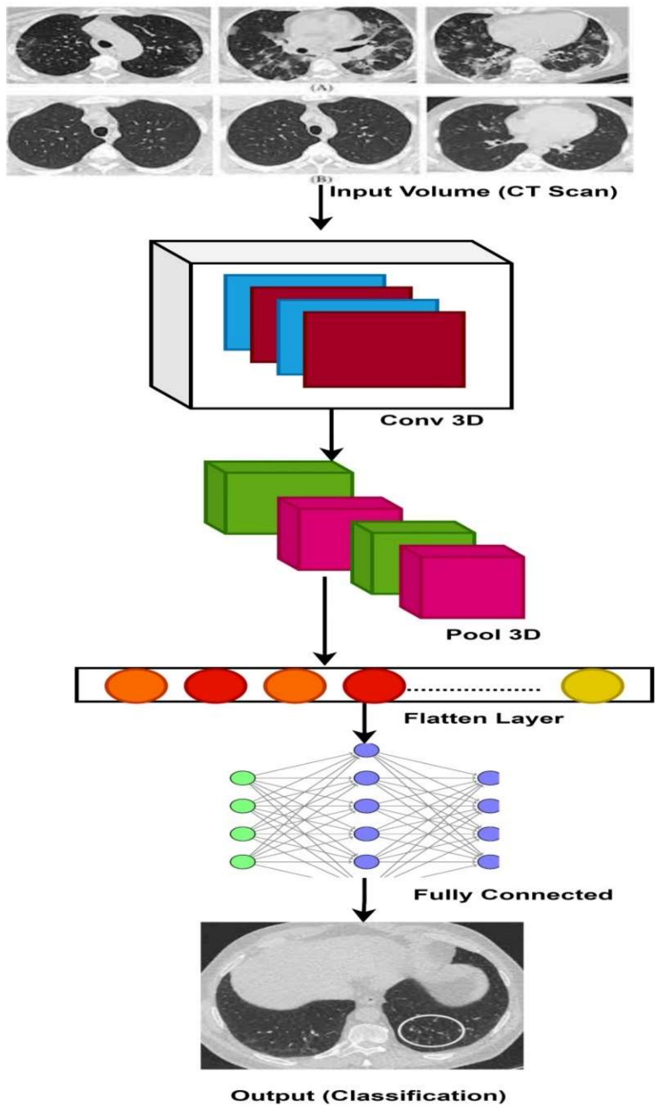

Figure 1. 3D CNN Architecture

Figure 1 illustrates that various layers are intended to capture local information in the early levels while gradually learning more abstract and complicated aspects in deeper layers. A typical 3D CNN consists of the following basic layers:

- Input layer:
  - The input layer receives three-dimensional volumetric data, such as a CT scan of the lungs.
- 3D convolutional layers:
  - Convolutional layers extract local patterns and features from the input data.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

  - In 3D CNNs, filters travel across all three dimensions, allowing the network to learn spatial hierarchies.

- 3D Pooling Layers:

  - Pooling layers reduce the spatial dimensions, lowering computing effort and focusing on the most important aspects.

  - Max-pooling is a common technique in 3D CNNs for retaining the most significant values in each pooling region.

  - Average pooling determines the average of the elements that are present in the feature map area that the filter covers.

  - Min pooling: produces each pooling window's minimal value and discards the remaining values. Min pooling is helpful in removing the lowest-resolution or darkest features from the feature maps, such as gaps, holes, and shadows.

  - By using median pooling, the remaining values are discarded and the median value from each pooling window is output. Since median pooling yields the middle value, which is unaffected by extreme values, it is helpful in eliminating outliers and noise from feature maps.

  - Adaptive pooling generates a fixed-size feature map by changing the pooling window's size and stride based on the input size. Because adaptive pooling produces a feature map with a consistent size that can be sent to the CNN's next layer, it is helpful for handling inputs of various sizes and resolutions.

- Activation layers:

  - Activation functions, such as ReLU (Rectified Linear Unit), add nonlinearity to the network, allowing it to understand complicated correlations in data.

  - SoftMax allows CNNs to output a probability distribution over the multiple classes.

  - The sigmoid function is a useful tool for probability representation. Its range is 0 to 1, but its domain is all real numbers.

- Fully Connected Layers:

  - Fully linked layers use the flattened information from the preceding layers and learn high-level representations before generating final predictions.

  - These layers connect each neuron to every neuron in the next layer.

- Output Layer:

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

- The output layer generates the final prediction or classification using the learnt characteristics.

The design is commonly made up of 3D convolutional layers, pooling layers, and fully connected layers, which allow the network to learn hierarchical representations of volumetric information. The use of 3D CNNs has proven significant effectiveness in tasks such as lung disease identification, with enhanced accuracy achieved by considering the spatial context of anomalies inside medical pictures. Regardless of their usefulness, 3D CNNs' computational needs should be addressed since they may require significantly more resources for training and inference than their 2D counterparts.

3.2 CNN based Lung Abnormality detections.

The main focus is on image-based computer-aided diagnosis (CADx) employing convolutional neural networks (CNNs) [14] to identify and classify lung abnormalities. The authors highlight the advantages of image-based CADx versus feature-based CADx, which needs an image-feature extractor. The CNN-based technique, which does not require a feature extractor, is thought to be effective for differentiating between lung nodules and diffuse lung illnesses. The work offers an image-based computer-aided detection (CADe) technique that uses regions with CNN features (R-CNN) and is especially developed to identify various lung abnormalities. The authors assess the efficacy of this image-based CADx utilizing CNN and CADe with R-CNN for lung nodules and diffuse lung illnesses. Deep learning for pulmonary image processing [15] includes categorization, detection, and segmentation of lung disorders. Compared to classic feature-based CAD algorithms, the study underlines the superiority of CNN-based CAD methods, which do not require an image-feature extractor. The research describes and assesses image-based CAD algorithms designed for diverse lung abnormalities, including lung nodules and diffuse lung illnesses. The authors believe that deep learning will dramatically improve the performance of CAD systems, resulting in transformational changes in radiologists' work. Detecting lung nodules in CT images with a raw patch-based CNN. The authors provide a Computer-Aided Detection (CAD) [16] system that uses CNNs and CT image segmentation algorithms to identify lung nodules in low-dose CT images. Notably, they directly feed raw CT image patches into CNNs, lowering system complexity. The Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI) dataset is used to compare ResNet's performance to that of other CNN designs. Results show cutting-edge efficacy, with the best model reaching excellent detection sensitivity. The study focuses on detecting chest X-ray anomalies with a CNN [17] model that has been tuned by hyperparameter tuning. The authors use methods like Adam and RMSprop to optimize hyperparameters such as the pooling layer, convolutional layer, dropout layer, target size, and epochs. Hyperparameter tuning attempts to improve the CNN model's accuracy in detecting chest X-ray abnormalities. The study, which used 4538 chest X-ray images, found that hyperparameter optimization improves the accuracy of the CNN model, emphasizing the implications for improving the accuracy and reliability of chest X-ray image interpretation, and thus the detection and treatment of lung diseases.

3.3 3D-CNN on Lung Diseases Detection

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

The application of a computer-aided diagnosis (CAD) [18] system with 3D Convolutional Neural Networks (3D CNNs) for lung cancer categorization in CT images. The authors use a dataset from the 2017 Kaggle Data Science Bowl to identify lung tissue from CT images by using thresholding as an initial segmentation approach. However, because of limitations, a modified U-Net trained on LUNA16 data is used for nodule detection. The U-Net output, albeit producing false positives, directs the selection of locations with segmented lungs. These areas are then input into 3D CNNs to get the final lung cancer categorization. The suggested CAD system achieves 86.6% test set accuracy, exceeding existing literature CAD systems through a more efficient and generalized methodology. The attention switches to detecting chronic obstructive pulmonary disease (COPD) [19] utilizing CNNs applied to multi-view snapshots of 3D lung airway trees derived from CT images. The authors use a deep CNN model that was built independently for ventral, dorsal, and isometric views and improved using Bayesian optimization. The ultimate forecast is determined by a majority vote of the three viewpoints. The custom developed CNNs outperform off-the-shelf CNNs and pre-trained CNNs with fine-tuning, with an accuracy of 88.2%. COPD class-discriminative areas are mostly seen in the central airways, presenting a viable technique for reliable CT-based diagnosis. A computer-aided detection method for lung nodule identification in low-dose CT that employs 3D CNNs [20]. Using existing information about lung nodules and confounding anatomical features, the method creates nodule candidates while reducing structural variability by predicting local orientation. These candidates are sent into a deep 3D CNN, which is trained to distinguish between nodule and non-nodule inputs. The system achieves cutting-edge performance by utilizing data augmentation and regularization approaches, beating a similar hybrid system that use standard shallow learning. The study highlights the benefits of using a priori models to reduce the problem space in complex deep neural networks and emphasizes the advantages of 3D CNNs over 2D CNNs in volumetric medical image analysis.

Introduces a 2D-3D cascaded CNN method for lung nodule categorization [21], detection, and segmentation. The authors suggested a unique picture preprocessing approach based on a maximum intensity projection methodology. The Lung Image Database Consortium (LIDC), LNDb Challenge Dataset, and Indian Lung CT Image Database (ILCID) clinical datasets were used to evaluate their SquExUNet segmentation and 3D-NodNet classification models, respectively. DrasCLR [22] is a self-supervised system for learning disease-related and anatomy-specific representations from 3D lung CT scans. The authors emphasize the lack of annotated data and suggest two domain-specific contrastive learning methodologies. The study underlines the relevance of include anatomical context in the self-supervised learning framework and shows gains in a variety of downstream tasks on large-scale lung CT datasets. Automatic lung nodule detection with an adaptable and attentive 3D CNN [23]. The suggested technique has two stages: candidate nodule discovery and false positive reduction. They initially use an attentive technique to capture globule, spital, and fine-grained information, followed by an adaptive 3D CNN structure to reduce false positives. The trials were carried out using the publicly accessible LUNA16 dataset. The task of decreasing false positives in lung nodule identification with a Multi-Branch Ensemble Learning architecture based on 3D CNNs (MBEL-3D-CNN) [24]. The authors integrate three fundamental ideas: building a 3D-CNN, using a multi-branch network to account for the heterogeneity of lung nodules, and using ensemble learning to improve generalization.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

Offline hard mining techniques are used to process indistinguishable positive and negative samples. The suggested approach is assessed using the LUNA16 dataset.

3.4 Real-world implications of 3D CNN-based lung disease identification

The use of Deep Convolutional Neural Networks (Deep CNNs) [25] to detect pneumonia in chest X-ray images. The work focuses on overcoming issues in identifying lower respiratory tract infections and introduces a customized Deep CNN model. The study utilizes a large dataset of 12,000 chest X-rays, including both pneumonia-affected and healthy samples. A strong training set benefits from rigorous preprocessing approaches like as noise abatement, normalization, and data augmentation. The Deep CNN model, which uses complicated convolutional architectures, designed dropouts, and contemporary activation functions, delivers high accuracy, specificity, and sensitivity metrics. The findings highlight Deep CNNs' transformational capabilities in pneumonia detection using X-rays, highlighting significant real-world implications for enhancing diagnostic precision in clinical environments. Using a 3D CNN, we classified Chronic Obstructive Pulmonary Disease (COPD) [26]. The System discusses the need of proper COPD diagnosis, given the expected growth in COPD as a main cause of mortality worldwide. The work uses a dataset from the ECLIPSE project to create a 3D CNN for COPD risk categorization. The emphasis is on using deep learning methods based on three-dimensional convolutional neural networks to achieve more accurate categorization using tomographic pictures. The study's goal is to help optimize and reduce the computing costs of deploying 3D CNNs for COPD classification, which might improve diagnosis accuracy and early intervention in real-world medical settings. The creation of a unique hybrid 2D/3D CNN architecture for COVID-19 [27] detection using chest X-ray images. With the fast spread of the COVID-19 pandemic, early detection is critical. The study uses chest X-ray technology, and unlike many recent studies that depend primarily on 2D CNNs, it takes a mixed method that includes 3D CNN features. The suggested architecture consists of a pre-trained deep model (VGG16), a shallow 3D CNN, a depth-wise separable convolution layer, and a spatial pyramid pooling module. The System seeks to address 3D CNN constraints, such as increasing computing costs, by adding transfer learning and particular architectural components. The results indicate the hybrid approach's promise for COVID-19 screening, with good sensitivity, specificity, and overall accuracy. The study's real-world applications include the creation of more effective screening approaches for respiratory infections, particularly during pandemics, that take advantage of both 2D and 3D CNNs in medical picture processing.

In recent years, the use of 3D CNNs has emerged as a potential approach to enhancing lung disease detection using medical imaging techniques such as CT scans and X-rays. These developments have considerable promise for real-world applications in healthcare, notably in the areas of early illness diagnosis and prognosis. Several research have looked at the effectiveness of 3D CNNs in this domain, offering insight on their implications and the datasets used to evaluate their performance. A comparison of 2D and 3D CNN techniques for identifying lung nodule malignancy risk [28]. This study utilized a huge dataset of CT scans from the Lung Image Database Consortium collection (LIDC-IDRI). By directly comparing slice-level 2D CNN, nodule-level 2D CNN, and nodule-level 3D CNN techniques, the study gave insights into the usefulness of 3D CNNs in collecting subtle aspects crucial to lung disease detection. The findings

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

demonstrated the ability of 3D CNNs to combine nodule-level data and contextual information from several directions, improving performance above typical 2D CNN techniques. A hybrid CNN-RNN technique to survival analysis in lung cancer screening research. This novel technique examined long-term survival outcomes by evaluating CT images and adding time series data [29]. By combining CNNs' skills in collecting imaging characteristics with RNNs' capacity to represent temporal relationships, the study showed encouraging results in predicting cardiovascular death. This technique demonstrates the potential of CNNs to contribute to personalized medicine by allowing for more accurate prognostic evaluations in lung cancer screening programs.

Creating a deep learning-based diagnosis system for common respiratory disorders utilizing CT and chest X-ray datasets [30]. This complete strategy required the deployment of many networks trained on large-scale real-world information. The system performed well in anomaly detection and illness diagnosis, indicating its potential as a useful tool for doctors in the early detection and management of respiratory disorders. The use of heterogeneous datasets from various institutions demonstrated the resilience and generalizability of the suggested technique, underlining its real-world usefulness. The efficacy of CNN-based and transformer-based models for detecting lung cancer using CT images [31]. Using advanced training techniques and a collection of medical photographs, the study gave insights into the performance characteristics of both methods. Despite the rising popularity of transformer-based models in computer vision, the findings indicate that CNNs are still very effective for detecting lung cancer, especially when trained using self-supervised learning approaches. This emphasizes the necessity of adopting proper model architectures and training procedures to achieve peak performance in real-world applications.

4. Compare the effectiveness of 3D CNNs in CT scans and X-rays

The efficiency of 3D CNNs in CT scans and X-rays depends on the datasets used. CT scans give volumetric information for 3D analysis, whereas X-rays provide 2D projections. CT datasets frequently have precise anatomical features, allowing for full 3D feature extraction, but X-ray datasets may lack depth information, thereby restricting the use of 3D CNN capabilities. Dataset changes in terms of dimensionality and content are critical in determining the relative performance of 3D CNNs in distinguishing lung illnesses from CT scans and X-rays.

4.1 Comparative Analysis of CNN and 3D-CNN Lung Disease Detection

Each research makes a unique contribution, but differences in datasets and methodological features (Shown in Table 1) highlight the need of having a thorough grasp of the trade-offs between advantages and downsides when using deep learning models to diagnose lung illness.

Table.1 Comparative Analysis of CNN and 3D-CNN Lung Disease Detection Approaches

S.No	Paper	Dataset	Methodology	Drawbacks
1	Malik et al. (2023) [32]	Chest x-rays and CT scans	CDC Net (CNN model with residual	• Limited discussion on generalizability

			network and dilated convolution)	to diverse populations. • Evaluation focused on specific pre-trained models.
2	Bharati et al. (2020) [33]	NIH Chest X-ray image dataset	VDSNet (Hybrid CNN model with VGG, data augmentation, and spatial transformer network)	• No explicit discussion on computational complexity. • Validation accuracy drops slightly for sample dataset.
3	Hussein et al. (2022) [34]	X-ray images	Hybrid architecture of CLAHE and CNN	• Limited information on the size and diversity of the dataset. • Specific focus on CLAHE and CNN hybrid architecture.
4	Bhandary et al. (2020) [35]	Chest X-Ray and lung CT scan images (LIDC-IDRI)	Two DL techniques: MAN (modified AlexNet) and Fusion of handcrafted and learned features	• Limited discussion on the interpretability of the DL models. • No detailed analysis of false positives or false negatives.
5	Alakwaa et al. (2017) [18]	Kaggle Data Science Bowl, 2017	Modified U-Net trained on LUNA16 data for nodule detection; 3D CNN for lung cancer classification	• Initial segmentation approach using thresholding may not capture all lung nodules accurately • False positives generated by U-Net nodule detection
6	Du et al. (2020) [19]	Central Hospital Affiliated to Shenyang	Deep CNN models trained on multi-view snapshots of 3D lung airway	• Limited explanation of class-discriminative regions

		Medical College dataset (280 participants)	trees extracted from CT images	• Potential challenges in generalizability to larger and more diverse datasets
7	Huang et al. (2017) [20]	Dataset with 99 CT scans	3D CNN for lung nodule detection using nodule candidates generated by geometric-model-based filter	• Requires a priori knowledge about lung nodules and confounding anatomical structures • May suffer from overfitting without proper regularization
8	Dutande et al. (2021) [21]	Lung Image Database Consortium – Image Database Resource Initiative (LIDC), LNDb Challenge Dataset, Indian Lung CT Image Database (ILCID) clinical dataset	SquExUNet segmentation model and 3D-NodNet classification model for lung nodule detection and classification	• Limited discussion on generalizability to diverse datasets • Specific to lung nodule detection and classification
9	Yu et al. (2024) [22]	Large-scale datasets of lung CT scans	DrasCLR framework for self-supervised learning of disease-related and anatomy-specific representations	• Complexity of conditional hyper-parameterized network • Potential challenges in incorporating anatomical context into the SSL framework
10				

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

	Zhao et al (2023) [23]	Dataset with 888 CT scans that were selected from LIDC-IDRI	3D CNN is proposed for automatic pulmonary nodule detection, which contains two parts: the candidate nodule detection and false positive reduction	• Challenge in trade-off sensitivity and FP/s. • The system is less sensitive under high confidence in the false positive reduction stage
11	Cao et al (2019) [24]	The LUNA16 Challenge screened 888 CT data from a publicly available LIDC dataset containing 2610 lung nodule	Multi-Branch Ensemble Learning architecture based on the three-dimensional (3D) convolutional neural networks (MBEL-3D-CNN)	• Low false positive rates to the evaluation parameters which is critical to improve the automated level of the current computer-aided diagnosis system
12	Matamala et al (2023) [26]	Large-scale datasets of lung CT scans	3DCNN Model for COPD classification	• Accuracy slightly drops for sample dataset.
13	Bayoudh et al (2020) [27]	ChestX-ray images	2D/3D CNN based on cross-domain adaptation approach for COVID-19 screening	• Collecting and annotating medical image collections is a very challenging task.
14	Ali Riahi et al (2022) [36]	Dataset with 6484 X-ray images	Bi-dimensional Empirical Mode Decomposition (BEMD) technique and 3DCNN model to detect the COVID-19 virus.	• Decomposition of images of great size using the BEMD consumes more computational time.
15				

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

	Samritika et al (2021) [37]	3,877 images dataset of CT and X-ray images	Covid-19 Detection using convolutional neural networks (CNN)	• It only looks at the posterior and anterior (PA) views of X-rays, therefore other X-ray perspectives like anterior-posterior (AP), lateral, and so on.

5. Challenges and Opportunities

Integration with various imaging modalities is a considerable problem and potential in the field of lung disease detection with 3D CNNs. The use of numerous imaging modalities, such as CT scans, MRIs, and PET scans, can give complementary information, improving the accuracy and resilience of illness detection systems. Researchers may be able to increase the sensitivity and specificity of 3D CNN models for detecting various lung illnesses by combining data from diverse sources. This integration necessitates the development of advanced fusion algorithms that can successfully mix data from various sources while retaining significant characteristics.

5.1 Integration with other imaging modalities

The integration of 3D CNN-based lung disease identification with other imaging modalities, such as combining CT scans with advanced techniques like magnetic resonance imaging (MRI) or positron emission tomography (PET) (Shown in Figure 2), holds promising potential. This multimodal approach can provide a more comprehensive understanding of pulmonary conditions, enhancing diagnostic accuracy and enabling a more nuanced assessment of lung diseases for improved patient care.

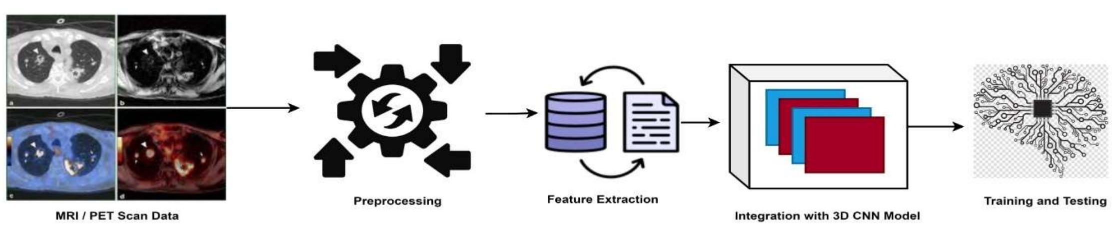

Figure 2. Performance of 3D CNN in other modalities

- Enhanced diagnostic accuracy:

  Combining data from different imaging modalities allows for a more thorough assessment of lung health, which may lead to more accurate diagnosis.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

- Various forms of Detection:

  Various imaging modalities reveal unique features of lung structure and disease. Integrating various modalities can give complementary information, improving our overall understanding of lung disorders.

- Improved disease characterization:

  By combining data from many imaging modalities, researchers may better define different types of lung illnesses based on their distinct imaging fingerprints.

- Data fusion challenges:

  Integrating data from many modalities presents issues with alignment, standardization, and fusion. Addressing these problems necessitates the development of sophisticated data fusion algorithms that are customized to the unique characteristics of each modality.

5.2 Potential advancements in 3D CNN architectures

- Optimized network Architectures:

Continued improvements in 3D CNN architectures are critical to enhancing the efficiency and performance of lung disease detection systems. Researchers are investigating innovative network topologies, such as attention mechanisms, graph convolutional networks, and capsule networks, to improve the representational capability of 3D CNNs.

- Integration of prior knowledge:

Integrating domain-specific knowledge of lung anatomy and disease into 3D CNN designs might help them extract important features and generate more accurate predictions. This might entail including anatomical priors, physiological limitations, or disease-specific features into the network architecture.

- Efficient training strategies:

Deep 3D CNNs demand a substantial amount of processing resources and data. Transfer learning, semi-supervised learning, and federated learning are examples of advanced training methodologies that might assist reduce these issues and increase the scalability of 3D CNN-based lung disease diagnosis systems.

- Interpretability and explainability:

As 3D CNN models get more complicated, there is an increasing demand for ways to understand and explain their results. Advancements in model interpretability techniques, such as attention maps, saliency maps, and feature visualization, can help clinicians understand the rationale behind the model's decisions and build trust in their use for clinical decision-making.

5.3 Fuzzy Logic for Lung Disease Identification in CT and X-ray

In medical imaging, fuzzy logic has been widely used, especially for lung detection in CT and X-ray pictures. Fuzzy logic helps with the sensitive interpretation of small variations in radiographic patterns related to lung structures by utilizing its capacity to tolerate ambiguity and imprecision. Considering the gradual changes found in lung imaging, this method allows for a more sophisticated classification. Fuzzy logic can be useful, but only if the right parameters are tuned and expert knowledge is included. Although providing a useful tool for lung identification, difficulties could occur when dealing with intricate diseases or unclear aspects of the image that call for a more thorough examination.

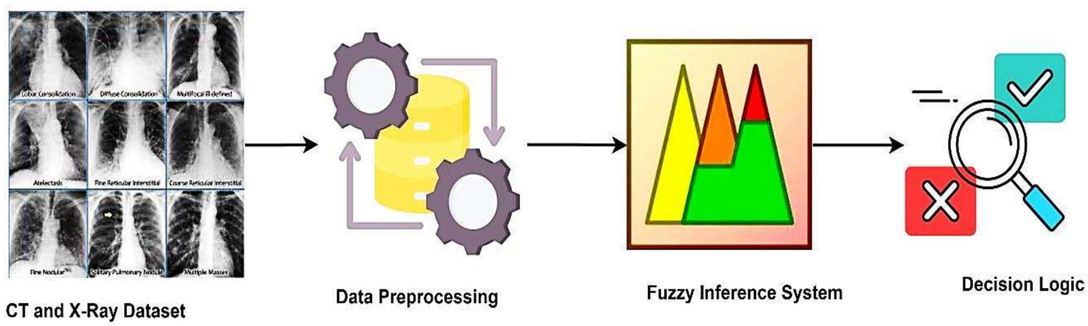

Fig 3. Fuzzy Logic-Based Lung Disease Identification Workflow

In the Figure 3, visually represents the sequential steps involved in the "Fuzzy Logic-Based Lung Identification Workflow." The input phase involves preprocessing of CT or X-ray images, followed by the application of a Fuzzy Inference System utilizing linguistic rules and membership functions. The subsequent decision logic, based on fuzzy outputs, culminates in the output of fuzzy-based lung identification. The diagram succinctly captures the logical flow of the fuzzy logic approach for lung disease identification in medical imaging. Fuzzy Logic (FL) describes systems in terms of a combination of numeric and linguistic. Fuzzy algorithms are often robust [38], the reasoning process is often simple, so computing power is saved. It has shorter development time than conventional methods. This is a very interesting feature, especially in real time systems such as online diagnose applications, FL is flexible and easy to implement machine learning techniques, It is a very convenient method for uncertain or approximate reasoning. However, FL suffers from a difficulty to find suitable membership values for fuzzy systems, and it suffers from a difficulty to store the rule-base that might require a significant amount of memory.

6. Conclusion

This comprehensive paper investigated the performance of 3D Convolutional Neural Networks (3D CNNs) for detecting lung abnormalities in medical images. A detailed evaluation of numerous research and approaches reveals that 3D CNNs have tremendous potential for expanding the area of medical image analysis, particularly in the context of lung problems. The

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

studied literature demonstrates 3D CNNs' adaptability and resilience, stressing their potential to collect detailed spatial characteristics in three dimensions, hence improving lung anomaly detection accuracy. The shift from typical 2D CNNs to 3D models is a significant step forward, enabling for greater in-depth analysis of volumetric medical pictures. While problems like as computational complexity and resource constraints are acknowledged, the general belief is that the benefits of using 3D CNNs exceed these drawbacks. The research reviewed show that 3D CNNs have the potential to improve early detection, provide significant insights to doctors, and ultimately contribute to better patient outcomes. As the area evolves, further research and developments in 3D CNN designs are expected, creating new opportunities for innovation and refinement in the identification and categorization of lung anomalies in medical imaging. This survey not only consolidates current information, but it also emphasizes the critical role that 3D CNNs may play in influencing the future of medical image analysis, notably in the field of lung disease detection.

References

1. Xie, M., Liu, X., Cao, X., Guo, M., & Li, X. (2020). Trends in prevalence and incidence of chronic respiratory diseases from 1990 to 2017. Respiratory research, 21(1), 1-13.

2. Pugh, M. J., Jaramillo, C. A., Leung, K. W., Faverio, P., Fleming, N., Mortensen, E., ... & Morris, M. J. (2016). Increasing prevalence of chronic lung disease in veterans of the wars in Iraq and Afghanistan. Military medicine, 181(5), 476-481.

3. Coultas, D. B., Zumwalt, R. E., Black, W. C., & Sobonya, R. E. (1994). The epidemiology of interstitial lung diseases. American journal of respiratory and critical care medicine, 150(4), 967-972.

4. Montnemery, P., Adelroth, E., Heuman, K., Johannisson, A., Johansson, S. Å., Lindholm, L. H., ... & Löfdahl, C. G. (1998). Prevalence of obstructive lung diseases and respiratory symptoms in southern Sweden. Respiratory medicine, 92(12), 1337-1345.

5. Maio, S., Baldacci, S., Carrozzi, L., Pistelli, F., Angino, A., Simoni, M., ... & Viegi, G. (2016). Respiratory symptoms/diseases prevalence is still increasing: a 25-yr population study. Respiratory Medicine, 110, 58-65.

6. Olson, A., Hartmann, N., Patnaik, P., Wallace, L., Schlenker-Herceg, R., Nasser, M., ... & Cottin, V. (2021). Estimation of the prevalence of progressive fibrosing interstitial lung diseases: systematic literature review and data from a physician survey. Advances in therapy, 38, 854-867.

7. Singh, S. P., Wang, L., Gupta, S., Goli, H., Padmanabhan, P., & Gulyás, B. (2020). 3D deep learning on medical images: a review. Sensors, 20(18), 5097.

8. Liu, X., Gao, K., Liu, B., Pan, C., Liang, K., Yan, L., ... & Yu, Y. (2021). Advances in deep learning-based medical image analysis. Health Data Science, 2021.

9. Dutta, P., Upadhyay, P., De, M., & Khalkar, R. G. (2020, February). Medical image analysis using deep convolutional neural networks: CNN architectures and transfer learning. In 2020 International Conference on Inventive Computation Technologies (ICICT) IEEE (pp. 175-180).

10. Niyas, S., Pawan, S. J., Kumar, M. A., & Rajan, J. (2022). Medical image segmentation with 3D convolutional neural networks: A survey. Neurocomputing, 493, 397-413.

11. Altaf, F., Islam, S. M., Akhtar, N., & Janjua, N. K. (2019). Going deep in medical image analysis: concepts, methods, challenges, and future directions. IEEE Access, 7, 99540-99572.

12. Yu, H., Yang, L. T., Zhang, Q., Armstrong, D., & Deen, M. J. (2021). Convolutional neural networks for medical image analysis: state-of-the-art, comparisons, improvement and perspectives. Neurocomputing, 444, 92-110.

13. Singha, A., Thakur, R. S., & Patel, T. (2021). Deep learning applications in medical image analysis. Biomedical Data Mining for Information Retrieval: Methodologies, Techniques and Applications, 293-350.

14. Kido, S., Hirano, Y., & Hashimoto, N. (2018, January). Detection and classification of lung abnormalities by use of convolutional neural network (CNN) and regions with CNN features (R-CNN). In 2018 International workshop on advanced image technology (IWAIT) IEEE (pp. 1-4).

15. Kido, S., Hirano, Y., & Mabu, S. (2020). Deep learning for pulmonary image analysis: classification, detection, and segmentation. Deep Learning in Medical Image Analysis: Challenges and Applications, 47-58.

16. Wang, Q., Shen, F., Shen, L., Huang, J., & Sheng, W. (2019). Lung nodule detection in CT images using a raw patch-based convolutional neural network. Journal of digital imaging, 32, 971-979.

17. Saifullah, S., Yuwono, B., Rustamaji, H. C., Saputra, B., Dwiyanto, F. A., & Dreżewski, R. (2023). Detection of Chest X-ray Abnormalities Using CNN Based on Hyperparameter Optimization. Engineering Proceedings, 56(1), 223.

18. Alakwaa, W., Nassef, M., & Badr, A. (2017). Lung cancer detection and classification with 3D convolutional neural network (3D-CNN). International Journal of Advanced Computer Science and Applications, 8(8).

19. Du, R., Qi, S., Feng, J., Xia, S., Kang, Y., Qian, W., & Yao, Y. D. (2020). Identification of COPD from multi-view snapshots of 3D lung airway tree via deep CNN. IEEE Access, 8, 38907-38919.

20. Huang, X., Shan, J., & Vaidya, V. (2017, April). Lung nodule detection in CT using 3D convolutional neural networks. In 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017) IEEE 379-383.

21. Dutande, P., Baid, U., & Talbar, S. (2021). LNCDS: A 2D-3D cascaded CNN approach for lung nodule classification, detection and segmentation. Biomedical signal processing and control, 67, 102527.

22. Yu, K., Sun, L., Chen, J., Reynolds, M., Chaudhary, T., & Batmanghelich, K. (2024). DrasCLR: A self-supervised framework of learning disease-related and anatomy-specific representation for 3D lung CT images. Medical Image Analysis, 92, 103062.

23. Zhao, D., Liu, Y., Yin, H., & Wang, Z. (2023). An attentive and adaptive 3D CNN for automatic pulmonary nodule detection in CT image. Expert Systems with Applications, 211, 118672.

24. Cao, H., Liu, H., Song, E., Ma, G., Xu, X., Jin, R., ... & Hung, C. C. (2019). Multi-branch ensemble learning architecture based on 3D CNN for false positive reduction in lung nodule detection. IEEE access, 7, 67380-67391.

25. Nessipkhanov, D., Davletova, V., Kurmanbekkyzy, N., & Omarov, B. (2023). Deep CNN for the Identification of Pneumonia Respiratory Disease in Chest X-Ray Imagery. International Journal of Advanced Computer Science and Applications, 14(10).

26. Matamala Avrova, E. V. (2023). Implementation of a 3D CNN for COPD classification (Bachelor's thesis, Universitat Politècnica de Catalunya).

27. Bayoudh, K., Hamdaoui, F., & Mtibaa, A. (2020). Hybrid-COVID: a novel hybrid 2D/3D CNN based on cross-domain adaptation approach for COVID-19 screening from chest X-ray images. Physical and engineering sciences in medicine, 43, 1415-1431.

28. Yan, X., Pang, J., Qi, H., Zhu, Y., Bai, C., Geng, X., ... & Ding, X. (2016, November). Classification of lung nodule malignancy risk on computed tomography images using convolutional neural network: A comparison between 2d and 3d strategies. In Asian Conference on Computer Vision (pp. 91-101). Cham: Springer International Publishing.

29. Lu, Y., Aslani, S., Zhao, A., Shahin, A., Barber, D., Emberton, M., ... & Jacob, J. (2023). A hybrid CNN-RNN approach for survival analysis in a Lung Cancer Screening study. arXiv preprint arXiv:2303.10789.

30. Wang, C., Ma, J., Zhang, S., Shao, J., Wang, Y., Zhou, H. Y., ... & Li, W. (2022). Development and validation of an abnormality-derived deep-learning diagnostic system for major respiratory diseases. NPJ Digital Medicine, 5(1), 124.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

31. Gai, L., Xing, M., Chen, W., Zhang, Y., & Qiao, X. (2023). Comparing CNN-based and transformer-based models for identifying lung cancer: which is more effective?. Multimedia Tools and Applications, 1-17.

32. Malik, H., Anees, T., Din, M., & Naeem, A. (2023). CDC_Net: Multi-classification convolutional neural network model for detection of COVID-19, pneumothorax, pneumonia, lung Cancer, and tuberculosis using chest X-rays. Multimedia Tools and Applications, 82(9), 13855-13880.

33. Bharati, S., Podder, P., & Mondal, M. R. H. (2020). Hybrid deep learning for detecting lung diseases from X-ray images. Informatics in Medicine Unlocked, 20, 100391.

34. Hussein, F., Mughaid, A., AlZu'bi, S., El-Salhi, S. M., Abuhaija, B., Abualigah, L., & Gandomi, A. H. (2022). Hybrid clahe-cnn deep neural networks for classifying lung diseases from x-ray acquisitions. Electronics, 11(19), 3075.

35. Bhandary, A., Prabhu, G. A., Rajinikanth, V., Thanaraj, K. P., Satapathy, S. C., Robbins, D. E., ... & Raja, N. S. M. (2020). Deep-learning framework to detect lung abnormality–A study with chest X-Ray and lung CT scan images. Pattern Recognition Letters, 129, 271-278.

36. Ali Riahi , Omar Elharrouss, Somaya Al-Maadeed (2022) , "BEMD-3DCNN-based method for COVID-19 detection" , Computers in Biology and Medicine Volume 142, 105188.

37. Samritika Thakur & Aman Kumar,(2021)"X-ray and CT-scan-based automated detection and classification of covid-19 using convolutional neural networks (CNN)" Biomedical Signal Processing and Control Volume 69, 102920

38. Warda M. Shaban, Asmaa H. Rabie, Ahmed I. Saleh, M.A. Abo-Elsoud (2021) "Detecting COVID-19 patients based on fuzzy inference engine and Deep Neural Network" Applied Soft Computing Journal 99, 106906