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Advancements and challenges in deep learning techniques for lung disease diagnosis

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ABSTRACT

This study explores the application of deep learning (DL) techniques in diagnosing lung diseases using screening methods such as Chest X-Rays (CXRs) and computed-tomography (CT) scans. The motivation for this research stems from the need for advanced diagnostic tools in healthcare, with DL showing significant potential in medical image analysis. Despite advancements, challenges such as high costs of CT scans, processing time constraints, image noise, and variability persist. To address these issues, the study conducts a thorough literature survey to identify diverse preprocessing techniques, detection algorithms, and classification models designed for CXR analysis. In conclusion, this work contributes to the advancement of medical imaging technologies by offering innovative solutions, acknowledging existing limitations, and addressing the challenges in lung disease diagnosis. Future research should focus on further refining these techniques and exploring their application in broader clinical settings.

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1. INTRODUCTION

The global epidemic of COVID-19 has undoubtedly had an enormous effect on individuals worldwide, bringing about major changes to their way of life, employment, and social interactions. In the past few years, there have been a lot more deaths, which is one of the worst effects because of the global epidemic [1]. SARS-CoV-2, a coronavirus, is responsible for COVID-19 [2], has led to a surge in mortality rates [3], overwhelming healthcare systems and posing unprecedented challenges to public health worldwide [4]. Apart from its immediate effects, a number of chronic issues, primarily pertaining to the airway system, have been linked to COVID-19 [5]. Among the myriad complications, lung diseases have emerged as a prominent concern [6]. There are three primary categories of lung diseases: lung circulation, airway, and lung tissue. Each of these kinds of conditions has its own unique features and therapeutic options that need to be considered when managing patients [7]. Many different kinds of illnesses go under the umbrella term "respiratory diseases," and they all have the potential to severely affect lung function and general health. Among the most common conditions affecting the airways are chronic-obstructive pulmonary-disease (COPD), asthma, atelectasis, bronchiolitis, bronchiectasis (including cystic-fibrosis), and cardiomegaly [8], [9]. These diseases frequently exhibit characteristics of airway inflammation or obstruction, resulting in the manifestation of symptoms such as wheezing, breathing difficulties and cough. Furthermore, lung tissue diseases like pulmonary fibrosis, lung cancer, and effusion primarily affect the structure and function of lung tissues, impairing their ability to exchange oxygen and carbon dioxide efficiently [8], [9]. Additionally, lung circulation diseases such as pneumonia, pneumothorax, lower-respiratory tract-infections (LRTI), upper-respiratory tract-infections (URTI), and complications linked with COVID-19 can directly impact blood flow and oxygenation in the lungs, further exacerbating respiratory distress and increasing the risk of complications [8], [9]. These diverse respiratory diseases present unique challenges in diagnosis, management, and treatment, highlighting the critical importance of comprehensive healthcare approaches and ongoing research to improve outcomes for affected individuals.

Moreover, traditional methods for detecting respiratory diseases have long relied on imaging approaches like Chest X-ray (CXR) [10] and computed-tomography (CT) scans [11]. The aforementioned modalities provide significant contributions in terms of understanding the anatomical and physiological aspects of the lungs, helping healthcare professionals identify abnormalities, assess disease progression, and guide treatment decisions. CXR provides a two-dimensional view of the chest, highlighting areas of opacity or consolidation that may indicate infections, tumours, or other pulmonary conditions [12]. CT scans, on the other hand, offer a more detailed and three-dimensional perspective, enabling the visualization of subtle abnormalities and providing a clearer assessment of lung tissue and surrounding structures [13]. During the COVID-19 pandemic, innovative approaches to respiratory disease detection have emerged, including the use of saliva-based tests [14]. Saliva testing has gained traction as a non-invasive and convenient method for diagnosing respiratory infections, including COVID-19. It offers several advantages such as ease of collection, reduced risk of exposure for healthcare workers, and potential for large-scale testing initiatives. Moreover, advancements in sensor technology have revolutionized the detection and monitoring of respiratory diseases [15]. Sensors, ranging from wearable devices to portable diagnostic tools, can capture real-time data on lung function, breathing patterns, oxygen saturation levels, and biomarkers indicative of respiratory health or disease [16]. These sensors utilize various principles such as spectroscopy, impedance measurement, and gas sensing to provide accurate and timely information, empowering healthcare providers with valuable insights for early intervention and personalized treatment strategies [17]. The integration of these innovative approaches alongside traditional methods like CXR and CT scans marks a significant milestone in respiratory disease management, offering a comprehensive and multidimensional approach to diagnosis, monitoring, and therapeutic interventions.

The past few years have witnessed a noticeable inclination regarding the adoption of machine learning (ML) and deep learning (DL) methodologies for the purpose of lung prediction and classification within the domain of respiratory diseases [18]-[20]. This shift towards computational methods has enabled researchers and healthcare professionals to leverage large datasets and complex algorithms for enhancing accuracy and effectiveness of diagnosis and prognosis. Figure 1 illustrates the comprehensive process of lung prediction and classification, emphasizing the crucial steps involved. The workflow typically begins with preprocessing the data, whether it’s statistical data or images, to clean and prepare it for analysis. Following the initial data collection, a series of features are obtained from the dataset. These features play a crucial role in various classification and prediction tasks. These features may include physiological parameters, imaging characteristics, or biomarkers relevant to lung health and disease. ML and DL models then utilize these features to make predictions, classify lung conditions, and provide valuable insights for patient management and treatment planning.

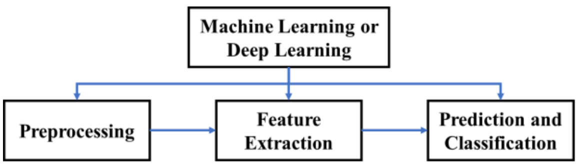

Figure 1. Overall process of lung prediction and classification

This work delves into a comprehensive study of various preprocessing approaches, detection, and classification methods employed in the domain of respiratory disease detection. It critically examines the strategies utilized in existing studies, highlighting the diversity in preprocessing techniques, detection algorithms, and classification methodologies. Furthermore, this work meticulously identifies the datasets utilized across different studies, shedding light on the variability and availability of data sources in this domain. Importantly, this study goes beyond mere documentation and analysis by identifying the limitations, issues, and challenges prevalent in the existing literature. However, this work doesn’t merely stop at identifying problems but also proposes potential solutions to address these challenges. By offering insights into effective preprocessing techniques, advanced detection algorithms, and robust classification strategies, this work aims to contribute significantly to the ongoing efforts in enhancing respiratory disease detection and management. Its contributions lie in bridging the gap between research findings and practical implementation, paving the way for more accurate, efficient, and accessible solutions for respiratory disease diagnosis and prognosis.

In this manuscript, in section 2, the literature survey is discussed where the preprocessing approaches, detection and classification approaches for respiratory disease detection is discussed. Also, the datasets used in this work are discussed. Further, in section 3, the limitation of the existing work is discussed. In section 4, the issues and challenges faced by the existing works are discussed. Finally, in section 5, the possible solutions are discussed and in section 6, the conclusion of the work is presented.

2. LITERATURE SURVEY

In this section, this work delves into the intricate world of preprocessing, detection, and classification approaches utilized in the realm of respiratory disease detection. These processes are pivotal in extracting meaningful insights from medical data, particularly in the context of respiratory health. The objective is not only to identify respiratory diseases accurately but also to streamline the analysis of medical images, sound data, and other relevant information. Hence, in the next section the preprocessing approaches presented by existing works are discussed.

2.1. Preprocessing approaches

This section delves into a comprehensive discussion on the various existing preprocessing approaches employed in the domain of respiratory disease detection using imaging techniques. Preprocessing is an essential step within the data evaluation or classification method as it significantly contributes to improving the overall quality, accuracy, and trustworthiness of data. The main objective of preprocessing aims to transform the initial input data into a format which is well-suited and optimal for the following processing stages, like extraction of features, detection, and classification. One of the common preprocessing approaches discussed in this section involves image enhancement techniques. The objective of these approaches was to enhance the visual appearance of CXR images through the modification of contrast, brightness, and clarity parameters. This modification leads to a significant improvement in the overall visibility of anatomical structures and abnormalities present in the images. Image enhancement plays a vital role in ensuring that subtle details and important features relevant to respiratory diseases are clearly visible and distinguishable. Additionally, preprocessing methods may also include noise reduction techniques to mitigate the impact of noise and artifacts present in the images. Noise, such as random variations in pixel intensity, can distort image quality and interfere with the accuracy of disease detection algorithms. Filtering or smoothing techniques are commonly used in preprocessing processes to decrease noise and increase the signal-to-noise ratio (SNR) of images. The different works along with their focus, dataset used and dataset type is given in Table 1.

Table 1. Existing preprocessing approaches

Ref	Year	Focus	Dataset used	Dataset type
[21]	2020	Preprocessing of CXR images utilizing enhancement techniques.	79 baseline CXR images acquired from hospital, standard dataset [22] for evaluation	Multiclassification dataset: viral, bacterial, fungal, lipoid, unknown classes. Image dataset.
[23]	2021	Preprocessing on CXR using DL	COVID-DB [24], COVID-19 [25], COVID-19-AR [26], NIH CXR [27], Pneumonia CXR [28]	Binary and multiclassification: COVID datasets (pneumonia, normal), NIH CXR (pneumonia, normal, others), pneumonia CXR (normal, viral pneumonia, bacterial pneumonia). Image dataset.
[29]	2021	Preprocessing methods for COVID-19 CXRs	18,479 CXRs (8,851 normal, 6,012 non-COVID infected, 3,616 COVID-infected)	Multiclassification: normal, non-COVID, COVID individuals. Image dataset.
[30]	2022	Preprocessing methods for CXRs	Dataset from [31] with 6,939 CXRs images (COVID, normal, pneumonia classes)	Multiclassification: COVID patients, normal, pneumonia. Image dataset.
[32]	2022	Preprocessing of lung X-ray images	6,168 frontal-view chest radiographs from five sources [33]	Binary classification: tuberculosis (TB) and non-TB. Image dataset.
[34]	2022	Preprocessing of CXR for identification of pneumonia	Two datasets: [35] (bacterial pneumonia, healthy, viral pneumonia) and [29] (COVID-19)	Multiclassification: bacterial pneumonia, viral pneumonia, healthy; COVID-19, virus, bacteria, normal. Image dataset.
[36]	2023	Provide better quality of CXR images	Chest-14 dataset [37]-[40] with 20,000 images	Multiclassification: cardiomegaly, atelectasis, infiltration, effusion, infiltration, pneumonia, mass nodule, pneumothorax. Image dataset.
[41]	2023	Providing better enhanced CXRs for classifier	CXR14 [40] dataset with 112,120 X-ray images	Multiclassification: cardiomegaly, atelectasis, infiltration, effusion, infiltration, pneumonia, mass nodule, pneumothorax. Image dataset.
[42]	2023	Processing of CXRs	11,652 CXRs from one hospital, 3,358 from another hospital (CR, DR images)	Multiclassification: cardiomegaly, atelectasis, infiltration, effusion, infiltration, pneumonia, mass nodule, pneumothorax. Image dataset.

2.2. Detection and classification of respiratory diseases

This section delves into a comprehensive discussion on the detection and classification approaches employed in the realm of respiratory diseases. Detecting and accurately classifying respiratory diseases is crucial for timely diagnosis, effective treatment planning, and improved patient outcomes. Various methodologies and techniques have been developed and utilized to address the complexities and challenges associated with respiratory disease detection and classification. One of the primary approaches discussed in this section involves the use of ML and DL algorithms for image-based detection and classification. These algorithms are trained on large datasets of CXR images, CT scans, or other imaging modalities to learn patterns and features indicative of specific respiratory conditions. For instance, CNNs have shown remarkable success in automatically detecting abnormalities, lesions, or characteristic patterns associated with diseases like pneumonia, lung cancer, or pneumothorax in medical images. Furthermore, statistical and data-driven approaches are also explored for detecting respiratory diseases using non-imaging data such as demographic information, clinical parameters, and biomarkers. These approaches often involve the use of statistical models, ML algorithms, and predictive analytics to analyse and interpret data patterns, identify risk factors, and predict disease outcomes.

Moreover, hybrid approaches combining imaging and non-imaging data are gaining traction for more comprehensive and accurate disease detection and classification. By integrating multiple data sources and leveraging advanced analytics techniques, such as feature selection, ensemble learning, and hybrid models, researchers and healthcare professionals can enhance the sensitivity, specificity, and overall performance of respiratory disease detection systems. Additionally, the adoption of AI technologies, including natural-language-processing (NLP) for analysing clinical notes, electronic-health-records (EHRs), and medical reports, has further enriched the capabilities of respiratory disease detection and classification. Overall, this section provides a comprehensive exploration of the diverse methodologies, algorithms, and technologies utilized for detecting and classifying respiratory diseases. By leveraging advanced computational techniques, data-driven insights, and interdisciplinary approaches, the field continues to make significant strides in improving diagnostic accuracy, patient care, and public health outcomes related to respiratory conditions. The summary of existing detection and classification approaches is given in Table 2 [43], [44].

Table 2. Existing detection and classification approaches

Ref	Year	Focus	Dataset used	Type
[45]	2020	COPD detection using saliva dataset	Saliva samples from 319 individuals divided into healthy and COPD, demographic info	Binary classification: healthy and COPD patients. Statistical dataset (age, gender, smoking, classes).
[46]	2023	Classification of Pneumothorax using CXRs images	Kaggle CXRs DICOM images (12,089 images) [47]	Binary classification: normal and pneumothorax patients. Image dataset.
[48]	2023	Detection of lung cancer from saliva samples	Exasens dataset with COPD, healthy, asthma, and infected patients [49]	Multiclass classification: COPD, healthy, asthma, infected. Statistical dataset (age, gender, smoking, classes).
[50]	2023	Detection of lung tumor using CT scans	LIDC-IDRI [51], Simba lung dataset [52]	Binary classification: normal and lung lesion. DICOM CT scan image dataset.
[53]	2023	Classification of lung disease using CXR images	NIH CXR [44], IU-Xray [54], MIMIC CXR dataset [55]	Binary classification: normal and diseased patient. Image and report dataset.
[56]	2023	Classification of different chest diseases using CXR images	Various sources dataset with CXR images	Multiclass classification: lung cancer, atelectasis, consolidation lung, tuberculosis, pneumothorax, edema, pneumonia, pleural thickening, normal using CXR. Image dataset.
[57]	2023	Classification of pneumonia and normal patients using CXR	CXR dataset with COVID-19, normal, pneumonia samples	Binary classification: pneumonia or normal. Image dataset.
[58]	2024	Detection of lung abnormality using chest CT scan and CXR scan	CXR and CT scan datasets [59], [60]	Multiclass classification: lung opacity, normal, viral pneumonia and COVID-19, normal, viral pneumonia. Image dataset.
[61]	2023	Classification and localization of lung disease from CXR	COVID-19 radiography dataset [62]	Multiclass classification: normal, lung opacity, pneumonia. Image dataset.
[63]	2023	Detection of lung disease using electrocardiogram (ECG) dataset	ECG dataset with COPD and healthy classes	Binary classification: COPD and healthy. Statistical dataset.
[64]	2023	Detection of lung chronic disease using different kinds of datasets	ICBHI lung sound database [65], WBCD [66], Z-Alizadehsani [67], Exasens, Diabetes datasets [68]	Multiclassification (ICBHI), binary classification (WBCD, Z-Alizadehsani, Exasens, Diabetes). Statistical datasets.
[69]	2023	Detection of lung disease using cancer tissues images	LC25000 dataset with cancer tissue images [70]	Binary classification: cancerous or non-cancerous images. Image dataset.

2.3. Datasets

In the preceding literature survey, a variety of datasets were utilized to investigate different aspects of respiratory diseases and their detection/classification methodologies. These datasets play a crucial role in training and evaluating ML models, DL algorithms, and statistical approaches. Each dataset has its unique characteristics, such as the type of data it contains, the number of samples, and the classes or categories represented. The datasets used in the survey encompass a range of modalities, including CXR images, CT scan images, sound data, and statistical data derived from saliva samples or patient records. The complete summary of the datasets is provided in Table 3.

Table 3. Summary of datasets used in the previous work

Dataset name	Description	Type	Source
Hospital CXR	Collected from a hospital having 79 baseline CXRs from various individuals.	Image dataset	[22]
COVID-DB	This dataset consists of 123 frontal view CXRs.	Image dataset	[24]
COVID-19	Collected from various sources.	Image dataset	[25]
COVID-19-AR	Consists data of 105 individuals having 31935 DICOM images (CT, DX, CR). Also, a clinical data is provided.	Image dataset	[26]
NIH CXRs	The dataset comprises of 108948 frontal view CXRs of 32717 individuals.	Image dataset	[27]
Pneumonia CXRs	The dataset consists of 5,232 CXRs, including 3,883 characterized as depicting pneumonia (2,538 bacterial and 1,345 viral) and 1,349 normal, from a total of 5,856 patients.	Image dataset	[28]
COVQU	This dataset consists of 18,479 CXR images with 8851 normal, 6012 non-COVID lung infections, and 3616 COVID-19 CXR images.	Image dataset	[29]
Kaggle dataset	This data consists of 6939 CXR images collected from various sources.	Image dataset	[31]
Chest radiographs	The entire dataset contains 6,168 frontal-view chest radiographs obtained from five different sources.	Image dataset	[32]
RSNA pneumonia dataset	This dataset consists of 30000 frontal CXRs from 112000 NIH dataset and CXR8 dataset.	Image dataset	[34]
Quality assurance dataset	This dataset consists of 29120 CXR images taken from CXR-14 and from various clinical sources.	Image dataset	[36]
CXR-14 dataset	CXR-14 is a medical imaging dataset which comprises 112,120 frontal-view CXR images of 30,805 (collected from the year of 1992 to 2015) unique patients.	Image dataset	[40]
CR, DR images dataset	This dataset consists of more than 2000+ CXRs taken from various sources.	Image dataset	[42]
Saliva dataset	Saliva samples collected from 319 individuals, divided into healthy and COPD patients, includes demographic info.	Statistical dataset	[45]
Kaggle CXR images	Digital Imaging and Communications in Medicine (DICOM) images from Kaggle, used for pneumothorax classification.	Image dataset	[46]
Exasens dataset	Dataset containing saliva samples from 399 individuals, including COPD, healthy, asthma, and infected patients.	Statistical dataset	[48]
Lung image database consortium (LIDC-IDRI)	CT scan images from 1,018 low-dose lung CTs, used for lung lesion classification.	DICOM CT scan image dataset	[50]
NIH CXR dataset	Large collection of 112,120 X-ray images with disease labels from 30,805 patients, used for lung disease classification.	Image and report dataset	[53]
Various sources CXR images	Dataset from multiple sources containing CXR images, used for classifying different chest diseases.	Image dataset	[56]
COVID-19 radiography dataset	Dataset with 21,165 CXR images, including normal, lung opacity, pneumonia cases, used for lung disease classification.	Image dataset	[61]
ECG dataset	Dataset with electrocardiogram data from 12 patients, used for COPD detection.	Statistical dataset	[63]
ICBHI lung sound database	Sound dataset with classes like COPD, asthma, bronchiolitis, used for lung sound classification.	Sound dataset	[64]
LC25000 dataset	Dataset with 25,000 images of cancer tissue in the lungs and colon, used for lung cancer classification.	Image dataset	[69]
OpenI CXR dataset	Dataset with diverse CXR images, used for classifying different lung diseases.	Image dataset	[71]

3. FINDINGS

In this section, we aim to highlight the limitations observed in the previous works discussed in the literature. These limitations encompass various aspects of medical image processing and analysis, which are crucial to address for the advancement and applicability of ML and DL models in healthcare settings. The complete summary is given in Table 4.

Table 4. Limitations of previous approaches

Ref	Limitations with respect to cost, speed and processing
[21]	High cost of implementation due to complex preprocessing techniques like FABEMD and CLAHE. Processing speed may be slower due to the intensive preprocessing. Performance may vary depending on the dataset used, especially if it lacks diversity.
[23]	Implementation cost may be moderate due to image resizing methods. Speed could be affected slightly during image preprocessing. Performance highly reliant on the quality and diversity of the dataset used for training.
[29]	Implementation cost can be moderate, but using multiple image enhancement techniques might increase computational expenses. Speed might be affected by the processing complexity of enhancement techniques. Performance depends on the efficacy of the chosen enhancement methods and the diversity of the dataset.
[30]	Moderate implementation cost for ML-based classification methods. Speed can be fast depending on the algorithm used for pre-processing. Performance highly dependent on the quality and size of the training dataset.
[32]	Implementation cost can be moderate for lung BCET and augmentation methods. Speed might be slightly slower due to the preprocessing steps. Performance may vary based on the quality and variety of the data used for evaluation.
[34]	High cost for multi-channel-based image processing and deep neural network implementation. Speed may vary depending on the complexity of image processing algorithms. Performance highly reliant on the quality and quantity of annotated CXR images.
[36]	Implementation cost could be high for DL-based quality assurance systems. Speed might be impacted by the computational requirements of DL models. Performance can be excellent for image correction tasks but may vary for regression-based corrections.
[41]	High cost for implementing DL models and pre-processing techniques like CLAHE. Speed may be slower due to the complexity of DL architectures. Performance highly reliant on the quality and diversity of the training data.
[42]	Moderate implementation cost for AI model development. Speed can be fast, especially with efficient image processing pipelines. Performance may vary based on the dataset used and the model's generalization capabilities.
[43]	High cost for developing custom DL frameworks for multi-class diagnosis. Speed may vary depending on the complexity of DL architectures. Performance highly dependent on the quality and diversity of the dataset used for training.
[45]	Moderate cost for ML implementation on saliva data but high cost if integrated into neuromorphic chips. Speed can be fast for ML algorithms. Performance depends on the quality and representativeness of the saliva dataset.
[46]	High cost for developing and training scratch CNN architectures. Speed may vary based on the complexity of CNN models. Performance highly reliant on the quality and diversity of the dataset used for classification.
[48]	High cost for IoT-enabled healthcare monitoring and DL model optimization. Speed can be slower due to data processing and optimization. Performance depends on the accuracy of feature selection and model training.
[50]	High cost for developing and optimizing lung tumor detection algorithms. Speed may vary depending on the complexity of feature fusion modules. Performance highly reliant on the accuracy of lung tumor localization and classification.
[53]	High cost for developing graph neural network-based disease co-occurrence matrices. Speed can be slower due to graph-based computations. Performance depends on the accuracy of disease co-occurrence predictions.
[56]	Moderate cost for fusion model development and DL training. Speed can be fast for trained DL models. Performance highly reliant on the diversity and quality of the dataset used for classification.
[57]	Moderate cost for transfer learning and DL model development. Speed can be fast for trained DL models. Performance depends on the accuracy of feature extraction and DL model training.
[58]	Moderate cost for data augmentation and DL model development. Speed can be fast for trained DL models. Performance highly reliant on the quality and diversity of augmented datasets.
[61]	High cost for developing and training DL models for multi-class abnormality detection. Speed may vary depending on the complexity of object detection models. Performance depends on the accuracy of multi-class abnormality localization and classification.
[63]	High cost for developing and training deep TL frameworks. Speed can be fast for trained DL models. Performance highly reliant on the quality and diversity of the electrocardiogram signal dataset.
[64]	High cost for developing and training PSORF-based classifiers. Speed can be fast for trained PSORF models. Performance depends on the accuracy of feature selection and classifier optimization.
[69]	High cost for developing secure IoMT-based transfer learning techniques. Speed may vary depending on the complexity of transfer learning models. Performance highly reliant on the accuracy of disease prediction and classification.

The issues and challenges identified from the above limitations are as follows:

- Cost: CT scans are generally more expensive than CXRs, which can pose a financial burden on patients, healthcare facilities, and insurance providers. This cost factor can limit access to advanced imaging techniques for certain patient populations or in resource-constrained settings.
- Processing time: CT scans typically require more processing time compared to CXRs. The intricate nature of CT imaging, which captures cross-sectional images of the body, necessitates complex reconstruction algorithms and computational resources. This longer processing time can lead to delays in diagnosis and treatment, especially in emergency situations where rapid assessment is crucial.
- Radiation exposure: CT scans expose patients to higher levels of ionizing radiation compared to CXRs. While the radiation doses from modern CT scanners are generally considered safe, repeated or unnecessary CT scans can cumulatively increase the risk of radiation-related health issues, such as cancer. Minimizing radiation exposure is a key consideration in medical imaging, particularly for vulnerable populations such as children and pregnant women.

- Accessibility and portability: CXRs are more accessible and portable than CT scanners. X-ray machines are commonly available in medical facilities, clinics, and even mobile healthcare units, making them convenient for routine screenings, follow-up exams, and point-of-care diagnostics. In contrast, CT scanners are larger, stationary equipment that may require specialized facilities and trained personnel for operation.
- Diagnostic accuracy: while CT scans offer superior spatial resolution and detailed anatomical information compared to CXRs, the diagnostic accuracy of both modalities depends on the specific clinical scenario. In many cases, CXRs can provide sufficient information for initial assessment, triage, and monitoring of pulmonary conditions. CT scans are typically reserved for cases requiring more precise characterization of lesions, evaluation of complex pathologies, or staging of diseases.
- Resource allocation: given the varying capabilities and costs associated with CXRs and CT scans, healthcare providers must allocate resources based on clinical need, cost-effectiveness, patient safety, and diagnostic efficacy. Integrating decision support tools, artificial intelligence algorithms, and evidence-based guidelines can help optimize imaging utilization and improve patient outcomes.

Technological advancements: ongoing advancements in imaging technology, such as dual-energy X-ray imaging, low-dose CT protocols, and artificial intelligence-driven image analysis, continue to enhance the capabilities and efficiency of both CXRs and CT scans. Balancing these technological innovations with considerations of cost, processing time, radiation safety, and clinical utility remains a key challenge in medical imaging practices.

4. POSSIBLE APPROACH

To address the cost disparity between CT scans and CXRs in medical imaging, a viable solution involves the development of a DL framework specifically designed for CXRs. This framework encompasses preprocessing, detection, and classification stages to optimize the use of CXRs for lung disease diagnosis. In the preprocessing phase, DL algorithms can be employed to effectively denoise CXRs, enhancing image quality by improving contrast and brightness. Various enhancement techniques can be integrated to ensure that the resulting images provide clear and informative representations of lung structures. Moving to the detection phase, DL models can be trained to recognize deviations in CXRs indicative of lung abnormalities, distinguishing between images from healthy individuals and those with lung pathologies. Leveraging DL's capacity for pattern recognition and feature extraction, this phase aims to identify various variations that may signify disease presence. Finally, the classification approach within the DL framework can facilitate the accurate categorization of different types of lung diseases based on features extracted from CXRs. By leveraging DL's capabilities in image analysis and classification, this proposed framework not only addresses the cost constraints associated with CT scans but also harnesses the diagnostic potential of CXRs for comprehensive lung disease assessment.

5. CONCLUSION

In this comprehensive study, we have delved into the realm of medical imaging, specifically focusing on the use of DL frameworks for the diagnosis of lung diseases using CXRs as a cost-effective alternative to CT scans. The literature survey conducted in this work revealed a wealth of research and advancements in the field, showcasing various preprocessing techniques, detection algorithms, and classification models tailored for CXR analysis. Despite the progress made in this domain, several limitations and challenges persist. The high cost associated with CT scans remains a significant barrier for many healthcare facilities and patients, underscoring the need for cost-effective alternatives such as CXRs. Additionally, issues related to processing time, image noise, and variability in CXR quality pose considerable challenges in developing robust and reliable DL frameworks for lung disease diagnosis. However, our study proposes viable solutions to address these challenges. By developing a DL framework that integrates preprocessing techniques to enhance CXR quality, detection algorithms to identify abnormalities, and classification models for accurate disease categorization, this work aims to optimize the use of CXRs as an accessible and efficient imaging modality. These solutions not only mitigate the financial burden associated with CT scans but also harness the capabilities of DL in image analysis and pattern recognition, leading to more reliable and cost-effective diagnostic tools for lung diseases. In conclusion, this work contributes to the ongoing efforts in advancing medical imaging technologies, particularly in the realm of lung disease diagnosis, by proposing innovative solutions, acknowledging limitations, and addressing challenges through the utilization of DL frameworks designed for CXR analysis.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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