RESEARCH ARTICLE

Synthesizing Radiological Insights: Enhancing Lung Disease Classification through Multimodal Imaging

CS Kumari*, K. Seethalakshmi

Department of Computer Science and Engineering, Vel Tech Rangajaran Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India.

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ABSTRACT

Precisely categorizing lung diseases is essential for effective medical treatments. This paper presents a comprehensive analysis of advanced methods in lung disease classification, with a focus on integrating diverse imaging techniques like computerized tomography (CT), X-rays, and magnetic resonance imaging (MRI). These imaging approaches collectively enhance the understanding of pulmonary conditions, aiding in early detection and differential diagnosis. The paper initially explains the fundamental principles of CT, MRI, and X-rays, highlighting their unique characteristics and roles in elucidating lung structures. It explores state-of-the-art methodologies, encompassing both traditional machine learning using engineered features and the expanding domain of deep learning utilizing neural networks to classify intricate diseases. A wide range of prevalent lung ailments, spanning from pneumonia and lung cancer to chronic obstructive pulmonary disease (COPD), are covered. Each domain delves into the considerations for adapting imaging modalities, involving data pre-processing, feature extraction, and algorithmic orchestration. Comparative evaluations of performance metrics offer insights into the effectiveness and limitations of each approach. Furthermore, the paper outlines the challenges associated with classifying lung diseases, including limited annotated data, complexities in model interpretation, and the seamless integration of algorithmic outcomes into clinical practices. As for future research avenues, the paper suggests innovative directions such as data augmentation, integrating multi-modal imaging information, and advancing transparent artificial intelligence (AI) frameworks to enhance their acceptance in clinical settings.

Keywords: Deep learning, Object detection, Neural networks, Tensor flow, Safety, Transfer learning.

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INTRODUCTION

Contemporary society confronts a diverse range of challenges and scenarios of environmental pollutants stemming from various sources. The contemporary lifestyle in developing nations besides impacting physical health, it also leverages mental well-being. Statistical analysis indicates that lung disorders are associated with the majority of four out of top 10 causes of death which is shown through the chart with 10 deadliest diseases in the world with the comparison of deaths in year 2000 and 2015 as per data collected from.[1] Therefore, safeguarding lives from lung-related ailments is a crucial topic for discussion. Cigarette smoke, car exhaust emissions, and pollutants emitted by companies utilizing hazardous chemicals are the main contributors to air pollution. The present-day lifestyle and diet are responsible for the increasing prevalence of lung and respiratory diseases. Lower respiratory infections, ranking as the fourth leading cause of mortality, stand as the deadliest communicable diseases globally. Although there were 46,000 fewer deaths in 2019 compared to 2000, the consistently high number of 2.6 million fatalities is worrisome. Notably, cases of lung cancer have risen from 1.2 million to 1.8 million globally, solidifying its position as the sixth leading cause of death.[2] Numerous nations grapple with providing sufficient medical resources and medications for their populations, especially in developing countries like India. Statistics from the health ministry indicate a ratio of approximately 2,000 doctors per 1,000 people. Lower-middle-income households constitute the majority of the country's population, resulting in significant occurrences of deaths related to lower respiratory illnesses and chronic obstructive pulmonary disease (COPD). Specifically, lung cancer deaths have increased by 41,100 in upper-middle-class households, which is twice the combined number of deaths in all income classifications.[2,3] It's important to note that not everyone is susceptible to lung diseases, as the probability can differ based on an individual's specific physical and environmental conditions. Travel significantly contributes to the transmission of infections, with frequent travellers exhibiting a range of symptoms depending on their destination and mode of transportation.

**Author for Correspondence: cshyamalakumari90@gmail.com*

While travelling, it is crucial to acknowledge the significant role that viral pathogens play in transmitting infectious diseases. Notably, pathogens like rhinoviruses, measles, and mumps pose considerable risks. However, special attention must also be given to viruses with the potential to cause severe ailments, such as the Middle East respiratory syndrome–related coronavirus (MERS-CoV), as well as those attributed to highly pathogenic avian influenza viruses.[4] Extensive clinical research findings have illuminated the nature of respiratory infections, particularly those affecting the upper respiratory tract. Most cases tend to be mild and do not result in incapacitation. Common manifestations of upper respiratory tract infections include rhinorrhea (runny nose) and pharyngitis (sore throat). On the other hand, pneumonia, a prevalent disease primarily affecting the lower respiratory tract, demands considerable attention due to its potentially severe implications.[5] Symptoms associated with these infections encompass fever, dyspnea (shortness of breath) or chest pain, headache, and cough. COPD is a grave concern directly linked to long-term exposure to smoking. The devastating consequences of this destructive habit lead to the development of conditions such as emphysema and chronic bronchitis. It is essential to recognize that a single cigarette contains an astonishing array of approximately 600 ingredients, which when combusted, unleash above 7,000 chemicals. Among these chemicals, approximately 69 are known carcinogens, displaying highly toxic properties. Acetone, benzene, butane, acetic acid, cadmium, ammonia, lead, arsenicand nicotine serve as only a handful of instances.[6] The detrimental effects of these toxins on the lungs are profound, since it undermines the body's inherent defence mechanisms, making it more susceptible to infections. In particular, these toxins trigger inflammation in the airways, leading to gradually destroy the delicate air sacs, both of which are critical components contributing to the emergence of COPD. Importantly, it is fortune mentioning that while the majority of lung diseases can be attributed to environmental factors, certain conditions, such as emphysema, have a genetic predisposition.[7] Therefore, it is essential to consider both genetic and environmental factors in understanding the complexities of lung diseases.

Respiratory diseases, including COPD, tuberculosis, pneumonia, bronchial asthma andlung cancer are widely acknowledged in the medical field. When evaluating patients with respiratory illnesses, physicians must thoroughly review the patient's medical history and conduct a comprehensive physical examination. However, these intricate details present challenges for computer processing and cannot be easily integrated into automated systems. Classifying respiratory diseases based on respiratory impedance curves or derived parameters is a complex task that necessitates the expertise and experience of trained healthcare professionals. Inductive learning techniques have proven to be valuable in various medical specialties, such as oncology, urology, and liver pathology, as well as in predicting survival rates in hepatitis, cardiology, neuropsychology, gynecology, and perinatology. The introduction of automated diagnostic protocols has significantly enhanced the accuracy of medical diagnoses made by skilled physicians. However, identifying patterns is essential for effective diagnosis and categorization. When dealing with vast amounts of information, pinpointing these sequences becomes a daunting task.

In the recent past, several successful algorithms pertaining to machine learning have been developed, albeit with minimal error rate improvement. While sophisticated systems are utilized in the realm of healthcare settings, machine learning systems continue to be primarily utilized for probing purposes. Particularly in the realm of image identification, machine learning algorithms heavily depend on computer vision techniques, collectively referred to as deep learning. These algorithms require extensive training on large datasets to grasp the distinguishing features of specific disease classes and generate reliable models for validation. The efficacy of deep learning models primarily hinges on the following key factors:

- The quality and comprehensiveness of the dataset used for training.
- The selection of an appropriate model type, tailored to the specific problem at hand.
- Each of these points must be taken into consideration to assess the fidelity of the model.

Dataset

A deep learning model's foundation hinges on the availability and quality of the dataset employed. Gaining an appropriate dataset poses significant challenges, especially in the framework of medical diagnosis models, where access to internet data is limited due to privacy concerns and potential data misuse. Ensuring the dependability and effectiveness of the paradigm, the dataset used for training must come from a trustworthy source. The collected images must exhibit high quality, accurately capturing all relevant features necessary for accurate interpretation by the model. Since a single image may encompass multiple underlying features of a disease, a comprehensive dataset is essential. Certain medical societies may provide a restricted amount of medical testing data, subject to prior authorization from the appropriate governing body.

Choice of Model

When selecting a model for deep learning training, consideration must be given to the explicit architectural stipulations of the specific task in question, as well as the appropriate configuration of hyperparameters. A thorough understanding of the data is a key factor in selecting the appropriate model architecture. In scenarios where ample data is available, constructing a model from the ground up involves meticulously defining each stratum of the convolutional neural network.[65] This approach primarily involves using readily accessible training scripts to train the model from its foundational state. Conversely, if the available data is limited, the transfer learning methodology can be readily configured within the model. Transfer learning models leverage pretraining on a vast number of parameters, enabling fine-tuning based on the characteristics of the given dataset. TensorFlow and PyTorch offer a selection of pre-trained transfer learning models to suit diverse needs. The selection of a transfer learning model depends on the intended application and the desired level of accuracy. For instance, if the model is intended for deployment on mobile devices, a lightweight model such as MobileNet or similar architectures may be preferred.

This study aims to deliver a comprehensive review of machine learning models that researchers have employed in recent years, examining the nature of the data-sets used and analyzing the models employed for disease classification purposes. The initial segment examines relevant works within the realm of lung disease detection, while the subsequent section delves into the different prototypes adopted and the corresponding achieved certainty. Ultimately, this paper concludes by identifying an optimal model tailored to address the precise demands of the given task

Related Works

Naman Gupta *et al.*[8] designed an algorithm for the detection and classification of COPD. The target was achieved by following the steps in Figure 1.

The procedure entails the following sequential steps

Data Collection

The effectiveness of the machine learning model heavily relies on the utilization of reliable datasets sourced from reputable origins, encompassing a substantial number of images. A multitude of datasets are readily accessible for the explicit purpose of lung disease detection. In certain instances, researchers themselves undertake the task of dataset collection to ensure heightened accuracy. Table 1 provides an overview of the diverse datasets available for training a lung disease model. Furthermore, numerous other sources on the internet offer freely available datasets intended specifically for educational and research purposes. Sample lung CT scan data is visualized in Figure 2.

Image Pre-processing

The general course of action for developing a machine learning model involves a well-defined activity that includes image filtering. Given that the images within the schema may vary in size, have different file extensions, or contain noisy or

Table 1: Various datasets used for lung disease prediction

References	*Dataset used*
Shimpy Goyal and Rajiv Goyal[9]	C19RD, CXIP
S. S. Kanitkar *et al.*[11]	Automated Detection and Classification of Cancer in Whole-slide Lung Histopathology
A. Teramoto *et al.*[12]	UCI machine learning
O. Ozdemir *et al.*[13]	LUNA 16
D. Sharma *et al.*[14]	Dataset from the Lung Image Database Consortium (LIDC)
K. Punithavathy *et al.*[15]	PET/CT images
M. Vas *et al.*[16]	Self-collected
A. Asuntha *et al.*[17]	Self-collected

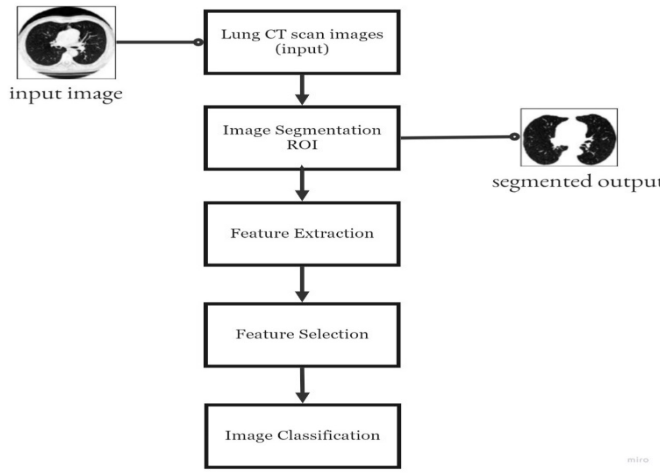


Figure 1: The steps followed for image classification of lung disease

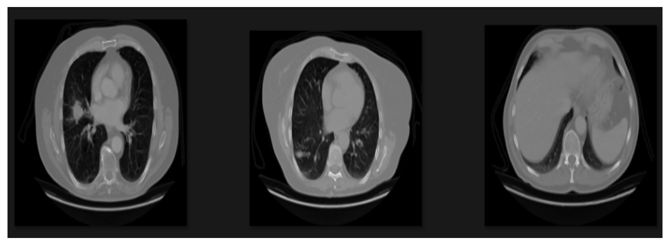


Figure 2: Sample CT scan data

blurry elements, it is essential to clean them before proceeding with model creation. Table 2 outlines the various image pre-processing techniques employed by different authors to prepare the dataset for training a machine learning model.

Naman *et al.*[8] delve into attribute elicitation algorithms and conduct comprehensive experimentation across various models. The authors initially utilize the region of interest (ROI) as a pivotal feature for extracting the region influenced by the ailment during the initial phase of image processing. Figure 3 illustrates the image transformation employed for disease detection purposes.

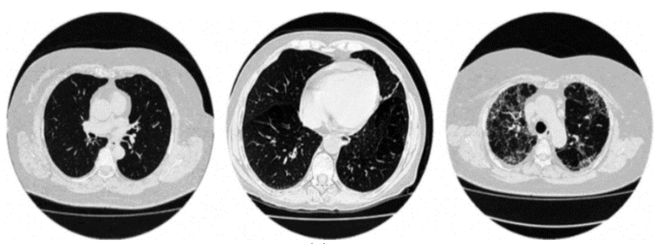
The following section of the paper[8] elaborates on the utilization of bio-inspired algorithms for feature extraction. Table 3 offers insight into the achieved accuracy through the use of various feature extraction methods in conjunction with tested algorithms, specifically SVM, RF, KNN algorithm and decision tree (DT). The employed methods include improvised grey wolf (IGWA), improvised cuttle fish (ICFA) and improvised crow search (ICSA).

For training purposes, a k-value of 6 was set for K-Nearest Neighbor (KNN), while this methodology utilized 10-fold cross-validation to validate the results. The attained accuracy was contrasted with the accuracy obtained in earlier studies, ultimately concluding that the ICWA-KNN model yielded optimal performance.

Shimpy Goyal and Rajiv Goyal[9] introduce an innovative framework for pneumonia and COVID-19 detection and classification using deep learning. Chest X-ray images were used as training data, with pneumonia and COVID-19 as

Table 2: Diverse image pre-processing techniques employed to pre-process data for machine learning modeling

References	*Image pre-processing used*
Identification of lung cancer through the utilization of marker-controlled watershed transform technique.[11]	Employed Gaussian and Gabor filtering methods to enhance the image quality and accentuate important features.
Automated categorization of various lung cancer types from cytological images employing deep convolutional neural networks.[12]	Utilized Gaussian and Convolutional edge enhancement filtering techniques to emphasize edges and enhance image details.
A probabilistic deep learning system in three dimensions for the identification and assessment of lung cancer through the utilization of low-dose CT scans.[13]	Employed an adaptive Gaussian filtering approach to effectively reduce noise and enhance image clarity.
Detection of lung cancer through the application of image processing methods.[14]	Utilized Wiener filtering, a sophisticated method for noise reduction, to improve image quality and restore fine details.
Examination of statistical texture characteristics for the purpose of automated identification of lung cancer in PET/CT images.[15]	Applied CLAHE (Contrast Limited Adaptive Histogram Equalization) technique to enhance the image contrast while preserving local details.
A system designed for detecting lung cancer through the processing of lung CT images.[16]	Employed a median filtering technique to effectively reduce impulsive noise and improve the overall image quality.
Utilization of deep learning techniques for both the identification and categorization of lung cancer, as discussed in the paper titled "Deep Learning for Lung Cancer Detection and Classification" within the cossntext of Multimedia Tools and Applications.[17]	Utilized an adaptive bilateral filtering method to enhance image details while simultaneously reducing noise and preserving edges.



(a)

(b)

(c)

Figure 3: (a) Original Images depicting healthy lungs,lungs with fibrosis and lungs with COPD respectively, (b) Segmented lung images corresponding to the original images and (c) Ground Truth images delineating the Regions of Interest (ROI) for the respective original images.

the two distinct classes. The model was trained on two separate datasets: the C19RD dataset and the CXIP dataset. The model was built using F-RRN-LSTM, incorporating adaptive intensity value adjustment, median filtering, and histogram equalization. Additionally, median filtering was

Table 3: Evaluating the accuracy comparison among different classifiers with different methods of feature extraction

Categorizer	*Method*	*Consistency (%)*
KNN	IGWA	99.40
	ICSA	98.60
	ICFA	96.60
RF	IGWA	99.20
	ICSA	99.00
	ICFA	97.30
SVM	IGWA	99.00
	ICSA	98.00
	ICFA	95.40
DT	IGWA	98.40
	ICSA	97.00
	ICFA	94.00

Table 4: Accuracy[9] on C19RD and CXIP datasets on different classifiers

Dataset Used	*Classifier*	*Robust normalization (%)*	*Raw Feature (%)*	*Min-Max normalization (%)*
C19RD	F-RNN-LSTM	95.04	89.36	93.55
	Ensemble	87.93	85.95	87.74
	KNN	85.72	81.54	82.98
	SVM	87.88	81.94	84.27
	ANN	91.22	87.95	89.92
CXIP	F-RNN-LSTM	94.31	87.82	92.16
	Ensemble	84.18	80.01	82.58
	KNN	83.08	79.44	82.76
	SVM	86.73	79.69	81.76
	ANN	85.55	79.89	83.94

Table 5: Experimental comparison of all algorithms used[18]

Type of Data	*Classification Method*	*Precision (%)*	*Sensitivity (%)*	*Recall (%)*	*Accuracy (%)*
Text Data with 12 classes	k-NN	67	100	100	67
	SVM	73	91	91	73
	GB	58	64	64	58
Audio Data with 12 classes	k-NN	64	99	99	64
	SVM	63	96	96	63
	GB	48	53	53	48
Text and Audio Data with 12 classes	k-NN	66	100	100	66
	SVM	70	99	99	70
	GB	58	69	69	58
Healthy and Normal text data versus Sick text data	k-NN	94	98	98	95
	SVM	100	55	55	75
	GB	98	99	99	98
Healthy and Normal audio data versus Sick audio data	k-NN	94	92	94	92
	SVM	89	88	88	88
	GB	98	85	85	91
Healthy and Normal text and audio data versus Sick text and audio data	k-NN	90	96	96	92
	SVM	100	43	43	64
	GB	97	95	95	97

Table 6: Analysis of SVM, KNN, and GB[18]

Classes	*GB (%)*	*SVM (%)*	*k-NN (%)*
Healthy and Normal text data / Sick text data	98	75	95
Healthy and Normal audio MFCC features	91	88	92
Text data with 12 diseases	58	73	67
Healthy and Normal text data and audio with MFCC features	97	64	92
12 diseases with audio MFCC features	48	63	64
12 diseases with text data and audio MFCC features	58	70	66

Table 7: MSD-NET comparison with similar models to assess their performance

Infection type	*Method*	*Spec.*	*DSC*	*Sen.*
Ground-Glass Opacities	U-Net	0.9775 ± 0.010	0.6034 ± 0.073	0.72 31 ± 0.011
	U-Net ++	0.9675 ± 0.004	0.7160 ± 0.052	0.8017 ± 0.014
	Attention U-Net	0.9665 ± 0.012	0.7226 ± 0.026	0.8038 ± 0.019
	U-Net+CBAM	0.9675 ± 0.005	0.7037 ± 0.039	0.8172 ± 0.013
	MSD-NET	0.9742 ± 0.005	0.7422 ± 0.038	0.8593 ± 0.018
Interstitial Infiltrates	U-Net	0.9756 ± 0.008	0.6423 ± 0.081	0.7361 ± 0.025
	U-Net ++	0.9847 ± 0.008	0.6971 ± 0.034	0.7829 ± 0.018
	Attention U-Net	0.9812 ± 0.007	0.7158 ± 0.024	0.7953 ± 0.011
	U-Net+CBAM	0.9431 ± 0.008	0.6824 ± 0.032	0.7975 ± 0.018
	MSD-NET	0.9869 ± 0.005	0.7384 ± 0.021	0.8268 ± 0.020
Consolidation	U-Net	0.9863 ± 0.005	0.7526 ± 0.036	0.8209 ± 0.026
	U-Net ++	0.9865 ± 0.003	0.8041 ± 0.042	0.8172 ± 0.009
	Attention U-Net	0.9814 ± 0.008	0.8012 ± 0.041	0.8147 ± 0.015
	U-Net+CBAM	0.9827 ± 0.004	0.8005 ± 0.052	0.8727 ± 0.021
	MSD-NET	0.9889 ± 0.007	0.8769 ± 0.015	0.8645 ± 0.017

Table 8: Various classification techniques and their corresponding accuracies

Classification Technique	*Accuracy (%)*
Fuzzy Particle Swarm Optimization (FPSO) andConvolutional Neural Network (CNN)[17]	95.62
MLP, SVM and KNN[20]	MLP - 95.40, SVM- 96.70, KNN- 95.30
Knowledge-based Collaborative Deep Learning[21]	91.6
2D Deep Convolutional Network[22]	97.20
Convolutional Neural Network (CNN)[23]	69
Transfer learning[24]	97.10
Stochastic diffusion search algorithm and Neural Networks[25]	89.63
ANN[26]	96.67
DTCNN and ELM[27]	94.57
Decision Tree and Support Vector Machine (SVM)[28]	DT-72 and SVM-75
3D Probabilistic Deep Learning and V-Net architecture[29]	87
VGG16, Res Net 50 and CNN[30]	97.9
Watershed Transform and GLCM[31]	87
Gaussian Blur, Inception-V3, Otsu Threshold, , Mobile Netand VGG-8[32]	97
3D and 2DCNN and HFFM[33]	Dice Score – 88.8
Laplace, Gaussian & Sobel filtering, Multilayer perceptron, SVM and KNN[34]	96.70
Knowledge-based Collaborative Deep Learning, U-Net and 3D-GLCM-SVM[35]	91.60
ELMand DTCNN[36]	94.57
Cancer Imaging Archive (TCIA)[37]	98.42
2D Convolutional Neural Network (2DCNN) and Regions with Convolutional Neural Networks (R-CNN)[38]	95.4
CNN, Deep Belief Network, Restricted Boltzmann Machine and Stacked Denoising Autoencoder[39]	82.2
coarse-to-fine convolutional neural network (CF-CNN)[40]	81.66
Support Vector Machine (SVM) and XGBoost[41]	79.7
3D DPN, 10-fold cross-validation and 3D Faster R-CNN[42]	81.42
Feature-Based Framework and Support Vector Machine[43]	90
Neighborhood gray-tone difference matrices and Spatial gray-level dependence matrices[44]	79.7
Faster R-CNN[45]	91.4
Spatial Interdependence Matrix, Visual Information Fidelity and OPF classification[46]	98.2
MC-CNN[47]	87.14
Morphological operations, ADAM and Semi-Supervised Multi-Task Learning[48]	91
Median Filter, Gaussian Filter, Watershed Segmentation and SVM[49]	92
1D Convolution Neural Network (CNN)[50]	96 +- 3
CNN, DNN and SAE[51]	84.15
CDD-CNN[52]	89.05
Context-Dependent Deep Learning (CDDL)[53]	92.97
COVIDetectioNet[54]	91.34
CNN-RN[55]	92.67
ResNeXt-50[56]	91.58
CNN-E[57]	92.54
CNN[58]	88.8
DCNN[59]	85
CNN, RNN and LSTM[60]	Pneumonia- 98.55, Tuberculosis- 97.99
EfficientNet[61]	94.3
CNN and SVM[62]	CNN - 95.2 , SVM - 93.7
LDDNet[63]	96.3
Fine-tuned ResNet50[64]	93.5

applied to eliminate noise in contrast-enhanced images. The segmentation method aimed to achieve precise ROI extraction while minimizing computational time. The model integrated conventional soft computing methods such as artificial neural networks (ANN), support vector machine (SVM), K-nearest neighbor (KNN), and Ensemble for detection and classification purposes. The paper concludes by proposing the integration of deep learning techniques, specifically recurrent neural network (RNN) using long short-term memory (LSTM), to develop a novel RNN-LSTM model for automatic detection and enhanced accuracy in lung disease diagnosis.

In Table 4, the achieved accuracy on the aforementioned datasets is presented, highlighting the performance of the RNN-LSTM algorithm. The scholarly article also explains the benefits of using the RNN-LSTM model, which demonstrated a commendable accuracy of 95.04% on the C19RD dataset and an impressive 94.31% on the CXIP dataset.

Orla M. and colleagues[10] utilized the IMRD UK EMR primary care database to create an innovative machine-learning model. They developed a gradient-boosting tree approach using bootstrap aggregation, which effectively captures and handles non-linear relationships, interactions, and missing data. The methodology prioritized important variables such as age, symptom timing (cough), treatments with macrolides and inhaled corticosteroids (ICS), and lung function tests (LFTs), with a primary focus on non-tuberculous mycobacterial lung disease (NTMLD). The most common pre-existing diagnoses and treatments among NTMLD patients included COPD, asthma, penicillin, macrolides, and inhaled corticosteroids. In comparison to random testing, the utilization of machine learning significantly improved the identification of NTMLD patients by a factor of one thousand, showcasing an impressive area under the curve (AUC) value of 0.94.

Murat Aykanat and co-authors[18] conducted a comparative study involving various algorithms to classify respiratory conditions. This research involved both text and audio data analysis. The dataset was collected using an electronic stethoscope and associated software, containing patient information and 17,930 lung sound samples obtained from 1,630 subjects. The team evaluated the performance of three algorithms - SVM, K-NN, and GB - for the task of classifying respiratory diseases. Additionally, X-ray images of different lung regions were integrated into the analysis to help identify affected areas. The researchers employed 18 distinct classification methods to categorize and examine the outcomes, and these detailed findings are presented in Table 5.

The SVM, K-NN, and GB algorithms were executed on six datasets, with the accuracy for each recorded. Table 6 illustrates the assessment of accuracy achieved across the six datasets.

Zheng B *et al.*[19] utilized a dataset of CT scans obtained from patients infected with COVID-19, which was collected by The Affiliated Hospital of Qingdao University. The dataset comprised multiple CT scans taken on different dates, and the patients' age ranged from 23 to 67 years. The proposed approach was implemented using the PyTorch framework and employed the MSD-NET algorithm.

To meet specific requirements, the existing U-Net model was adapted using the concepts of PCB, CAB, and RRB. The images were resized to dimensions of 512x512. To address potential over fitting due to limited datasets, various data augmentation techniques were employed, including random flipping and rotation. The Adam optimizer was used with an initial learning rate of 0.001. After every 100 epochs, the learning rate was gradually reduced by a factor of 0.1. The performance of the proposed model was compared against four widely-used medical image segmentation models: U-Net, U-Net++, U-Net+CBAM, and Attention U-Net. A comprehensive analysis of the results is presented in Table 7, where the evaluation metrics encompasses dice similarity coefficient (DSC), sensitivity (Sen.), and specificity (Spec).

The developed model underwent testing and comparison with various implementations for COVID-19 detection using CT scans images. Additionally, Table 8 lists the remaining models employed in different research domains related to the detection of lung diseases, comparing classification techniques based on accuracy as the evaluation metric.

CONCLUSION

In conclusion, the systematic literature review underscores the remarkable potential of machine learning techniques, particularly deep learning methodologies, in the domain of lung disease classification. The empirical evidence showcased within the review accentuates the exceptional performance of deep learning models such as CNN and LSTM, which have consistently achieved the highest levels of accuracy in discerning various lung diseases. Concurrently, the notable success of alternative machine learning techniques including SVM, RF, KNN, and Ensemble Learning underscores the diversity of tools available for effective lung disease classification. The judicious selection of a specific technique hinges upon the distinct exigencies posed by the classification task at hand, as well as the unique characteristics of the dataset being employed. While deep learning methods have proven their mettle, the pragmatic applicability of traditional machine learning approaches should not be underestimated, especially in scenarios with limited data availability or specific computational constraints. Furthermore, the review's insightful proposition of amalgamating multiple techniques or embracing hybrid paradigms to enhance classification robustness is a testament to the multifaceted nature of lung disease diagnosis. As the field advances, these innovative fusion strategies could potentially yield comprehensive and accurate results, catering to the intricacies of varied lung conditions. In light of the review's findings, future research endeavors stand to be greatly enriched by focusing on extensive validation exercises conducted on larger and more diverse datasets. Such endeavors would not only affirm the efficacy of the identified techniques but also unveil their adaptability across a broader spectrum of real-world scenarios. Additionally, the review's call to explore emerging methods and to establish standardized evaluation metrics and protocols is pivotal for the continued progression of lung disease classification studies. A unified framework for assessment will empower researchers to draw meaningful comparisons across studies, fostering a collective advancement in the field.

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