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Automated Detection of Pulmonary Pathologies through Deep Learning in Lung Ultrasound

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Abstract: The current surge in newly reported pulmonary diseases and the possibility of further epidemics necessitate the immediate development of a novel Deep Learning (DL) model to facilitate early diagnosis and treatment. Lung ultrasound (LUS) has the potential to detect symptoms of a pulmonary infection, based on growing evidence from various nations. Several characteristics of ultrasonic imaging make it well-suited for routine use: Small hand-held systems, unlike X-ray or computed tomography (CT) equipment, are easier to clean because they are encased in a protective sheath. LUS, on the other hand, enables patient triage in settings other than hospitals, such as tents or homes, and it can detect lung activity during the early stages of the disease while also monitoring affected patients at the bedside on a daily basis. This review paper discusses the potential applications of LUS imaging for disease segmentation and categorization. The paper investigates the open-access LUS dataset and examines image processing algorithms that could increase pulmonary disease detection and segmentation accuracy. We also discuss the many segmentation strategies available for LUS images. Next, we present the currently available DL approaches for LUS image categorization. This survey can be extremely beneficial to researchers struggling with disease diagnosis using LUS images, providing excellent advice on how to proceed with their investigation and determine the source of the problem.

Keywords: *Ultrasound Images, Pulmonary Disease, Deep Learning, Segmentation, Pre-processing, Benchmark Data, Accuracy*

1. Introduction

Lungs, which expand and contract to absorb oxygen and expel carbon dioxide, are critical components of the human body [1]. Pulmonary diseases (also known as lung diseases) are respiratory ailments that affect the lungs [2]. Both respiratory and pulmonary function, or the capacity to breathe and the efficiency with which the lungs work, can be affected by lung disease. A variety of lung disorders can be caused by infections with viruses, bacteria, and fungi [3]. Mesothelioma, asthma, lung cancer, and other lung diseases are all linked to environmental exposure [4]. Conditions like chronic bronchitis, Chronic Obstructive Pulmonary Disease (COPD), and emphysema are examples of chronic lower respiratory disorders. Chronic lower respiratory infections are a leading cause of death in the United States. Respiratory disorders such as asthma and COPD cause constriction or blocking of the airways, limiting airflow. Several lung disorders, including pulmonary fibrosis and pneumonia, impair the lungs' ability to hold air [5]. Cellular abnormalities are the underlying cause of lung cancer. Many incidences of lung cancer begin in the lungs, but occasionally, the illness metastasizes from elsewhere in the body. Small cell and non-small cell lung cancers originate and spread in distinct ways, and hence respond to treatment differently. Every year, lung cancer takes the lives of an incredible number of individuals. According to the statistics obtained, about 1.6 million people died in the year of the poll. One of the most frequent respiratory infections, pneumonia claimed the lives of 1.23 million kids younger than the age of five in 2020, based on the "Pneumonia and Diarrhea Progress Report 2020" [6]. Research from "The Global Impact of Respiratory Disease" conducted by the Forum of International Respiratory Societies estimates that 10.4 million persons experienced mild or severe tuberculosis indications, with 1.4 million losing their lives [7]. From December 2019, a new coronavirus disease (COVID-19) has caused significant lung damage and respiratory issues. Furthermore, COVID-19 is one of several viruses or bacteria that can cause pneumonia.

Overall, smoking cigarettes is the most common cause of lung cancer. Another risk factor for developing the illness is inhaling cigarette smoke [8]. Other environmental factors related to lung disorders are air pollution, radon gas, asbestos, and chemicals. Human lives can be saved, and survival rates improved if the aforementioned diseases are detected in their early stages of infection. Experts must be present to assess scanned images and diagnose ailments. According to data from the Union Health Ministry, rural Community Health Centers (CHCs) lack 75.1% of the doctors they need [9]. As a result, using DL algorithms allows for a novel approach. DL is a branch of artificial intelligence that deals with representation learning. The potential of this technology to take visual data, evaluate it, and then deliver insights based on previously trained data. DL algorithms can extract features and patterns from image

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datasets and then apply these features to categorize new test images that the model has never seen before. Extensive research has been conducted by scholars from around the world, with hopeful results. These works can strengthen existing approaches or open the path for previously unachievable ones. Improvements in this area have the potential to accelerate illness identification and categorization, resulting in the quick eradication of infectious diseases.

The paper is structured as follows: Section I discusses pulmonary disease and the need for DL in diagnosis. Section II outlines why we choose LUS over other modalities. Section III depicts the research flow of lung disease diagnosis with LUS images. Section IV discusses data acquisition and the necessary data processing steps. Sections V and VI describe the different approaches for segmentation and classification of LUS images. Section VII discusses the challenges of DL and LUS image processing. Section VIII concludes the survey.

2. Why Ultrasound Image

People all throughout the world are concerned about a lack of trustworthy tools for detecting and tracking lung illnesses. Chest X-rays and CT are the gold standard for detecting and monitoring specific lung illnesses [10]. However, ionizing radiation, which is essential to these modalities but can be harmful to patients in high doses or when used frequently, especially during continuous monitoring, is a major concern [11, 12]. One of the risks identified by the US Food and Drug Administration is an increased risk of acquiring cancer in later life. Young people are particularly concerned about radiation exposure because they are more vulnerable to its effects than adults. Furthermore, CT is both expensive and not usually available at the bedside. Invasive intracardiac hemodynamics and devices, biomarker measures, and chest X-rays are now used to monitor some disorders, such as pulmonary edema, that cannot be observed with CT.

Ultrasound technology may surpass the limitations of current monitoring systems by providing a more secure, portable, and cost-effective option [13]. To start, as a radiation-free diagnostic option, ultrasonography could be very helpful for patients experiencing many examinations, pregnant women, and kids. Second, because ultrasound equipment is so portable, patients in developing countries, rural areas, and other remote locales may have access to them. Third, the cost of ultrasound instruments and examinations is significantly lower than that of CT or MRI, allowing a larger range of facilities to adopt the technology and help more patients. As a result, ultrasonography is especially crucial for long-term healthcare concerns related to an aging population and rising chronic illness rates. Since the 1990s, there has been conjecture that ultrasonic imaging could provide useful diagnostic information regarding lung tissue [14].

In addition, there is no need to transfer the patient for LUS, thanks to the portability of ultrasound instruments, which could reduce the danger of infection that follows.

Acute lung damage, cardiogenic pulmonary edema, pneumonia, and other lung disorders can all be effectively evaluated with LUS [15]. Figure 1 depicts four frequent features used to detect various problems in LUS. The A-line represents a normal lung surface since air comprises most of a healthy lung. This artifact is a horizontal pleural reverberation effect that results from repeated reflections. As a consequence, A-lines are created when the visceral pleural plane reflects ultrasonic waves, which in turn cause acoustic reverberations across the skin surface and the pleural plane. The interlobular septum, or B-lines, is shown by a vertical hyperechoic artifact that extends from the top to the bottom of the screen, resembling a laser. The decrease in the air-to-tissue-to-fluid ratio causes the pleural plane to stop reflecting light, resulting in the formation of B-lines. This causes the pleural plane to show several isolated B-lines, which point to changes in the subpleural tissue. The pulmonary interstitial syndrome is visually represented by a wide region of B-lines in the intercostal space, which is also called fusion B-lines or B2-lines. Lastly, a liver-like echo pattern of the lung parenchyma, measuring 15.0 mm in thickness, is indicative of a pulmonary consolidation.

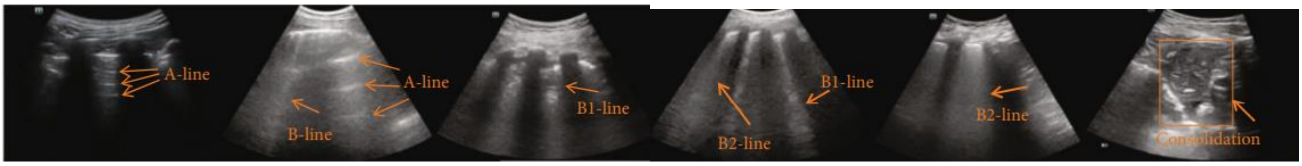

Fig. 1. LUS image features [16]

3. Pulmonary Diseases Detection Methodology

Pulmonary disease detection using LUS images is divided into two stages: segmentation and classification. In both stages, the first step involves image pre-processing to enhance the image quality to achieve better accuracy. Segmentation is performed to accurately predict the affected region, and it is based on two types: discontinuity and dissimilarity. For classification, the best option is a DL model to handle more complex tasks with reliable outcomes. Finally, the results of both segmentation and classification are evaluated to identify the best techniques. The methodology workflow is depicted in Figure 2.

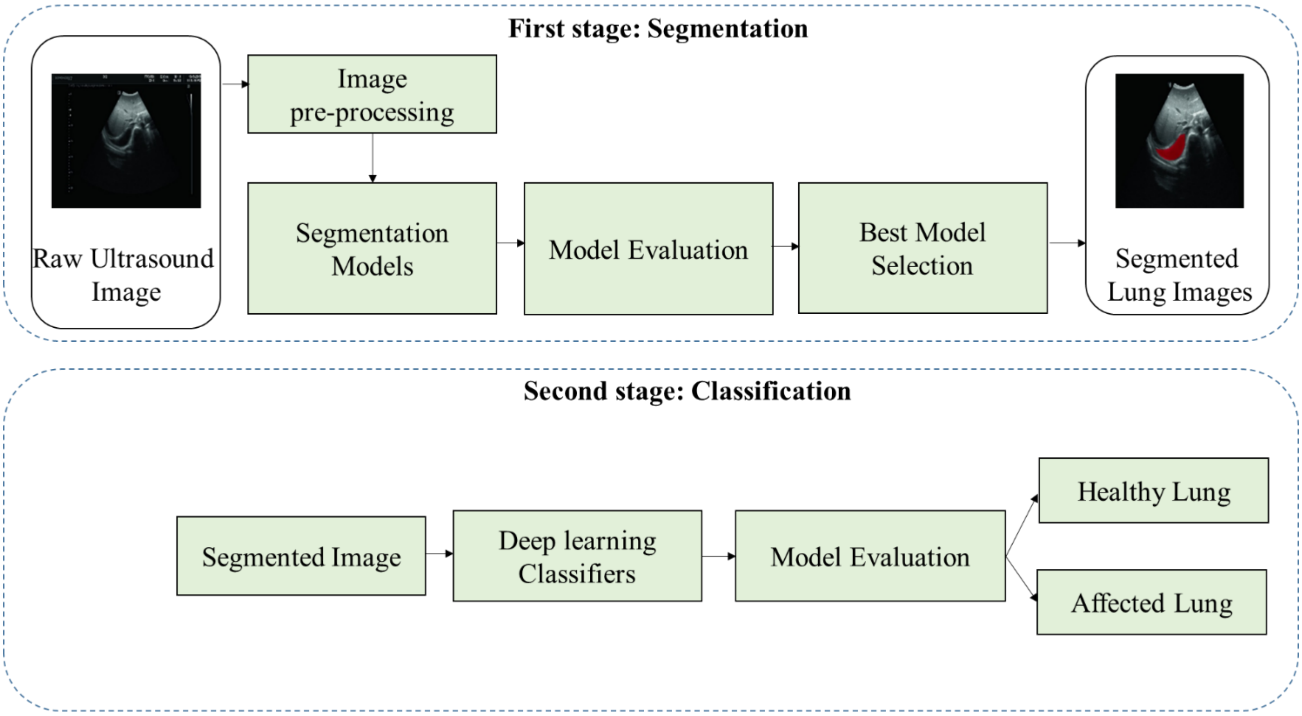

Fig. 2. Research flow of pulmonary disease detection.

4. Data Acquisition and Processing

The reliable data collection from a publicly accessible dataset and its processing are detailed in this section.

4.1. Data Collection

The accuracy of pulmonary detection results is highly influenced by the quality of the data used. There are two methods for gathering LUS image data: creating your own from hospitals or obtaining data from a website. This section gives an overview of the freely accessible dataset. Pneumonia, lung collapse, COVID-19, benign, and malignant pulmonary diseases are all included in these datasets. It is commonly advised, and often required, to use large datasets for AI training. Data samples from popular LUS datasets are summarized in Table 1.

Table 1: Public dataset of LUS images

Ref	Dataset	Disease	Samples
[17]	POCUS	COVID-19, Pneumonia, and Normal	654-C, 277-P and 172- N
[18]	Enlarged POCUS		33 images and 106 videos. 63-C, 34-BP, 7-VP and 35-N.
[19]	New POCUS		59 images and 202 videos.
[20]	ICLUS-DB	COVID-19, Normal	30 cases of COVID-19
[21]	Extended ICLUS-DB	COVID-19, Normal	277- Videos from 35 Individuals. 17-C, 4-SC and 14-N
[22]	COVIDx-US	COVID-19, pneumothorax, lung collapse and normal	173 ultrasound videos and 21,570 processed images of 147 patients
[23]	UDIAT	Benign and Malignant	163 US images, 110-B, and 53-M
[24]	BUSI		630 US images, 421-B and 209-M.

[25]	OASBUD		100 US images, 48-B, and 52-M.
[26]	RODTOOK		149 US images, 59-B, and 90-M
Note: N-Normal, C-COVID-19, P-Pneumonia, BP- Bacterial Pneumonia, VP- Viral Pneumonia, B- Benign, M- Malignant			

4.2. Data Processing

Preprocessing is required for proper image recognition and categorization. Preprocessing procedures are commonly used for the following applications:

- Data variability in model performance is decreased or eliminated by merging images from many datasets with different image sizes and acquisition parameters.
- Increasing the image contrast.
- Bringing the darker disease zone into sharper focus than in the original image.

According to the literature, the preprocessing stage consists of a wide range of actions and is depicted in Figure 3. The pre-processing sequence typically begins with image resizing, followed by transformation, encoding, filtering, normalization, and augmentation.

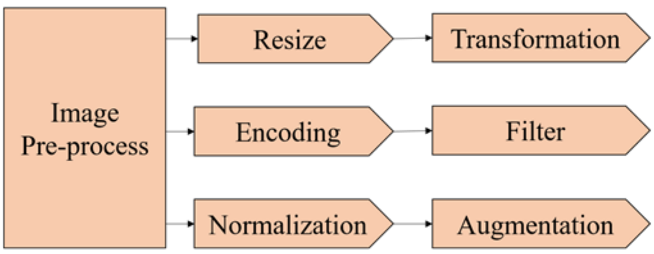

Fig. 3. LUS Image Pre-processing Steps

Resize: One of the first steps in preparing images for computer vision is to resize them to a consistent dimension. Various images may have different levels of detail, aspect ratios, and orientations, all of which might affect the model's accuracy and performance. Resizing images can lower the model's computational cost and memory use by reducing the number of pixels to process [27]. It is crucial to adopt an appropriate scaling method, such as nearest neighbor, bilinear, bicubic, or Lanczos interpolation, because resizing images might produce distortion, loss of clarity, or aliasing effects.

Transformation: Brightness transformations alter the brightness of pixels and are determined by their properties. The following are the most common operations for changing the brightness of pixels: Histogram equalization, sigmoid stretching, and gamma correction/Power Law Transform.

Encoding: A variety of image encoding techniques exist, including binary, grayscale, and one-hot encoding that can be used to transform the visual appearance of images. The model's processing and learning times can speed up by applying image encoding to reduce the input's complexity and dimensionality. Encoding images can also aid in the extraction of useful information and features such as edges, forms, and colors [28]. Thresholding, histogram equalization, and principal component analysis are some of the image encoding procedures and techniques accessible.

Filter: Applying a filter to an image allows you to change or improve its features while extracting vital information like blobs, edges, and corners [29]. A kernel is a tiny array applied to each pixel and its neighbors in an image to define a filter. It discusses some of the most basic filtering techniques. The majority of smoothing procedures begin with a low-pass filter. Averaging close pixels decreases pixel value discrepancies and smoothes out the image. A high-pass filter can make an image appear sharper. Unlike the low-pass filter, these filters emphasize the image's finer features. When computing an image's first derivatives, a directional filter, also known as an edge detector, might be useful. When there is a considerable value difference between two neighboring pixels, the slopes or first derivatives become most visible. Directional filters can target any direction inside a specific area. A Laplacian filter is a type of edge detector that monitors the rate of change in the first derivatives and then uses that information to calculate the image's second derivatives. This establishes whether the values of neighboring pixels change intermittently or at the boundary.

Normalization: Image normalization is a popular pre-processing approach in computer vision. This requires transforming the image's pixel values to a specific range, such as [0, 1] or [-1, 1] [30]. Image normalization improves model stability and convergence by lowering the volatility and skewness of the data distribution. Image normalization can improve an image's brightness and contrast, allowing the model to better differentiate edges and features. Batch normalization, z-score standardization, and min-max scaling are three methods for normalizing images.

Augmentation: By rotating, adding noise, cropping, shifting, scaling, or changing the hue, among other arbitrary manipulations, image augmentation can transform current photos into new ones [31]. Augmenting images can increase the quantity and variety of training data, which in turn improves the model's durability, generalizability, and decreases the likelihood of overfitting. Additionally, image augmentation can mimic a variety of real-life phenomena, including lighting, occlusion, and perspective shifts. The feasibility of offline versus online image augmentation is dependent on the data's availability and complexity.

5. Disease Segmentation

Image segmentation is a necessary step in any image analysis method. Segmentation is the process of separating an image into individual pixels [32]. The difficulty at hand determines the extent to which the separation is applied. When an application's target objects are no longer visible, segmentation must stop. Most image segmentation algorithms split images based on the similarity and discontinuity of intensity levels. Figure 4 illustrates the segmentation algorithms under similarity and discontinuity techniques.

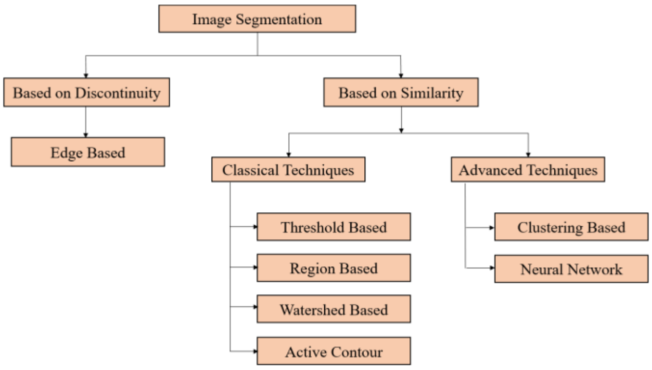

Fig. 4. Segmentation techniques for pulmonary pathologies detection

5.1. Based on Discontinuity

Discontinuity refers to sharp shifts or breaks in pixel values, such as the edges or boundaries of multiple objects or sections in an image [33]. Discontinuities are common in images with a significant shift in tone, color, or texture. The edges of objects or other scene features may line up with these changes. The primary purpose of discontinuity-based segmentation algorithms is to capture these rapid alterations. This method contains algorithms for detecting edges.

Edge-based: Edge detection is an essential part of image segmentation. Edge detection algorithms alter the grayscale of the source image to create edge images. Edge detection in computer vision and image processing is all about locating the important distinctions in a grayscale image and recognizing the geometrical and physical properties of the objects in the scene [34]. Recognizing the borders between items and the backdrop in an image, as well as their forms, is a fundamental process. When looking for big-intensity value discontinuities, edge detection is the most typical technique. Edge detection is a popular research topic because it enables more complex image processing. Grayscale allows you to view-point, line, and edge discontinuities. You can use spatial masks to detect all three types of image discontinuities.

Numerous edge detection algorithms are described in the image segmentation literature. Roberts, Prewitt, Kirsh, Robinson, Sobel, Marr-Hildreth, and Canny are a few examples.

5.2. Based on Similarity

Similarity-based segmentation is based on the idea that pixels in the same area or object tend to have similar qualities, like intensity, color, or texture [35]. The attributes of pixels should be identical if they are part of the same object or area. This method is predicated on the idea that homogeneity or similarity in terms of particular features can be used to identify regions of interest. Threshold, Neural Network (NN), watershed, region, active contour, and clustering are some examples of similarity-based segmentation methods.

Classical Techniques

The four classical techniques for segmentation, namely threshold, region, watershed, and active contour, are detailed below.

Threshold-based: Thresholding is the user-friendly, simple, and efficient segmentation technique for LUS images, as well as the most prevalent. It classifies image pixels directly into areas based on features (standard deviation, mean, intensity, color, and so on), using either a threshold or many thresholds [36]. Assume there is a threshold th that separates pixels in an image into two groups. Global thresholding is a method in which th remains constant throughout the image, whereas adaptive/local thresholding describes a method in which th varies based on local features. Global thresholding becomes ineffective in situations when there is poor object-background contrast, excessive noise, or inconsistent lighting. On the other hand, global thresholding works quickly and effectively when the background and object intensity distributions are sufficiently divergent.

Region-based: Based on the concept of homogeneity, this technique considers the fact that neighboring pixels within a region share similar characteristics but differ from pixels outside of that region [37]. The purpose of region-based segmentation is to extract a bigger, more uniform region from the image while minimizing outliers. Regardless of how homogeneous the zones are, there is a way to detect major changes in the characteristics of the pixels around them. The simplest technique to segment the image using the similarity assumption is to compare each pixel to its neighbor and check for similarities. A single pixel is "added" to an existing pixel, just as a region is "grown" when the conclusion is positive. When the likeness test produces an inaccurate result, growth is halted. Region-based approaches can be divided into two categories: Methods for developing regions as well as splitting and merging them.

Watershed-based: The watershed transformation is a typical image segmentation method for grayscale images that treats an image's gradient magnitude as a topographic surface. Watershed lines serve as region boundaries and are represented by pixels with the highest gradient magnitude intensities [38]. When precipitation falls on any pixel inside a shared watershed line, it finally reaches a common local intensity minimum. A segment is represented by a catch basin, which is built up of pixels that drain to the same minimum. Grayscale images can be viewed as topographic reliefs, with each pixel's grey level reflecting its height within the relief. As a raindrop descends on a topographic relief, it finally reaches a local minimum. To the untrained eye, the borders of neighboring raindrop catchment basins reveal the relief's watershed. Various types of watershed lines can be computed using image processing. Graphs can define watershed lines using nodes, edges, or a mix of the two. The continuous domain can also be used to establish watershed boundaries. Additionally, there are several watershed computation algorithms.

Active Contour: Image segmentation and Active Contour models have a long history of collaborating. Many applications, including image segmentation and motion tracking, have made substantial use of it over the last ten years. Under certain image constraints, active contour seeks to alter an initial curve to the object's borders [39, 40]. From an implementation standpoint, active contour investigates two fundamental models: level sets and snakes. Snakes employ a predetermined movement pattern to conserve energy. The contour is moved particularly in a level set using a certain degree of function. To begin, active contour models can be quickly constructed using a systematic energy minimization approach, allowing for the consolidation of several prior knowledge sources. Second, as a segmentation output, they can generate simple, smooth, and closed contours that can be easily applied to other applications such as form analysis and recognition. Because of its speed and efficacy in detecting object boundaries, the active contour method was frequently used for image segmentation.

Advanced Techniques

The two advanced techniques for segmentation, namely clustering, and neural network, are detailed below.

Clustering Based: Clustering is the most used method because most image pixels lack labels. Clustering methods are often classified in two ways: hierarchical and partitional, depending on how the clusters arise [41]. Hierarchical clustering groups data at various levels of similarity using a dendrogram, which is a tree-like structure. The most frequent ways of hierarchical splitting are agglomerative and divisive. Partitional clustering is a more popular and preferred method than hierarchical clustering, especially for large datasets, due to its processing efficiency. This clustering algorithm uses similarity as a measure. In a typical partitional clustering situation, data items are divided into clusters based on an objective function, to increase the similarity of data items inside each cluster. This is performed by comparing each data item's similarity to each cluster. The aim function in partitional clustering is frequently the minimization of the within-cluster similarity criterion, which is usually determined using the Euclidean distance. Each created cluster is assessed using the objective function, which returns the best representation. There are two types of partitional clustering algorithms: soft clustering and hard clustering.

Neural Network: The sophistication of image features and object differences (such as size and posture) has increased significantly with the advancement of image-collecting technologies. Because of the complexity of modern image segmentation and the difficulty of extracting useful information from low-level features (such as color, brightness, and texture) using feature extraction methods based on manual or heuristic rules, there is a growing demand for image segmentation models with greater generalizability [42]. Before the introduction of DL, image segmentation frequently used random forests and semantic texton forests to construct semantic segmentation classifiers. The segmentation effect and performance have improved significantly in recent years as DL algorithms are increasingly used in segmentation activities. The initial method used pixel classification with an NN trained on small parts of the image. This patch classification method was utilized since the NN's fully connected layers require images of a specific size. The accessible NNs include LeNet-5, AlexNet, DenseNet, UNet, Inception, ResNet, Spatial Pyramid Pooling Net, Long Short-Term Memory (LSTM), DeepLab, Recurrent Neural Network (RNN), feature pyramid network, and VGG [43-45].

6. Disease Detection using DL Model

DL models outperform more conventional ML algorithms in terms of accuracy. It has several applications, but image classification is one of its primary ones. The identification of novel DL network topologies and advancements in technology have led to an enormous rise in the accuracy and reliability of DL models used for categorizing images in recent years. Some of the most commonly used DL models for pulmonary disease prediction are presented in Figure 5.

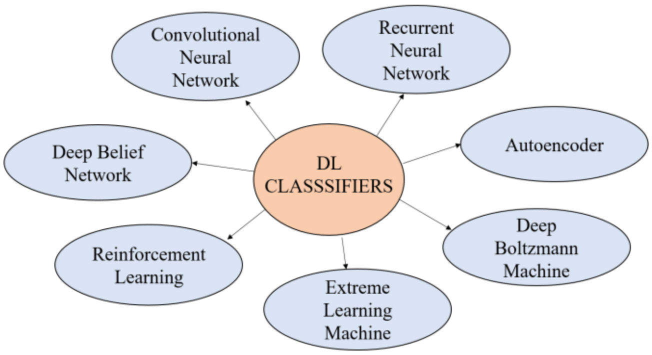

Fig. 5. DL Classifiers for Pulmonary Pathologies Detection

Convolutional Neural Network (CNN)

CNNs are the foundation of image classifiers. CNNs are a subset of NNs with similar layer designs. CNNs have four layer types: pooling, fully connected, ReLU, and convolutional [46]. An image classifier makes use of these layers to assign labels to images. The convolutional layer extracts image features by scanning filters. The ReLU layer corrects all negative values to zero. Increasing the model's non-linearity is the goal. One way to reduce the size of an image's file while simultaneously enhancing calculation speed is by using pooling layers. Max pooling is the most popular approach since it takes the maximum value from each subregion. Finally, a completely connected layer is utilized by the CNN. It gathers all the data, sorts it by importance, and then finds the final category.

RNN:

Typically, RNNs are trained using data that is given in a sequential or time-series format. Ordinal or temporal challenges that utilize these DL approaches include language transformation, speech identification, and image captioning, among others [47]. Similar to Feed-Forward Neural Networks (FFNN) and CNNs, RNNs acquire new knowledge through training data [48]. The information they've stored in their "memory" can affect both the current input and its result. The three main categories of RNNs are Bi-directional-RNNs, LSTMs, and GRUs.

Deep Autoencoder (AE):

There is a type of NN called an AE that can learn how to describe raw data in a compressed way. The encoder and the decoder are the two main components of an AE [49]. The input is compressed by the encoder, and then an attempted reconstruction of the original input is done using the compressed version by the decoder. The encoder model is retained after training while the decoder is eliminated. The next step is to train another AI model using the encoder's features extracted from raw data.

Deep Belief Network (DBN):

DBNs, a subtype of DL algorithms, overcome the difficulties associated with standard NNs. This is accomplished through the use of stochastic latent variable layers that make up the network. Binary latent variables, such as feature detectors and hidden units, are referred to as stochastic since they can take on any value within a certain range. After the first two levels of a DBN, there is no direction at all, although there are directed connections to the layers below. DBNs differ from more traditional NNs in that they can be both generative and discriminative models. Another distinction between DBNs and other DL networks, such as Restricted Boltzmann Machines and AEs, is that they do not use raw inputs. Rather, they begin with an input layer that employs one neuron for each input vector, iterating through several levels, and then, in the final layer, they use the activations of the preceding layers to calculate output probabilities [50].

Deep Boltzmann Machine (DBM)

A DBM is a model that includes additional hidden layers and non-directional connections between nodes [51]. DBM learns features from raw data through a hierarchical technique, applying them as hidden variables to each subsequent layer. DBM, like DBN, uses a Markov random field to pre-train each layer for the large unlabeled data set, with the upper layer feeding back to the lower levels [52]. Backpropagation is used to alter the training algorithm. The training information, weight initialization, and adjustment parameters must all be defined during the DBM training process. When the parameters are set to their ideal values, the DBM predicts that temporal complexity constraints will arise.

Extreme Learning Machine (ELM)

The ELM, with its strong generalizability and lightning-fast processing speed, is a popular and effective classifier with several applications [53]. ELM is a version of FFNNs in which the neurons in the input and hidden layers are randomly assigned. ELM training is much faster than typical DL approaches since it eliminates the need for gradient-based iterative adjustments. Immediate optimization of the resultant mapping matrix is possible after hidden node biases and input weights are generated at random. Its theoretical demonstration of universal approximation powers was successful. ELM demonstrated effectiveness in both supervised and unsupervised learning contexts [54].

Reinforcement Learning (RL):

RL is one potential technique for addressing image classification challenges. RL is based on the concept of an agent learning to maximize a reward signal through trial and error as it interacts with its environment. To accurately identify images, RL algorithms must first learn to prioritize features and determine which actions to take. In image classification, the state representation includes encoding the raw pixel values into a format that the RL agent understands. CNNs are commonly used methods for extracting relevant features from images. The agent may choose to pick specific regions for further research, modify features, or focus on specific spots within an image. Designing a suitable reward function is critical. It might be determined by how effectively images are identified; more incentives would be given for correct classifications, while penalties would be paid for incorrect ones [55]. The optimum strategy for image categorization is discovered using RL algorithms such as Q-learning, Deep Q Networks (DQN), or Policy Gradient techniques. Several recent works on pulmonary disease using LUS images are given in Table 2.

Table 2. Survey on recent research on pulmonary disease using LUS images

Ref	Data	Disease	Pre-processing	Segmentation	Classification	Metrics
[56]	POCUS	COVID	Resize, Crop, Augmentation	-	InceptionV3	Pr-91.85% Re-91.35% F1-91.35%
[57]	San Matteo Hospital	COVID	Resize, Color Transformations, Augmentation	-	ResNet50	Ac-99% Pr-99.4% Re-98.93% F1-98.94%
[58]	Own	COVID	Noise Reduction, Augmentation	V-U-Net	-	DICE-0.8632
[59]	POCOVIDNet	Pneumonia and COVID	Resize, Augmentation	U-Net	U-Net	mIoU-0.711 Ac-84.9% Pr-82.2% Re-79.2% F1-80.5%
[60]	COVIDx-US	COVID	Augmentation	-	COVID-Net US-X efficient neural network	Ac-84.6% AUC-82.8%
[61]	COVIDx-US	COVID	Filter	-	Hybrid (Inception-V3 and GRU)	Ac-94.44% Re-93.75% Pr-95.45%
[62]	COVIDxUS	Pneumonia and COVID	Video Extraction, Normalization, Augmentation	-	SqueezeNet	Ac-99.75% Re-99.4% Pr-99.6%

[63]	Royal Melbourne Hospital	pleural effusion	Color Conversion, Crop, Resize	-	Regularised Spatial Transformer Network	Ac- 92.4%%
[64]	Own	Abnormal Lung Parenchyma	Augmentation	-	VGG-16	Au- 88.2% Pr- 88.85% Re- 83.5% F1- 86.05%
Note: Ac- Accuracy, Pr-Precision, Re-Recall, F1-F1 Score, mIoU- mean Intersection over Union						

7. Challenges and Solutions

DL algorithms for the segmentation and classification of pulmonary disease have been nearly successful; nonetheless, significant challenges have to be overcome. This section focuses on various open challenges.

Insufficient Data:

Predicting pulmonary diseases demands a vast amount of data for effective training and reliable evaluation. One alternative is to utilize data augmentation techniques to artificially expand the dataset size. Another method is to leverage lessons from models trained on larger datasets to smaller ones. The third strategy, which combines the prior two, overcomes the problem of small samples.

Image amplification for segmentation:

As previously stated, data amplification is a popular technique in segmentation and classification to address the issue of limited datasets. These strategies involve manipulating data to generate more training data for DL models. However, the effectiveness of these techniques is influenced by the quality and diversity of the initial dataset. Additionally, before using the generated samples to train DL models, they must be validated for suitability. Data amplification, synthesis, and generative approaches are key components in training DL models for plant pest identification.

Annotation Bias

"Annotation Bias" refers to the difficulty of manually segmenting tumor regions when multiple medical practitioners or radiologists provide different annotations. The reported findings could be attributed to variations in the background, comprehension, or subjective biases of the annotators. The author [65] suggests that training and evaluating DL models for anomaly segmentation may encounter difficulties if the annotations produced contain errors or inconsistencies. To tackle this problem, it is necessary to collect annotations from a diverse range of experts, authenticate them, and subsequently subject them to thorough editing and revision to guarantee both consistency and accuracy.

Limitation in DL

DL holds significant promise for computer vision applications; however, three major drawbacks need addressing. First, an inadequate understanding of the disease's biology can lead DL models to make incorrect diagnoses, highlighting the limitations of our current knowledge of the disease. Second, due to a lack of diversity in the training data, the model's performance can be subpar in certain groups, emphasizing the importance of representative datasets. Third, computing demands, bias, overfitting, and insufficient generalizability pose additional challenges in image-based diagnosis.

Moreover, the explainability of the model becomes crucial in image-based disease detection, given the sometimes complicated and hard-to-interpret data. Despite DL's great potential, the production, development, and deployment of DL models necessitate a thorough examination of these constraints.

Data Privacy and Security:

Medical data, particularly ultrasound images, are subjected to strong privacy restrictions due to the delicate nature of the content. An essential consideration revolves around the secure interchange and examination of such data for scientific objectives. It is possible to train models using decentralized datasets and explore federated learning without the need to transfer raw data. To safeguard patients' privacy during the construction of the model, privacy-preserving methods such as homomorphic encryption can be employed, allowing for secure computation of encrypted data.

Imbalance Class

If the dataset is imbalanced, and some diseases are underrepresented, biased models may exhibit strong performance in the majority class but perform poorly in minority classes. Employing generative models like Generative Adversarial Networks (GANs) or using data augmentation approaches can assist in achieving class distribution parity. Another option is to employ oversampling techniques for minority classes. These methods enhance the model's capacity to generalize by providing a comprehensive representation of all classes.

8. Conclusion

DL is a promising method for addressing challenging healthcare problems. DL has demonstrated excellence in disease detection through preprocessing, feature extraction, selection, categorization, and segmentation. This study evaluates the technical characteristics of DL architecture in the context of pulmonary disease segmentation and classification using LUS images. The number of articles on DL-based pulmonary disease detection using LUS images has steadily increased. However, there is a lack of comprehensive research papers in this field. This study aims to fill this knowledge gap by conducting a thorough literature review on DL for pulmonary disease detection from 1990 to 2023, reviewing a total of 65 articles. The paper describes the collection of open-access LUS data for pulmonary disease and provides detailed insights into various preprocessing stages such as resizing, normalization, encoding, transformation, and augmentation. It facilitates a reliable examination of pulmonary disease segmentation based on the similarity and discontinuity of LUS images, discussing promising approaches under both methods. The available DL architectures for the classification of normal and affected lungs are described in detail. Challenges like insufficient data, annotation bias, data privacy and security, class imbalance, etc., are explained, and potential solutions are suggested. In conclusion, investigating how DL has been utilized in pulmonary disease diagnosis is crucial to ensure that future research remains on track and improves the efficacy of disease detection systems.

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