A Systematic Review on Deep Learning Technique Based Lung Disease Classification and Detection

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Abstract- This paper presents a comprehensive survey of deep learning techniques applied to the detection of lung diseases in medical images. While several studies have been conducted on this topic, there is a lack of surveys that provide taxonomy and analyze recent trends in the field. The objectives of this paper are to establish taxonomy of state-of-the-art deep learning-based Lung disease systems, visualize recent research trends, and identify remaining challenges and potential future directions. A total of ninety-eight articles published from 2016 to 2022 were reviewed and analyzed. The taxonomy comprises seven common attributes found in the surveyed articles, including image types, features, data augmentation, types of deep learning algorithms, transfer learning, ensemble of classifiers, and types of lung diseases. This taxonomy can serve as a valuable resource for researchers to plan their contributions and guide future research activities. Moreover, the identified potential future directions can lead to further improvements in the efficiency and expand the range of deep learning-aided Lung detection applications.

I INTRODUCTION

Diseases of the airways and the other components of the lungs are referred to collectively as lung diseases or respiratory disorders [1]. Lung-related illnesses include pneumonia, tuberculosis, and Corona virus Disease 2019 (COVID-19). About 334 million individuals worldwide have asthma, according to the Forum of International Respiratory Societies [2]. In addition, 1.6 million people die from lung cancer each year, 1.4 million people die from tuberculosis, and millions more die from pneumonia. Millions of people were infected as a result of the global Lung Disease epidemic, which also put a pressure on the healthcare system [3-4]. Lung diseases are among the leading causes of death and disability on this planet, which should come as no surprise. The likelihood of a patient achieving a full recovery and living a longer life depends on how quickly the condition is identified [5,6]. Skin tests, blood tests, sputum sample tests, chest X-ray exams, and computed tomography (CT) scan exams are some of the classic techniques used to diagnose lung illness [7, 8]. When used to medical images with the goal of identifying illnesses, deep learning has lately shown tremendous potential. Lung disease is one of these conditions.

The term "deep learning" refers to a subfield of machine learning that involves the creation of algorithms motivated by the brain's own structure and function. This newfound ability to recognize, quantifies, and classifies patterns in medical images is made possible by recent developments in machine learning, particularly deep learning. [9]. such advancements have been particularly helpful in the medical imaging field. Deep learning makes it feasible to learn features only from data, rather than having to manually construct features based on domain-specific expertise. These advancements would not have been possible without deep learning's capacity to do this. Deep learning is rapidly becoming the most cutting-edge technique available, which is resulting in enhanced performance across a wide range of medical applications. As a consequence of this, these developments let clinicians recognize and categories certain medical disorders more effectively [10].

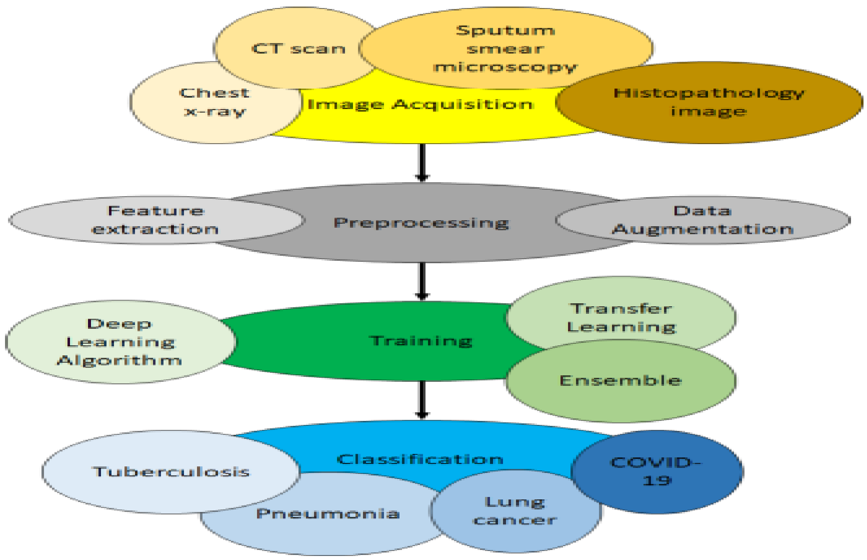

Figure 1. Overview of using deep learning for Lung disease detection

Numerous articles in the literature explore the use of deep learning for Lung disease diagnosis. To the best of our knowledge, however, in the previous five years there has been published only one survey report that assesses the state-of-the-art work in this field. [11]. in that particular piece of research, both the origins of deep learning and some of its more recent uses in pulmonary imaging are discussed. The article also describes major uses of deep learning techniques on a variety of lung ailments, including pulmonary nodule disorders, pulmonary embolism, pneumonia, and interstitial lung disease. In addition, this article presents an examination of many common deep learning network architectures that are employed in medical image processing. Their survey, on the other hand, does not adequately give taxonomy or conduct an analysis of the developing trend in recent work. Taxonomy is a classification system that illustrates the relationships between different bodies of work and sorts them into groups based on the characteristics that have been recognized as having the potential to enhance the reader's comprehension of the subject matter. The direction of future research in a certain field can be gleaned from an examination of existing literature, which is what trend analysis does. This study provides a classification of deep learning applications for pulmonary diseases as well as an analysis of current trends in this field. Persistent issues are also addressed, along with future possibilities.

This study aims to accomplish the following goals: Our goals are to: (1) create a taxonomy of the present state-of-the-art deep learning based Lung disease detection systems; (2) visualize the patterns of recent work in the subject; and (3) identify the remaining problems and outline probable future techniques in this domain.

II LITERATURE SURVEY

In this section, the technique of how deep learning is applied to diagnose lung disorders from medical photographs is detailed. The images used in this procedure are from the medical field. Image preprocessing, training, and classification make up the bulk of the procedure. Classifying photographs of lungs into those depicting healthy lungs and those depicting lungs infected with disease is a common method for disease detection. The Lung disease classifier, also known as a model, can only be learned by training. When a neural network is trained, it learns to identify images that belong to a particular class. The use of deep learning allows for the training of a model with the capability of assigning class labels to images. Gathering photos of lung tissue that is affected by the ailment to be recognized is the first step in using deep learning for lung illness identification. The next thing that needs to be done is to teach the neural network how to identify different diseases. The final stage is to assign categories to newly acquired pictures. In this step, the model is presented with fresh photos that it has never seen before, and it is asked to make a prediction regarding the class of those images.

Image Acquisition Phase

Obtaining photographs is the initial step in the process. In order to generate a categorization model, the computer will need to learn from previous examples. In order to identify an object, the computer must examine a large number of pictures. Deep learning models can be trained using a variety of different forms of data, including speech data and time series data, for example. In the context of the research that is discussed in this article, the relevant data that is necessary to diagnose lung illness will be photographs. A chest X-ray, a CT scan, a sputum smear microscopy, and an image from histopathology are all examples of images that could be used. Images that will subsequently be utilized to train the model are what this stage ultimately produces as its output.

Preprocessing Phase

The preprocessing phase comes in at number two. In this case, the image might be enhanced or changed so that the overall image quality is improved. It is possible to apply Contrast Limited Adaptive Histogram Equalization, often known as CLAHE, in order to make the images more contrasty.Image modification techniques such as lung segmentation [12-13] and bone elimination [14] could be utilized in order to define the region of interest (ROI), which would then allow for the diagnosis of Lung disease to be carried out on the ROI. The detection of edges is another method that might be employed to create an alternative data representation [15]. The photos could have data augmentation added to them in order to obtain a greater quantity of the data that is now available. The process of feature extraction might also be carried out so that the deep learning model could recognize significant features that are used to identify a certain object or class. The outcome of this stage is a collection of photos, each of which has either had the quality of the image improved or had any undesired things eliminated. Images that have been improved or altered and which will subsequently be utilized in training are the product of this stage.

Training Phase

In the third and last stage, training, three more factors may be considered. These features include, for instance, the choice of a deep learning algorithm, the use of transfer learning, and the deployment of an ensemble. Besides the convolutional neural network (CNN), there are other deep learning algorithms including the deep belief network (DBN), multilayer perception neural network (MPNN), and recurrent neural network (RNN). The complexity of algorithms causes vast variation in their learning processes. Certain algorithms are more effective when used with particular sorts of data. CNN is especially effective when dealing with visual content. The type of data that is now available should determine which deep learning method is selected. Transfer learning refers to the process of applying knowledge obtained from one model to another. The term "ensemble" is used to describe the practice of utilizing many models in the classification procedure. Training time can be reduced, classification accuracy can be improved, and overfitting can be minimized by employing transfer learning and ensemble [16].

Classification Phase

The fourth and last part of the process is called classification, and it involves the trained model making a prediction about which class an image belongs to. For instance If a model is trained on X-ray photographs of healthy lungs and images of tuberculosis-infected lungs, then it should be able to correctly classify new photos (photos that the model has never seen before) into the same two categories. This is because the model has been taught to recognize the difference between the two categories of pictures. The model will assign the image a likelihood score. The likelihood score indicates the degree to which an image is most likely to be associated with a specific class. Once this process is complete, the image will be labeled based on the models predicted probability score.

The Taxonomy of State-of-The-Art Work on Lung disease Detection Using Deep Learning

This section provides a classification of the existing literature on the use of deep learning for the diagnosis of lung illness. The study's initial contribution is this classification scheme. The goal of the taxonomy is to distil the key ideas and main points of the prior work and present them in a more coherent framework. The taxonomy will now include these seven qualities as part of its classification system. These characteristics were selected because they are ubiquitous and can be found in all of the articles that are being analysed for this survey. Image kinds, features, data augmentation, types of deep learning algorithms, transfer learning, the ensemble of classifiers, and types of lung diseases are the seven attributes that are covered in the taxonomy.

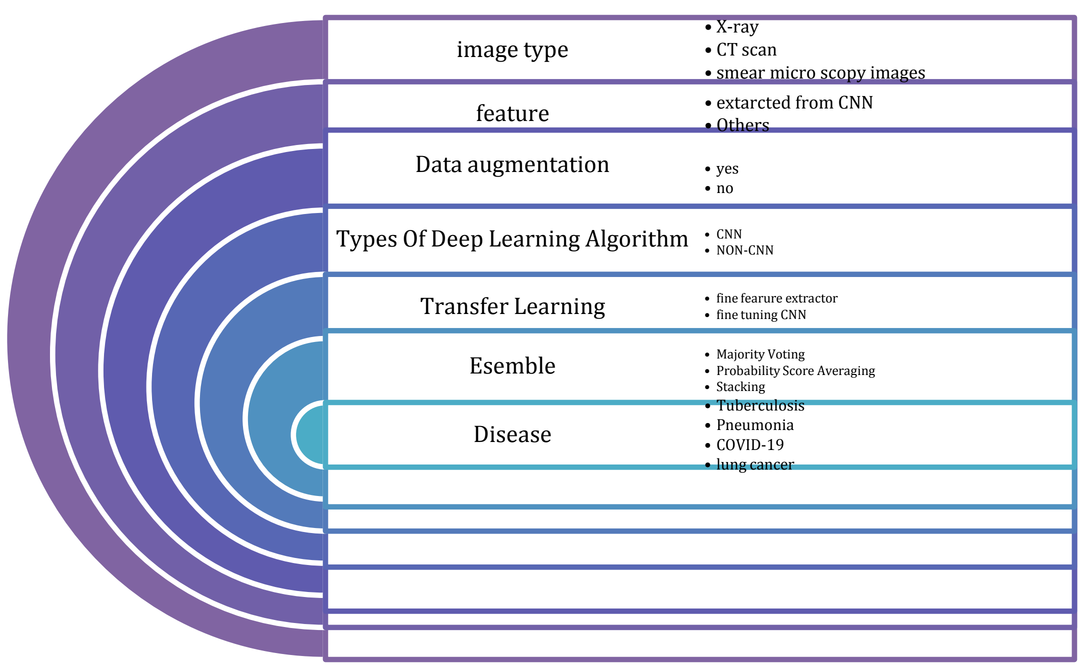

Figure 2. Taxonomy of Lung disease detection using deep learning.

Image Type-In the publications that were analysed, four different kinds of images were utilized to train the model. These included images from sputum smear microscopy, chest X-rays, and CT scans. Histopathology images were also included. It is important to highlight that in addition to positron emission tomography (PET) and magnetic resonance imaging (MRI), there are other imaging methods available. Both positron emission tomography (PET) and magnetic resonance imaging (MRI) scans have the potential to diagnose medical disorders and assess how well ongoing treatment is working. On the other hand, none of the articles that were analysed made use of PET or MRI scans.

Chest X-rays-X-rays are a useful diagnostic tool that can aid in the diagnosis and treatment of many different medical disorders [17]. The most common type of medical X-ray examination is the chest X-ray, which provides pictures of the heart, lungs, airways, and spine in addition to the chest bones. In the past, capturing X-ray images for medical purposes required exposing photographic films, which then had to be processed before the resulting images could be examined. Digital X-rays are employed, rather than traditional ones, so that this issue can be resolved [18]. Figure 11 displays numerous instances of chest X-rays taken from a variety of datasets, each of which depicts a different lung disease.

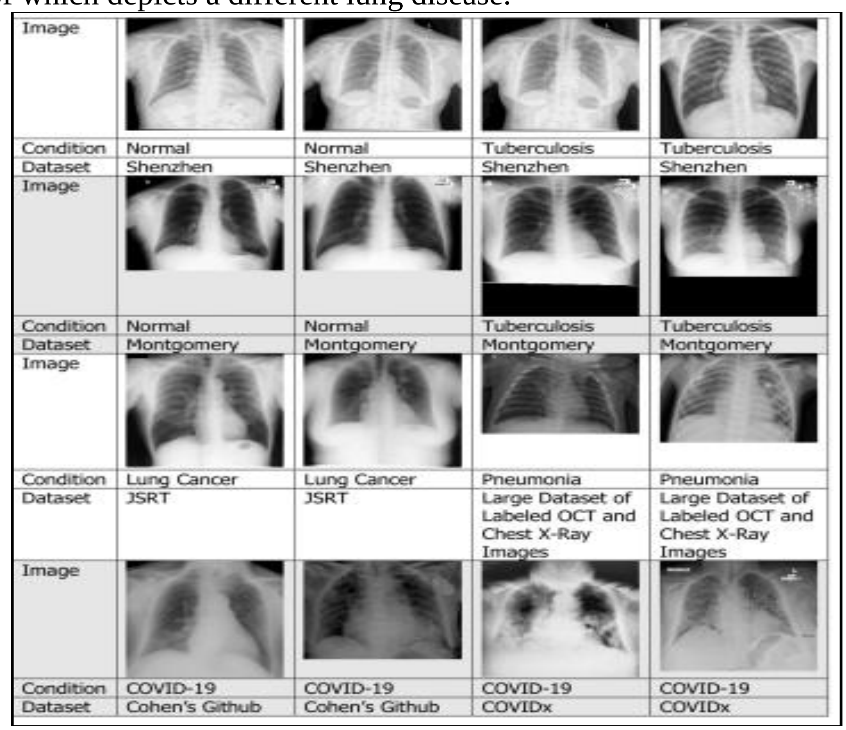

Figure3 Examples of chest X-ray images.

The vast majority of the analysed studies made use of chest X-rays in their research. X-rays were utilized in the diagnosis of a variety of conditions, such as tuberculosis [19], pneumonia [20], lung cancer and Lung Disease.

CT Scans-Computer processing power is used in computed tomography (CT) scans to create cross-sectional images at different planes of depth from 360-degree panoramic photographs of the patient's body. the picture slices can be displayed one at a time, or they can be layered to form a three-dimensional representation of the patient [20]. This image will display the patient's tissues, organs, skeleton, as well as any anomalies that are present. Images obtained from a CT scan provide viewers with greater levels of detail than those from an X-ray. Examples of CT scan pictures derived from a variety of datasets are presented in Figure 3. Numerous studies that can be found in the body of published research have made use of CT scans in order to diagnose lung disease. For instance, CT scans have been used to diagnose tuberculosis, lung cancer [21], and Lung Disease.

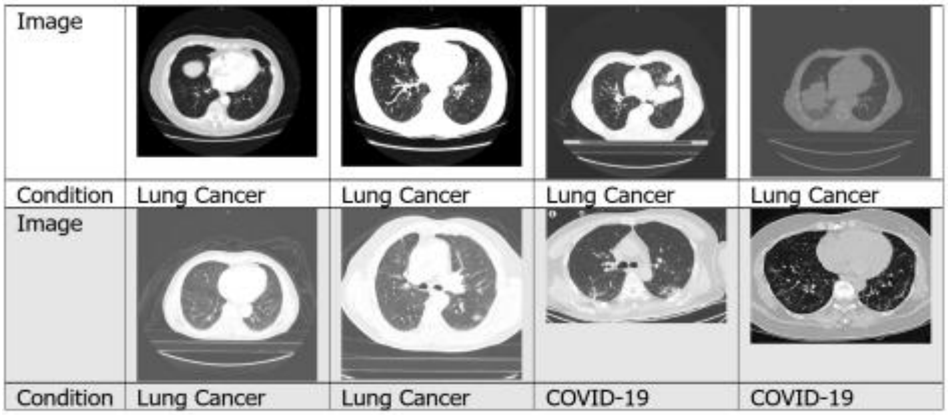

Figure 4. Examples of CT scan images

Sputum Smear Microscopy Images

Lungs and respiratory airways create viscous fluid called sputum. Spreading a thin layer of the sputum sample on a glass slide is what's called a sputum smear [27]. Only five of the included studies [22] really used microscopy images of sputum smears. Sputum smear microscopy images are shown as Figure 5 below.

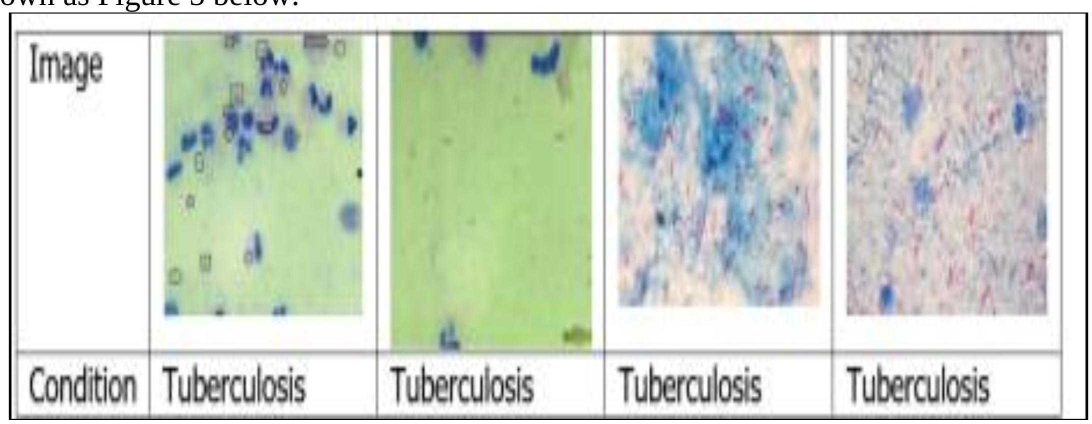

Figure 5. Examples of sputum smear microscopy images

Histopathology Images

Histopathologists examine biopsies and surgical specimens under a microscope on glass slides to learn more about the causes and manifestations of disease. This can be done in both diagnostic and investigative settings. In order to make the various components of the tissue more easily visible, the sections are stained with either one or many stains [23]. A few illustrations of histology are presented here in Figure 6. Only one of the publications that were looked at, by [24], made use of histopathology photographs.

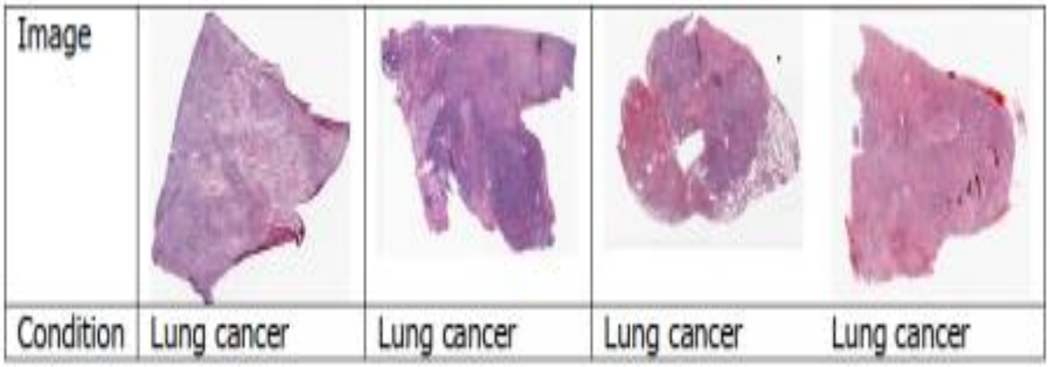

Fig.6 histopathology images

Features-In the field of computer vision, a feature is a significant piece of information taken from an image and expressed as a set of numerical values that can be applied to the resolution of a particular problem [25]. Depending on the type of feature, it could take the form of a particular structure within the image, such as a point, edge, colour, size, shape, or object. It just makes sense that the different kinds of photos would have an impact on the overall quality of the features. A procedure that generates new features by utilizing already defined features is known as feature transformation.

There is a possibility that these new features will not have the same level of representation as the original features did; but, there is also a possibility that they will have a greater capacity for discrimination in a different space than the original space. The goal of feature transformation is to supply an algorithm for machine learning that is used for object recognition with a feature that is more valuable to the algorithm. Features such as Shape features such as primitive length, edge frequency, autocorrelation, size, orientation, bounding box, eccentricity, extent, centroid, scale-invariant feature transform (SIFT), regional attributes area, and accelerated Additionally, Gabor, GIST, Local Binary Patterns (LBP), Tamura Texture Descriptor, Colour and Edge Direction Descriptor (CEDD), Hu Moments, Colour Layout Descriptor (CLD), Edge Histogram Descriptor (EHD), Pyramid Histogram of Oriented Gradients (PHOG), Histogram of Oriented Gradients (HOG), Intensity Histograms (IH), Shape Descriptor Histograms (SD)curvature descriptor histograms (CD), and fuzzy colour and texture histograms (FCTH) are all histogram-based representations of features. Some studies even segmented lungs before using those data to train their models. Most of the studies examined in the prior research used CNN features that were created automatically from the data. Since CNN can learn and extract features automatically, no human labour is needed in the creation of features [26].

Data Augmentation-The scientific community is in agreement that having more images can assist in improving the accuracy of training, which is why it is essential to have a large training dataset while working with deep learning. When compared with a powerful algorithm that only uses a little amount of data, a weak algorithm that uses a substantial amount of data can achieve a higher level of accuracy [27]. An additional barrier is the uneven distribution of classes. In the process of training for binary classification, if the number of samples belonging to one class is significantly higher than the number belonging to the other class, the model that is produced will be biased. When there is an equal or balanced distribution of samples across all classes, performance of deep learning algorithms is at its peak.

Utilizing picture augmentation is one technique to enhance the size of the training dataset without having to acquire additional photos. The original photographs are altered in some way to produce the augmented versions. This can be accomplished by employing a variety of processing techniques, including as rotating, flipping, translating, zooming, and adding noise Figure 7 displays several examples of photos that have been enhanced in some way.

The amount of useful data in a dataset may also be helped along by data augmentation. Take, for instance, a dataset about cars that consists of two labels: X and Y. One of the subsets of the dataset contains pictures of automobiles with the label X, but they are all oriented to the left. The other group has pictures of cars with the designation Y, but every single one of them is turned to the right. Following training, a test image of an automobile with the label Y that is turned to the left is given into the model, and the model assigns the X label to the car. The neural network is searching for the most evident properties that distinguish one class from another. Because of this, the prediction is incorrect. In order to avoid this, a straightforward option is to horizontally mirror the photos that are now included in the dataset so that they are viewed from the other side. We are able to improve the overall performance of the system by introducing important features and patterns through the process of augmentation.

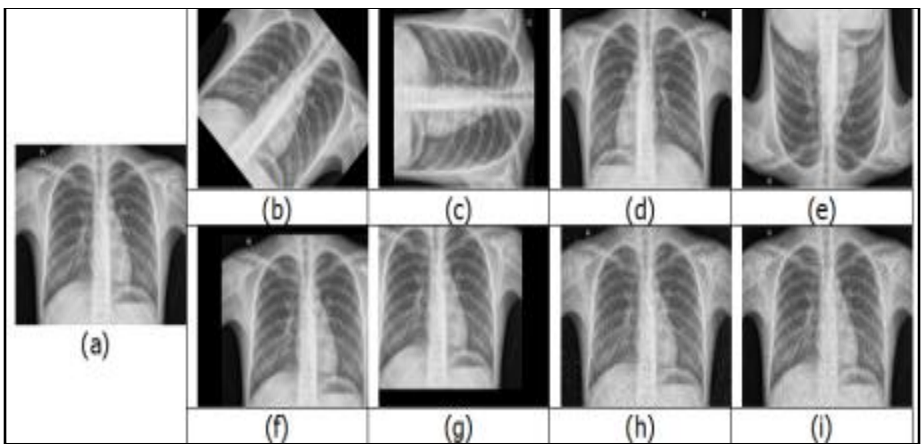

Figure 8 Examples of image augmentation: (a) original; (b) 45◦ rotation; (c) 90◦ rotation; (d) horizontal flip; (e) vertical flip; (f) positive x and y translation; (g) negative x and y translation; (h) salt and pepper noise; and (i) speckle noise

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In addition to this, data augmentation helps prevent overfitting. The term "over fitting" describes the situation in which a neural network learns a function with a very large variance, such as the perfect modelling of training data. The problem of overfitting can be remedied by data augmentation, which involves supplementing the model with additional, diverse data [28]. This variety in the data helps to lower the variance and increases the model's ability to generalize.

A limited dataset has inherent biases that cannot be eliminated by data augmentation alone [29]. Data augmentation has a number of drawbacks, including longer training times, higher computing costs for transformations, and higher memory costs.

Types of Deep Learning Algorithm

Finding patterns in photos is a particular strength of CNN, the most used deep learning algorithm. Like the neural networks in the human brain, CNNs consist of neurons with biases and weights that may be trained. Each neuron receives several different signals. An input weighted total is then determined. After passing the weighted sum through an activation function, a result is generated. Convolution layers are what set CNN apart from other neural networks. Figure 9 depicts an illustration of CNN architecture [44]. Convolutional layer, pooling layer, fully-connected layer, and other layers make up a CNN. A process known as a "convolution" is carried out by the convolutional layer. A set of weights are multiplied by the input in a linear operation called convolution. A kernel or filter is the name given to the collection of weights. The filter cannot handle the size of the supplied data. The filter is multiplied by a portion of the input whose size is equal to the filters, resulting in a dot product. After that, the dot product is added to create a single value. To control overfitting, the pooling layer gradually shrinks the spatial dimension of the representation. This minimises the number of network parameters and calculations. To apply an element-wise activation function, such sigmoid, to the activation created by the preceding layer, a rectified linear unit (ReLu) is added to the CNN. Additional information regarding CNN is available in [44, 45].In most cases, when it comes to learning, CNN consists of two components in particular feature extracting and classifying. The input data undergoes a convolutional operation during the feature extraction phase, wherein a filter or kernel is applied. After that, we go to the next stage, which is to generate a feature map. During the classification stage, the CNN will calculate the likelihood that the image has been labeled with a specific category. CNN is particularly beneficial for picture classification and recognition due to the fact that it automatically learns features and does not require the user to manually extract features [30]. Transfer learning is another method that may be utilized to retrain CNN and then apply it to a new domain [31]. Transfer learning has been demonstrated to result in improved categorization performance.

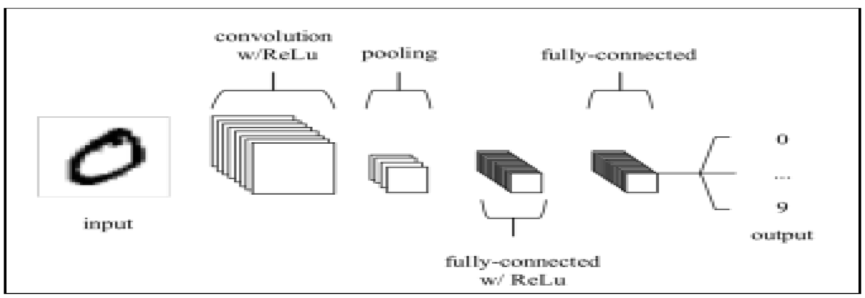


Figure 9 Example of a CNN structure.

The DBN algorithm is yet another example of deep learning. A limited Boltzmann machine, or DBN, can be characterized as a stack of other RBMs [32]. With the exception of the first and last layers, each layer in the DBN serves two different tasks. This layer is both the input layer for the nodes that follow it and the output layer for the nodes that came before it. A DBN's initial RBM is constructed to be as accurate as possible at recreating the input it was fed. After that is done, the first RBM's hidden layer is treated as the second RBM's visible layer, and the two RBMs are trained jointly using the first RBM's outputs. This process is carried out in an endless loop until each layer of the network has been trained. Following the completion of this preliminary training, the DBN developed a model that is able to recognize recurring themes within the data. Objects in photographs, video sequences, and data captured from motion can all be recognized with the help of DBN. The references [33-36] provide additional information regarding DBN.
A further illustration of deep learning is provided by the DBN algorithm. It is possible to characterize a restricted Boltzmann machine, also known as a DBN, as a stack of other RBMs [37].Every layer in the DBN is responsible for a pair of distinct responsibilities, with the exception of the first and last layers. The layer serves as the input layer for nodes that come after it and the hidden layer for nodes that come before it. The preliminary RBM is constructed with the goal of accurately recreating, to the greatest extent that is practically possible, the input that was used to educate a DBN. After then, the outputs from the first RBM are used to train the

second RBM, and the hidden layer of the first RBM is deemed to be the visible layer for the second RBM. This process is repeated indefinitely until all of the layers of the network have been educated and is ready to function. After this early training was finished, the DBN generated a model that is able to distinguish repeating themes within the data. This model was a success, and it was implemented. With the assistance of DBN, it is possible to distinguish objects contained inside still images, video sequences, and data obtained from motion.

Transfer Learning

Transfer learning has been a prominent technique in the field of computer vision due to the fact that it enables correct models to be constructed. A model that is trained for one domain can be transferred to another domain and employed there using transfer learning. Transfer learning can be carried out with or without the use of a model that has already been pre-trained.

In machine learning, a pre-trained model is one that has already been developed to address a problem with similar characteristics. A model that has been trained on one problem is used as a jumping-off point for solving a similar job, rather than building a new model from scratch. In most cases, the features learnt by a pre-trained model during training on a task that is different from the current task are still relevant. Through a series of forward and backward iterations, the training process for a deep learning model finds the optimal weights to distribute throughout the network's nodes. Using models that have already been trained on large datasets allows for the weights and architecture to be directly applied to the present problem at hand. Using pre-trained models enables this feat. One benefit of adopting a pre-trained model is a reduction in the expense associated with training a new model. Because pre-trained weights were used, the model just has to learn the weights of the most recent few layers to start producing accurate results.

Image Net serves as the basis for the pre-training of many CNN architectures [38]. The pictures were obtained from various websites on the internet and then categorized by real people making use of the crowd-sourcing platform Amazon Mechanical Turk. The ILSVRC makes use of a subset of Image Net that has around 1000 examples of each of the 1000 categories. In total, there are around 1.2 million photos used for training, 50,000 images used for validation, and 150,000 images used for testing.

Two applications of transfer learning are fine-tuning and feature extraction from CNN. The two uses are mutually advantageous. Fine-tuning a CNN model involves keeping the weights of some layers the same while altering the weights of other layers [52]. Typically, only the last layers of a model are retrained, while the earlier layers' weights are preserved. This is due to the fact that characteristics learned in the first layers are extremely versatile and may be used to many different problems. In order for previously trained models to acquire high-level attributes unique to the new dataset, the top-level layers of the models must be retrained. When the training dataset is large and very analogous to the original dataset from which the pre-trained model was produced, this strategy is often recommended. Since the model was trained using the training dataset, this makes sense. Nonetheless, CNN is frequently employed in this role. In order to use the network as a fixed feature extractor for the new dataset, it must first have its final fully-connected layer removed [39, 40] (this layer outputs the probabilities for being in each of the 1000 classes from ImageNet). It is common practise to apply the learnt characteristics of a model that was trained on a larger dataset from the same domain to projects for which only a small dataset is available. Once features have been extracted, they are utilised to teach a classifier. Some things to think about while using transfer learning: Verifying that the pre-trained model was trained using data that is comparable to the new target dataset is the first step. The second phase involves using a slower learning rate for CNN weights that are being fine-tuned [41], as we expect the weights to be somewhat correct and do not want to rapidly skew them.

Ensemble of Classifiers

The process of making a prediction using more than one classifier at the same time is referred to as ensemble classification [42]. The variance of predictions is reduced by using an ensemble, which leads to the production of forecasts that are more accurate than those produced by any one model. According to research that can be found in published works, the ensemble methods that are utilized include stacking, majority voting, and probability score averaging.

Each model produces a forecast for each test instance or, to put it another way, casts a vote for a class label in majority voting. And the label that receives the most votes is the one that is used to determine the final prediction [43]. A variant of majority voting known as weighted majority voting is also available. In this variant, the votes of particular models are given more consideration than those of other models. For instance, the prediction scores of each model are added up and divided by the total number of models in the procedure known as probability score averaging .An alternate approach is weighted averaging, which multiplies each model's prediction score by a weight before calculating the average of the models. [44-46] and both contain examples of studies that use probability score averaging in their research.

An algorithm learns how to best combine the input predictions in order to produce a more accurate output prediction through the process of stacking ensemble. The algorithm accepts as input the outputs of weaker models and attempts to learn how to do so. [47-50]

III METHODOLOGY OF RESEARCH

In order to comprehend the DL Lung Disease applications, the SLR technique is used in this part. A systematic literature review (SLR) is an in-depth analysis of all relevant research. Use this section to finish your in-depth analysis of how DL techniques were used in COVID-19. Next, we check the reliability of the procedures used to choose the studies. In the parts that follow, we'll examine the search strategy, questions we asked, and how we made our final decisions. Infected MRI images are employed as a source for the diagnosis of lung disease in this systematic review, which seeks to provide a survey of several machine-learning & deep neural network algorithms.

Data Collection

Searched databases

Science Direct, Scopus, Springer, the ACM Digital Library, and the IEEE Digital Library (IEEE Explore) were the five databases utilised for this literature review. The poll looked at the years 2015 through 2022.

Searched Terms:

A search term including ("Convolutional Neural Network" OR "Machine Learning" OR "Artificial Neural Network" OR "Deep Learning") was established for the literature review. AND ("Lung Diseases" OR "Lung Diseases Detection & Classification" OR "Crop Pest Classification" Lung Diseases"

Inclusion criteria:

In order to track down the paper that fits your needs The papers were initially filtered based on titles and abstracts, and afterwards duplicates were deleted.

Exclusion criteria

Articles that did not focus on deep learning/CNN for the identification and classification of lung illness or other diseases were disregarded.

Data Analysis

Data analysis has been completed after identifying over a hundred papers as appropriate for the review, with the following factors taken into account:

Year of Publication

Researchers have focused more on using CNN/Deep learning to diagnose lung illnesses in recent years. As a result, understanding when this interest began to emerge requires knowing the year it was published.

Purpose of the study

Tasks such as discoloration and lesion identification, classification, segmentation, etc. were conducted for various reasons in the research of lung disease.

Deep Learning Architecture

Several deep learning designs have been used to the problem of lung disease detection. These include the Deep Neural Network, the Convolutional Neural Network, and the Recurrent Neural Network.

The process of article selection

The article selection and search procedure for this study may be broken down into four stages. This procedure is shown in Fig. 2. First-stage paper-searching keywords and terms are shown in Table 3. These papers were compiled as a result of a search of widely used online databases. Some of the more prominent applied electronic databases include Scopus, IEEE Explore, Springer Link, Google Scholar, ACM, Elsevier, Emerald Insight, MDPI, Taylor & Francis, Wiley, Peerj, JSTOR, Dblp, DOAJ, and ProQuest. Journal articles, conference proceedings, books, book chapters, notes, technical studies, and issues dedicated to a certain topic are also uncovered. There were a hundred papers produced in the first stage. Distribution of newspapers by the publisher is seen in Fig.10

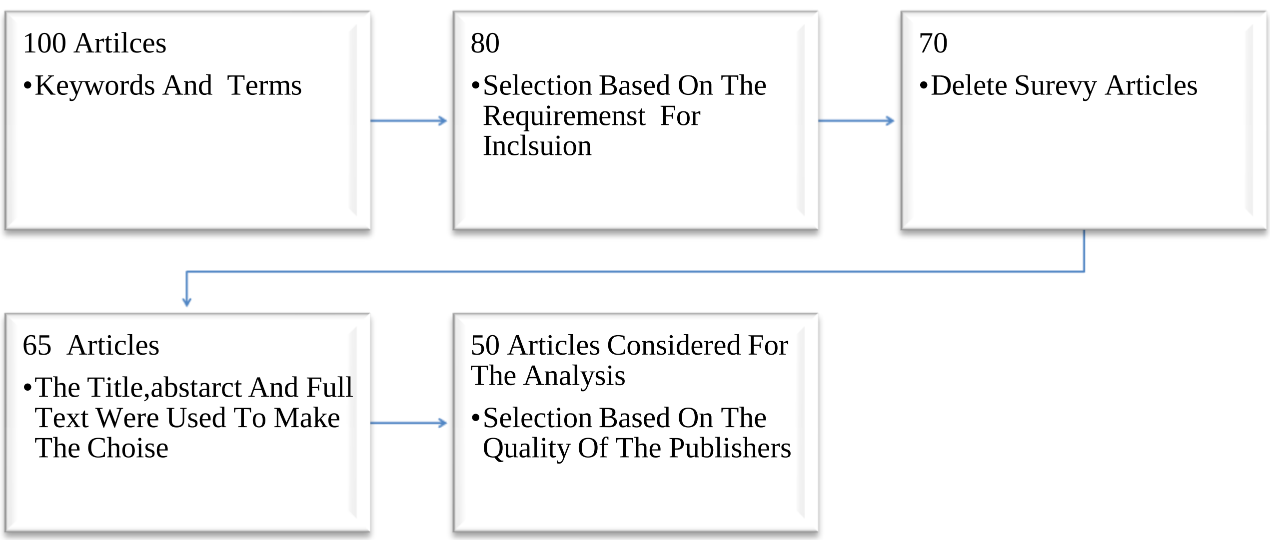


Fig.10 the Phase of Articles Searching and Selection Process

Table 1 Stage 1 is the publisher's distribution of the papers.

Journals	Number Of Papers
Other Journals	24
MDPI	15
Elsevier	16
Springer	20
ACM	15
Hindawi	10
IEEE	23

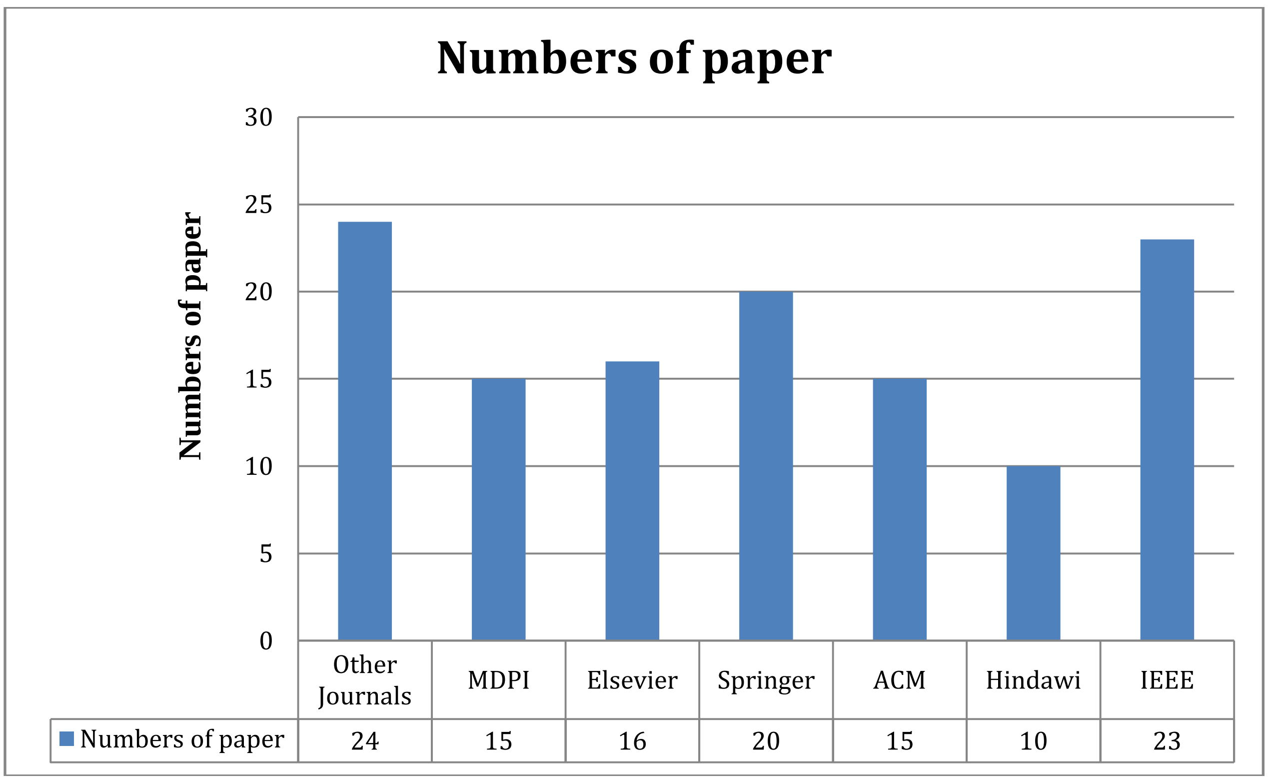


Fig. 11.Stage 1 is the publisher's distribution of the papers.

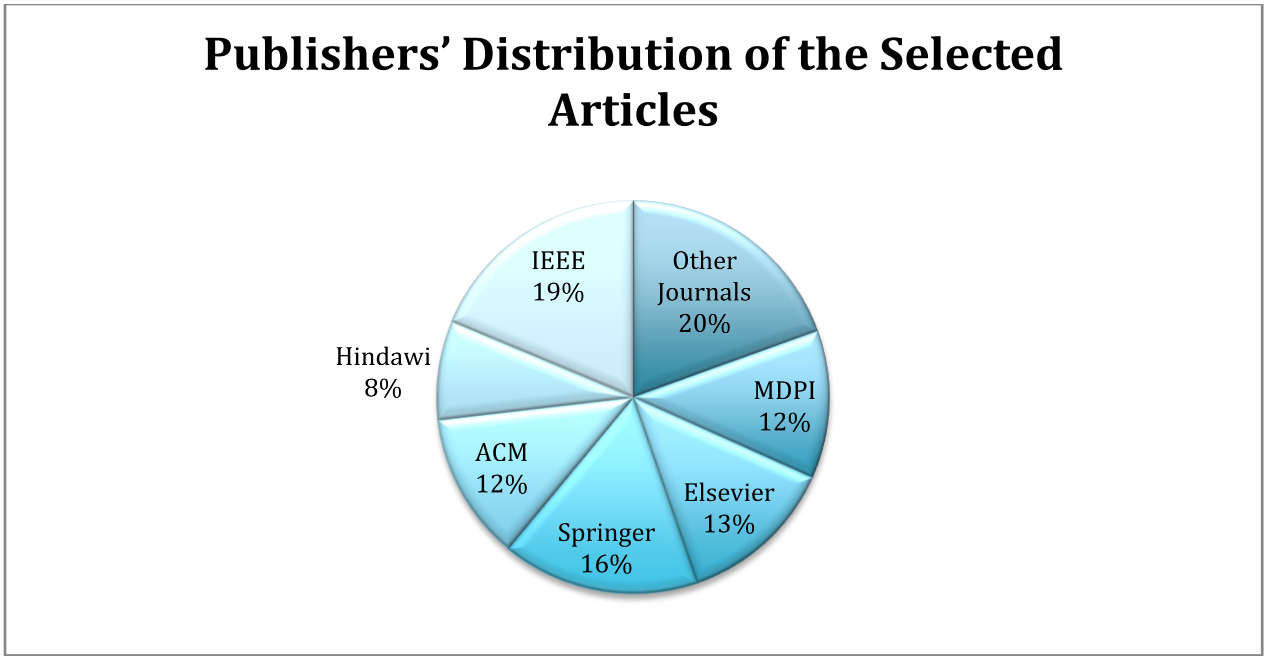


Fig. 12 the publishers' distribution of the selected articles.

Distribution of the selected articles based on journals

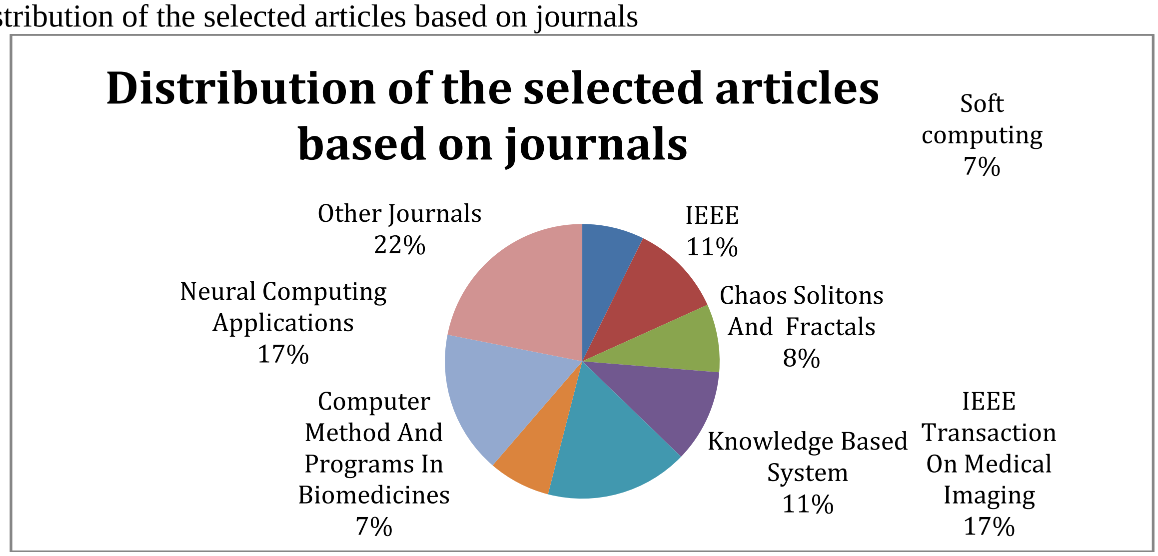
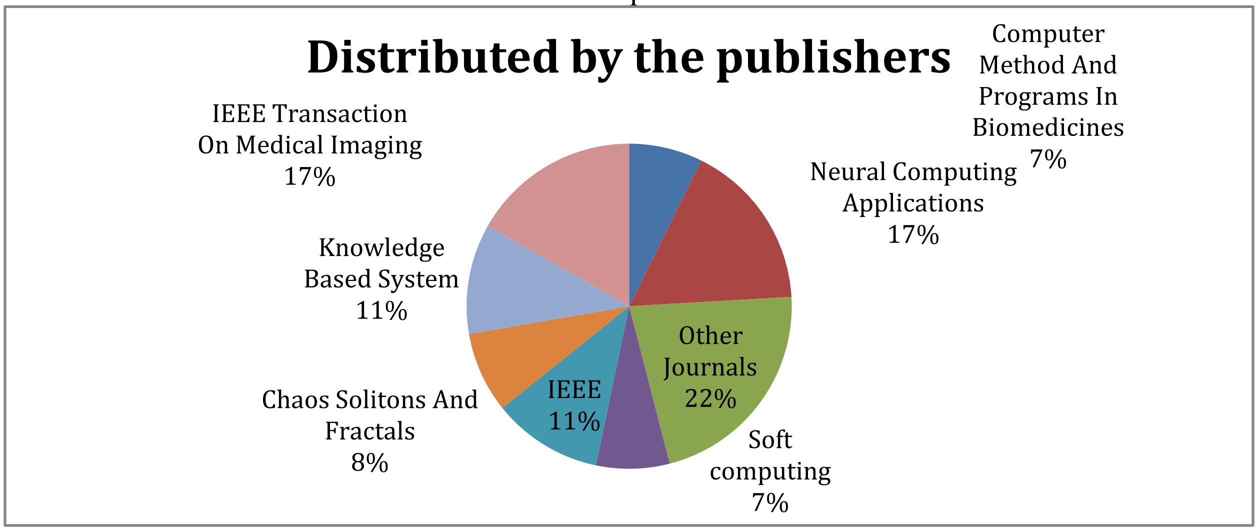


Fig.13 Distribution of the selected articles based on journals

Table 3 the publishers'



distribution of the selected articles.

Fig. 14 the papers are distributed by the publishers.

Selected Articles	Number of Articles.
Computer Method And Programs In Biomedicines	10
Neural Computing Applications	23
Other Journals	30
Soft computing	10
IEEE	15
Chaos Solitons And Fractals	11
Knowledge Based System	15
IEEE Transaction On Medical Imaging	23

V CONCLSUION

In conclusion, deep learning has emerged as a powerful approach for lung disease classification in medical imaging. Through the extensive review of literature and analysis of various studies, this survey has provided valuable insights into the state-of-the-art deep learning techniques employed in this domain. The taxonomy developed in this study encompasses key attributes such as image types, features, data augmentation, types of deep learning algorithms, transfer learning, ensemble of classifiers, and types of lung diseases. This taxonomy provides a structured framework for researchers to understand the different components and choices involved in deep learning-based lung disease classification. By visualizing the patterns of recent work, this study has shed light on the current research landscape and popular methodologies. It highlights the advancements made in the field, such as the utilization of multi-modal data sources, explainable AI techniques, and real-time and scalable deep learning systems.

However, despite the progress made, there are several challenges that need to be addressed. Limitations in existing approaches, including issues related to data availability and annotation, as well as the interpretability and explain ability of deep learning models, pose significant hurdles. These challenges call for further research and development to enhance the efficiency and reliability of deep learning-aided lung disease classification.

In terms of future directions, the study suggests integrating multi-modal data sources to capture a more comprehensive view of lung diseases. Additionally, developing explainable AI techniques can increase transparency and trust in the decision-making process. Transfer learning across different diseases can leverage existing knowledge and improve classification performance. Furthermore, the development of real-time and scalable deep learning systems can enable faster and more efficient diagnosis.

In summary, deep learning holds immense potential in the field of lung disease classification in medical images. The findings of this survey provide a foundation for researchers to plan their contributions and activities, while also highlighting the remaining challenges and potential future directions. By addressing these challenges and advancing the field, deep learning can further enhance the accuracy and effectiveness of lung disease diagnosis and contribute to improved patient care.

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