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Detection and Classification of Lung Diseases for Pneumonia: A Survey

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Abstract: The recent developments of deep learning support the identification and classification of lung diseases in medical images. Hence, numerous work on the detection of lung disease using deep learning can be found in the literature. This paper presents a survey of deep learning for lung disease detection in medical images. There has only been one survey paper published in the last five years regarding deep learning directed at lung diseases detection. However, their survey is lacking in the presentation of taxonomy and analysis of the trend of recent work. The objectives of this paper are to present a taxonomy of the state-of-the-art deep learning-based lung disease detection systems, visualise the trends of recent work on the domain and identify the remaining issues and potential future directions in this domain. The taxonomy consists of seven attributes that are common in the surveyed articles: image types, features, data augmentation, types of deep learning algorithms, transfer learning, the ensemble of classifiers and types of lung diseases. The presented taxonomy could be used by other researchers to plan their research contributions and activities. The potential future direction suggested could further improve the efficiency and increase the number of deep learning aided lung disease detection applications.

Keywords: *deep learning; lung disease detection; taxonomy; medical images*

Introduction

Lung diseases, also known as respiratory diseases, are diseases of the airways and the other structures of the lungs [1]. Examples of lung disease are pneumonia, tuberculosis and Coronavirus Disease 2019 (COVID-19). According to Forum of International Respiratory Societies [2], about 334 million people suffer from asthma, and, each year, tuberculosis kills 1.4 million people, 1.6 million people die from lung cancer, while pneumonia also kills millions of people. The COVID-19 pandemic impacted the whole world [3], infecting millions of people and burdening healthcare systems [4]. It is clear that lung diseases are one of the leading causes of death and disability in this world. Early detection plays a key role in increasing the chances of recovery and improve long-term survival rates [5, 6]. Traditionally, lung disease can be detected via skin test, blood test, sputum sample test [7], chest X-ray examination and computed tomography (CT) scan examination [8]. Recently, deep learning has shown great potential when applied on medical images for disease detection, including lung disease. Deep learning is a subfield of machine learning relating to algorithms inspired by the function and structure of the brain. Recent developments in machine learning, particularly deep learning, support the identification, quantification and classification of patterns in medical images [9]. These developments were made possible due to the ability of deep learning to learned features merely from data, instead of hand-designed features based on domain-specific knowledge. Deep learning is quickly becoming state of the art, leading to improved performance in numerous medical applications. Consequently, these advancements assist clinicians in detecting and classifying certain medical conditions efficiently [10].

Numerous works on the detection of lung disease using deep learning can be found in the literature. To the best of our knowledge, however, only one survey paper has been published in the last five years to analyse the state-of-the-art work on this topic [11]. In that paper, the history of deep learning and its applications in pulmonary imaging are presented. Major applications of deep learning techniques on several lung diseases, namely pulmonary nodule diseases, pulmonary embolism, pneumonia, and interstitial lung disease, are also described. In addition, the analysis of several common deep learning

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network structures used in medical image processing is presented. However, their survey is lacking in the presentation of taxonomy and analysis of the trend of recent work. A taxonomy shows relationships between previous work and categorises them based on
the identified attributes that could improve reader understanding of the topic. Analysis of trend, on the other hand, provides an overview of the research direction of the topic of interest identified from the previous work. In this paper, a taxonomy of deep learning applications on lung diseases and a trend analysis on the topic are presented. The remaining issues and possible future direction are also described.

Medical diagnosis based on imaging techniques and computer aided diagnosis forms an important basis to take clinical decisions. CT images forms an impvportant basis for doctors to take clinical decisions on the kind of lung cancer treatment to be given for the patients. And X-ray imaging modality is the primary method for detecting Pneumonia. In this chapter, the literature review of various methods approached by researchers involved in Pneumonia and lung cancer detection is discussed.

The process of how deep learning is applied to identify lung diseases from medical images is described. There are mainly three steps: image preprocessing, training and classification. Lung disease detection generally deals with classifying an image into healthy lungs or disease-infected lungs. The lung disease classifier, sometimes known as a model, is obtained via training. Training is the process in which a neural network learns to recognise a class of images. Using deep learning, it is possible to train a model that can classify images into their respective class labels. Therefore, to apply deep learning for lung disease detection, the first step is to gather images of lungs with the disease to be classified. The second step is to train the neural network until it is able to recognise the diseases. The final step is to classify new images. Here, new images unseen by the model before are shown to the model, and the model predicts the class of those images. The overview of the process is illustrated in Figure 1.

Image Acquisition Phase

The first step is to acquire images. To produce a classification model, the computer needs to learn by example. The computer needs to view many images to recognise an object. Other types of data, such as time series data and voice data, can also be used to train deep learning models. In the context of the work surveyed in this paper, the relevant data required to detect lung disease will be images. Images that could be used include chest X-ray, CT scan, sputum smear microscopy and histopathology image. The output of this step is images that will later be used to train the model. Alterations to the environment, changes in climate, changes in lifestyle, and other factors are contributing to a rapid increase in the adverse effects of disease on human health. This has resulted in an elevated risk to one's health. It is estimated that approximately 3.4 million individuals passed away in 2016 as a result of chronic obstructive pulmonary disease (COPD), which is mainly caused by smoking and pollution, while asthma claimed the lives of 400,000 people [1,2]. The danger of lung diseases is extremely high, particularly in nations that are still developing and those with poor middle incomes, where millions of people are struggling against both extreme poverty and air pollution. The World Health Organization (WHO) estimates that over 4 million people lose their lives prematurely each year due to diseases that are associated to household air pollution. These diseases include asthma and pneumonia. Because of this, it is vital to take the required steps to limit the amount of carbon output and air pollution. In addition, it is necessary to put in place effective diagnostic technologies that can play a role in the early detection of lung disorders. Since late December 2019, a new coronavirus disease known as COVID-19 has been causing severe damage to the lungs and difficulty breathing in those who are infected with it. In addition, pneumonia, a type of lung disease, may be caused by the virus that is responsible for COVID-19, or it may be caused by another viral or bacterial infection [3]. [Causes of pneumonia] As a result, diagnosing lung disorders at an earlier stage is more crucial than it has ever been. Learning algorithms like machine learning and deep learning have the potential to play an important part in achieving this goal. Recent years have seen a rise in the significance of digital technology around the globe. With the assistance of the deep learning approach, the study presented in this paper can point physicians and other researchers in the right direction for diagnosing lung disease. As part of the dataset, a significant number of X-rays of the lung are employed. The system that has been presented here can also help to improve the accuracy of disease detection, which can protect a large number of vulnerable people and bring the overall disease rate down. The expansion of the population is one of the reasons why the health plan has not yet been put into place [3,4]. Numerous researchers have conducted studies to investigate the relationship between machine learning systems and the prediction of diagnostic information from X-ray images [5–7]. It is past time to find a solution to this conundrum given that computers are now in the hands of those who manage them and the vast majority of records are available to the general public. The expansion of computer science for use in health and medical science initiatives is one way that this solution can contribute to a reduction in the cost of medical care. The NIH chest X-ray image dataset is obtained from the Kaggle repository [8,9], which is a completely open source computing environment, in order to carry out the implementation. In this research, a brand-new hybrid classification technique is presented, and this approach was successfully applied to the dataset that was described earlier in order to diagnose lung disease. The invention of a brand new algorithm for hybrid deep learning that is suitable for the prediction of lung disease based on X-ray pictures is the primary contribution that comes from this research. The arrival of Covid-19 posed a severe risk to human life that began in China in November 2019 and then expanded over the rest of the world. It has been estimated that more than 63,2 million people around the world have already been infected, with around 1.47 million people losing their lives as a result of the disease. Continuously providing nations with the required information to defend themselves against Covid-19 is the World Health Organization (WHO) (Fong et al. 2021). The United States of America, India, Brazil, Russia, France, Italy, and China are some of the nations that have suffered the most as a result of this risk (Salepci et al. 2020)[10]. In spite of the fact that several countries were working on the manufacture of the vaccine during the first six to eight months of the Covid-19, no vaccination against this menace was developed. Finally, a few countries have been successful in creating a vaccine for the Covid-19 virus, which is currently undergoing either the testing or research stage. People who are infected with the COVID-19 virus typically exhibit moderate to mild symptoms, including fever, cough, and shortness of breath. On the other hand, individuals suffered from severe pneumonic disorders in their lungs, which ultimately led to their demise (Elibol 2020; Padda et al. 2020; Smith et al. 2020; Sharma et al. 2020). The majority of those who passed away as a result of Covid-19 had suffered from severe chest congestion (pneumonia) as a direct result of a considerable drop in oxygen level, which ultimately resulted in a catastrophic heart attack (Chen et al. 2021). On the other hand, pneumonia is a form of lung disease that causes inflammation in the human body's air sacs that are located within the lungs. This condition is known as pneumonitis. It's possible that your lungs will fill up with a substantial amount of fluid, which will make it difficult for you to breathe. Infections with viruses (such as COVID-19 or the flu), bacterial infections, and the common cold all have the potential to cause pneumonia. As a result of the emergence of the Covid-19 sickness, it has become an extremely difficult task for medical professionals to diagnose lung infections (either viral or bacterial pneumonia or Covid-19 pneumonia) from chest X-ray images (Bentivegna et al. 2020; Tabatabaei et al. 2020; Zhan et al. 2021). Novel Coronavirus Infected Pneumonia (NCIP) is the name given to the lung illness that is brought on by a newly discovered coronavirus (Fong et al. 2021). In addition to this, lung cancer is an additional form of illness that poses a considerable risk to human beings (Sun et al. 2016; Zhou et al. 2002)[11].

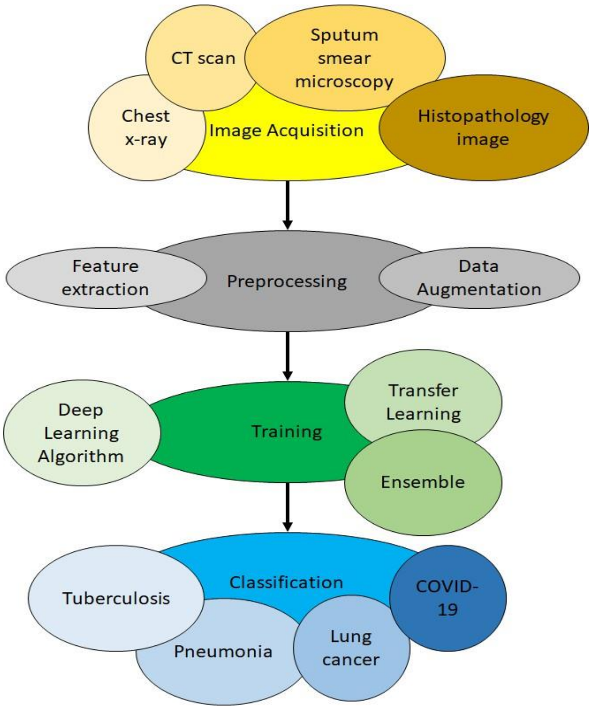

Figure 1. Overview of using deep learning for lung disease detection[1].

Preprocessing Phase

The second step is preprocessing. Here, the image could be enhanced or modified to improve image quality. Contrast Limited Adaptive Histogram Equalisation (CLAHE) could be performed to increase the contrast of the images [12]. Image modification such as lung segmentation [13] and bone elimination [14] could be used to identify the region of interest (ROI), whereby the detection of the lung disease can then be performed on the ROI. Edge detection could also be used to provide an alternate data representation [15]. Data augmentation could be applied to the images to increase the amount of available data. Feature extraction could also be conducted so that the deep learning model could identify important features to identify a certain object or class. The output of this step is a set of images whereby the quality of the images is enhanced, or unwanted objects have been removed. The output of this step is images that were enhanced or modified that will later be used in training.

Training Phase

In the third step, namely training, three aspects could be considered. These aspects are the selection of deep learning algorithm, usage of transfer learning and usage of an ensemble. There are numerous deep learning algorithm, for example deep belief network (DBN), multilayer perceptron neural network (MPNN), recurrent neural network (RNN) and the aforementioned CNN. Different algorithms have different learning styles. Different types of data work better with certain algorithms. CNN works particularly well with images. Deep learning algorithm should be chosen based on the nature of the data at hand. Transfer learning refers to the transfer of knowledge from one model to another. Ensemble refers to the usage of more than one model during classification. Transfer learning and ensemble are techniques used to reduce training time, improve classification accuracy and reduce overfitting [16].

Classification Phase

In the fourth and final step, which is classification, the trained model will predict which class an image belongs to. For example, if a model was trained to differentiate X-ray images of healthy lungs and tuberculosis-infected lungs, it should be able to correctly classify new images (images that are never seen by the model before) into healthy lungs or tuberculosis-infected lungs. The model will give a probability score for the image. The probability score represents how likely an image belongs to a certain class. At the end of this step, the image will be classified based on the probability score given to it by the model.

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

In this section, a taxonomy of the recent work on lung disease detection using deep learning is presented, which is the first contribution of this paper. The taxonomy is built to summarise and provide a clearer picture of the key concepts and focus of the existing work. Seven attributes were identified for inclusion in the taxonomy. These attributes were chosen as they were imminent and can be found in all the articles being surveyed. The seven attributes included in the taxonomy are image types, features, data augmentation, types of deep learning algorithms, transfer learning, the ensemble of classifiers and types of lung diseases. Figure 2 shows the taxonomy of state-of-the-art lung disease detection using deep learning.

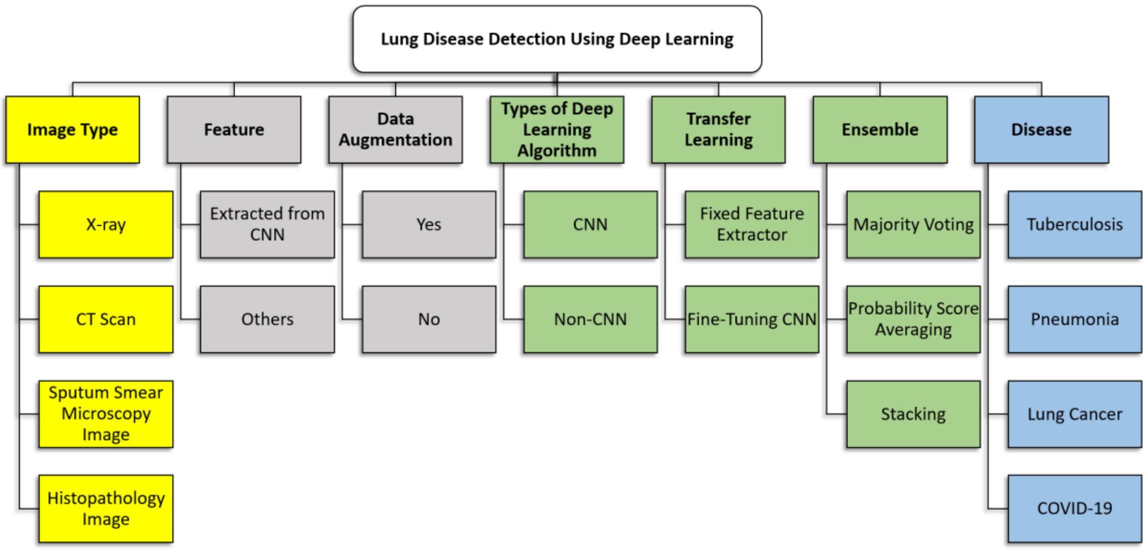

Figure 2. Taxonomy of lung disease detection using deep learning[1].

Image Type

In the papers surveyed, four types of images were used to train the model: chest X-ray, CT scans, sputum smear microscopy images and histopathology images. It should be noted that there are other imaging techniques exist such as positron emission tomography (PET) and magnetic resonance imaging (MRI) scans. Both PET and MRI scans could also be used to diagnose health conditions and evaluate the effectiveness of ongoing treatment. However, none of the papers surveyed used PET or MRI scans.

Chest X-rays

An X-ray is a diagnostic test that helps clinicians identify and treat medical problems [17]. The most widely performed medical X-ray procedure is a chest X-ray, and a chest X-ray produces images of the blood vessels, lungs, airways, heart and spine and chest bones. Traditionally, medical X-ray images were exposed to photographic films, which require processing before they can be viewed. To overcome this problem, digital X-rays are used [18]. Figure 3 shows several examples of chest X-ray with different lung conditions taken from various datasets.

Among the papers surveyed, the majority of them used chest X-rays. For example, X-rays were used for tuberculosis detection [19], pneumonia detection [20], lung cancer detection [14] and COVID-19 detection [21].

CT Scans

A CT scan is a form of radiography that uses computer processing to create sectional images at various planes of depth from images taken around the patient's body from different angles [22]. The image slices can be shown individually, or they can be stacked to produce a 3D image of the patient, showing the tissues, organs, skeleton and any abnormalities present [23]. CT scan images deliver more detailed information than X-rays. Figure 4 shows examples of CT scan images taken from numerous datasets. CT scans have been used to detect lung disease in numerous work found in the literature, for example for tuberculosis detection [24], lung cancer detection [25] and COVID-19 detection [26].

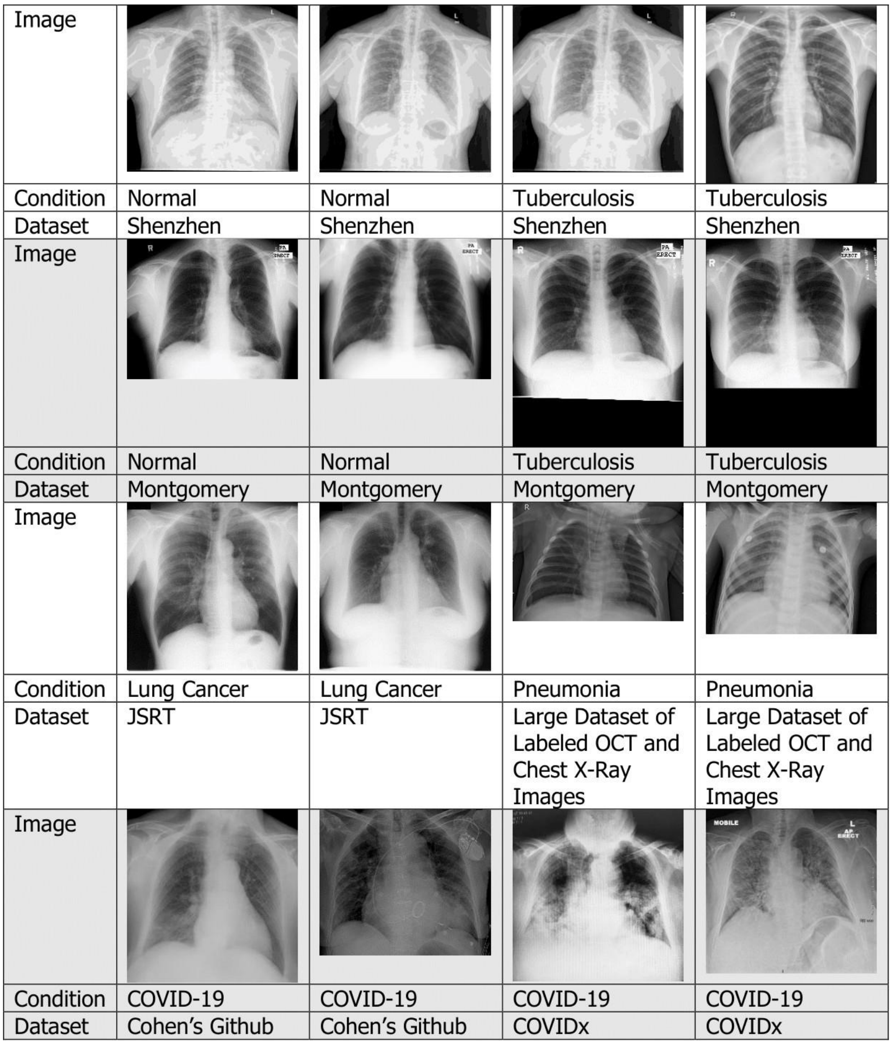

Figure 3. Examples of chest X-ray images[1].

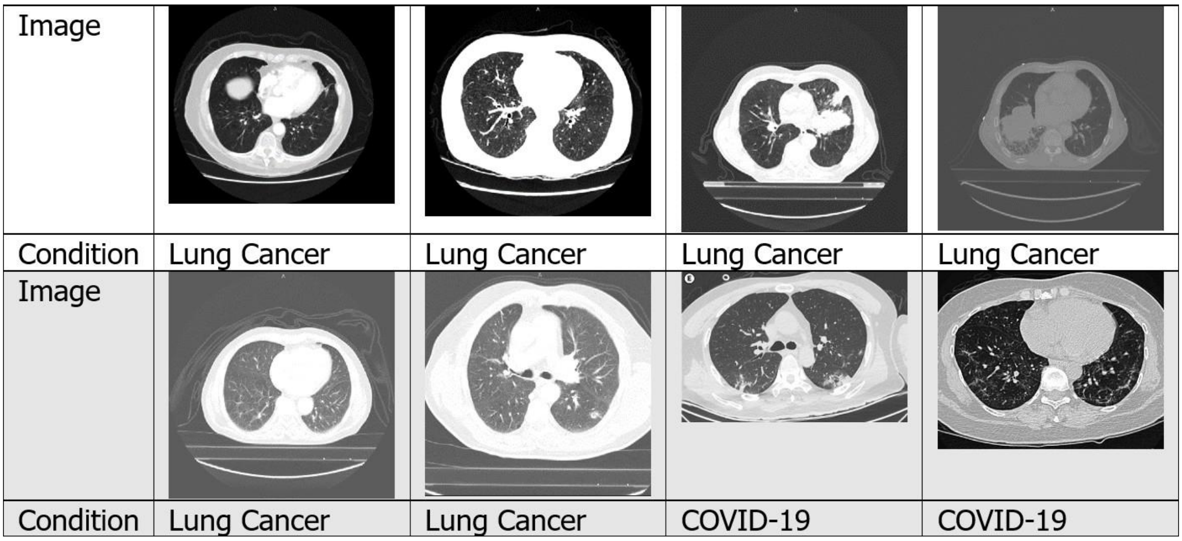

Figure 4. Examples of CT scan images[1].

Sputum Smear Microscopy Images

Sputum is a dense fluid formed in the lungs and airways leading to the lungs. To perform sputum smear examination, a very thin layer of the sputum sample is positioned on a glass slide [27]. Among the papers surveyed, only five used sputum smear microscopy image [28–32]. Figure 5 shows examples of sputum smear microscopy images.

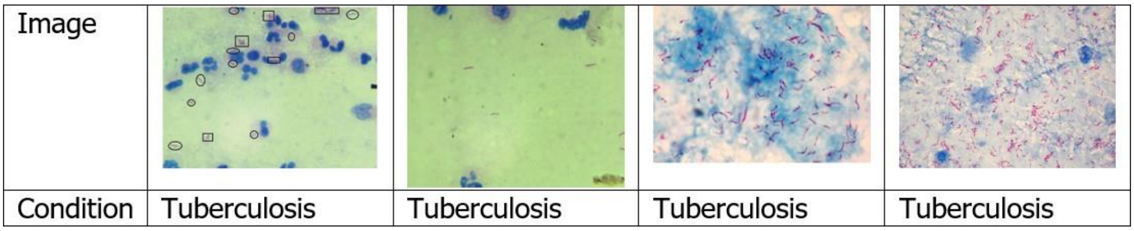

Figure 5. Examples of sputum smear microscopy images[1].

Histopathology Images

Histopathology is the study of the symptoms of a disease through microscopic examination of a biopsy or surgical specimen using glass slides. The sections are dyed with one or more stains to visualise the different components of the tissue [33]. Figure 6 shows a few examples of histopathology images. Among all the papers surveyed, only Coudray et al. [34] used histopathology images.

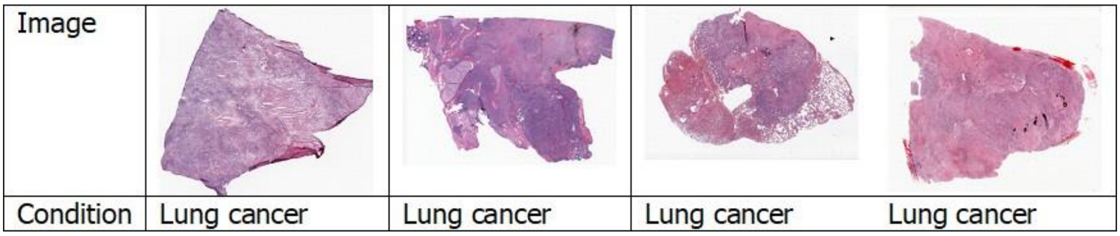

Figure 6. Examples of histopathology images[1].

In computer vision, features are significant information extracted from images in terms of numerical values that could be used to solve specific problem [35]. Features might be in the form of specific structures in the image such as points, edges, colour, sizes, shapes or objects. Logically, the types of images affect the quality of the features.

Feature transformation is a process that creates new features using the existing features. These new features may not have the same representation as to the original features, but they may have more discriminatory power in a different space than the original space. The purpose of feature transformation is to provide a more useful feature for the machine learning algorithm for object identification. The features used in the surveyed papers include: Gabor, GIST, Local binary patterns (LBP), Tamura texture descriptor, colour and edge direction descriptor (CEDD) [36], Hu moments, colour layout descriptor (CLD) edge histogram descriptor (EHD) [37], primitive length, edge frequency, autocorrelation, shape features, size, orientation, bounding box, eccentricity, extent, centroid, scale-invariant feature transform (SIFT), regional properties area and speeded up robust features (SURF) [38]. Other feature representations in terms of histograms include pyramid histogram of oriented gradients (PHOG), histogram of oriented gradients (HOG) [39], intensity histograms (IH), shape descriptor histograms (SD), gradient magnitude histograms (GM), curvature descriptor histograms (CD) and fuzzy colour and texture histogram (FCTH). Some studies even performed lung segmentations before training their models (e.g., [13,14,36]).

From the literature, a majority of the works surveyed used features that are automatically extracted from CNN. CNN can automatically learn and extract features, discarding the need for manual feature generation [40].

Data Augmentation

In deep learning, it is very important to have a large training dataset, as the community agrees that having more images can help improve training accuracy. Even a weak algorithm with a large amount of data can be more accurate than a strong algorithm with a modest amount of data [41]. Another obstacle is imbalanced classes. When doing binary classification training, if the number of samples of one class is a lot higher than the other class, the resulting model would be biased [6]. Deep learning algorithms perform optimally when the amount of samples in each class is equal or balanced. One way to increase the training dataset without obtaining new images is to use image augmentation. Image augmentation creates variations of the original images. This is achieved by performing different methods of processing, such as rotations, flips, translations, zooms and adding noise [42]. Figure 7 shows various examples of images after image augmentation.

Data augmentation can also help increase the amount of relevant data in the dataset. For example, consider a car dataset with two labels, X and Y. One subset of the dataset contains images of cars of label X, but all the cars are facing left. The other subset contains images of cars of label Y, but all the cars are facing right. After training, a test image of a label Y car facing left is fed into the model, and the model labels that the car as X. The prediction is wrong as the neural network search for the most obvious features that distinguish one class from another. To prevent this, a simple solution is to flip the images in the existing dataset horizontally such that they face the other side. Through augmentation, we may introduce relevant features and patterns, essentially boosting overall performance.

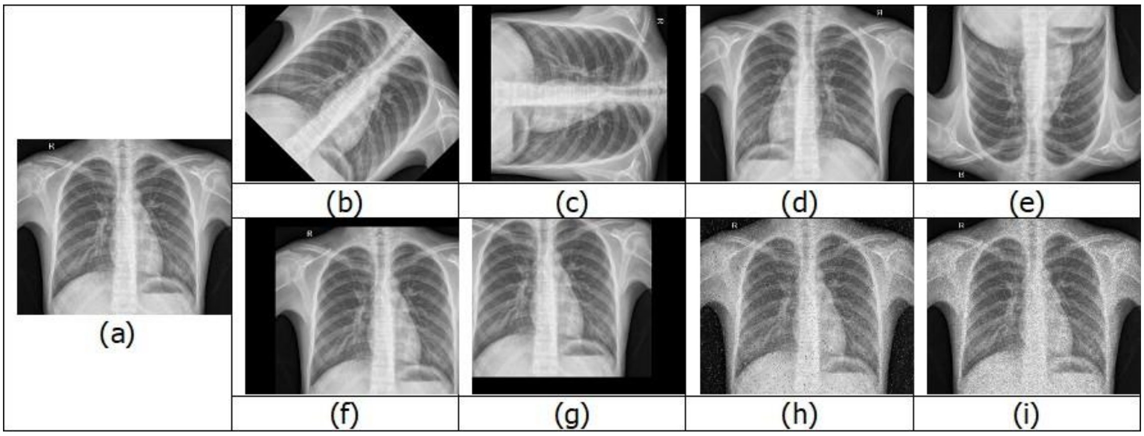

Figure 7. Examples of image augmentation: (**a**) original; (**b**) 45° rotation; (**c**) 90° rotation; (**d**) horizontal flip; (**e**) vertical flip; (**f**) positive x and y translation; (**g**) negative x and y translation; (**h**) salt and pepper noise; and (**i**) speckle noise[1]

Data augmentation also helps prevent overfitting. Overfitting refers to a case where a network learns a very high variance function, such as the perfect modelling of training results. Data augmentation addresses the issue of overfitting by introducing the model with more diverse data [43]. This diversity in data reduces variance and improves the generalisation of the model.

However, data augmentation cannot overcome all biases present in a small dataset [43]. Other disadvantages of data augmentation include additional training time, transformation computing costs and additional memory costs.

Types of Deep Learning Algorithm

The most common deep learning algorithm, CNN, is especially useful to find patterns in images. Similar to the neural networks of the human brain, CNNs consist of neurons with trainable biases and weights. Each neuron receives several inputs. Then, a weighted sum over the inputs is computed. The weighted sum is then passed to an activation function, and an output is produced. The difference between CNN and other neural networks is that CNN has convolution layers. Figure 9 shows an example of a CNN architecture [44]. A CNN consists of multiple layers, and the four main types of layers are convolutional layer, pooling layer and fully-connected layer. The convolutional layer performs an operation called a “convolution”. Convolution is a linear operation involving the multiplication of a set of weights with the input. The set of weights is called a kernel or a filter. The input data are larger than the filter. The multiplication between a filter-sized section of the input and the filter is a dot product. The dot product is then summed, resulting in a single value. The pooling layer gradually reduces the spatial size of the representation to lessen the number of parameters and computations in the network, thus controlling overfitting. A rectified linear unit (ReLu) is added to the CNN to apply an elementwise activation function such as sigmoid to the output of the activation produced by the previous layer. More details of CNN can be found in [44,45].

CNN generally has two components when learning, which are feature extraction and classification. In the feature extraction stage, convolution is implemented on the input data using a filter or kernel. Then, a feature map is subsequently generated. In the classification stage, the CNN computes a probability of the image belongs to a particular class or label. CNN is especially useful for image classification and recognition as it automatically learns features without needing manual feature extraction [40]. CNN also can be retrained and applied to a different domain using transfer learning [46]. Transfer learning has been shown to produce better classification results [19].

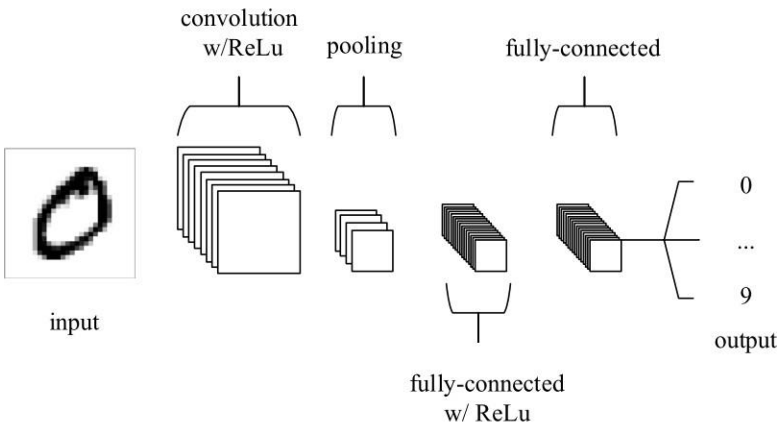

Figure 8. Example of a CNN structure[1].

Another deep learning algorithm is DBN. DBN can be defined as a stack of restricted Boltzmann machines (RBM) [47]. The layer of the DBN has two functions, except for the first and final layers. The layer serves as the hidden layer for the nodes that come before it, and as the input layer for the nodes that come after it. The first RBM is designed to reproduce as accurately as possible the input to train a DBN. Then, the hidden layer of the first RBM is treated as the visible layer for the second one, and the second RBM is trained using the outputs from the first RBM. This process keeps repeating until every layer of the network is trained. After this initial training, the DBN has created a model that can detect patterns in the data. DBN can be used to recognise objects in images, video sequences and motion-capture data. More details of DBN can be found in [31,48].

One more example of a deep learning algorithm used in the papers surveyed is a bag of words (BOW) model. BOW is a method to extract features from the text for use in modelling. In BOW, the number of the appearance of each word in a document is counted, then the frequency of each word was examined to identify the keywords of the document, and a frequency histogram is made. This concept is similar to the bag of visual words (BOVW), sometimes referred to as bag-of-features. In BOVW, image features are considered as the "words". Image features are unique patterns that were found in an image. The general idea of BOVW is to represent an image as a set of features, where each feature contains keypoints and descriptors. Keypoints are the most noticeable points in an image, such that, even if the image is rotated, shrunk or enlarged, its keypoints are always the same. A descriptor is the description of the keypoint. Keypoints and descriptors are used to construct vocabularies and represent each image as a frequency histogram of features. From the frequency histogram, one can find other similar images or predict the class of the image. Lopes and Valiati proposed Bag of CNN features to classify tuberculosis [19].

Transfer Learning

Transfer learning emerged as a popular method in computer vision because it allows accurate models to be built [49]. With transfer learning, a model learned from a domain can be re-used on a different domain. Transfer learning can be performed with or without a pre-trained model.

A pre-trained model is a model developed to solve a similar task. Instead of creating a model from scratch to solve a similar task, the model trained on other problem is used as a starting point. Even though a pre-trained model is trained on a task which is different from the current task, the features learned, in most cases, found to be useful for the new task. The objective of training a deep learning model is to find the correct weights for the network by numerous forward and backward iterations. By using pre-trained models that have been previously trained on large datasets, the weights and architecture obtained can be used and applied to the current problem. One of the advantages of a pre-trained model is the reduced cost of training for the new model [50]. This is because pre-trained weights were used, and the model only has to learn the weights of the last few layers.

Many CNN architectures are pre-trained on ImageNet [51]. The images were gathered from the internet and labelled by human labellers using Amazon's Mechanical Turk crowd-sourcing tool. ILSVRC uses a subset of ImageNet with approximately 1000 images in each of 1000 classes. Altogether, there are approximately 1.2 million training images, 50,000 validation images and 150,000 testing images.

Transfer learning can be used in two ways: (i) fine-tuning; or (ii) using CNN as a feature extractor. In fine-tuning, the weights of the pre-trained CNN model are preserved on some of the layers and tuned in the others [52]. Usually, the weights of the initial layers of the model are frozen while only the higher layers are retrained. This is because the features obtained from the first layers are generic (e.g., edge detectors or colour blob detectors) and applicable to other tasks. The top-level layers of the pre-trained models are retrained so that the model learned high-level features specific to the new dataset. This method is typically recommended if the training dataset is huge and very identical to the original dataset that the pre-trained model was trained on. On the other hand, CNN is used as a feature extractor. This is conducted by removing the last fully-connected layer (the one which outputs the probabilities for being in each of the 1000 classes from ImageNet) and then using the network as a fixed feature extractor for the new dataset [53]. For tasks where only a small dataset is available, it is usually recommended to take advantage of features learned by a model trained on a larger dataset in the same domain. Then, a classifier is trained from the features extracted.

There are several issues that need to be considered when using transfer learning: (i) ensuring that the pre-trained model selected has been trained on a similar dataset as the new target dataset; and (ii) using a lower learning rate for CNN weights that are being fine-tuned, because the CNN weights are expected to be relatively good, and we do not wish to distort them too quickly and too much [53].

Ensemble of Classifiers

When more than one classifier is combined to make a prediction, this is known as ensemble classification [16]. Ensemble decreases the variance of predictions, therefore making predictions that are more accurate than any individual model. From work found in the literature, the ensemble techniques used include majority voting, probability score averaging and stacking.

In majority voting, every model makes a prediction for each test instance, or, in other words, votes for a class label, and the final prediction is the label that received the most votes [54]. An alternate version of majority voting is weighted majority voting, in which the votes of certain models are deemed more important than others. For example, majority voting was used by Chouhan et al. [55].

In probability score averaging, the prediction scores of each model are added up and divided by the number of models involved [56]. An alternate version of this is weighted averaging, where the prediction score of each model is multiplied by the weight, and then their average is calculated. Examples of works which used probability score averaging are found in [15,57].

In stacking ensemble, an algorithm receives the outputs of weaker models as input and tries to learn how to best combine the input predictions to provide a better output prediction [58]. For example, stacking ensemble was used by Rajaraman et al. [12].

Type of Disease

In this section, the deep learning techniques applied for detecting tuberculosis, pneumonia, lung cancer and COVID-19 respectively. The first three diseases were considered as they are the most common causes of critical illness and death worldwide related to lung [2], while COVID-19 is an ongoing pandemic [3]. We also found that most of the existing work was directed at detecting these specific lung-related diseases.

Tuberculosis

Tuberculosis is a disease caused by Mycobacterium tuberculosis bacteria. According to the World Health Organisation, tuberculosis is among the ten most common causes of death in the world [59].

Tuberculosis infected 10 million people and killed 1.6 million in 2017. Early detection of tuberculosis is essential to increase the chances of recovery [5].

Two studies used Computer-Aided Detection for Tuberculosis (CAD4TB) for tuberculosis detection [60,61]. CAD4TB is a tool developed by Delft Imaging Systems in cooperation with the Radboud University Nijmegen and the Lung Institute in Cape Town. CAD4TB works by obtaining the patient's chest X-ray, analysing the image via CAD4TB cloud server or CAD4TB box computer, generating a heat map of the patient's lung and displaying an abnormality score from 0 to 100. Murphy et al. [60] showed that CAD4TB v6 is an accurate system, reaching the level of expert human readers. A technique for automated tuberculosis screening by combining X-ray-based computer-aided detection (CAD) and clinical information was introduced by Melendez et al. [61]. They combined automatic chest X-ray scoring by CAD with clinical information. This combination improved accuracies and specificities compared to the use of either type of information alone.

In the literature, several works use CNN to classify tuberculosis. A method that incorporated demographic information, such as age, gender and weight, to improve CNN's performance was presented by Heo et al. [62]. Results indicate that CNN, including the demographic variables, has a higher area under the receiver operating characteristic curve (AUC) score and greater sensitivity then CNN based on chest X-rays images only. A simple convolutional neural network developed for tuberculosis detection was proposed by Pasa et al. [63]. The proposed approach is found to be more efficient than previous models but retains their accuracy. This method significantly reduced the memory and computational requirement, without sacrificing the classification performance. Another CNN-based model has been presented to classify different categories of tuberculosis [64]. A CNN model is trained on the region-based global and local features to generate new features. A support vector machine (SVM) classifier was then applied for tuberculosis manifestations recognition. CNN has also been used to classify tuberculosis [65–67]. Ul Abideen et al. [68] used a Bayesian-based CNN that exploits the model uncertainty and Bayesian confidence to improve the accuracy of tuberculosis identification. In other work, a deep CNN algorithm named deep learning-based automatic detection (DLAD), was developed for tuberculosis classification that contains 27 layers with 12 residual connections [69]. DLAD shows outstanding performance in tuberculosis detection when applied on chest X-rays, obtaining results better than physicians and thoracic radiologists.

Lopes and Valiati proposed Bag of CNN

features to classify tuberculosis [19] where feature extraction is performed by ResNet, VggNet and GoogLenet. Then, each chest X-ray is separated into subregions whose size is equal to the input layer of the networks. Each subregion is regarded as a "feature", while each X-ray is a "bag".

Several works that utilised transfer learning are described in this paragraph. Hwang et al. obtained an accuracy of 90.3% and AUC of 0.964 using transfer learning from ImageNet and training on a dataset of 10848 chest X-rays [70]. Pre-trained GoogLeNet and AlexNet were used to perform pulmonary tuberculosis classification by Lakhani and Sundaram [57], who concluded that higher accuracy was achieved when using the pre-trained model. Their pre-trained AlexNet achieved an AUC of 0.98 and their pre-trained GoogLeNet achieved an AUC of 0.97. Lopes and Valiati used pre-trained GoogLenet, ResNet and VggNet architectures as features extractors and the SVM classifier to classify tuberculosis [19]. They achieved AUC of 0.900–0.912. Fine-tuned ResNet-50, ResNet-101, ResNet-512, VGG16, VGG19 and AlexNet were used by Islam et al. to classify tuberculosis. These models achieved an AUC of 0.85–0.91 [71]. Instead of using networks pre-trained from ImageNet, pre-training can be performed on other datasets, such as the NIH-14 dataset [72]. This dataset contains an assortment of diseases (which does not include tuberculosis) and is from the same modality as that of the data under consideration for tuberculosis. Experiments show that the features learned from the NIH dataset are useful for identifying tuberculosis. A study performed data augmentation and then compared the performances of three different pre-trained models to classify tuberculosis [73]. The results show that suitable data augmentation methods were able to rise the accuracies of CNNs. Transfer learning was also used by Abbas and Abdelsamea [74], Karnkawinpong and Limpiyakorn [75] and Liu et al. [76]. A coarse-to-fine transfer learning was applied by Yadav et al. [77]. First, the datasets are split according to the resolution and quality of the images. Then, transfer learning is applied to the low-resolution dataset first, followed by the high-resolution dataset. In this case, the model was first trained on the low-resolution NIH dataset, and then trained on the high-resolution Shenzen and Montgomery datasets. Sahlol et al. [78] used CNN as fixed feature extractor and Artificial Ecosystem-Based Optimisation to select the optimal subset of relevant features. KNN was used as the classifier.

Several works that utilised ensemble are described in this paragraph. An ensemble method using the weighted averages of the probability scores for the AlexNet and GoogLeNet algorithms was used by Lakhani and Sundaram [57]. In [79], ensemble by weighted averages of probability scores is used. An ensemble of six CNNs was developed by Islam et al. [71]. The ensemble models were generated by calculating the simple averaging of the probability predictions given by every single model. Another ensemble classifier was created by combining the classifier from the Simple CNN Feature Extraction and a classifier from Bag of CNN features proposals [19]. Three classifiers were trained, using the features from ResNet, GoogLenet and VggNet, respectively. The Simple Features Ensemble combines all three classifiers, and the output is obtained through a simple soft-voting scheme. A stacking ensemble for tuberculosis detection was proposed by Rajaraman et al. [12]. An ensemble generated via a feature-level fusion of neural network models was also used to classify tuberculosis [80]. Three models were employed: the DenseNet, ResNet and Inception-ResNet. As such, the ensemble was called RID network. Features were extracted using the RID network, and SVM was used as a classifier. Tuberculosis classification was also executed using another ensemble of three regular architectures: ResNet, AlexNet and GoogleNet [79]. Each architecture was trained from scratch, and different optimal hyper-parameter values were used. The sensitivity, specificity and accuracy of the ensemble were higher than when each of the regular architecture was used independently. The authors of [15,81] performed a probability score averaging ensemble of CNNs trained on features extracted from a different type of images; the enhanced chest X-ray images and the edge detected images of the chest X-ray. Rajaraman and Antani [82] studied and compared various ensemble methods that include majority voting and stacking. Results show that stacking ensemble achieved the highest classification accuracy.

Other techniques used to classify tuberculosis images include k-Nearest Neighbour (kNN), sequential minimal optimisation and simple linear regression [38]. A Multiple-Instance Learning-based approach was also attempted [83]. The advantage of this method is the lower labelling detail required during optimisation. In addition, the minimal supervision required allows easy retraining of a previously optimised system. One tuberculosis detection system uses ViDi Systems for image analysis of chest X-rays [84]. ViDi is an industrial-grade deep learning image analysis software developed by COGNEX. ViDi has shown feasible performance in the detection of tuberculosis. The authors of [36] introduced a fully automatic frontal chest screening system that is capable of detecting tuberculosis-infected lungs. This method begins with the segmentation of the lung. Then, features are extracted from the segmented images. Examples of features include shape and curvature histograms. Finally, a classifier was used to detect the disease.

For CT scans related tuberculosis detection works, a method called AECNN was proposed [85]. An AE-CNN block was formed by combining the feature extraction of CNN and the unsupervised features of AutoEncoder. The model then analyses the region of interest within the image to perform the classification of tuberculosis. A research study explores the use of CT pulmonary images to diagnose and classify tuberculosis at five levels of severity to track treatment effectiveness [24]. The tuberculosis abnormalities only occupy limited regions in the CT image, and the dataset is quite small. Therefore, depth-ResNet was proposed. Depth-ResNet is a 3D block-based ResNet combined with the injection of depth information at each layer. As an attempt to automate tuberculosis related lung deformities without sacrificing accuracy, advanced AI algorithms were studied to draw clinically actionable hypotheses [86]. This approach involves thorough image processing, subsequently performing feature

extraction using TensorFlow and 3D CNN to further augment the metadata with the features extracted from the image data, and finally perform six class binary classification using the random forest. Another attempt for this problem was proposed by Zunair et al. [87]. They proposed a 16-layer 3D convolutional neural network with a slice selection. The goal is to estimate the tuberculosis severity based on the CT image. An integrated method based on optical flow and a characterisation method called Activity Description Vector (ADV) was presented to take care of the classification of chest CT scan images affected by different types of tuberculosis [88]. The important point of this technique is the interpretation of the set of cross-sectional chest images produced by CT scan, not as a volume but as a series of video images. This technique can extract movement descriptors capable of classifying tuberculosis affections by analysing deformations or movements generated in these video series. The idea of optical flow refers to the approximation of displacements of intensity patterns. In short, the ADV vector describes the activity in image series by counting for each region of the image the movements made in four directions of the 2D space.

For sputum microscopy images-related tuberculosis detection works, CNN was used for the detection and localisation of drug-sensitive tuberculosis bacilli in sputum microscopy images [29]. This method automatically localises bacilli in each view-field (a patch of the whole slide). A study found that, when training a CNN on three different image versions, namely RGB, R-G and grayscale, the best performance was achieved when using R-G images [28]. Image binarisation can also be used for preprocessing before the data were fed into a CNN [30]. Image binarisation is a segmentation method to classify the foreground and background of the microscopic sputum smear images. The segmented foreground consists of single bacilli, touching bacillus and other artefacts. A trained CNN is then given the foreground objects, and the CNN will classify the objects into bacilli and non-bacilli. Another tuberculosis detection system automatically attains all view-fields using a motorised microscopic stage [32]. After that, the data are delivered to the recognition system. A customised Inception V3 DeepNet model is used to learn from the pre-trained weights of Inception V3. Afterwards, the data were classified using SVM. DBN was also used to detect tuberculosis bacillus present in the stained microscopic images of sputum [31]. For segmentation, the Channel Area Thresholding algorithm is used. Location-oriented histogram and speed up robust feature (SURF) algorithm were used to extract the intensity-based local bacilli features. DBN is then used to classify the bacilli objects.

The most popular way for detecting Pneumonia infection and locating the affected area in the lungs is to use chest X-rays Jaeger *et al.* (2014). In addition, the chest X-ray is the most used radiological diagnostic tool for diagnosing a variety of lung disorders Demner-Fushman *et al.* (2016). Obtaining radiological inspectors in remote locations to analyse a larger number of chest X-rays is a difficult undertaking, according to Dou *et al.*(2016). Technologies have recently been applied to tackle problems in a variety of medical diagnosis procedures. Deep learning and machine vision methods are mostly used to aid in the detection of cancer and genetic diseasesMoeskops *et al.* (2016)[89].

Deep learning is a form of machine learning in AI that uses unstructured information to analyze. Jamaludin *et al.* (2017). Furthermore, constructing and constructing a deep learning method to handle any problem takes more time and computer resources. To bypass the difficulties of developing deep learning models, transfer learning approaches are developed. Olaf Ronneberger *et al. (*2015). Transfer learning is the process of taking the knowledge gathered by a deep learning network while addressing one problemand applying it to a different issue Azimi *et al.* (2018). The previous deep learning approach weights were fine-tuned using the data set for the current challenge. CNN is a multi-layer collection of nodes that detects visual motifs immediately from pixel pictures with little or no preparation. InceptionNet, ResNet, AlexNet, and VGGNet are the most prominent transfer learning approaches that use CNN to solve picture categorization problems.

Cross modality (CTMRI) before boosted deep learning for strong lung tumour segmentation from limited MR datasets is demonstrated by Jiang *et al.*(2019). Kasinathan *et al.* (2019) proposed an active contour model and CNN classifier for automated 3-D lung tumour identification and classification. Discordance of epidermal growth factor receptor alteration between original lung tumour and matched distant metastases in non-small cell lung cancer was proposed by Lee *et al.* (2019). Murray *et al.* (2019) discovered a protein that inhibits lung tumour growth and regulates differentiation. The relative relevance of DT-diaphorase and hypoxia in the bio activation of E09 by human lung carcinoma cell lines is proposed by Plumb *et al.* (1994). Prioritizing Circ RNA-disease relationships with a convolutional neural network based on multiple similarity feature fusion is proposed by Fan *et al.* (2020). The lung Cancer: a multi modality method to staging and therapy is proposed by Golomb *et al.*(1979). Kasem Khalil *et al.*(2018) show how to design a Neural Network architecture in an efficient way. Kasinathan *et al.*(2019) show how an active contour model and CNN classifier may be used to detect and classify 3-D lung tumours. Maghari *et al.*2020 suggests using a single neural network to predict ratings. The DT-diaphorase activity and messenger RNA content in human non-small cell lung carcinoma: connection to the responsiveness of lung tumourxenografts to mitomycin were raised by Malkinson *et al.*(1992). The medical Image Retrieval Approach by Texture Features Fusion is demonstrated by Ning *et al.* (2018). The Hausdorff Distance is used. Nishio *et al.* (2018) suggested a deep convolutional neural network with transfer learning for CAD[90].

Depending on the number of convolutional layers, VGGNetsare categorized into two kinds: VGG16Net and VGG19Net. The VGG19Net has greater overall performance than the VGG16Net. The VGG19Net is made up of nineteen convolutional layers and has a relatively homogeneous design, according to Litjens *et al.* (2017). It is now the most popular method for extracting characteristics from photos in the community. The VGG19Net's weight configuration is open source and has been utilized as a baseline feature extractor in a variety of other purposes and problems. The VGG19Net, on the other hand, has 48 layers and 20 million variables, making Roth's job a little more difficult Boudria *et al.* (2019), Boysen *et al.* (2019)[91].

Chen *et al.* (2021) introduced the Three-dimensional CNN architecture to provide a radiological evaluation of spinal lumbar MRIs and also pinpoint the expected diseases utilizing intervertebral disc sizes. The authors Azimi *et al.* (2018) developed a Convolutional Neural Network-based ECG data categorization model and implemented it in IOTs. This method classifies the patient's health condition using existing ECG data. The cost of installation was reduced, and the device's mobility was boosted, thanks to edge processing devices. Coche *et al.* (2016) examined the applications and difficulties of IoTand deep learning approaches in smart linked health systems via wearable or invasive devices. The authors also explored the unsolved problems with sensed and collected medical data. Conde *et al.* (2020) presented a scalable Internet of Things device for heart disease diagnostics.The detected data from the Internet of Things device was processed using the logistic regression approach. The vast volume of data acquired from patients was stored and retrieved via cloud services. ROC analysis was used to assess the efficiency of the regression models in predicting heart disease[92]. Cristin *et al.* (2020)

used boundary data and algorithms including the Gabor filter, Markov chain, and Haralick to extract textural properties from lung cancer CT images. The proposed system was dubbed 'BRISC.' The system's performance was tested using 2424 photographs, and it was found to be 88 percent accurate.

Shin *et al.*(2016) developed a CBIR system based on shape and texture evaluation. The authors use the inverse of Euclidean distance to estimate picture resemblance. The top one hundred and 20 photographs returned are utilized to categorize the photos from the input query. The metrics used are shown by the area beneath the curve, and the achieved result is 0.84. To determine pairwise similarity, Simsek *et al.* (2020) used lexical and perceptual similarity retrieval as well as weighted network creation. The quickest route is constructed graphs return photos that are similarto the search picture. Using HOG and multi-resolution retrieval, SVM categorization, and cosine image similarity, data was extracted at a range of levels, namely minimal, meaningful, and situational, from the LISS dataset. Given CNN architectures' improved performance, we compared the performance of two different CNN models in the CBIR method in this study. For fissure identification, Dabade *et al.*(2017) proposed a stochastic fissure segmentation method. The reliability of an augmentation filter of 1 nm for an oblique crack in the left lung was 73 percent, and 87.6 percent for the horizontal split in the right lung[93]. Chen *et al.*(2020) proposed a lobe fissure tracking system based on a redesigned optimization technique. The region edges are enhanced using the Robinson and Kirsch filters. The intensity of lobe fissure is determined using Otsu's approach. The Robinson & kirsch filters are used to improve the image. The ant colony method is a method for detecting.

The Role of CT Scans And X-Rays to Diagnosis Lung Cancer

A method for segmenting the fissure from lung CT scans was described by Demner *et al.* (2016). The watershed approach is used to identify the region that includes both non-fissure and fissure areas. Finally, the accessory fissure and non-fissure zone are removed using a removal procedure. To segment, the lung region, Dou *et al.* (2016) used a thresholding method followed by morphological operations. The pulmonary vessels are segmented using the threshold method and linked component evaluation. The fissure is then enhanced using the Hessian matrix method, and the fissures are recognized using mask construction and linked component method[94].

The form property of the lung fissure was used by Dutta *et al.* (2020), which comprises 4 steps: lung region recognition, binarization, preliminary fissure detection, and fissure elongation. To discover the fissure zones, Eichner *et al.* (2019) used watershed transformation accompanied by the graph search approach. El-Mahelawi *et al.*(2020) scanned them adaptively in a sagittal view. For the first segmentation of lung regions, region growth is used. A line improvement filter based on a Hessian matrix is used, followed by a uniform cost filter. Landslide fissure modeling for multi-scale edge detection was described by Fan *et al.* (2020). The linear dark curving characteristics are removed. The cracks are detected using a Gaussian matched filter that combines the first component of a Gaussian filter. Ferreira Junior *et al.* (2018) used a genetic system to locate fissures in CT scans automatically. The automatic threshold method is used to segment the input lung CT images. The ROI region has been split. The ROI is subjected to a bandpass filter. The image is segmented using morphological operations[95].

The first stage was reported by Geetharamani *et al.* (2019), who used the fissure sweeping approach to determine the fissure area. They employed the watershed transform in the second step to localize the positions and corrugations of the fissures in the fissure area. They evaluated their technique on 6 clinical CT images with thicknesses ranging from 3 mm to 8 mm and found 86-96 percent accuracy for the lateral fissure in the left lung, 89-90 percent accuracy for an oblique fissure in the right lung, and 100 percentaccuracy for an oblique fissure and lateral fissure in the right lung, respectively. Ghazaly *et al.* (2020) stated that they used a sweeping technique to determine the fissure location at first. Finally, wavelet analysis was employed to locate fissure locations and corrugations in the fissure region. They put their technique to the test on nine high-resolution CT pictures of lung size[96].

The results were only tested for specific noises, such as speckle noise. Hou *et al.* (2017) aimed to develop a lung cancer detection system using CT lung scans. To eliminate salt and pepper noise, median filtering is performed first, and then a Gaussian filter has been used to eliminate speckle noise. Medical images are influenced by many types of sounds, which are removed using the filtering approach, according to the literature review. Huang *et al.* (2020) and Hung *et al.* (2019) both show threshold-based segmentation. GLCM was used to extract textural and architectural features from fundus images; however, feature extraction takes longer[97].

To retrieve the ROI from diverse medical images supplied, we used a level set-based segmentation algorithm Jamaludin *et al.* (2011). The first stage is to determine the limit of an input image so that all pixels are below the threshold range of zero and the value is used as the actual picture. This helps to preserve the original image's attributes and keep all values the same as the original image beside the pixels that aren't needed for the analysis.Then certain minor ignorable sections are removed using a morphological method. Finally, for classification, the variationalthresholding method is used. For big image sets, the thresholding-based segmentation technique had lower accuracy and took longer to compute. Jue *et al.*(2019) proposed a method for adding local membership data into the conventional FCM classification method. The methods LMKLFCM, the traditional FCM, LDFCM, and LMFCM were introduced. With the KL data distance functioning as a fuzzifier, the goal is to minimize the traditional FCM value with a unity fuzzifier coefficient. The accuracy of the segmentation findings was poor, and it needed foreknowledge of image data[98].

In a preprocessing stage, brain pictures of gliomatumors Kage *et al.* (2019), which have a wide range of shape, size, and visual attributes, are automatically segmented and normalized to the same scale. The improved images are then separated using 3D super-voxels depending on their intensities. The borders of the actual picture were aligned to the saliency map using an edge-aware filtering method, which enhanced the tumor's boundaries. Then, from super-voxels, a collection of robust feature extraction is derived for tumor classification in brain pictures. Brain tumor segmentation utilizing FCM and K-means clustering approaches Kalainayakan *et al.* (2016) necessitates a thorough grasp of pathology as well as the intensity and form of the MRI picture. The fundamental issue with segmentation is that each tumor is unique in terms of form, volume, position, and severity. This approach was primarily used to test brain images, but it also had an impact on extracting features[99].

A method of obtaining information from images for decision- making and resolving image segmentation by recognizing the boundaries or pixels between various regions from which intensity is taken. A comparison study of medical picture segmentation techniques was presented by Khobragade *et al.* (2016) and Kim *et al.* (2019). The following is a list of resources[100].

Poor contrast quality and noise are two of the most typical flaws in medical photographs. Kweik *et al.* (2020) developed a morphological transformation technique for improving contrast and quality in medical data. In the Top-Hat and Bottom-Hat transforms, a disk-shaped mask has been used, and this mask is crucial to the procedure. The structural qualities of things are used in mathematical functions. Image enhancing approaches that are automated are thought to be a difficult optimization challenge. This hybrid model is used to find the global optimum and determine the best transformation config. Image contrast augmentation is regarded as a challenge of optimization Liu *et al.* (2017). The implementation of meta-heuristic and soft computing-based techniques was contrasted in Lu *et al.* (2019). Noise as well as other quality-related issues, such as poor contrast, blurring, and difficulty extracting appropriate information, plague the pictures modalities. Traditional biomedical image-enhancing approaches are somewhat reliant on the image type and medium. The image enhancement method has been classified as automated and quantified using specific characteristics. For the goal of enhancement, a transformation method will be employed, and the resulting outcome will be evaluated using some assessment criteria. Ma *et al.* (2019) provided APSO with a parameterized lineartransformation that uses both local and global picture information. An objective criterion for quantifying picture enhancement is applied here, which takes into account the image's entropy and edge detection. Edge information (E), Entropy (H), and Fitness (F) are used to describe the input images and provide information on their size (F). The simulation results reveal that the APSO-based image enhancement method outperformed previous techniques, however, precision is still a drawback. The medical picture is more precise and clear visual data in the created image to clinical diagnosis as the detailed info increases. The resulting images have superior results to the original medical photographs, and the procedure is easy and efficient. Nuyttens *et al.* (2020)[101].

The Role Of Neural Networks To Diagnosis Cancer

The numerical qualities of numerous visual features are analyzed, and data is organized into groups. Training and testing are two common processing processes in classification systems. During the training phase, the characteristics of common image characteristics are identified, and testing is conducted using these features. Obinikpo *et al.* (2017)

ANN is used to create a system for detecting and classifying brain cancer Park *et al.* (2019). The main problem in detecting the tumor's edge is that the tumor appears very dark on the image. Histogram equalization was used to solve this problem. The term "segmentation" refers to the division of an image into its constituent pieces or objects. This process's generated tiredness could contribute to diagnostic mistakes. Only the image data were used to test the system. With a few tweaks, the technique might be used to classify other forms of tumors as well.

Paul *et al.*(2016) proposed a probabilistic neural network for lung cancer detection and classification that was focused on detecting lesions. An input layer, hidden layer, summation layer, and output layer are the four levels of the PNN. After carefully selecting settings, the majority of the nodules may be seen. The Input Layer, Radial Basis, and Competitive Layer are the three layers of PNN. The vector distances between the input vector and the row weight vectors in the weight matrix are calculated by the Radial Basis Layer. Based on the distance between them, the competitive layer picks the training pattern that is closest to the input pattern. Following the application of the image to the PNN, it will determine the type of cancer-based on the factors evaluated. This technique can be made even more effective by increasing the database size and including all types of tumor photos.

The DNN design comprises input nodes, hidden neurons, and output units; the DNN does not have a convolution layer. The SAE has a hidden layer of a single sparse autoencoder, and lung nodule diagnosis is an image analysis challenge. Russo *et al.* (2019) Ensemble learning is models that are made up of numerous weaker models that are learned separately and then integrated in some way to create a final prediction Rymaazewaki *et al.* (2020).

Segmentation techniques, which also included skull stripping and morphological operations for preprocessing, were used to classify brain tumors using neural networks Sandhiya *et al.* (2020). The wavelet transforms were used to decompose and extract features from an MR image. Finally, AdaBoost classification techniques were utilized to identify discriminative characteristicsfrom MRI images to classify them as cancerous or benign. Adabooster classifier was created by smoothing the images utilizing partial differential models. In this case, the algorithm was less accurate. Chen *et al.*(2017) The influence of CNN scaling factor on pulmonary nodule categorization is mostly focused on the automatic recognition of lung nodules using a CAD system, which saves radiologists time by eliminating the need to evaluate a huge proportion of CT scans to discover nodules. Gang *et al.*(2018) advocated density estimation in machine learning for chest x-ray detection of lung disease, focusing primarily on matrix factorization like lung delineation, ast-SNE, and bone shade elimination. When these datasets were matched to various pre-processed data, it was discovered that they had the greatest training speed and accuracy. Golan *et al.*(2016) The suggested image retrieval identification in CT scans using cnn model concentrates on a CAD system that evaluates a large quantity of image data based on numerous changes of chest radiography in their shape and dimension without utilizing any clusters. Jiang *et al.*(2017) With the steady advancement of machine learning, the technique which may be used to images has also advanced qualitatively, resulting in the concept of deep learning-based medical picture categorization. Jin *et al.*(2017) The suggested training deep locational lung characteristics using 3D dcnn for early detection of cancer emphasizes on rapid and precise diagnosis of lung cancer, which is critical for pulmonary cancer patients' survival rates. Deep temporal lung characteristics are investigated for this purpose. With the lung segments that have been tested andtrained, a CNN structure is being built. Ke *et al.*(2019) suggested a method for detecting deteriorated lung regions in x-ray images using a neural network in conjunction with heuristic methods. Minor alterations in pulmonary tissue architecture can be detected using the suggested neuro-heuristic technique. Kido *et al.*(2018) suggested an image-based CADx algorithm that employs CNN and areas with CNN characteristics to recognize and identify lung anomalies. As a result, the use of an input images exactor is not required. CADx necessitates the presence of lung anomalies like diffuses & nodules the disease. The diagnosis of lung anomalies is also done using a CADe technique that employs R-CNN. CADx is used to test the efficiency, and CADe is used to discover any errors. Li *et al.*(2017) The texture characteristics of the Lung were extracted using the CE filter and stationary WT, and the white cluster network was generated using AdaBoost[101].

Luo *et al.*(2017) proposed using 3D CNNs to classify lung nodules depending on shape and appearance, with the goal of studying existing transfer learning technologies in the area of computer-aided diagnostics. To identify pulmonary nodules in Tomography images, a 3D CNN is utilized. Mukherjee *et al.*(2014) suggested a method for automatically detecting pulmonary nodules depending on geometric parameters. This method uses shape criteria such fullness, irregularity, size, and aspect proportion to classify malignant and benign lung nodules. Most of these solutions necessitate appropriate specialized skills or a significant amount of time and effort to develop and execute. Priya *et al.*(2021)Medical image categorization study has yielded numerous study outcomes and was implemented clinically. Machine learning doesn't really necessitate any healthcare expert knowledge, nor does it necessitate engineering tech features. This may acquire key qualities like colour and edge using the first layer, and then utilize the underlying surface to learn more complex features of lung imaging data sets. ReboucasFilho *et al.*(2019) examine the efficacy of the OPF classifier in the function of detecting lung disorders on CT images in aspects of pulmonary picture classification methodologies study. The study compares 3 extracting features approaches and 7 distance measuring routines. Rossetto *et al.*(2017) suggested neural network - based for lung disease CT scan classification, focusing on lung carcinoma, which has become a critical and major health issue. If early diagnosis is provided, the patients will have the greatest chance of recovery. DL provides this option for lung disease early detection. As a result, the precision rate may be enhanced while the false positive rate is reduced. Several preprocessing approaches were utilised in this.

Shin *et al.*(2016) To learn CNN and RNN, pick OpenI dataset and retrieve accessible chest X-ray radiography data and treatment data. They employ the characteristic of the network recovered by CNN and the accompanying picture characterization as feed to the Recurrent neural network in this procedure. Then, in a Recurrent neural network, they utilize the picture's state variables at all T-Times to mean pool and have an mean statement as picture background. Then, CNN and RNN are retrained. Their system training procedure applies to healthcare image analysis, however their actual efficiency is poor[102].

Y. Bar *et al.*(13) Investigate the capacity of a CNN trained on a non-medical data to detect various diseases in lung parenchyma. It normalised all variables and lowered the complexity of visual information from the medical diagnostic section by PCA, and then he chose the AlexNetpretrained model by ImageNet to learn beyond and categorise lung nodules. Its primary benefit is that it addresses the issue that huge data sets are rarely accessible in the medical sector; nevertheless, the trials were done on private datasets and can not be matched to the findings of others.

Supanta *et al.*(2018) To overcome the issues of minimal visibility and highlighting of these characteristics, a technique to identify and recognize lung nodules from computerized radiography pictures was presented. Then, in 2012, AlexNet, a well-known NN model created by Krizhevsky *et al.*(2012), took 1st position in the ImageNet image categorization contest, outperforming the 2nd position by 10%.

Woźniak *et al.*(2018)A novel lung tumor classification system centered on stochastic neural networks has been suggested. This technique is basic, yet it has a decent classification effect and can detect nodules with low resolution. To features extracted from a lung picture.

Woźniak *et al.*(2018) developed an artificial pulmonary illness decision assistance method for x-ray medical pictures centered on Bio-Inspired Approach. The approach models approval that indicates where unhealthy cells are often sure to emerge by simulating the procedure of medical tests of lung disorders. The system is accurate, however it is inefficient in terms of time difficulty. Sangamithraa *et al.*(2016) present a neural network-based identification system to evaluate the proteomic structure of cancer screening. This method is broken down into three stages: statistical significance testing for feature classification, Radial Basis Function Neural Network (RBFNN) and Probabilistic Neural Network (PNN) for classification, and ROC analysis for optimization. When compared to the existing approach in experimental observation, the new approach proves to be the best[103].

Supriya *et al.* (2019) developed a method that uses a CAD analysis to identify GGO nodules in CT images of the chest. The use of a Gabor filter on CT images helps to improve the detecting process. Some of the morphological strategies used to trace out the high-impact valued objects include the threshold procedure and labeling. The cancer-affected candidates are then identified using feature analysis on these objects. Following the feature analysis, template matching between several Gaussian reference approaches and possible cancer candidates was performed to determine their resemblance. 715 slices with 25 GGO nodules were used to test this procedure. With a 0.76 False Positive rate per slice, this approach achieved 92 percent sensitivity. Artificial Neural Networks were employed in this method to reduce the number of FP finds. Finally, the FP is reduced to 0.25 FP/Slice, but the sensitivity is also reduced to 0.25 FP/Slice Taftietial (2018).

Hernandez- Cisneros suggested three EANNs and

DoG for the categorization of micro-calcification clusters in mammograms (2020). They compared their suggested strategy to a back propagation-trained feed-forward Neural Network (NN). Talasilla *et al.* (2017) the optimal mass set for a neural net is discovered here using Genetic Algorithms, as well as the initial mass set while using the backpropagation neural learning algorithm, changing its variables, and developing its architecture to improve overall precision, responsiveness, and selectivity in neural networks. Teramoto *et al.* (2017) devised a strategy that outperformed networks built using basic propagation. Fogel's evolutionary programming approach has been modified to provide this new strategy for evolving neural networks. It uses fine needle aspirate data to diagnose lung cancer. Data visualization and pre-processing characterization are used to portray the gentle and unprocessed data in a visual interpretation manner. This is a symmetrized representation of the data. Teramoto *et al.* (2016).

Wei *et al.* (2018) examine hybrid lung segmentation for computer-aided diagnosis of chest CT images. This approach is divided into three stages. The first step is to use the inverse seeded region growth and linked component labeling method to differentiate the airways and lungs. The next stage is dimensional region growth to eliminate the trachea and major airways. The third stage consists of deriving the lung boundaries from the first and second stages' results. A two-level ANN architecture is used in this computer-aided diagnosis technique. This first Artificial Neural Network (ANN) design detects suspicious areas in low-resolution photos. The input is sent to the second ANN (ANN) architecture from the initial output data to locate the peaks of all pixels in the questionable region in the curvature peaks. Small tumors have a distinct signature in the form of a curvature-peak characteristic, making them easy to identify. To offer a positive recognition, the result of this network was fuzzified at a predefined relevance level[104].

The Role Of Cad Technique For Disease Diagnosis

Wiecaorek *et al.* (2020) Using helical CT scans, they established a CAD method for disease diagnosis.This strategy can reduce time complexity while increasing diagnosis confidence. This procedure consists of two stages: analysis and diagnosis. The lung and pulmonary blood vessel area will be removed, and its characteristics will be analyzed using the image processing method in the analysis step. These characteristics, as well as the tumor's location, were used to develop the diagnostic rule. Yamamoto *et al.* established a comparative reading for lung cancer relying on helical CT images on the computer-aided diagnosis. This paper uses an automatic approach based on CAD to identify lung cancer at an early stage. This device detects the questionable region in a CT scan of the lungs instantly. Every slice of the picture from the past and current CT scans is examined using a matching technique and interface to determine the suspicious region's characteristics. Wisely *et al.*(2020)give computer-aided diagnostics for lung CT utilizing artificial life models. Several strategies in the CAD system, center of maximal balls, include region growing, form models, and active counter, but it is thought that the biological simulations of ants, also known as artificial life models, are at the heart of this method. The image's ribcage is first recognized using a 3D region expanding method. The active contour is then employed to create the limited area around the ribs, and it is set up to restore the vascular and bronchial tree flawlessly and cleanly.

Wisley *et al.* (2020) suggested a novel CAD method for early lung nodule detection. The volumetric variations in the detected lesion over time are used to calculate the growth rate of the identified lung nodule. This method's process is divided into five phases. The first step is to divide the lung area on the CT scan and then locate the lung nodule within the segmentation process. We next utilize non-rigid registration to match the two LDCT images and correct the motion artifacts induced by the patient's motions and breathing. It is followed by the segmentation of discovered lung nodules, and the final stage is to quantify the tumor's volumetric changes. Lin *et al.* (2020) developed a neural fuzzy model design of a diagnosis rule to identify lung nodules. The initial image segmentation used to segment the lung and extract the region of interest in the divided lung region included morphology closure, labeling, and thresholding. We can get parameters like surface area, mean luminance, and circulation from the region of interest, and we'll apply the neural fuzzy model's diagnosis criteria to detect the nodules.

Walfram *et al.* (2019) established a completely automated computational method for identifying lung nodules in thorax helical CT imaging. The pictures from a CT scan of the lungs can be analyzed in 2d and 3d. Section by section, the lung image is processed to form a segmented lung volume for subsequent investigation. By giving the divided lung volume with several grey-level thresholds, a sequence of thresholded lung volumes is created. Using 18 point connection, a contiguous three-dimensional architecture on the lung could be discovered within every thresholded lung capacity. The volume criteria are used to choose the first lung nodule applicant. Grey-level and morphological characteristics were determined for each nodule candidate. Rule-based techniques are used to reduce the number of nodule candidates that correlate to non-nodule options, and then linear classification technique is used to integrate the attributes of other candidates.

Yao *et al.* (2016) developed an improved method for computer- aided identification of lung nodules in chest CT. The CAD procedure is used to remove air from outside the patient's soft tissue and bone structure. The lung region is next subjected to three-dimensional region classification to detect lung nodules using rule-based research. Krishna *et al.* (2017) proposed the Hopfield neural network for multispectral unsupervised categorization of MR images. Winner-take-all neurons produce the crisp categorization map. T2-weighted pictures of the skull and proton density-weighted imaging are used to do this. Lee *et al.* (2019) introduced a novel approach called Quoit filter (Q-filter). This method isolates the high amplitude fluctuation in the lungs' baseline. It detects cancer applicant shadows using CT cross-section of lung regions, reducing the number of cross-sections evaluated by the doctor[105].

Kumar *et al.* (2018) developed a Massive Training Neural Network-based image processing method. This approach greatly aids radiologists in detecting the nodule overlapping on the ribs in chest radiography. This non-linear filter is used to train the chest radiograph inputs and their accompanying teaching images. To train the MTANN, the linear- output multilayer ANN technique was employed to develop the linear-output back-propagation (BP) method. Dual-energy reduction is used to distinguish the bones from the soft tissues. The energy dependence of X-ray attenuation on diverse materials is used in this separation. The researchers investigated and provided a statistical appraisal and verification for exhibiting the pulmonary nodules' ellipsoidal geometrical structure in Multi-slice X-ray computed tomography (CT) images. Lekshmanan *et al.* (2016) This method combines a multi-scale joint separation with a model-fitting approach and expands the robust mean shift-based research to linear space concept. This method was validated by comparing the cross-section of CT images from two clinical data sets with a three-dimensional nodule in quasi-real-time. The suggested approach has three stages: model assessment, model validation, and volume observations. Ingrid Sluimer *et al.* suggest a registration strategy for segmentation.

Ling *et al.* (2017) presented research on a genetic method for segmenting medical images. On 2D (two-dimensional) prostrate slices of pelvic computed tomography images, our technique effectively segments them. The level set function is used by the genetic algorithm to represent the segmenting curve. Shape and textual priors obtained from manually divided images constrain the evolution of the segmenting curve across succeeding generations. The author also looked at how the previous algorithm had been improved and compared the suggested approach to GENIE, a GA-based segmentation tool, and a simple texture separation algorithm (Laws texture measures). The original test was conducted on a small population of contours and yielded insignificant findings in terms of prostate area convergence. The results can be enhanced by expanding the method to 3 components and including spatial relationships between anatomical markers.

Mienye *et al.* (2021) reported a unique method for detecting lung nodules. The CAD approach is used to recognize pulmonary nodules in computed tomography (CT) images. Mixtures of image processing techniques were used to identify the pulmonary parenchyma. After extraction, 3D geometric features based on region growth were used to identify the nodule. This method successfully detects malignant tumors while having a low false- positive detection rate. Nasser *et al.* (2019) developed a new CT lung nodule CAD method. This approach can distinguish between GGO nodules and solid nodules. The lung region segmentation from CT data is done using a fuzzy thresholding algorithm, and then the Dot map and volumetric form index map are generated. Dot map is computed using Eigenvalues from Hessian matrices, volumetric shape reference map on local Gaussian, and mean corrugations. These maps are calculated for each Voxel to better items with high spherical components within the lungs of a certain shape. By providing a good structure description, the "dot" characteristics and shape index clustering set the path for early nodule candidate development. This method's advantages include adaptability to various imaging settings, quick computing, and a detection accuracy rate. The nodule allows it to be used in clinical settings.

Oxnard *et al.* (2011) offered an initial inquiry employing a uniquemode of bi-static radar device for lung cancer diagnosis known as FSR. For cancer diagnosis and localization, the dispersed signal obtained from the tumor is analyzed for Doppler frequency. The design of the three systems was studied using the mechanical motion of the transmitter and receiver. This approach describes the simulated output of a CST Microwave Studio and provides feasibility study results for using it for lung cancer diagnosis. The peculiarity of the Radar Cross Section (RCS) of the lung picture can be used to forecast malignancy in tumors and lung tissue. To calculate the RCS parameter, example images scanned with an electromagnet that contains fatty tissue and tumor are generated. Ramani *et al.*(2021) suggested a new method for detecting clustered micro-calcifications (MCs) in mammograms. The CAD technique is utilized to identify MC accurately, as its presence is an early indicator of lung cancer. The suggested dual SVM algorithm based on bagging and boosting improved the detection performance. Microcalcification must be identified. In this approach, there are 3 phases: image processing, feature extraction, and the BB-TWSVM module. The fundamental truth of MCs is assumed as prior in mammography. Each MC is pre-processed using a high pass filter and an artifact reduction filter. Then, using these clustered feature extractors, data from 164 photos are extracted. The detection approach for MC's detection is designed using a classification problem and reinforcement learning. The BB- TWSVM classifier is used to determine the absence or presence of MCs. Experimentally, the CAD scheme produces significant success in diagnosing lung cancer[106].

Two critical issues in mammography interpretation for lung cancer in MR-images were described by Shaukat *et al.* (2019). Vijh *et al.* (2019) propose using SVM learning to automate the detection of MCs in digital mammograms. For detection, supervised learning with the SVM approach was created. The developed approach was evaluated on 76 mammograms including 1120 MCs. FROC (Free-Response Receiver Operating Characteristic) curves are used to estimate detection performance. The newly created SVM architecture method outperforms outdated algorithms.Machine learning is a branch of AI that employs a variety of optimization, probabilistic, and statistical approaches to enable computers to "learn" from past experiences and identify difficult-to-detect patterns from complex, noisy, or large data sets, and thus plays an important role in cancer detection and treatment. Usama *et al.* (2020) suggested a feature extraction strategy that included SVM, K-nearest neighbors, and probabilistic neural network classifiers. To characterize malignant or benign tumors discovered in the lungs, researchers used hierarchical clustering, signal-to-noise ratio feature ranking, and sequential forward selection-based feature selection. With the two widely used lung cancer benchmark datasets, the SVM classifiers algorithms give the best overall accuracy of 96.33 percent and 98.80 percent inlung cancer diagnosis. The performance of this technique was evaluated using the Wisconsin diagnostic lung cancer dataset. When compared to other current techniques, the proposed approach provided significant performance. The method focuses on solving two issues in Van de Worp *et al.* (2021) suggested‘stumor identification technique from mammography. Extracting features that categorize tumours and detecting suspicious regions with a low brightness to their context were the two issues. The detection method consists of four steps: mammography enhancement, tumor area segmentation, feature extraction from the segmented tumor area, and finally the application of the SVM classifier. Understanding minute variances will improve the quality. The procedures in the enhancement process are top-hat operation, DWT, and filtering. The image's contrast is boosted through contrast stretching. Thresholding segmentation improves lung cancer identification and treatment, and the divided lung area is then subjected to feature extraction. The SVM classifier is used to categorize the tumor at the end of the process. The sensitivity of 75 mammographic pictures from the mini-MIAS database was examined and found to be 88.75 percent.

Warheit *et al.* (2016) present the genotyping technique for strain typing in animals especially rat. The PCR amplification technique was used to identify DNA restriction segments, and it only required a small amount of genetic material. AFLP can swiftly and effectively survey a target genome without the requirement for prior sequence knowledge. According to Flatten *et al.* (2019) CT screening is most commonly utilized in the microbiological, botanical, and human genome areas.Hopewell *et al.* (2019) demonstrated theLungtumor NF-κBsignaling promotes T cell–mediated immunesurveillance.

SVM, as demonstrated by Lekshmanan *et al.* (2016), is an effective method for Classification of lung columnar cells using feed forward back propagation neural network.It demonstrate that the pattern recognition system of the SVM method can be applied to a wide range of biological data by using DNA microarray hybridization experiments to identify unknown genes in gene expression data, and Mienye *et al.* (2020) used to improve sparse autoencoder based artificial neural network approach for prediction of heart disease ANN may be used to find translation initiation areas and to recognize splice sites Potghan *et al.* (2020) SVM can also be used to cluster AFLP data to obtain high accuracy discrimination of cancer and non-cancer tissues. Rani *et al.*(2021) is used to create Superpixel with nanoscale imaging and boosted deep convolutional neural network concept for lung tumor classification, and the jackknife test is used to verify the effectiveness of data separation. It's also known as a leave-one-out test since only one data point from each dataset is utilized as test data, while the rest is used to learn the technique. One has been chosen as test data out of 74. SVM with linear kernel was used to train remaining cancer and normal data. It is divided into two categories: positive data and negative data[107].

Conclusion

The focus of this paper was on current advancements in pneumonia and lung cancer detection approaches. To improve the effectiveness of pneumonia and lung cancer detection, a variety of strategies have been developed and employed. In lung disease detection techniques, several applications such as deep convolutional neural networks, image processing, DCGAN, and data augmentation, CBIR are applied. Each method has its own set of pros and disadvantages. Many studies are still being conducted since it is critical to diagnose cancer as early as feasible. The qualities and characteristics of existing approaches are mostly responsible for these advances.

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