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Review article

The effectiveness of deep learning vs. traditional methods for lung disease diagnosis using chest X-ray images: A systematic review

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A B S T R A C T

Recently, deep learning has proven to be a successful technique especially in medical image analysis. This paper aims to highlight the importance of deep learning architectures in lung disease diagnosis using CXR images. Related articles were identified through searches of electronic resources, including IEEE, Springer, Elsevier, PubMed, Nature and, Hindawi digital library. The inclusion of articles was based on high-performance artificial intelligence models, developed for the classification of possible findings in CXR images published from 2018 to 2023.

After the quality assessment of papers, 129 articles were included according to PRISMA guidelines. Papers were studied by types of lung disease, data source, algorithm type, and outcome metrics. Three main categories of computer-aided lung disease detection were covered: traditional machine learning, deep learning-based methods, and combination of aforementioned methods for all lung diseases.

The results showed that various pre-trained networks including ResNet, VGG, and DenseNet, are the most frequently used CNN architectures and would result in a notable increase in sensitivity and accuracy. Recent research suggests that utilizing a combination of deep networks with a robust machine learning classifier can outperform deep learning approaches that rely solely on fully connected neural networks as their classifier. Finally, the limitations of the existing literature and potential future research opportunities in possible findings in CXR images using deep learning architectures are discussed in this systematic review.

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1. Introduction

Pulmonary diseases are among the most significant general diseases. According to World Health Organization (WHO), global death rate is reported to have increased as a result of lung disease [1]. In 2019, lung diseases, including chronic obstructive pulmonary disease (COPD) and lung cancer, accounted for approximately 3.3 million deaths worldwide [2]. The death rate from lung diseases is expected to increase in the coming years due to the aging of the population and the increasing prevalence of risk factors such as tobacco use, air pollution, and occupational exposure [3–5].

Early diagnosis and management of lung diseases is extremely crucial and helps prevent the progression of the disease and reduce the risk of complications. Imaging plays a vital role in lung disease diagnosis. There are several imaging methods used to provide a comprehensive evaluation of lung diseases and guide appropriate treatment. Chest X-ray (CXR), Computed Tomography (CT) scan and Magnetic Resonance Imaging (MRI) are examples of medical imaging modalities and diagnostics tools to visualize the lungs and detect any abnormalities [6].

CXR imaging is a rapid, widely used, and non-invasive available techniques [7]. As the first-line imaging tool for chest assessments, CXR has a low radiation dose and a short processing time [8]. Quality of CXR images is less than the other modalities like CT, MRI. Low quality of CXR encourages using deep learning (DL) to gain the same performance as the other modalities. So, CXR has a potential to provide a large amount of data for developing DL algorithms successfully. Fig. 1 shows 14 examples of common thorax diseases, presented in the NIH-14 dataset [9].

A growing interest in Artificial Intelligence (AI) architectures in diagnostic imaging has been observed in the past few years. A significant benefit of AI has been its ability to recognize complex patterns in imaging data and provide quantitative information about radiographic images. Radiologists can use AI algorithms as a second or concurrent reader and these algorithms have an added effect on their performance [10]. It is estimated that utilizing AI algorithms has 10% more accuracy than an average radiologist [11,12].

Traditional computer vision is a subset of AI that have been used for medical image analysis. The methods rely on handcrafted features with domain knowledge, followed by segmented object identification and classification. The difficulty with this traditional approach is that it is necessary to design filters manually to extract features and choose which features are important in each given image. A growing number of classes increases the difficulty of feature extraction [13]. Traditional machine learning (ML) and DL methods can resolve multifaceted complications by gaining insight knowledge from simple representations.

Over the past decade, there has been a clear shift towards the utilization of DL in various fields, including the medical industry, where it is poised to become a crucial component of routine clinical practice, particularly in the field of diagnostic imaging. The promising advancements in DL technology offer immense potential for improving patient outcomes, reducing costs, and increasing efficiency in medical diagnosis, paving the way for a future where DL is integral to the practice of medicine [14–16].

As a result, DL approaches are widespread due to their ability to learn precise representations and maximize the benefits of in-depth knowledge. DL methods such as Convolutional Neural Networks (CNNs) mostly improve prediction performance using big data and plentiful computing resources and have pushed the boundaries of what was possible [13]. Thus, this computer-aided solutions can be used as a support tool for an effective and efficient diagnosis process by reducing human error and effort. CNN can reach the expert-level performance in classifying common lung diseases and related findings and reduce radiologists' workload and reported error rates [17].

This systematic review provides insight into different datasets used in the reviewed literature. The work explores and summarizes the findings in the domain of lung disease classification with CXR images and presents several possible future directions. The other objective is to assess their performance and generate new insights into DL-based health-related issues. In contrast to similar works, this research compares the performance of deep learning, traditional approaches, and a combination of them both, while related works only consider one of these methods.

The overview of the literature indicates CNN-based models are the most commonly used algorithms for classification and automatic detection of possible findings from CXR images. With hybrid ensemble strategies for multiclass classification, the highest accuracy was 99.2%. Combining deep learning and traditional machine learning, increase the sensitivity and specificity of algorithms. Using these findings, developers and researchers can choose appropriate techniques and datasets and explore possible future directions to build a better system.

The rest of the paper is as follows: Section 2 describes the method used to conduct this systematic review, starting with the identification of papers and the screening process based on the PRISMA guidelines. In Section 3, we briefly introduce the preprocessing technique. Section 4 discusses the application of machine learning algorithms to detect possible findings in CXR images. In Section 5, we discuss the current research status and future directions. Finally, Section 6 includes the systematic review conclusion.

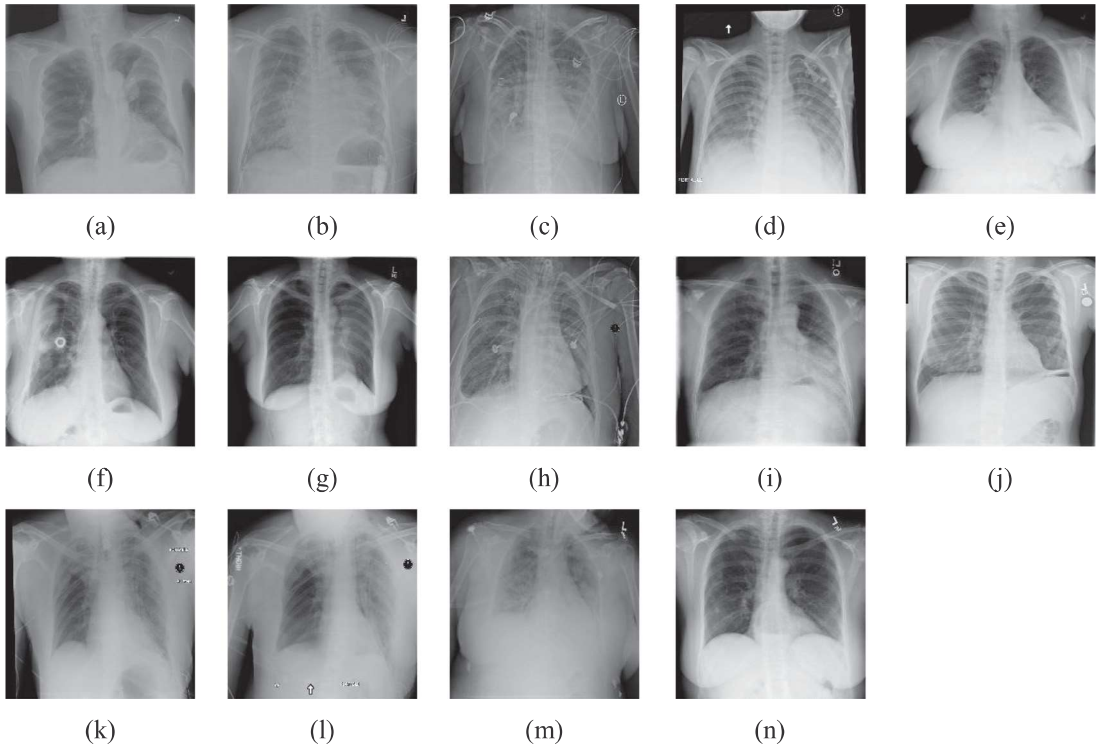

Fig. 1. Random samples of frontal CXR images presented in the NIH-14 dataset: (a) Atelectasis, (b) Cardiomegaly, (c) Infiltration, (d) Effusion, (e) Mass, (f) Nodule, (g) Pneumonia, (h) Pneumothorax, (i) Fibrosis, (j) Pleural Thickening, (k) Emphysema, (l) Consolidation, (m) Edema, (n) Hernia [9].

2. Methods

2.1. Overview

The research methodology used for performing systematic review is Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA). The method clears all the steps followed from identification to the screening articles. In accordance with the PRISMA model, we searched and identified the relevant studies that used AI techniques to detect possible findings in CXR images. This paper answers the following research questions concerning the targets of the study:

RQ1: What is the effectiveness of deep learning vs. traditional machine learning methods for detection of possible findings in CXR images?

RQ2: Which datasets and training data have been utilized most extensively?

RQ3: What validation strategies and evaluation metrics were used for measuring the model performance?

RQ4: How is the efficiency of different types of deep learning and its architectures in promoting the classification of possible findings in CXR images?

RQ5: Which machine learning and deep learning architectures were proposed for the detection of possible findings in CXR images?

RQ6: What are the challenges faced by the researchers in constructing deep learning-based diagnostic models?

A comprehensive literature search was performed in PubMed, IEEE, Elsevier, Nature, Hindawi, Springer and Google Scholar database. This search was carried out to retrieve all relevant studies in literature which developed an AI technique for the diagnosis and classification of possible findings in CXR images. There is a wide range of reputed sources included in the aforementioned databases. We used the advanced search feature in each of these databases, with keywords contained (Disease Name), (ML/DL Method), and (Chest X-ray imaging method) combined with operations like "AND" and "OR" for the search query.

The search terms in this article mainly include "thorax", "radiography", "lung diseases", "artificial intelligence", "deep learning", "machine learning", "convolutional neural networks", "computer aided diagnosis", "physicians", "CXR image", "Pneumonia", "Covid-19", "Atelectasis", "Consolidation", "Infiltration", "Pneumothorax", "Edema", "Emphysema", "Fibrosis", "Effusion", "Pleural-Thickening", "Cardiomegaly", "Nodule Mass", "Hernia".

2.2. Data acquisition

To narrow down the search scope further, the study selection criteria were based on the available filtering options, including: (1) Original research studies published in the year range from 2018 and 2023, (2) studies related to the detection of possible findings in CXR images, (3) articles written in the English language, (4) Studies contains AI algorithms with an accuracy rate of over 90%, (5) journal article or conference papers, (6) studies relevant to the purpose of the review, (7) Sample size should be of at least 1000 patients. (8) It should be noted that the literature review papers, comparative studies that do not present new methods, and non-human studies were excluded from consideration for this review.

The search results comprised 3186 articles from the stated databases. Following the eligibility criteria, the PRISMA flow chart in Fig. 2, illustrates the article selection process in each stage. The study selection process was initiated by removing incomplete and duplicated articles. In the next step, papers were then evaluated based on their abstracts and, in certain cases, introductions to determine whether they met the inclusion criteria. At the end of the second round of the selection process, a total of 815 articles were included.

By using the PRISMA guidelines, two researchers reviewed the titles and abstracts of retrieved articles and applied inclusion

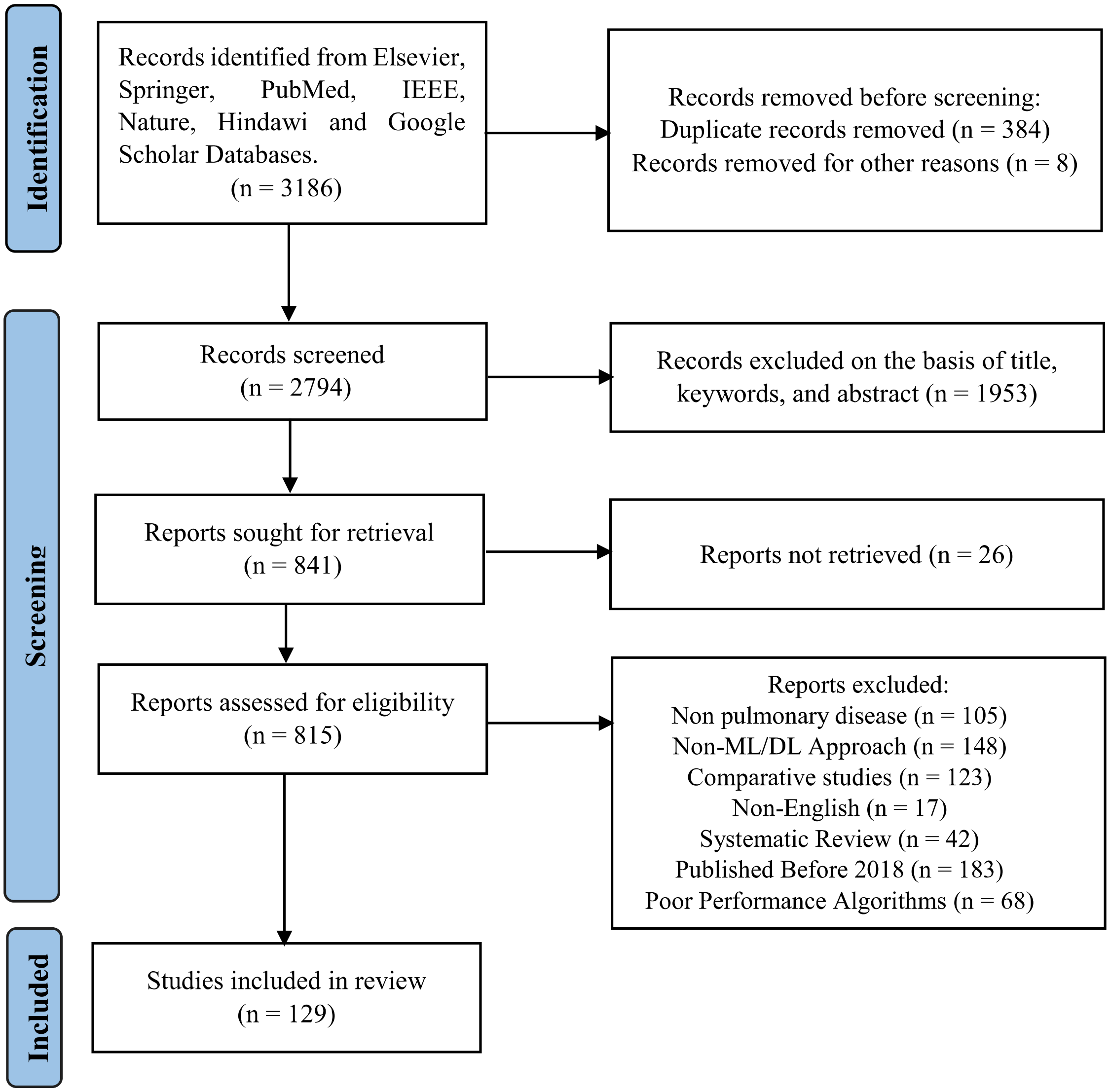

Fig. 2. PRISMA flowchart for literature research and study selection.

and exclusion criteria. Disagreements between the studies were resolved through discussion.

Data extraction was conducted to investigate various available datasets, preprocessing techniques, AI and machine learning methods and algorithm metrics. The data extraction process was performed by S.S and A.S, and the extracted data were synthesized and analyzed to summarize the existing research and identify the potential scopes for future research. Third investigator was consulted to resolve any disagreements.

The usage of convolutional neural networks as a principal method of analysis was investigated. In 2018, only 15 studies employed CNNs, 7 of these studies embraced explainability methods in tandem with CNN. The ensuing year, 2019, bore witness to the emergence of 37 papers that employed CNN as their analytical methodology, with 12 of them implementing explainability methods in tandem with the CNN approach. However, it was in the year 2020 that the use of CNN methods reached a zenith, as an astonishing 89 papers utilized this technique, with an impressive 26 of them incorporating explainability methods.

As we progress through the years, the number of research papers utilizing CNN and related techniques has increased significantly. In 2021, our analysis revealed that 26 papers employed CNN, with one utilizing the CNN domain adaptation and explainability methodology, another employing the CNN Vision Transformer and explainability technique, and two more utilizing both CNN and Vision Transformer methodologies. In 2022, the number of papers utilizing CNN increased to 79, with 25 of them incorporating explainability methods. Additionally, one study made use of the CNN Vision Transformer and explainability technique, while another utilized the Vision Transformer method exclusively. Finally, in 2023, the number of papers utilizing CNN reduced to four, with one of them utilizing the CNN domain adaptation methodology. The Fig. 3 illustrates the evolution of deep learning architectures from 2018 to 2023. This investigation included comparative studies.

The systematic review included 129 articles after applying the stated inclusion–exclusion process in three stages. Out of 129 articles, 116 (90%) were published as original journal research, while 13 (10%) articles were conference papers. All the selected articles were published or archived in online databases between 2018 and 2023. Fig. 4 shows the overview of databases that were used in this review.

3. Image preprocessing techniques

Image preprocessing is an essential step before the development of a prediction or segmentation model. Researchers use

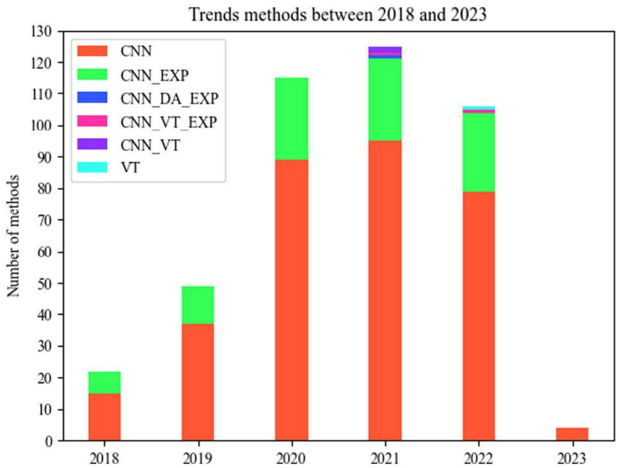

Fig. 3. Trend of deep learning architectures between 2018 and 2023.

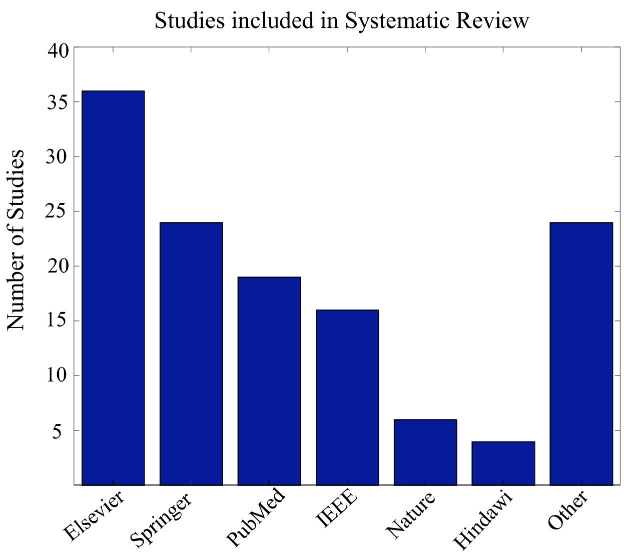

Fig. 4. Overview of papers selected from different databases. The bar plot illustrates the numbers of papers selected from Elsevier, Springer, PubMed, IEEE, Nature, Hindawi, and other journals.

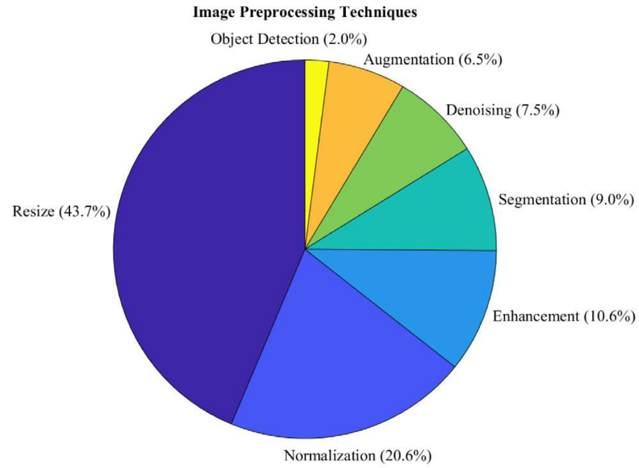

Fig. 5. The percentage of repetition of image processing techniques in this systematic review.

different preprocessing techniques to improve the network's accuracy, speed, and generalization capability. It can also help to reduce noise and suppress unwanted distortions in datasets. As a result, the image preprocessing step would improve the training ability of CNNs, and consequently, the classification performance [18]. Typical image processing algorithms are categorized into image enhancement, image segmentation, data augmentation, and object detection for specific applications in CXR images. Image resizing, augmentation, and data normalization are among the most widely used preprocessing techniques. Image normalization or feature scaling adjusts the values of the data to a common scale without changing the range. Medical practitioners can effectively use normalization for analyzing the severity of diseases [19]. Most of the articles use several different image preprocessing techniques [18]. Fig. 5 shows the percentage of repetition of image processing techniques used in this systematic review.

3.1. Data augmentation

A major problem in the medical domain is the availability of large datasets with reliable ground-truth annotation. Deep CNN requires a large amount of training data otherwise it may overfit and tends to be less accurate. Through data augmentation, additional training samples can be generated to addresses the issue of overfitting. The technique is especially useful when the dataset is small and image augmentation generates variations of the original images. This is possible by randomly applying different transformations, including rotations, flips, translations, zooms and noise addition. Another advantage of the data augmentation is the enhancement of the model's generalization ability during training.

Brunese et al. used data augmentation by setting the random image rotation setting to 15 degrees clockwise or counterclockwise to ensure the proposed models generalization [20]. To enhance the network training process, Sirazitdinov et al. applied a range of data augmentation techniques, including vertical and horizontal flipping, random degree rotation, random brightness, gamma transforms, random Gaussian noise, and blurring. These approaches also serves as an additional regularization and generalization strategy [21]. Rakshit et al. reduced the chances of overfitting by augmentation of the data. They randomly cropped and resized images by using bilinear interpolation to form $224 * 224$ images [22].

3.2. Enhancement

CXRs are imaging modalities that are prone to low contrast, which can make it difficult to accurately interpret the images. Low contrast can be due to various reasons, such as patient anatomy, image acquisition conditions, or image processing settings. Contrast, edge features, and noise in images have a large influence on the classification and identification of diseases. In these cases, more details in low contrast CXRs images can be obtain by structural information enhancement and noise suppression. Contrast Limited Adaptive Histogram Equalization (CLAHE) can be useful in improving the visibility of important structures and details in CXR images [23,24].

Lee and his team gathered experimental data from various medical institutions, resulting in images with varying contrast and dimensions. To address this issue, they standardized the image size and applied the CLAHE preprocessing method prior to training the model [25]. As a preprocessing step, image enhancement is a powerful procedure to locally enhance the image desired patterns without introducing excessive noise or distorting important details. This is possible by limiting contrast amplification at a predefined value on the histogram before computing the cumulative distribution function [26].

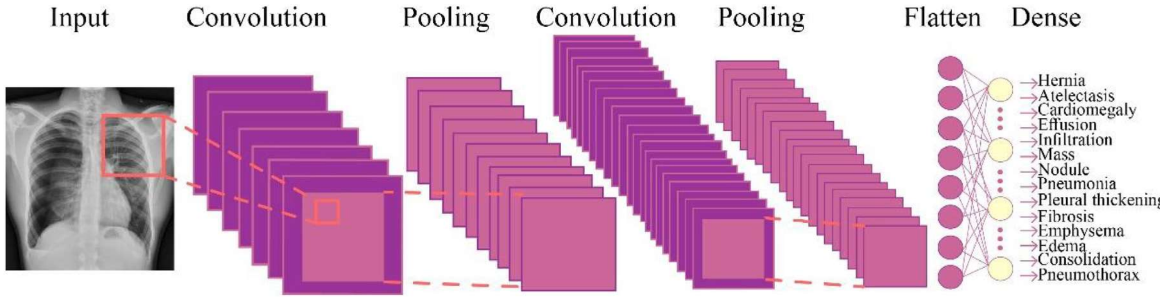

Fig. 6. A typical convolutional neural network structure for classification of 14 common lung diseases. Input CXR image, layers, and outputs are illustrated showing the system operation principle.

3.3. Segmentation

Segmentation involves dividing an image into segments or regions, each identifying a different object or section of the image. Image segmentation is usually necessary for chest radiographs to detect nodules, consolidation, opacities, cavities, and (Region of Interest) ROIs. As well as providing additional diagnostic information, segmentation can quantify and measure the size and shape of the structures observed. Since the images are separated from their backgrounds and isolated, this allows for more precise and accurate analysis. In this review, segmenting images is often carried out using U-Net CNNs trained on large datasets of labeled images. Therefore, meaningful information can be extracted from images, for example object recognition, scene analysis, and medical image analysis [27,28].

Narayanan et al. proposed a novel method for lung image segmentation as a preprocessing step by implementing a U-Net architecture. A classification accuracy of 98.3% and Intersection over Union (IoU) of 0.95 for the Shenzhen dataset for 100 CXR images sets a new benchmark [29]. In another related study, Narayanan et al. used image segmentation to detect whether the diagnosed pneumonia condition is due to bacterial or viral effects. The proposed CNN model without lung segmentation has shown 96.7% training accuracy and 96% validation accuracy. In comparison, the same CNN model with lung segmentation has achieved 98.5% training accuracy and 98.3% validation accuracy for detecting bacterial vs. viral pneumonia, showing the performance increase due to the segmentation [30].

3.4. Object detection

Object detection techniques in CXR images help to automatically identify and locate specific regions of interest in the images, such as lung nodules or consolidations, that may indicate the presence of diseases. Object detection systems can highlight regions and provide a confidence score to assist the radiologist in diagnosing. Every object has distinguishing qualities and unique characteristics. Object detection methods consist of mathematical models and millions of parameters to learn properties of objects and discover new instances. Object detection models have shown possible applications in the field of lung disease detection, screening, infection risk assessment and anomaly detection [31].

4. Deep learning approaches

In recent years, deep learning algorithms have become popular in detecting and diagnosing diseases in medical image analysis, such as breast cancer, respiratory infections, prostate cancer, skin lesions, and Alzheimer's disease [32]. The power of deep learning methods in health care system is because of their ability to handle large amounts of data, improved accuracy, automation, and increased efficiency. The goal of deep learning in medical image analysis is to extract information efficiently and effectively, store knowledge, and reuse it to improve clinical diagnosis [33]. The application of DL methods includes abnormality detection, disease classification, computer aided diagnosis and retrieval. In Sections 4.1 to 4.7, we will describe commonly used DL architectures included in this systematic review.

4.1. Convolutional neural networks

CNNs are a category of deep learning neural networks specifically designed to process data with grid-like topologies, like images [34]. In CNNs, each layer is designed to automatically detect and learn local patterns or features in the input data, such as edges, textures, and objects, through a process called convolution. Convolutional layers are followed by activation functions, which introduce non-linearity into the model, allowing it to learn complex data representations [35]. Additionally, pooling layers are often inserted between consecutive convolutional layers to reduce the feature maps' spatial dimensions and control overfitting. A typical CNN architecture illustrated in Fig. 6, showing the configuration and the principle of CNNs for classification of 14 common lung diseases.

In the context of lung disease diagnosis, CNN can be trained to identify and classify diseases based on CT scans and CXR images [36–38]. The advantage of using CNNs for classification of possible findings is that they are able to learn and identify complex patterns and features in medical images that may not be easily visible to human experts. This can lead to more accurate and efficient diagnoses, especially in cases where the disease is in its early stages and the symptoms are not yet easily noticeable.

Bhatt et al. has presented a CNN model with two convolutional layers and two fully connected layers for pneumonia diagnosis. The evaluation and training are conducted on publicly available optical coherence tomography (OCT) and Chest X-ray Images datasets. They used ADAM optimizer and showed high accuracy of 96.2% [39].

Padma and Kumari developed a diagnostic tool on an open-source dataset of COVID-19. They built a CNN from scratch comprising convolutional layers and max-pooling layers followed by fully connected layers. The proposed approach showed validation accuracy of 98.3% and sensitivity of 99.1% [40]. In summary, due to the ability to automatically and adaptively learn meaningful representations, CNNs are widely used in computer vision tasks including image classification [41].

4.2. Transfer learning

Creating CNN model from scratch is a challenging and time-consuming process. In contrast, models that have been pre-trained, provide more functionality than models created from beginning. It is common to employ pre-trained networks to extract features, perform transfer learning, and classify data.

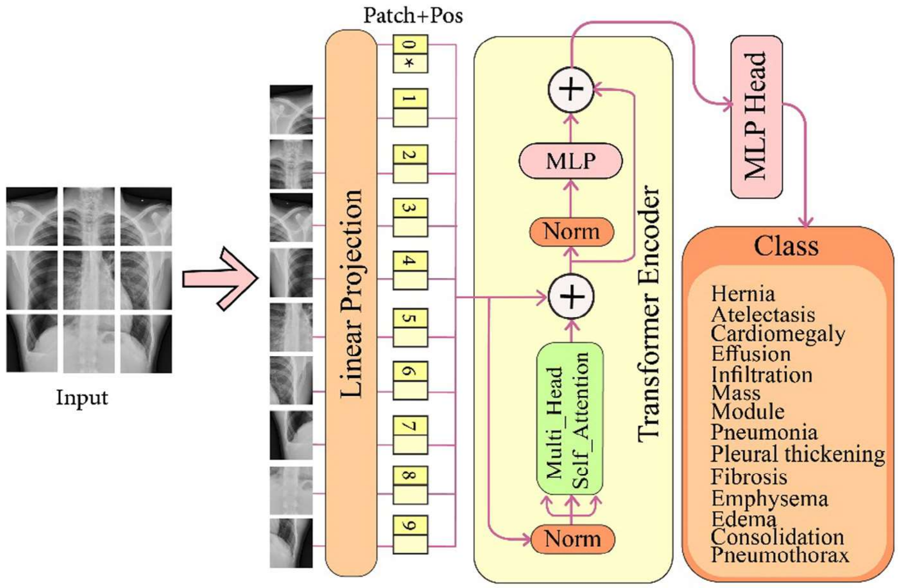

Fig. 7. The vision transformers architecture. A CXR image is split into patches and embedded using linear projection, then fed into transformer encoder for a classification task.

Transfer learning has been shown to be effective in reducing the amount of data required to train a new model and can help improve the accuracy and speed of the learning process.

Transfer learning technique is a subtype of teacher–student learning in which knowledge is transferred from pre-trained models to new models that are being trained on related but different tasks. The larger, more complex model essentially serves as a teacher to the shallower student model, providing it with additional information and guidance to help it learn better. The basic idea is that the teacher model is used to produce a set of outputs for the input data that are used to train the student model. The student model tries to mimic the outputs of the teacher model on the source task, while also being trained on the target task [42–44]. This allows the student model to leverage the knowledge learned by the teacher model on the source task to improve its performance on the target task.

Transfer learning in CXR image analysis involves using a pre-trained deep learning model on a large dataset and fine-tuning it on a smaller dataset. In addition, transfer learning can also be used as feature extractors [45]. To take advantage of the learned features from a larger dataset in a similar task, feature extractors replace the last fully connected layer with pre-trained weights and freeze all previous layers [46]. In order to maximize the performance of a pre-trained network, it is recommended that it be trained on a similar dataset and at a lower learning rate [47,48].

To classify CXR images as pneumonia or Covid-19, Choudhuri et al. used a pre-trained VGG-16 model after fine-tuning the top layers [49]. The dataset used in this study comprised 1368 CXR images obtained from three open-sourced databases: (1) COVID CXR database, (2) COVID-19 Radiography Dataset, and (3) COVID-19 CXR Dataset. They found an accuracy of 96.6% in the CNN built from scratch, but 98.3% in the VGG-16 based model. Several studies demonstrate that transfer learning improves classification accuracy over building and training a network from scratch [50].

4.3. Domain adaptation networks

Deep learning algorithms used in computer-aided medical image analysis usually suffer from the domain shift problem caused by different but similar distributions between source data and target data. Therefore, it is crucial to understand how to handle domain shifts when applying ML architectures to medical image analysis. Domain adaptation is a subfield of transfer learning, where a model is trained on source domain and fine-tuned on target domain. Domain adaptation is a useful technique that minimize distribution differences among different but related domains. The method can improve performance, reduce training costs, and enhance generalization ability where there is limited labeled data available [51].

Feng et al. proposed a deep supervised domain adaptation approach for pneumonia diagnosis using the Chest X-ray14 dataset. They transferred knowledge from a multi-label classification task in the source domain to a binary classification task in the target domain. This novel domain alignment strategy is proposed to align the source domain and the target domain according to the underlying semantics of the samples progressively. It explicitly minimizes the inter-class similarity and maximizes the intra-class similarity across different domains. The method outperformed all other methods by a large margin [52].

4.4. Vision transformers

Vision Transformers (ViT) is a deep learning architecture for image recognition tasks and uses the self-attention mechanism to process images. ViT replaces all the CNN structures with several transformer layers and reaches state of the art performance on image recognition.

It works by dividing an image into a grid of patches, and then fed them into a transformer encoder, which processes the image using self-attention to capture relationships between different parts. Multi-head self-attention further enhances this ability by allowing the model to attend to multiple, independent representations of the same input sequence in parallel. In multi-head self-attention, the input sequence is projected to multiple lower-dimensional representations, or "heads" each of which can attend to different parts of the sequence. As shown in Fig. 7, the output of the transformer encoder is then fed into a classifier to predict the image class [53].

Compared to CNNs, vision transformers have several advantages. First, it can handle images of arbitrary size, whereas CNNs require a fixed input size. Second, it can capture long-range

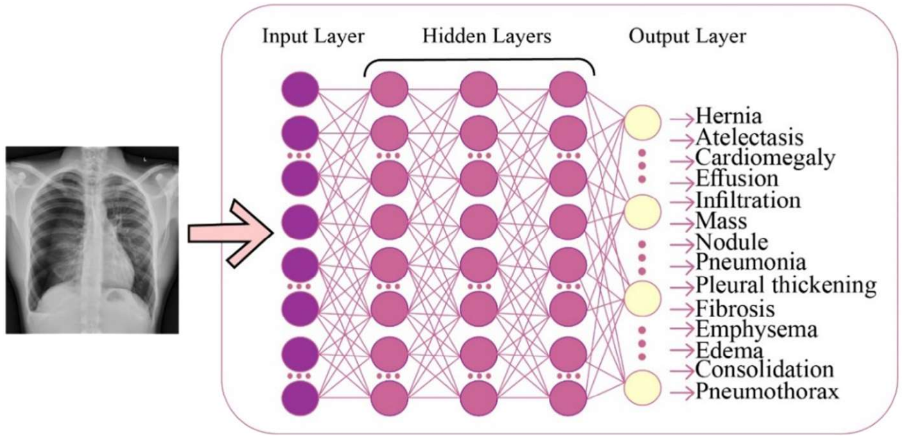

Fig. 8. Multilayer perceptron (MLP) neural network with three hidden layers for classification of possible findings in CXR images.

dependencies between different parts of an image, which is difficult for CNNs. Finally, it can be trained using large-scale language modeling techniques, such as pre-training on large datasets, which has been shown to be effective for improving image recognition performance [54]. In the context of lung disease detection from CXR images, ViT can be used to automatically identify patterns and abnormalities in the X-ray images. This is important because CXR images are complex and can contain a large amount of information, making it difficult for humans to accurately interpret them [55].

4.5. Multilayer perceptron

A fully connected multilayer neural network is called a Multilayer Perceptron (MLP). The input of the network is fed into the first layer, and each subsequent layer applies a set of weighted inputs and an activation function to produce an output. The nodes in each layer of an MLP are typically fully connected to the nodes in the next layer. Each connection has an associated weight that determines the strength of the connection. During training, the weights are updated iteratively through a process called backpropagation, which adjusts the weights to minimize the difference between the predicted output and the actual output [56,57].

As shown in Fig. 8, MLP architectures are useful in image classification tasks, including lung disease detection from chest X-rays. Ghosh et al. utilized MLP neural network as the classification head for the final diagnostic prediction of infection. Their proposed model comprises one input layer, two hidden layers with 256 and 64 nodes, and one output layer. The MLP model was chosen because of its efficiency in modeling complicated nonlinear relationships. RSNA publicly available dataset was utilized in their study [58].

4.6. Ensemble of classifiers

By combining multiple models, ensemble classification provides accurate results and improves robustness by reducing prediction dispersion. Predictions made by ensembles are more accurate than those made individually because the variance of predictions is reduced [51]. Ensemble learning is effective for multiple reasons including statistical, computational, representation learning [59], bias–variance decomposition [60], and strength-correlation [61]. These models are widely used in various applications, including healthcare, speech recognition, image classification, and forecasting.

Ensemble methods in disease diagnosis by CXR images can help improve the accuracy of diagnosis by combining the predictions of multiple models. Ensemble methods work by training multiple base models, each using different algorithms or architectures, and then combining their predictions to make a final prediction. This can lead to better results compared to using a single model, as the ensemble method can capture a wider range of features and patterns in the data. In the case of CXR image analysis for disease diagnosis, ensemble methods can be used to combine the predictions of multiple CNNs trained on the same dataset, or even to combine the predictions of multiple experts or decision-making systems.

Sirazitdinov et al. developed an ensemble of two convolutional neural networks, namely RetinaNet and Mask R-CNN for pneumonia detection and localization. Performance of the proposed pneumonia detection network was assessed and confirmed by a team consisting of four radiologists [21]. Karim et al. proposed an explainable deep neural network method for automatic detection of Covid-19 symptoms from CXR images. They performed ensemble on following three models: VGG-19, ResNet-18, and DenseNet-161. Evaluation results indicate their approach performance is 91.6%, 92.5%, and 96.1%, respectively for normal, pneumonia, and Covid-19 respectively [62].

4.7. Other neural architecture

There are several architectures based on deep neural networks that have been used for CXR image classification. This section discusses the related studies based on these widely used latest architectures. With the development of deep neural networks, attention mechanism has been used in various application. The attention mechanism is a cognitive function and inspired by human visual system [63]. The main idea of the attention-based algorithms is locating the most salient components of the feature maps in CNNs. In this state, the redundancy is removed, and the suitable features are prepared for machine vision applications [63,64].

Wang et al. propose the triple-attention learning model for a computer aided diagnostic task. The model included a pre-trained DenseNet-121 network for classification of fourteen thoracic diseases. Classification is carried out based on Chest X-ray14 dataset. The network then integrated with three attention modules for channel-wise, element-wise, and scale-wise attention learning. The channel-wise attention emphasizes the discriminative channels of feature maps, the element-wise attention enables model to focus on the regions of interests, and scale-wise attention facilitates to recalibrate the feature maps [65].

Li et al. developed an attention-based neural network for pneumonia diagnosis by using RSNA CXR images. In their proposed method, they improved a CNN to focus on disease-specific attended region. By applying this framework, the experimental results show improvement over the state-of-the-art object detection model in terms of accuracy and false positive rate [66].

5. Result and discussions

This section presents the results from the analysis of the 129 primary studies, based on the research questions stated previously. Section 5.1 summarizes utilized CXR public and private datasets with their characterizations. Section 5.2 presents a taxonomy of the recent work on diagnosing and classifying possible findings in CXR images. Tables 3, 4, and 5 summarize the studies on CXR classification that have considered both Covid-19 and pulmonary diagnosis, only Covid-19, and only pulmonary disease, respectively. Table 6 describes multi-diseases diagnosis methods. These results stated based on the research adopted model, obtained performance value, and type of contribution. Section 5.3 compares the contributions of deep learning-based algorithms and traditional machine learning methods. Section 5.4 provides critical insights into limitations and challenges in deep learning-based diagnostic models. Section 5.5 discusses potential research opportunities in lung disease diagnosis using deep learning algorithms.

5.1. Dataset

Based on the studied papers, a total of 24 distinct datasets were identified and analyzed. An outline of these datasets is presented in Table 1. According to our findings, Chest X-ray 14 (NIH-14) is the most frequently used dataset in our systematic review included studies. Since creating a large, annotated medical image dataset is not easy, most researchers rely on the following publicly available CXR datasets.

Table 2 presents the datasets and image type that were used, the number of images, the source, and the image view.

5.2. Comparison of deep learning methods

Numerous research studies have utilized deep learning-based models to classify pulmonary diseases using chest radiographs. Table 3 provides a comprehensive overview of the diagnostic methods for both Covid-19 and non-Covid-19 pulmonary diseases based on CXR images. The related studies have used transfer learning architecture instead of CNN built from scratch. It has been shown that some studies used several existing architectures to build ensemble models. Most of these ensemble models have used variations of the VGG, ResNet, and DenseNet architectures.

Furthermore, we have also observed the deep learning model used in several research for classifying or detecting Covid-19 patients. In the studies included in systematic review, various CNN architectures were used, and most of the work was focused on the ResNet algorithm.

Table 4 summarizes studies conducted during the 2022–2023 period that have focused on diagnosing Covid-19. Among these studies, 39% have utilized their own architecture, while the remaining studies have taken advantage of existing deep learning architectures.

A brief overview of the deep learning architectures applied for pulmonary disease detection are presented in Table 5. The adopted model data, accuracy and contribution of the reviewed papers are illustrated in this section. The maximum accuracy was 99.7% for the different architectures based on the Guangzhou Women and Children Medical Center (GWCMC) dataset [119]. The high performance obtained using hybrid ensemble strategy for binary and multi class pneumonia classification. Moreover, a multi-head attention mechanism is used to address the relationships of pixels in the CXR images [120].

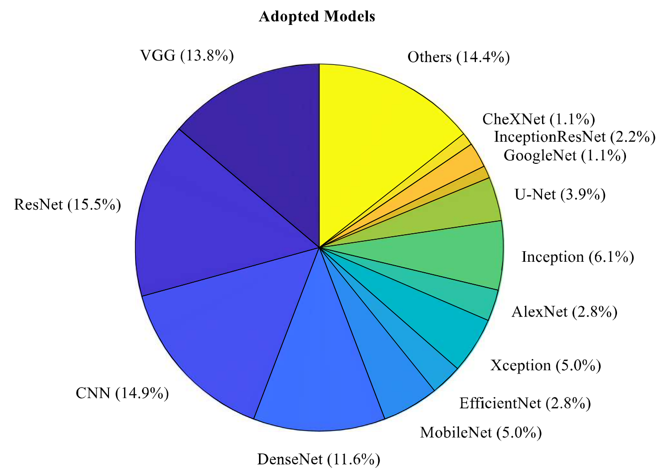

Fig. 9. An overview of adopted models that have been used in 129 articles included in this systematic review.

In chest X-rays, in addition to pneumonia, Covid-19 and nodules there are other diseases that can be detected, including cardiomegaly, edema, hernia, atelectasis, pneumothorax, and emphysema. Table 6 presents a summary of high-performance architectures for diagnosing of fourteen common thorax diseases using CXR images. It is observed that researchers have carried out their research and experimented through various state-of-the-art deep learning architectures such as ResNet, VGG, DenseNet and MobileNet [22,68,71,73].

The ResNet model was the most frequent model among the considered work. Thousands of images were used to train the ResNet model using the ImageNet dataset [178]. As a consequence, it gives a good accuracy when determining the classification of images. Besides, the DenseNet and VGG models were significant after the ResNet model for the detection of multiple diseases [179,180]. The highest accuracy of 99% is achieved by the study conducted by Siddiqui et al. which has pre-trained VGG-16 neural network and localization of the chest images [73].

Different model evaluation techniques have been used to assess the generalizability and performance of deep learning models on test data. Model parameters include accuracy, sensitivity, specificity, F1 score, and AUC are presented in Table 7.

Fig. 9 illustrates the CNN architectures adopted in various research papers along with their percentage of repetition. The diagram provides descriptive statistics of deep learning models for all 129 papers discussed in this review. It is evident from the diagram that ResNet, CNN, and VGG are the most popular deep learning architectures used for classification, accounting for 15.5%, 14.9%, and 13.8% of the models used, respectively. These models are widely recognized as proven neural network models in the field of image analysis techniques.

Several architectures have made concerted efforts to reduce training time and achieve faster convergence rates. some proposed algorithms exhibit the distinct advantage of requiring minimal computation time for training and testing. These models have fewer parameters and decrease the computational time, rendering them particularly well-suited for large-scale population screening [20,23,74,85,113,114,143,148,160,181]. Utilization of transfer learning, few shot learning, and adapted segmentation

Table 1
Summary of chest X-ray datasets included in systematic review studies.

Dataset	Ref	Diagnosis	Source	Publicity	Labeled
Chest X-ray 14/NIH-14	[20,22,23,25,67–93]	Pulmonary diseases	National Institutes of Health Chest X-ray	Public	NLP
RSNA	[21,25,62,66,80,88,94–110]	Pulmonary diseases	Radiological Society of North America	Public	Radiologists
Indiana	[111]	Pulmonary diseases	Indiana University School of Medicine	Public	Radiologists
Guangzhou	[112–120]	Pediatric pneumonia	Guangzhou Women and Children's Medical Center	Public	Radiologists
MC	[27,96,97,111,121–123]	Tuberculosis	Montgomery County, United States	Public	Radiologists
Open-I	[71,124]	Pulmonary diseases	National Library of Medicine	Public	Radiologists
Shenzhen	[27,84,85,95,107,118,119]	Tuberculosis	Guangdong Medical College, Shenzhen	Public	Radiologists
JSRT	[27,107,116,117,120]	Lung nodule	Japanese Society of Radiological Technology	Public	Radiologists
ChestX-ray8	[95,124–129]	Pulmonary diseases	National Institutes of Health Chest X-ray	Public	NLP
SIRM	[94,100–102,108,130–132]	Covid-19	Radiopaedia, and the Italian Society of Medical and Interventional Radiology	Public	Radiologists
SCH	[83]	Normal Pneumonia Pneumothorax Tuberculosis	Cheonan Soonchunhyang University Hospital	Public	Radiologists
Covid-19 Image Data Collection 2020	[20,78,84,89,94,96–98,101,102,105,124,126–148]	Covid-19/ Non-Covid-19 pneumonia	Cohen	Public	Radiologists
Kaohsiung Chang Gung CheXpert CHUAC	[149] [68] [135]	Pulmonary diseases Pulmonary diseases Covid-19	Kaohsiung Chang Gung Memorial Hospital Stanford Hospital A Coruna, Galicia, Spain	Private Public Private	Radiologists NLP Radiologists
Paul Mooney	[112,126,131,136,141,144,145,150–152]	Pneumonia	National Institutes of Health and Guangzhou Women and Children's Medical Center	Public	Radiologists
CXIP	[19,87,119,127,142]	Pneumonia	Kaggle	Public	Radiologists
C19RD	[19,153–157]	Covid-19	Qatar University	Public	Radiologists
NLM	[84,106,158]	Pneumonia Covid-19	National Library of Medicine, USA	Public	Radiologists and NLM
Zhang CXR	[101,106,107,111,115,151]	Pneumonia	National Institutes of Health (NIH) Clinical Center, USA	Public	Radiologists
V7-labs Covid-19 CXR	[159]	Covid-19	Kaggle	Public	Radiologists
Optical Coherence Tomography (OCT)	[120,160,161]	Pneumonia	University of California San Diego	Public	Radiologists
Tuberculosis (TB) Chest X-ray	[162]	Tuberculosis	Qatar University	Public	Radiologists
COVID-Xray-5k dataset	[163]	Covid-19	Minaee, New York University	Public	Radiologists
Tawsifur Rahman	[100,124,127,128,131,144,164]	Covid-19	Qatar University, University of Dhaka	Public	Radiologists
COVID-ChestXray-15k Belarus	[165] [106,123]	Covid-19 Tuberculosis	Ontario Tech University, Canada Thomas Jefferson University Hospital	Public Public	Radiologists Radiologists
NIAID TB	[106]	Tuberculosis Normal	Eastern Europe, Asia, Sub-Saharan Africa	Public	Radiologists

has demonstrated significant efficacy in decreasing both training time and the required size of training datasets [72,75,81,107,124,130,149,152,158,160].

An exceptional advantage of deep learning models is their ability to achieve the highest classification performance across a variety of evaluation metrics, including precision, f1-score, accuracy, and AUC values, as evidenced in certain studies [96,109,128,160,174,182]. As detailed in this section, some proposed architectures have demonstrated an accuracy exceeding 99% in the diagnosis of various lung diseases. These remarkable results arise from the skillful integration of methodologies such as ensemble classification, transfer learning, optimizer selection, appropriate filter utilization, and the choice of suitable classifier. To achieve competitive performance comparable to the state-of-the-art computer vision algorithms some papers focused on better generalization ability and avoid overfitting [77,81,83,107,121,151,159,162].

An additional notable aspect of a model is its robustness, accomplished with minimal computational resources. This distinctive characteristic empowers the model to be efficiently trained even on devices with low computing power, making it suitable for implementation in smaller IoT devices, like mobile phones [19,22,73,92,112,127,155,165,183].

CNN based models are often considered as black boxes because the lack of interpretability. Understanding the learned features and reasoning behind the model's detection can be difficult,

Table 2
Dataset description of existing works.

Dataset	Image type	Number	Source	View
Chest X-ray14	PNG	112 120	National Institutes of Health Clinical Center	Frontal
Shenzhen	JPEG	662	Guangdong Medical College, Shenzhen, China	Frontal
JSRT	PNG	154	Japanese Society of Radiological Technology	Frontal
MC	PNG	138	Department of Health and Human Services in partnership with Montgomery County	Frontal
Indiana	PNG	7470	various hospitals affiliated to the Indiana University School of Medicine	Frontal, Lateral
RSNA	DICOM	30 277	Radiological Society of North America	Frontal
CheXpert	DICOM	224 316	Stanford University Medical Center	Frontal, Lateral
Guangzhou	JPEG	5836	Guangzhou Women and Children's Medical Center	Frontal
PadChest	DICOM	206 222	Hospital Universitario de San Juan, Alicante (Spain)	Postero Anterior, Frontal
Open-I	DICOM	8121	National Library of Medicine, collected by Indiana University	Frontal
Chest X-ray8	PNG	108 948	National Institutes of Health Clinical Center	Frontal
SIRM	JPEG	10 000	Radiopaedia, and the Italian Society of Medical and Interventional Radiology	Frontal
SCH	TIFF	65 535	Cheonan Soonchunhyang University Hospital	Frontal
Covid-19 Image Data Collection 2020	JPEG	594	Cohen	Postero Anterior, Antero Posterior, Lateral
Kaohsiung Chang Gung	DICOM	3883	Kaohsiung Chang Gung Memorial Hospital	Postero Anterior, Antero Posterior, Lateral
CHUAC	PNG	720	A Coruna, Galicia, Spain	Frontal
Paul Mooney	JPEG	5863	National Institutes of Health and Guangzhou Women and Children's Medical Center	Antero Posterior
CXIP	PNG	5856	Kaggle	Frontal
C19RD	DICOM	18 000	Qatar University	Frontal, Lateral
TB (Tuberculosis) X-ray image	DICOM	4701	Health in Lima, Peru	Frontal, Lateral
NLM	DICOM	1056	National Library of Medicine, USA	Frontal
Zhang CXR	PNG	112 000	National Institutes of Health (NIH) Clinical Center, USA	Frontal
V7-labs Covid-19 CXR	JPEG	13 008	Kaggle	Frontal
Optical Coherence Tomography (OCT)	JPEG	5856	Mendeley Dataset	Frontal
Tuberculosis (TB) Chest X-ray	DICOM	4200	Qatar University, Kaggle	Frontal
COVID-Xray-5k dataset	PNG	5000	Minaee, New York University	Frontal
Tawsifur Rahman	PNG	21 165	Qatar University, University of Dhaka	Frontal
COVID-ChestXray-15k	PNG	15 000	Ontario Tech University, Canada	Frontal
Belarus	PNG	304	Thomas Jefferson University Hospital	Frontal, Lateral
NIAID TB	PNG	3087	Eastern Europe, Asia, Sub-Saharan Africa	Frontal

especially in deep architectures. Some of the studied papers offered the significant benefit of explainability, allowing users to gain insights into how the model works [20,25,67,90,118,133,164,168,169,177,180].

5.3. Effectiveness of Deep learning vs. Traditional methods

In recent years, deep learning architectures have grown rapidly and achieved impressive results in medical image analysis. In this section, we compared the performance of traditional machine learning algorithms with that of deep learning algorithms in classifying CXR images for the detection of thorax diseases. There were few articles published since 2018 that have used just machine learning method to classify lung diseases.

Topiwala and colleagues employed traditional machine learning methods to identify thoracic diseases in Chest X-ray8 dataset. They began by extracting features for logistic regression and Support Vector Machines (SVM), which enabled them to build independent binary classifiers for Cardiomegaly, Edema, Emphysema, Hernia, Pneumonia, Fibrosis, and Pneumothorax. Upon testing the logistic regression method accuracy on a separate dataset, Topiwala et al. obtained results ranging from 55 to 75 percent accuracy [184]. In another study, a four-stage computer-aided diagnosis system has been developed to help the detection of lung nodules in chest radiographs. By employing traditional machine learning techniques, the system has accomplished to identify nodules with a confidence level of 50% or more [185].

Cruz and their colleagues developed a machine learning system capable of classifying six lung conditions: normal, pleural effusion, pneumothorax, cardiomegaly, hyperaeration, and possible lung nodules. The system achieved an impressive overall accuracy rate of 92.59%. To prepare the data for analysis, the researchers employed several preprocessing techniques, including contrast-limited adaptive histogram equalization, top hat filtering, high-boost filtering, and circle detection. These techniques helped to enhance the quality of the input data and improve the accuracy of the classification model [186].

Chandra et al. proposed an automatic technique for detection of abnormal CXR images containing one or more tuberculosis related abnormalities. CXR images were obtained from two public datasets, namely the Montgomery set and Shenzhen set. They used hierarchical feature extraction scheme for classification of

Table 3
Summary of the diagnostic methods for both Covid-19 and non-Covid-19 pulmonary diseases based on CXR images.

Ref	Adopted models	Datasets	Acc %	Contribution
[20]	VGG-16	- ChestX-ray 14 - Covid-19 Image Data Collection 2020	97	An approach aimed to drastically reduce the time window approximately was presented.
[136]	InceptionRes- netV2 Xception	- Covid-19 Image Data Collection 2020 - Paul Mooney	97.6	A combined model consisting of InceptionResnetV2 and Xception algorithms are proposed for high performance Covid-19 and non-Covid-19 pulmonary diseases detection.
[89]	DenseNet20 Incepetion ResNetV2 InceptionV3 NASNetLarge ResNet50 VGG16	- ChestX-ray 14 - Covid-19 Image Data Collection 2020	99.8	Deep Convolutional Neural Networks (DCNN) model proposed to classify three different types of pneumonia, bacterial pneumonia, viral pneumonia, and Covid-19 pneumonia.
[166]	ResNet50 DenseNet	- Covid19 CXR dataset	98.3	The purpose of this paper was to detect and classify lung diseases by using deep learning-based architectures on CXR data.
[19]	Recurrent Neural Network	- CXIP - C19RD	95	The proposed framework combines the soft computing, machine and deep learning architectures for detection and classification of lung diseases for pneumonia and Covid-19.
[108]	Mobile Net v2	- RSNA - SIRM	99.2	In this study, Mobile Net V2 employed for automatic classification of pulmonary diseases, including Covid-19.
[135]	U-Net	- Covid-19 Image Data Collection 2020 - CHUAC - CXIP	98	A new method was proposed that allows to adapt the knowledge from a well-known domain with a high number of samples to a new domain with a significantly reduced number and greater complexity.
[105]	Xception ResNet50V2	- RSNA - Covid-19 Image Data Collection 2020	91.4	Multiple DCNNs were trained using advanced training techniques to classify X-ray images into three categories: normal, pneumonia, and Covid-19.
[159]	U-Net	- V7-labs Covid-19 CXR	99.4	The study proposed an algorithm that utilizes U-Net for diagnosing Covid-19 and pneumonia.
[88]	Vision Transformer	- ChestX-ray 14 - RSNA	96	A deep learning models developed for a multi-class classification problem to detect Covid-19, pneumonia, and normal cases using CXR images.
[158]	U-Net	- NLM	97.2	The improved cyclic GAN's mechanism to create a balanced dataset with more augmented or reconstructed CXR images by performing segmentation using the U-Net operation.
[167]	EfficientNetB0 EfficientNetB1 EfficientNetB2	- ImageNet	98	A multi-channel deep learning approach proposed for lung disease detection using CXR.
[168]	ResNet50	- Covid-Net	97	An explainable AI-based framework was proposed to address the challenge of classification result explainability in the healthcare domain using CXRs.
[124]	LDDNet	- Open-I - ChestX-ray8 - Covid-19 Image Data Collection 2020	97.1	A new deep learning framework for classification of pneumonia and Covid-19 diagnosis was proposed, and better performance than the existing algorithms of ResNet152 V2 and XceptionNet was attained.
[94]	VGG-19	- RSNA - SIRM - Covid-19 Image Data Collection 2020	96.5	Deep learning architecture for multi-class classification of Pneumonia, Lung Cancer, tuberculosis (TB), Lung Opacity, and most recently Covid-19 is proposed.
[153]	CNN	- C19RD	99.7	A lightweight shallow convolutional neural network architecture is proposed for classifying X-ray images of a patient with a low false negative rate.
[154]	VGG-19	- C19RD	97.1	In this paper, a classifier was developed for Covid-19, Pneumonia, and Healthy cases from the CXR by applying the transfer learning approach on the pre-trained VGG-19 architecture.
[101]	DenseNet-121 DenseNet-161 ResNet-18 ResNet-34 VGG-16 VGG-19	- RSNA - SIRM - Covid-19 Image Data Collection 2020	98.4	In this work, we propose 4 fully automatic approaches for the classification of chest X-ray images under the analysis of 3 different categories: Covid-19, pneumonia and healthy cases.
[131]	Xception	- SIRM - Covid-19 Image Data Collection 2020 - Paul Mooney - Tawsifur Rahman	99.3	Multi-classification method for Covid-19 diagnosis using CXR images was developed.

Table 4
Summary of Covid-19 diagnosis method by CXR images.

Ref	Adopted model	Datasets	Acc %	Contribution
[27]	ResNet50 DenseNet201 Inception-v3 Xception	- MC - Shenzhen - JSRT	98.9	A new method has been developed for detecting Covid-19 in chest radiographs, which is resilient to imbalanced classes in the training data.
[169]	CNN	- Covid-19 Image Data Collection 2020 - Paul Mooney	98.8	A novel deep neuroevolution-based image classification method to diagnose Covid-19 introduced. A new evolutionary algorithm is used to obtain the optimal accuracy.
[170]	CNN DNN	- Several publicly available datasets	93.2	Two algorithms have been presented for the detection of lung abnormalities, one utilizing a deep neural network on the fractal features of images, and the other utilizing convolutional neural network methods with the lung images.
[171]	CoroNet	- ImageNet	99	The proposed method (CoroNet) is a convolutional neural network designed to identify Covid-19 cases using chest X-ray images.
[172]	ResNet18 ResNet50 ResNet101 VGG16 VGG19	- Covid-19 Image Data Collection 2020 - Paul Mooney - Radiology Assistant X-ray Chest images/LK-JG-1	94.7	A novel application of a deep learning model is used for the detection of Covid-19 based on CXR images.
[173]	TLCoV	- Tawsifur Rahman	97.7	A novel automated Covid-19 screening model, called TLCoV, is proposed to fasten accurate screening of Coronavirus.
[130]	mAlexNet + BiLSTM	- SIRM - Covid-19 Image Data Collection 2020	98.1	Two deep learning architectures have been proposed that automatically detect positive Covid-19 cases using CXR images.
[146]	COVID-Net	- Covid-19 Image Data Collection 2020	95	By using transfer learning and leveraging pre-trained models Covid-19 was detected.
[109]	CXGNet	- RSNA	100	A tri-stage CXR image-based classification model proposed. An optimal feature selection technique named as enhanced grey-wolf optimizer with genetic algorithm developed which is denoted as CXGNet.
[25]	VGG-16 VGG-19	- ChestX-ray 14 - RSNA	95.9	An explainable deep learning algorithm for Covid-19 screening on CXR images was developed.
[174]	CovMnet	- Covid-19 CXR/Kaggle	97.4	Experiments are carried out for deep feature extraction, fine-tuning of CNN hyper parameters, and end-to-end training of the CNN model.
[175]	VGG-16	- CXR/Kaggle	100	VGG-16 based model was developed with high accuracy.
[147]	CheXNet	- Covid-19 Image Data Collection 2020	99.9	The proposed model classifies the binary classes Covid-19 and normal by a CNN model that used Chest X-ray14 dataset.
[78]	DenseNet	- ChestX-ray 14 - Shenzhen - Covid-19 Image Data Collection 2020	100	The proposed method of output neuron keeping, with twice transfer learning, outperformed the sole use of twice transfer learning and simple transfer learning in the 201-layer dense networks.
[137]	CNN	- Covid-19 Image Data Collection 2020	93	A DCNN based model for analysis of Covid-19 with data augmentation is proposed, which uses the patient's CXR images for the diagnosis of Covid-19 with an aim to help the physicians.
[144]	VGG-19 ResNet101 WideResNet 502	- Tawsifur Rahman	97.7	Multi-class classification framework that minimizes either false positives or false negatives that is useful in computer aided diagnosis was proposed in this study.
[138]	U-Net	- Covid-19 Image Data Collection 2020	97.1	Adaptive U-Net base lung segmentation and for automated Covid-19 Diagnosis was proposed.
[163]	DenseNet201	- COVID-Xray-5k	99.9	Several enhancements are proposed, including data augmentation, adjusted class weights, early stopping and fine-tuning, to improve the performance.
[155]	Cov-Net	- C19RD	99.66	Cov-Net architecture was developed for recognizing Covid-19 from chest X-ray images via machine vision.
[164]	CNN	- Tawsifur Rahman	96	Deep learning model for detection of Covid-19 utilizing the chest X-ray images was developed.
[102]	MFDNN	- SIRM - Covid-19 Image Data Collection 2020	93.2	MFDNN is a multi-channel feature deep neural network algorithm to identify Covid-19 from chest X-ray images.
[129]	ResNet50+ SAM+BiLSTM	- ChestX-ray8 - Covid-19 Image Data Collection 2020	98	Self-augmentation mechanism for Covid-19 detection using chest x-ray images developed.
[84]	U-Net	- ChestX-ray 14 - Covid-19 Image Data Collection 2020 - NLM	96.4	This study proposes 16 types of segmentation-based classification deep learning-based systems for automatic, rapid, and precise detection of Covid-19.

Table 5
Summary of pulmonary disease diagnosis method by CXR images.

Ref	Adopted model	Diseases	Datasets	Acc %	Contribution
[149]	ResNet DenseNet	Children pulmonary diseases	-Kaohsiung Chang Gung	92.5	One-versus-one scheme, the one-versus-all scheme and training a classifier model based on convolutional neural network.
[121]	ResNet18 AlexNet	Pulmonary abnormalities	- MC - JSRT	97	A method proposed for automatic segmentation of lungs in CXR for pulmonary abnormalities detection.
[120]	DenseNet201 VGG16 GoogleNet DenseNet201 InceptionResNet Xception	Pneumonia	- OCT	99.2	A hybrid explainable deep learning framework is proposed for accurate pneumonia identification. The hybrid workflow is developed by fusing the capabilities of both ensemble convolutional networks and the transformer encoder mechanism.
[112]	VGG16 VGG19 ResNet50 Inceptionv3	Pneumonia	- Guangzhou - Paul Mooney	92.3	A method for pneumonia detection in CXR images using CNN and transfer learning.
[107]	Hybrid CLAHE-CNN	Pulmonary disease	-RSNA	91	Hybrid architecture of contrast-limited adaptive histogram equalization and deep convolutional network for the classification of lung diseases proposed.
[106]	DenseNet201	Tuberculosis	-NLM -Belarus -RSNA -NIAID TB	98.6	Reliable model was developed from the CXR images using image pre-processing, data augmentation, image segmentation, and deep-learning techniques.
[160]	VGG-16 VGG-19	Pneumonia	- OCT	96.2	A combined approach using image processing and either VGG-16 or VGG-19, variants of DCNN for automatic detection of pneumonia from Chest X-ray image proposed.
[162]	Xception InceptionV3 InceptionResNet MobileNetV2	Tuberculosis	- TB Chest X-ray	99.4	The method was developed to reliably detect tuberculosis from chest X-ray images by utilizing image preprocessing, data augmentation, and deep learning classification techniques.
[151]	VGG-16	Pneumonia	- Paul Mooney	96.6	An efficient method to predict Pneumonia from CXR using VGG-16 architecture was proposed.
[148]	ResNet152 DenseNet121 ResNet18	Pneumonia	-ChestX-ray14	96.6	The attention-based transfer learning framework for efficient pneumonia detection in chest X-ray images was proposed.
[161]	VGG-19	Pneumonia	- OCT	98	VGG19 architecture customized for Pneumonia detection in Chest X-ray images.
[176]	CheXNet	Pneumoconiosis	- Chest X-ray	91.5	Deep ensemble learning method was proposed for the automatic detection of Pneumoconiosis in coal worker's chest X-ray radiography.
[145]	ResNet152V2 MobileNetV2 CNN LSTM	Pneumonia	- Paul Mooney	99.2	Four different models are developed by changing the used deep learning method; two pre-trained models, ResNet152V2 and MobileNetV2, a CNN, and a Long Short-Term Memory (LSTM) for Pneumonia diagnosis.
[97]	EfficientNet	Tuberculosis	- RSNA - MC - Covid-19 Image Data Collection 2020	97.2	This paper introduced an approach for Tuberculosis detection from CXR, Boosting the performance with vision transformer and transfer learning.
[115]	CNN	Pediatric Pneumonia	- Guangzhou -Zhang CXR	90.7	Ensemble of DCNN was introduced for diagnosis of Pediatric Pneumonia with in Chest X-Ray Images.
[99]	ResNet	Pneumonia	- RSNA -Zhang CXR	96.8	Effective Pneumonia detection using ResNet based transfer learning method was proposed.
[81]	CNN	Tuberculosis	- ChestX-ray14 - CXIP	95.6	Efficient deep network architectures developed for fast chest x-ray Tuberculosis screening and visualization.
[116]	ResNet18 Xception InceptionV3 DenseNet121 MobileNetV3	Pneumonia	-Guangzhou	98.4	Efficient Pneumonia detection model in Chest Xray images using deep transfer learning was developed.
[152]	CNN	Pneumonia	-Paul Mooney	98.5	This study develops a model that will help with the classification of chest x-ray medical images into normal vs. abnormal.
[82]	Inception	Abnormality	-ChestX-ray14	94.6	Deep convolutional neural networks architecture was proposed to classify binary normality in CXR images.
[177]	CNN	Pneumonia	-Zhang CXR	94.4	A new model to classify X-ray images for the detection of Pneumonia using neural networks was developed.

(*continued on next page*)

Table 5 (*continued*).

Ref	Adopted model	Diseases	Datasets	Acc %	Contribution
[83]	EfficientNetB7	Normal Pneumonia Pneumothorax Tuberculosis	-ChestX-ray14 SCH	96.1	In this study, a multi-class classification method proposed by learning lung disease images with CNN.
[23]	ChestNet	Consolidation	-ChestX-ray14	94.7	Deep learning architecture for detection of Consolidation on CXR images was developed. Transfer learning technique with well-known DCNNs are used to improve the accuracy of the models.
[123]	EfficientNetB3	Tuberculosis	-MC -Shenzhen -Belarus	98.7	In the study, an automatic Tuberculosis detection system developed using advanced DL models.
[85]	CNN	Tuberculosis	-ChestX-ray14	98.5	An efficient computer-aided detection system developed that will support radiologists to become well-informed when making TB diagnosis from patients' CXRs.
[117]	LBT-PC-DARTS	Pneumonia	-Guangzhou	94.2	In this study a neural architecture search (NAS) method is developed to find the best convolutional architecture capable of detecting pneumonia from chest X-ray.
[104]	GoogLeNet ResNet18 DenseNet12	Pneumonia	-Zhang CXR	98.8	A computer-aided diagnosis system developed for automatic pneumonia detection using chest X-ray images.
[118]	CNN	Pneumonia	-Guangzhou	95	In this study, the presence of the disease was tried to be determined using chest X-ray dataset.
[119]	PneumoniaNet	Pneumonia	-Guangzhou -Zhang CXR	99.7	A novel 50 layers CNN-based architecture was proposed that outperforms the state-of-the-art models.

healthy and unhealthy groups of patients. The performance of the algorithm is validated by two public datasets, namely the Montgomery set and Shenzhen set. The obtained accuracy was 95.6% for Montgomery collection, and 99.4% for Shenzhen dataset [187]. Das et al. have used ML techniques to analyze CXR images and predict pneumonia. The model was proposed by using some of the ML classifiers like logistic regression, neural network, and SVM that can detect the presence or absence of pneumonia in CXR images [188].

Sharma et al. developed a hybrid Inception-ResNet-v2 transfer learning model to automate the task of disease detection in CXR images with three categories, namely pneumonia, Covid-19, and normal. The best accuracy was achieved using a hybrid Inception-ResNet-v2 transfer learning model in conjunction with data augmentation and image enhancement. Comparative analysis showed SqueezeNet, VGG19, ResNet50, and MobileNetV2 accuracy are 97.3%, 91.7%, 90.3%, and 76%, respectively. While, two feature-based ML classification techniques, namely SVM with local binary pattern and decision tree with histogram of oriented gradients yield an accuracy of 88% and 87%, respectively [189].

Traditional ML classifiers offer a well-established and transparent model but reveal poor performance in utilizing complex healthcare big data. One reason is that ML techniques extract the features using costly handcrafted feature algorithms and then feed the extracted features to the ML classifier, such as SVM. Therefore, as the number of classes to classify increases, feature extraction becomes more and more difficult. However, it does not mean traditional machine learning architectures have become obsolete.

In contrast, DL achieved automatic feature extraction and classification using some hidden layers. In addition, CNN-based algorithms are distinguished for their ability to learn complex representations to enhance pattern recognition. So, deep learning provides greater accuracy and versatility at the cost of large amounts of computing power.

Current research indicates that combination of traditional machine learning and deep learning benefits the advantages and traits of both methodologies. As shown in Table 8, combined deep networks with a robust ML classifier outperform deep learning approaches for the CXR image classification tasks. In this case, handcrafted and learned features are used together to extract information and combination of different features is used to solve image classification problems.

5.4. Challenges in deep learning-based diagnostic models

Deep Learning models require a huge amount of annotated data, especially as they become increasingly complex with more layers and parameters, in order to achieve optimal performance. As a result, although technology has dramatically increased the amount of available data, accessing data, particularly in medical fields, remains challenging due to concerns regarding privacy, data bias and data scarcity [76,87,89,103,150,155,159].

The aforementioned deep learning algorithms operate with a substantial number of parameters that necessitate time consuming and rigorous training. Consequently, these architectures impose significant computational demands in terms of time and memory resources [106,111,134,141,154,180]. It is therefore necessary to balance between computational efficiency and model performance when deploying these advanced techniques.

Deep learning models are able to diagnose quickly however, it is difficult for researchers to understand how the model arrives as its decisions. This can be particularly problematic in those medical domains where transparency and interpretability are crucial. Also developing well-preformed models demand good hardware resources.

5.5. Future scope

The systematic review's findings offer promising avenues for future research in lung disease diagnosis using DL. By integrating these algorithms into radiology equipment, we can expect more accurate, safe, and rapid diagnoses of lung disease. However, for these systems to be effective for radiologists, they must provide not only high-performance diagnosis but also explainability and patient data privacy. Therefore, as a radiologist assistant, it is essential to ensure that these systems meet these criteria.

To enhance the performance of current DL architectures, incorporating advanced optimization algorithms is a highly effective solution. Additionally, utilizing ensemble models and evaluating the proposed method on multiple datasets can significantly improve accuracy prior to routine clinical applications. These steps are crucial for further enhancing the effectiveness of deep learning architectures and ensuring their practicality in real-world scenarios.

Table 6
Summary of multi-diseases (14 diseases) diagnosis method by chest X-ray images.

Ref	Adopted model	Datasets	Acc %	Contribution
[71]	ResNet-50	-ChestX-ray 14 -Open-I	–	A systematic evaluation of different approaches for CNN-based CXR classification on ChestX-ray14 proposed.
[70]	CheXNeXt	-ChestX-ray 14	–	A deep learning algorithm developed and validated. The classified abnormalities in CXRs are at a performance level of practicing radiologists.
[22]	Resnet-18	-ChestX-ray 14	–	The purpose of this research was to automate the classification of CXR images for fourteen different disease categories using a smaller number of parameters during training. Additionally, a heatmap was generated for each corresponding image to indicate the location of abnormality.
[73]	VGG-16	-ChestX-ray 14	99	A new approach was developed for the classification of lung diseases into 15 different categories with the help of transfer learning.
[69]	CNN BPNN CpNN	-ChestX-ray 14	92.4	Convolutional neural networks were presented for the classification of possible findings in CXR images.
[68]	DenseNet-121	-ChestX-ray 14 -CheXpert	–	Provides a novel approach for multi-label CXR classification of common thorax diseases.
[67]	MobileNet V2	-ChestX-ray 14	90	Modified model (MobileNet V2) presented for classification and prediction of lung pathologies using frontal thoracic CXR images.
[125]	DenseNet121 ResNet50	-ChestX-ray8	92	The performance of the two adopted pretrained networks DenseNet121 and ResNet50 was compared, and domain adaptation was also used to further improvement in performance.
[93]	ResNet-50	-ChestX-ray 14	–	In order to assist radiologists, a transfer learning-based classifier proposed for identification of 14 different thoracic diseases in CXR images.
[92]	Xception	-ChestX-ray 14	97.3	A method was developed for automatic classification of multiple lung disease from CXR images using Xception deep learning method.
[91]	AlexNet VGG-16	-ChestX-ray 14	98	Two new algorithm was developed based on AlexNet and VGG-16 deep learning models for the classification of CXR images.
[111]	VGG-16 ResNet-50 ResNet-101 MobileNet	-Indiana -MC -Shenzhen -JSRT -Zhang CXR	84.1	A first attempt towards utilizing incremental learning to periodically screen different pulmonary disorders from the CXRs irrespective of their scanner specifications developed.
[75]	MobileNet-v2 VGG-19 ResNet-32 ResNet-50 ResNet-152 DenseNet-121	-ChestX-ray 14	90	Different knowledge distillation (KD) training approaches, including original basic training, standard KD (deeper teachers teach lower-cost students), reversed KD (lower-cost students teach deeper teachers), defective KD (teachers trained over the first 50 iterations teach lower-cost students), and self-training KD (models teach themselves) was proposed.
[76]	CNN	-ChestX-ray 14	90	A classification method for different thorax diseases detection was developed by utilizing CNN method.
[77]	DenseNet	-ChestX-ray 14	–	Self-sequential attention layer based DenseNet (SAL-DN) model is proposed to enhance thoracic disease prediction on CXR.
[86]	ResNet	-ChestX-ray 14	98	This paper offers a comparative study on the various deep learning techniques that can process CXRs and are capable of detecting the different thoracic diseases.
[87]	Mo-bileLungNetV2	-ChestX-ray 14	97	The improved fine-tuned MobileLungNetV2 model is constructed using 16 blocks with new neural network layers and is trained on 300 epochs with hyper-parameters.
[79]	DenseNet-121	-ChestX-ray 14 -Shenzhen	–	A novel approach for recognition of thoracic diseases in CXR was developed using deep model.

The use of a decentralized federated learning model is a compelling alternative to traditional methods, where data is collected and processed on a central server to create a single training model for disease datasets. By implementing this technique, data is kept locally on devices, and a model is trained on these distributed devices. This approach significantly improves privacy and mitigates the risk of patient data breaches. Therefore, it is crucial to consider this approach as a viable solution for disease dataset training models, as it enhances data privacy, and security while maintaining the effectiveness of the model.

6. Conclusion

In this review study, we aim to highlight the effectiveness of different DL architectures, specifically for the purpose of diagnosing lung diseases. We also compared their performance with traditional machine learning methods. Based on PRISMA guideline, 129 articles were reviewed and their key concepts are summarized. This study conducted to analyze the existing papers and collect the recent advancement in the search field. Additionally, we have compiled a list of publicly available datasets that are commonly used by researchers and developers for the classification of possible findings in chest X-ray images. The key findings that address our research questions are discussed below in detail.

RQ1: What is the effectiveness of deep learning vs. traditional machine learning methods for detection of possible findings in CXR images? Traditional machine learning classifiers face challenges in analyzing complex healthcare big data, primarily due to the requirement for manual feature extraction algorithms. Conversely, DL has demonstrated the ability to extract features automatically and classify data using hidden layers, through the use of convolutional neural networks. As illustrated in Table 8 recent research suggests that combining traditional machine learning and deep learning architectures can produce

Table 7
An analysis of the accuracy, sensitivity, specificity and AUC metrics for multi-disease (14 lung diseases) diagnosis.

Ref	Adopted model	Accuracy (%100)	Sensitivity (%100)	Specificity (%100)	F1-Score	AUC
[71]	ResNet-50-large-VP	–	99.3	99.1	–	0.9983
[70]	CheXNeXt	–	75.4	91.1	–	0.909
[22]	Resnet-18	–	–	–	–	0.8494
[73]	VGG-16	99	–	–	–	–
[69]	CNN, BPNN, CpNN	92.4	–	–	–	–
[68]	DenseNet-121	–	–	–	0.561	0.877
[67]	MobileNet V2	90	45.3	97.3	0.556	0.810
[125]	DenseNet121 ResNet50	84 76	–	–	–	0.691 0.68
[93]	ResNet-50	–	–	–	0.66	0.911
[92]	Xception	97.3	97.2	99.4	–	–
[91]	AlexNet, VGG-16	96 98	96 99	96 98	–	0.98 0.97
[111]	VGG-16 ResNet-50 ResNet-101 MobileNet	84.1	–	–	0.8303	–
[75]	MobileNet-v2 VGG-19 ResNet-32 ResNet-50 ResNet-152 DenseNet-121	90	–	–	–	0.826
[76]	CNN	89.7	–	–	0.9014	–
[77]	DenseNet	–	–	–	–	0.8715
[86]	ResNet	98	–	–	–	–
[87]	MobileLungNetV2	97	–	99.8	–	–
[79]	DenseNet-121	–	–	–	–	90.2

superior results in image classification tasks. By using hand-crafted and learned features together, along with a combination of different features, a robust ML classifier can outperform DL approaches in CXR image classification tasks.

RQ2: Which datasets and training data have been utilized most extensively? Tables 1 and 2 list some of the most commonly used datasets and training data. Among them, ChestX-ray14 (NIH-14), RSNA, Covid-19 Image Data Collection 2020, and CXIP are some of the extensively used datasets for detection of possible findings in CXR images.

RQ3: What validation strategies and evaluation metrics were used for measuring the model performance? Various methods for evaluating deep learning architectures on test data have been employed to determine their performance and generalizability. Table 7 presents some commonly used metrics, such as accuracy, sensitivity, specificity, F1 score, and AUC, that are used to evaluate model performance.

RQ4: How is the efficiency of different types of deep learning and its architectures in promoting the classification of possible findings in CXR images? The study's findings demonstrated a notable improvement in the sensitivity and specificity of lung disease detection through the implementation of deep learning architectures. Our comparative analysis revealed that in all scenarios, Convolutional Neural Networks outperformed traditional machine learning models with a shallow design, as evidenced by their greater accuracy.

The efficiency of different types of deep learning architectures are shown in Tables 3–6. In summary, CNNs, RNNs, transfer learning, and attention mechanisms have all been shown to be effective in detecting various pathological conditions in CXR images. They work by applying convolutional filters to the input image, followed by pooling layers to reduce the dimensionality of the feature maps. This process is repeated multiple times, with the output of each layer being fed as input to the next layer. CNNs have been shown to be effective in detecting conditions such as pneumonia, tuberculosis, and lung cancer.

RQ5: Which machine learning and deep learning architectures were proposed for the detection of possible findings in CXR images? Fig. 9 provides an overview of the deep learning architectures that have been adopted, including popular methods such as CNNs, ResNet, DenseNet, and VGG. These architectures are widely utilized in various applications. There are several traditional machine learning architectures proposed for the detection of possible findings in chest X-ray images. By integrating traditional machine learning with DL architecture, it is possible to leverage the strengths and characteristics of both approaches. The combination of SVM, logistic regression, random forest, and PCA with deep learning architectures has demonstrated promising and consistent results that can be replicated.

RQ6: What are the challenges faced by the researchers in constructing deep learning-based diagnostic models? As DL architectures get more complex with more layers and parameters, they demand a vast amount of annotated data to attain the best possible performance. Despite the technological advancements that have dramatically increased the amount of available data, obtaining data, particularly in the medical domain, remains a challenge due to concerns surrounding privacy, data bias, and data scarcity.

In addition, while deep learning models can quickly make diagnoses, it can be challenging for researchers to comprehend the classification process behind these models. This lack of transparency and interpretability can be particularly problematic in medical fields where these factors are crucial.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Table 8
Overview of studies using combination of deep learning approaches with conventional methods for lung disease diagnosis.

Ref	Method	Diseases	Datasets	Acc%	Contribution
[190]	Ensemble + Logistic Regression	Tuberculosis	- MC -Shenzhen	90	This method presents a novel ensemble learning based automatic detection of tuberculosis using hybrid feature descriptors. The method combines handcrafted features with deep features (CNN) through ensemble Learning.
[191]	Shuffle and MobileNet + SVM classifier	Atelectasis	-ChestX-ray 14	96.7	A machine learning based algorithm (SVM) proposed for the classification of atelectasis and cardiomegaly. CXR images were segmented and then enhanced by using gray-level transformation techniques.
[192]	InceptionV3+ SVM	Pneumonia	-Guangzhou	93.1	A combination of DL and ML method proposed for diagnosis of pneumonia using CXR images.
[193]	CNN + SVM	Covid-19	-Covid-19 CXR	99	Fusion of CNN, SVM, and Sobel filter is proposed to detect Covid-19 using X-ray images.
[113]	Ensemble + PCA + Logistic Regression	Pneumonia	-Guangzhou	96.1	Combination of deep convolutional neural network with Principal Component Analysis (PCA) and logistic regression for diagnosis of pediatric pneumonia on CXR was proposed.
[182]	Inceptionv3 + ML classifiers	Covid-19	-COVID-Xray-5k dataset	96.6	This study introduces a Covid-19 detection model. Features were extracted then subjected to the proposed ensemble model-based classification phase, including SVM, CNN, and Optimized NN.
[183]	CNN + SVM	Covid-19	-Covid-19 Image Data Collection 2020 -Paul Mooney -Tawsifur Rahman	97.8	A framework was developed to detect Covid-19 cases from CXR images. A shallow VGG19 was used to extract the features and SVM was utilized as classifier.
[194]	MobileNet + SVM	Pneumonia Covid-19	-Tawsifur Rahman	99.5	A high-performance algorithm introduced for detection of coronavirus using deep convolutional neural networks and SVM.
[150]	AlexNet VGG-16 VGG-19	Pneumonia	-NLM	94.1	Combined deep features extracted to provide an efficient feature set consisting of totally 300 features. In the next step of the experiment, this feature set was given as an input to the decision tree, k-nearest neighbors, linear discriminant analysis, linear regression, and support vector machine learning models.
[195]	SqueezeNet + SVM	Pneumonia Covid-19	-Several publicly available datasets	98.8	Computer-aided tool developed for detection of Covid-19 pneumonia from CXR images using machine learning algorithm.
[128]	AlexNet + SVM	Pneumonia Covid-19 Normal	-Covid-19 Image Data Collection 2020 -Paul Mooney	98.6	Hybrid ensemble model for differential diagnosis between Covid-19 and common viral pneumonia by chest X-ray radiograph was proposed.
[181]	CNN + Random Forest	Pneumonia	-Public CXR dataset	97	The Random Forest classifier with deep activation features in CNN model developed for Pneumonia diagnosis from CXR images.

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