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A systematic survey on deep learning techniques for chest disease detection using chest radiographs

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Abstract

The lung is one of the most sensitive internal organs of the human body that gets infected by constant exposure to chemicals, particles, and infectious organisms in the atmospheric air. Due to this, the most dangerous chest diseases take place which are the leading cause of human disability and death throughout the world. These pulmonary diseases can be recognized by medical imaging techniques i.e. Chest radiography, Computed tomography, Pulmonary and bronchial angiography, Magnetic resonance imaging, Ultrasonography, and Nuclear medicine techniques. A massive amount of chest reports are generated every day that contain a large amount of anatomical and potentially pathological information, but manual detection and classification of chest abnormalities are considered a tedious and time-taking task. In addition, it also requires skilled radiologists as these reports are often difficult to read and differentiate the pathologies of the chest. To eradicate this issue and give a value-added solution; artificial intelligence and deep learning-based algorithms show excellent performance and have proven their effectiveness for object recognition and image segmentation. The primary aim of this study is to present a comprehensive analysis of the deep learning approaches used to identify various types of pulmonary pathologies on CXRs. In addition, we provide a detailed analysis of the most popular open-access CXR datasets, taxonomy of the state-of-the-art works to assist the researchers in preparing the plan for their research contribution, and discuss potential future research directions in this field. More than 350 research papers from various indexing services, including Web of Science, Scopus, PubMed, and IEEE, were considered for this review article. After several selection parameters, it is observed that most of the literature focuses on the DL approach with CXRs. However, few publications have focused on CT scans and Ultrasound images. Thus, 114 latest and highest-quality literature are chosen for detailed and qualitative analysis that shows how DL systems have been applied to recognize various respiratory diseases using CXRs.

Keywords**:** *chest x-rays (CXRs); chest diseases; CXR datasets, deep learning (DL); medical image processing; survey.*

1. Introduction

A large number of diseases that affect the worldwide population are chest-related because we take our breathing and respiratory health for granted. The structure of the respiratory system is quite complex. The lungs are divided into two sections called lobes, which help to oxygenate the blood. The left lung contains 2 lobes, and the right lung contains 3 lobes, so the right lung is bigger than the left lung. Pulmonary pathologies can arise when there are problems in any part of this system. Chronic bronchitis, as well as Asthma, Emphysema, Cystic fibrosis, Chronic Obstructive pulmonary disease (COPD), and Acute bronchitis diseases mainly affect the Airways (Athanazio, 2012), while Pulmonary edema, Tuberculosis, Lung cancer, Emphysema, and Acute respiratory distress syndrome (ARDS), Pneumonia, and Pneumoconiosis diseases affect the Air Sacs. A lung nodule is very common in human that forms a

small clump of cells if it is benign (noncancerous). Benign nodules can be caused by inflammation from numerous conditions i.e. bacterial infection, fungal infection, and small collections of normal cells. The noncancerous nodules do not spread to other parts of the human body. While malignant lung nodules are cancerous and can grow or spread quickly to another part of the body (Hollings, & Shaw, 2002). Early-stage cancer detection can reduce the mortality rate; in this regard, regular screening plays an essential role. Besides low-dose CT, CXR is another potential option for screening.

Medical imaging has non-invasive characteristics that reveal the interior structure of the body in a visual form for clinical analysis (Barsanti, Lenzarini, & Kusmic, 2015; Prior et al., 2017). There are different techniques of medical imaging i.e. X-ray, Ultrasound, CT scan, and MRI. Each imaging technique utilizes a different technology to generate an image. However, CXR uses electromagnetic radiation to produce the image. It is one of the simplest, cost-effective, ubiquitous, and widely used techniques that shows the inside structure of the human body to diagnose the abnormal condition of the chest, bones, skull, teeth, and so on. Figure 1 shows the sample of CXRs of some common diseases like pneumonia, covid-19, tuberculosis, lung cancer, and cardiomegaly.

In the radiographs, hard tissues like bones look whitish because they absorb the most radiation, while fatty and soft tissues absorb less radiation, so they look gray, and air-influenced parts look black due to the least radiation absorption. Thus, different tissues absorb different amounts of radiation, which makes the radiographs readable. As a result, a massive number of radiographic images are generated everyday but manual detection and classification of chest abnormalities are considered laborious and time taking task for radiologists and physicians. In addition, it also requires skilled radiologists as these radiographs are often difficult to differentiate from other chest abnormalities (Agrawal, & Choudhary, 2022). To eradicate this issue and give a value-added solution artificial intelligence and deep learning-based algorithms show excellent performance and have proven their effectiveness for object recognition and image segmentation (Asif et al., 2022).

There have been several review papers published on the area of deep learning in chest disease detection using CXRs (Kieu et al., 2020; Çallı et al., 2021; Moses, 2021; Jasthy, Vangipuram, & Dutta, 2021; Meedeniya et al., 2022). However, recent survey papers are far from exhaustive in terms of the detailed analysis of publicly available CXR datasets, literature and methodology surveyed, and discussion on challenges and future directions. This survey addresses these requirements efficiently.

The major contributions of this work are-

- Conducted a comprehensive survey with comparative analysis of the existing works on deep learning-based models for the identification of various chest diseases using chest radiographs.
- Presented a detailed analysis of the most popular open-access chest x-ray datasets.
- Created taxonomy of the state-of-the-art deep learning-based chest abnormalities detection models on CXR datasets.
- Identified the research gap and discussed the potential future directions for further improvement in this domain.

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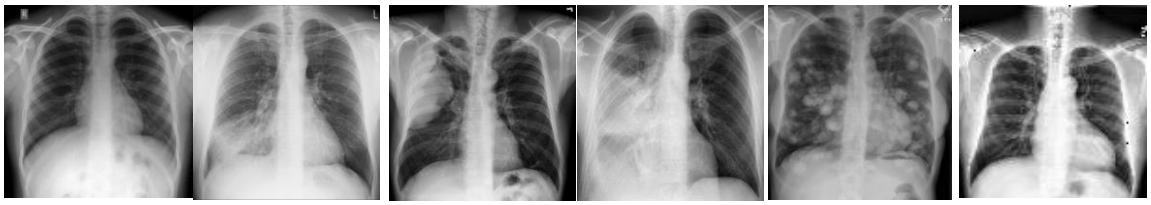

(a) (b) (c) (d) (e) (f)

Figure 1 Sample of CXRs (a) healthy (b) pneumonia (c) COVID-19 (d) tuberculosis (e) lung cancer (f) cardiomegaly

This work is arranged as: section 2 shows the research objective. Section 3 is all about the methodology, publicly available CXR datasets, and literature review. Section 4 discusses the general flow of the deep learning algorithm. Section 5 consolidates the different metrics used to evaluate the algorithm. Section 6 presents a comprehensive discussion of the conducted survey and points out the limitations of the existing models. Section 7 concludes the work and highlights future opportunities for further research.

2. Objectives

The major objectives of this survey are as follows: (1) present an extensive and systematic survey on the deep learning approaches to identify various types of pulmonary pathologies on CXRs, especially lung nodule, pneumonia, COVID-19, tuberculosis, and cardiomegaly (2) present a detailed analysis of open-access CXR datasets, (3) create the taxonomy of the state-of-the-art works to assist the researchers in preparing the plan for their research contribution and activities (4) identify the research gap and discuss the potential future directions in this field.

3. Methodology

This section discusses the research methodology used to conduct a systematic survey on the DL approaches for detecting various chest diseases using CXRs. This survey is conducted under the PRISMA guidelines (Tricco et al., 2018). Figure 2 represents the PRISMA flowchart. It illustrates all the steps followed for selecting eligible articles for a qualitative survey.

In the very first step, a suitable database, i.e., research articles, was identified as a primary source of reference. The Web of Science, IEEE Xplore, Scopus, ScienceDirect, Springer, and Pubmed databases were selected to identify the relevant articles. However, some significant research articles are also included in this survey that is indexed by Google Scholar; the number of citations is the main selection criteria for this type of article. This survey only considered recently published articles. However, some older articles that are relevant to this survey were also included. To find the articles, the following keywords were utilized: "deep learning", "chest x-ray", "classification", "segmentation", "localization", "lung disease", "CNN", and "detection". At the end of this step, we obtained 385 research articles, and then we performed screening operation to obtain the relevant works. After screening, only 114 articles were eligible for participation in this survey. Out of eligible articles, more than 90% were published in 2017 and onwards.

Articles that meet the following criteria are included and excluded if otherwise:

- Articles that considered at least one pulmonary disease.
- Articles must be used CXR medical imaging for screening pulmonary diseases. All others, such as CT, MRI, and Ultrasound based articles are excluded.
- Articles must contain at least one deep learning approach.
- Articles must be written in the English language.
- Articles must be full text. All others are excluded i.e. preprints, abstract.

3.1 The taxonomy of the state-of-the-art work on chest pathology recognition using deep learning

This part presents the taxonomy of the current work on CXR-based chest abnormalities detection using DL approaches that could enhance the reader's understanding of the topic. The taxonomy will provide a clear picture of existing work, as shown in Figure 3.

3.2 CXR datasets

A deep neural network is a data-hungry approach because it requires a large dataset for system training due to its large number of trainable parameters. High quality training datasets play a crucial role for increasing classification accuracy. In order to enhance the amount of the dataset, data augmentation can be used. Data augmentation avoids overfitting by creating artificial samples that differ from the actual dataset and generating more learning features to train the model which is advantageous for making the developed model more robust because small dataset may affect the performance of the system. It performs basic image processing operations like flipping, rotating, cropping, and padding. "ChestX-ray14" and "ChestX-ray8" are the most popular medical datasets consisting of 112120 frontal views of chest radiographs of 32717 unique patients, comprising classified images of 14 most popular chest pathologies, while the "ChestX-ray8" dataset has 108948 frontal views of 30805 patients with up to 8 different chest pathologies (Wang et al., 2017).

Several well-known publicly available medical datasets of chest radiographs are tabulated in Table 1. Dataset analysis is the major contribution of our work which will definitely help researchers in their future research to easily find the datasets for chest disease identification and will also save their time.

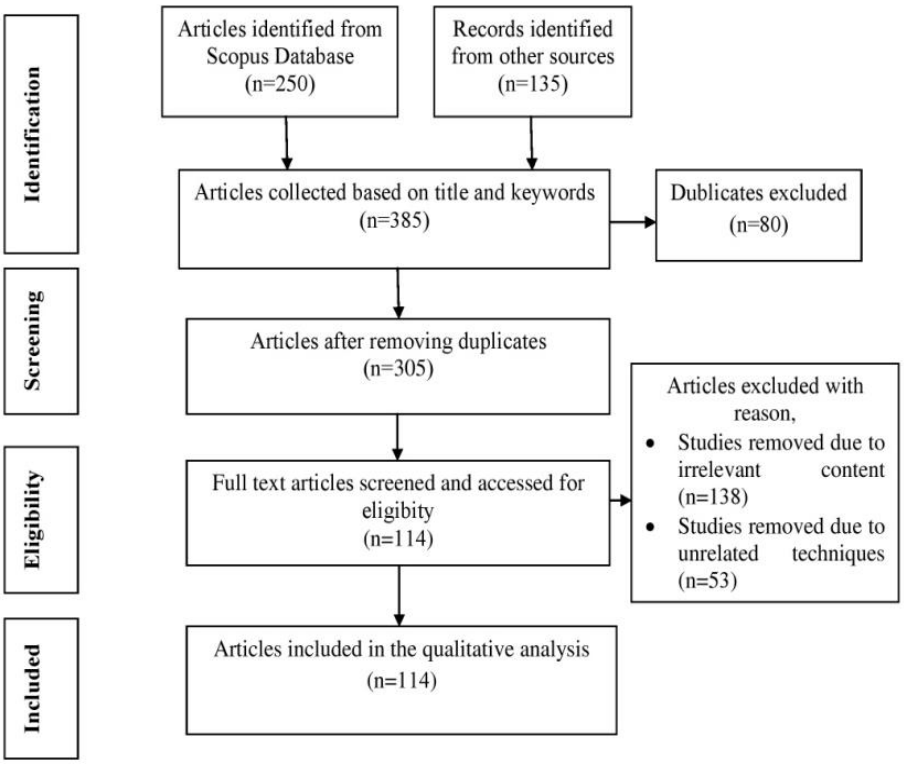

Figure 2 PRISMA structure for the selection of qualitative articles

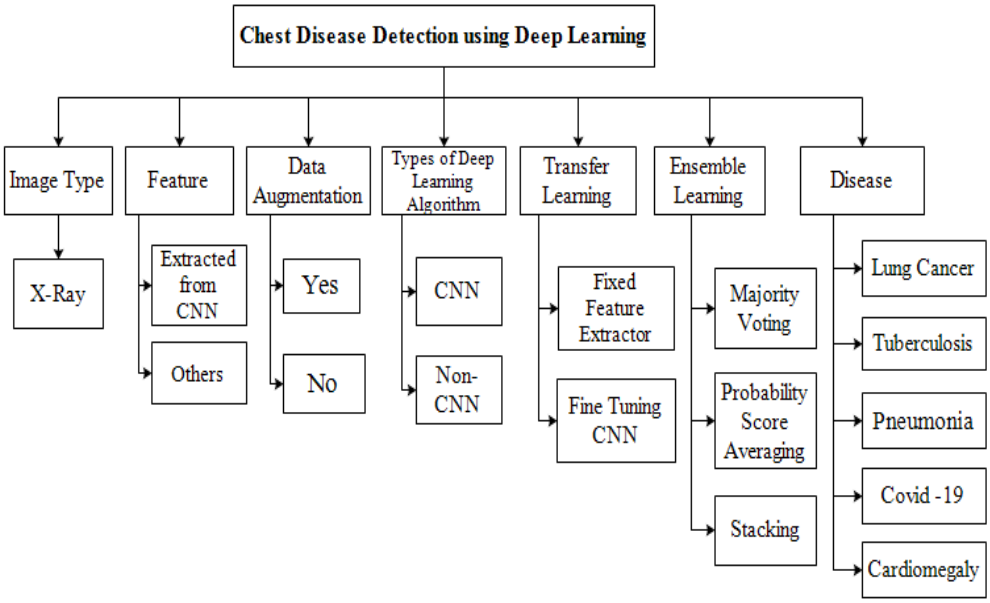

Figure 3 Taxonomy of the current work on CXR based chest abnormalities detection using deep learning

Table 1 Publicly available authentic dataset of CXRs

Name	Disease	Characteristics
Chest X-ray14 (Wang et al., 2017)	14 different lung disease	• Presently the biggest public repository of CXRs. • Total 112,120 frontal CXRs of 30,805 unique patients. • 14 observations • Image size is 1024 × 1024 with 8 bits grayscale. • The dataset can be accessible from: https://paperswithcode.com/dataset/chestx-ray14
Chest X-ray8 (Wang et al., 2017)	8 different lung disease	• Contains 108,948 frontal-view X-rays • 8 different lung disease • 1024 × 1024 image size • https://paperswithcode.com/dataset/chestx-ray8
Montgomery (Candemir et al., 2013)	Tuberculosis	• Total 138 frontal CXRs. • 80 cases are Normal and 58 cases are TB. • Images are in PNG 12-bit grayscale format. • The CXR scans size is either 4,020× 4,892 or 4,892× 4,020 pixels. • https://www.kaggle.com/datasets/raddar/tuberculosis-chest-xrays-montgomery
Shenzhen (Jaeger et al., 2014)	Tuberculosis	• Total 662 frontal CXRs. • 326 are Normal cases and 336 cases are TB. • Collected from Shenzhen No.3 hospital in Shenzhen, China. • Images are 8-bit grayscale PNG format with full resolution. • Size of image can vary but is approximately 3K × 3K pixels. • https://www.kaggle.com/datasets/yoctoman/shcxr-lung-mask
Mooney's kaggle dataset	Pneumonia	• Total 5,863 CXRs. • Image format JPEG. • Dataset contains two categories (Normal and Pneumonia). • https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia
CheXpert (Irvin et al., 2019)	14 common chest diseases	• Total 224,316 CXRs of 65,240 unique patients. • 14 observations. • Collected from Stanford hospital. • The images are stored in 8-bit grayscale JPEG format with actual resolution.
MIMIC-CXR E. (Johnson et al., 2019)	14 heart disease	• Total 377,110 CXRs from 65,379 unique patients. • Collected from Beth Israel Deaconess Medical centre. • Images are 8-bit grayscale JPEG format..
PadChest (Bustos, Pertusa, Salinas, & de la Iglesia-Vayá. 2020)	174 labels with different radiographic findings, and 19 differential diagnoses	• Total 160,868 CXRs from 67000 unique patients. • Collected from San Juan Hospital, Spain (2009 - 2017). • Images are stored as 16-bit grayscale DICOM format with full resolution. • https://bimcv.cipf.es/bimcv-projects/padchest/
Prostate, Lung, Colorectal, and Ovarian (PLCO) Cancer dataset (Zhu et al., 2013)	22 labels with 4 abnormalities and the abnormalities location	• Contains 185,421 chest radiographs from 56,071patients. • NIH distributes a standard set of 25,000 patients and 88,847 frontal view X-rays. • Image Format TIFF

Name	Disease	Characteristics
Ped- Pneumonia (Kermany, Zhang, & Goldbaum, 2018)	Normal, Viral and bacterial pneumonia	• Total 5856 pediatric CXRs • Collected from Guangzhou Women and Children's Medical Center, Guanghou, China. • Images are 8-bit grayscale JPEG format with various resolutions. • https://physionet.org/content/mimic-cxr/2.0.0/
JSRT Dataset (Shiraishi et al., 2000)	Lung nodule and Normal	• Total 247 CXRs with 2048×2048 resolution, pixel-size 0.175 mm, and depth 12-bit gray scale • 154 CXRs have nodules (where, 100 malignant cases and 54 benign), and 93 CXRs are Normal. • Image format DICOM
RSNA Pneumonia (Shih et al., 2019)	Pneumonia and Normal	• Total 30,000 CXR scans with pneumonia annotations. • 8 bit grayscale DICOM format with 1024×1024 resolution.
BIMCV (Vayá et al., 2020)	Covid-19	• It contains CXRs, CT scans and laboratory test results. • Released by the Valencian Region Medical Image Bank (BIMCV). • Total 25,554 samples from 9,129 patients where only 3293 image samples are chest radiographs from 1305 Covid19 patients. • The reports are in 16-bit PNG format and have the original resolution. • http://bimcv.cipf.es/ bimcv-projects/bimcv-covid19/
HM Hospitals (2020)	Covid-19	• Total 4,943 CXRs from 1725 patients as well as detailed results of laboratory testing. • Released by the HM hospitals group, Spain. • Image format DICOM.
COVIDGR (Tabik et al., 2020)	Covid -19	• Total 852 posterior- anterior CXRs. • Gathered from Hospital Universitario Clinico San Cecilio, Granada, Spain. • Image format JPEG.
SIIM-ACR	Pneumothorax	• Total 16000 CXRs from 16000 patients. • Where PA:11,000 and AP: 4,799 • Released for Kaggle open challenge on pneumothorax detection and segmentation. • DICOM files with 1024×1024 resolution • https://www.kaggle.com/c/siim-acr-pneumothorax-segmentation
CXR14-Rad-Labels (Majkowska et al., 2020)	Chest Diseases	• It consists of 4 labels for 4374 studies and 1709 patients. • Where, AP: 3,244 and PA: 1,132 • Image format PNG.
COVID-CXR (Cohen et al., 2020)	Covid-19	• Total 930 CXRS from 449 unique patients. • 8 bit PNG or JPEG files. • https://github.com/ieee8023/covid-chestxray-dataset
Indiana dataset (Open-i) (Demner-Fushman et al., 2015)	Pulmonary Diseases	• Total 7470 CXRs including lateral and frontal images of pathology annotations, i.e. pleural effusion or opacity, pulmonary edema, cardiac hypertrophy. • Collected from the various affiliated hospitals to the Indiana University School of Medicine.

Name	Disease	Characteristics
Belarus (Rosenthal et al., 2017)	Tuberculosis	• It consists of approx 300 frontal CXRs with confirmed tuberculosis. • Collected from different institutes under Ministry of Health, the Republic of Belarus to study drug-resistant TB. • Image size 2248 × 2248. • https://github.com/frapa/tbcnn/issues/1
KIT (Ryoo, & Kim, 2014)	Tuberculosis	• Total 10,848 CXRs, where 7020 normal cases and 3828 Tuberculosis cases. • Collected from Korea ttuberculosis institute.
VinDr-CXR Dataset (Nguyen et al., 2022)	14 common diseases	• VinDr-CXR is a large and diverse lesion annotated image dataset. • Released by the Vingroup Big Data Institute (VinBigdata) • DICOM image format along with the labels. • https:///www.kaggle.com/c/vinbigdata-chest-xray-abnormalities-detection/

3.3 Deep learning for chest abnormalities detection using CXR images

The main intention of performing an extensive and systematic survey is to choose and categorize the best available deep learning approaches for chest disease detection on CXRs. This study will definitely provide information about what is already done in the concerned area; also give a logical, sensible, and robust answer to the underlying question of the research. The search strategy is essential to executing a systematic review of the desired domain for getting meaningful and relevant information from the mass of data. We examined the Research papers, Case studies, WHO reports, and Reference papers from the related publications in detail. This section discussed the deep learning-based approaches applied by the researchers to detect various chest pathologies.

3.3.1 Pneumonia

Pneumonia is a lower respiratory lung infection typically due to bacteria, viral or fungal that causes inflammation of one or both lungs air sacs. In this infection, the air sacs may fill up with fluid and pus. So, the timely diagnosis of pneumonia is very essential to prevent its unpleasant consequences (including death). Varshni, Thakral, Agarwal, Nijhawan, and Mittal (2019) proposed an automatic pneumonia detection model from frontal CXRs using DenseNet-169 as feature extractor and SVM as classifier. Also, appraised the performance of pre-trained CNN models along with distinct classifiers for classifying normal and abnormal chest radiographs. And conclude that the pre-trained CNN model + supervised classifier algorithms outperform in analyzing pneumonia on CXR images. The two biggest limitations of this model: first is high computational power and secondly, only frontal view CXRs were considered while it has been observed that lateral view CXRs are also beneficial in the diagnosis. Stephen, Sain, Maduh, and Jeong (2019) presented a CNN model trained from scratch to detect and classify positive and negative pneumonia CXRs samples. Rahman et al., (2020) developed an approach to identify bacterial and viral pneumonia on CXRs. The classification accuracy of pneumonia and normal images, viral and bacterial pneumonia images, and viral, normal, bacterial pneumonia were 98%, 95%, and 93.3% respectively. Kundu et al., (2021) presented an ensemble of three CNN models: GoogLeNet, ResNet-18, and DenseNet-121 which are helpful for the automatic identification of pneumonia on CXRs. The model has been tested on two publicly available pneumonia CXR datasets. The system acquired 98.81% and 86.85 % accuracy, and 98.80% and 87.02% sensitivity on Kermany and RSNA datasets respectively. Zhang et al., (2021) proposed a VGG-based model with fewer layers and dynamic histogram equalization approach has been applied for the pre-processing purpose that is helpful for pneumonia identification. Manickam et al., (2021) presented a system for detecting pneumonia infection on CXRs that uses U-Net architecture-based segmentation and classifies

pneumonia using pre-trained ImageNet dataset models. The system acquired 93.06% accuracy, 88.97% precision, 92.71% F1-score, and 96.78% recall. The U-Net is the most demanding and widely used semantic segmentation framework for a CNN. The U-Net model was utilized by the authors (Kamil, & Hashem, 2022; Kumarasinghe et al., 2022; Lu et al., 2021; Rahman et al., 2021b; Munawaret al., 2020; Liu et al., 2020) for segmentation purpose. Ma, and Lv (2022) Swin transformer backbone network is applied to the application model of X-ray identification and analysis, and the system is optimized according to the CXR characteristics.

In addition, Li et al. (2022) proposed spatial attention superposition (SAS) and multilayer feature fusion (MFF) + YOLO (SAS-MFF-YOLO) model to diagnose and locate pneumonia with high precision and mAP on CXR datasets. Although, many research also has been done (Sirazitdinov et al., 2019; Jaiswal et al., 2019; Gabruseva, Poplavskiy, & Kalinin, 2020; Kolonne et al., 2021) with remarkable performance on pneumonia detection and localization. Table.2 summarizes previous works for pneumonia identification using deep learning.

3.3.2 COVID-19

Covid-19 is a contagious and deadly disease of the 21st century. The first known case of corona virus was reported in December 2019 in Wuhan (China) but over a short period, this virus spread worldwide with devastating impact on human health, and the economy of the country, resulting in the COVID-19 pandemic. Corona virus predominantly damages the lungs and creates respiratory ailments in humans, and in severe cases, the infection can cause multiple organ failure, breathing difficulties, and fatal pneumonia. CNN is a most prominent and potential deep learning algorithm for identifying irregularities anomalies and diagnostics in CXR (Amyar et al., 2020). Many deep learning-based studies proved that DL is reliable and suitable for accurate identification of COVID-19 (Wang, Lin, & Wong, 2020; Khasawneh et al., 2021; Arias-Garzón et al., 2021; Mousavi et al., 2022).

Mahajan, Raina, Zhi Gao, and Pandit (2021) proposed a hybrid model for COVID-19 detection on CXRs. In this study, CLAHE was used to enhance the medical image, also show the comparative analysis of four different DL models. Ensemble of DenseNet201+ Single Shot MultiBox Detector (SSD) 512 shows an excellent performance for Covid-19 identification. Jain et al., (2021) proposed an algorithm for COVID-19 detection on the posterior-anterior view of CXRs. The designed approach is mainly depending on the deep learning-based CNN model. This study also represents the comparative analysis of various models: Inception V3, Xception, and ResNeXt. However, Xception model generates the highest accuracy (i.e., 97.97%) than the other models. Singh, Kumar, Yadav, and Kaur (2021) presented a multi-objective adaptive differential evolution (MADE) based CNN approach for real-time COVID-19 detection on CXRs. Abdul Gafoor, Sampathila, and KS (2022) detected COVID-19 from chest radiographs using the CNN model. CNN has proven its effectiveness to identify COVID-19 with good F-1 score and accuracy. Saxena, and Singh (2022) developed a deep CNN model to facilitate COVID-19 identification. The model trained on five different well-known open-access datasets was also compared with four pre-trained CNN-based models. The acquired accuracy of the proposed model is 92.62±0.015%, which is bit higher than the competitive models.

In addition, some studies leveraged the YOLO and SSD algorithms for accurate localization and detection of COVID-19. (Ozturk et al., 2020; Arifin, Artanto, & Nurhasanah, 2021; Tahir et al., 2021). Table.3 summarizes previous works for COVID-19 diagnosis using deep learning.

Table 2 Summary of previous studies related to pneumonia identification on CXRs using DL algorithm

Authors	Disease	CXR Dataset	Model	Performance (%)
Varshni et al. (2019)	Pneumonia	Kaggle	DenseNet-169+ SVM	AUC = 80.2
Rahman et al. (2020)	Pneumonia (Bacteria, viral)	Kaggle	- AlexNet - SqueezeNet - ResNet18 - DenseNet201	The DenseNet gives the best classification performance of normal, bacterial and viral pneumonia - Accuracy = 99 - Precision = 96 - Recall = 93.2
Zhang et al. (2021)	Pneumonia	Kaggle	VGG-based CNN model	- Accuracy = 96.7 - Precision = 94.41 - Recall = 90.83 - F1 score = 92.86
Manickam et al. (2021)	Pneumonia (Bacteria, viral)	Kaggle	ResNet50	-Accuracy = 93.06 - Precision = 88.97 - Recall = 96.78 - F1-Score = 92.71
Zhang et al. (2021)	Pneumonia	Kaggle	VGG-based model architecture with fewer layers	- Accuracy = 96.068 - Precision = 94.408 - Recall = 90.823 - F1-score = 92.851 - AUC = 99.107
Kundu et al. (2021)	Pneumonia	-Kermany - RSNA	Ensemble of three CNN models: - GoogLeNet - ResNet-18 - DenseNet-121	-Accuracy = 98.81 and 86.85 -Sensitivity= 98.80 and 87.02 - Precision= 98.82 and 86.89 - f1-score = 98.79 and 86.95 on the Kermany and RSNA datasets, respectively.
Ma and Lv (2022)	Pneumonia	Kaggle	Swin transformer backbone network	-Validate-accuracy 97
Li et al. (2022)	Pneumonia	- RSNA -AI Research Institute	SAS-MFF-YOLO	-Precision = 88.1 -Recall = 98.2 -mAP = 67.9 -AP = 99 (on AI Research Institute dataset)
Kumarasinghe et al. (2022)	Pneumonia and Covid-19	V7-labs COVID-19 X-ray dataset	U-Net+ Ensemble	-Accuracy = 99. 36 -Precision = 99. 40 -Recall = 99.38 -F1-score = 99.39

Table 3 Summary of previous studies related to Covid-19 identification on CXRs using the DL algorithm

Authors	Disease	CXR Dataset	Model	Performance (%)
Wang et al. (2020)	COVID-19	COVIDx	COVID-Net	- Accuracy = 93.3 - Sensitivity = 91.0 - Positive predictive value = 98.9
Ozturk et al. (2020)	Covid-19	2 different public datasets	DarkCovidNet	-Accuracy = 98.8
Singh et al. (2021)	COVID-19	Public dataset	Multi-objective adaptive differential evolution based CNN model	- Accuracy = 94.48 - Sensitivity = 93.83 - Specificity = 94.53 - F-measure = 93.89
Arias-Garzón et al. (2021)	COVID-19	7 different public datasets	VGG19 + U-Net	- Accuracy = 99.6 - Precision = 99.7 - Recall = 99.6 - F1-score = 99.6
Mahajan et al. (2021)	COVID-19	- COVIDx - Mendeley	Ensemble of DenseNet201+ Single Shot MultiBox Detector (SSD) 512	-Precision = 93.01 - Recall = 94.98 - F1-score = 93.98
Jain et al. (2021)	COVID-19	Kaggle	- Inception V3 - Xception, - ResNet	The Xception gives the best result for COVID-19 detection with -Accuracy = 97.97
Arifin et al.(2021)	COVID-19 Normal, Viral Pneumonia	Public	-Single Shot Detection MobileNet V1 -Single Shot Detection MobileNet V2	V1- average accuracy = 92.48 V2-average accuracy = 94
Saxena and Singh (2022)	COVID-19	COVID-19 Image Data Collection - Covid-Net - RSNA - ActualMed COVID-19 CXRs - COVID-19 radiography database	Deep convolutional neural network	Accuracy = 92.62±0.015
Abdul Gafoor et al. (2022)	COVID-19	Kaggle	CNN	-Detection Accuracy= 94 - F1-Score = 90
Mousavi et al. (2022)	COVID-19, Viral, Bacterial, and Healthy classes	6 different public datasets	CNN and LSTM	- Accuracy = 99.4 - Specificity = 99.4 - Sensitivity = 99.4

3.3.3 Tuberculosis

Tuberculosis (TB), an airborne transmissible lung infection, is the leading cause of death worldwide. Tuberculosis is triggered by the Mycobacterium tuberculosis bacterium, which usually affects the lungs and can also affect other parts of the body, such as the spine, kidneys, and brain. Tuberculosis is treatable but requires early diagnosis. Early TB detection using reliable techniques can help to save patients' lives. Consequently, CAD-based diagnostic systems have been designed for the automatic identification of TB. Rahman et al. (2020) presented a transfer learning approach with deep CNN for the identification of pulmonary tuberculosis on CXRs. For the disease classification, nine different CNN model performances were evaluated. However, ChexNet deep CNN model outperforms others. The

acquired classification accuracy with segmentation is 99.9%. A pre-trained CNN was utilized by the authors (Faruk et al., 2021; Anu priya, & Vimina, 2021; Duong et al., 2021; Oltu et al., 2021; Ibrahim et al., 2021). Showkatian et al., (2022) utilized five different CNN pre-trained models such as Xception, Inception V3, ResNet50, VGG-16, and VGG-19 for classifying normal and tuberculosis cases from chest radiographic images. Among all models, ResNet, Exception, and VGG16 outperformed for automatic tuberculosis classification. However, several researchers proved that hybrid models outperformed over solitary models (Fati, Senan, & ElHakim, 2022; Ayaz, Shaukat, & Raja, 2021). Guo, Passi, and Jain (2020) developed an ensemble deep learning system for TB as well as other lung disease identification from CXRs. Fati et al., (2022) proposed two different approaches to identifying TB on two different datasets. The first and second approach is designed by hybridizing ResNet-50 + SVM and GoogLe Net + SVM respectively. The first approach achieved better outcomes on the second dataset with 99.8% tuberculosis detection accuracy. Oloko-Oba, and Viriri (2021) Ensembled EfficientNet models (version B0-B4) for the automatic detection of tuberculosis on two publicly available CXR datasets. An et al., (2022) introduced a lightweight tuberculosis recognition model named, E-TBNet for pulmonary tuberculosis detection that achieves accurate outcome. They mainly focused on reducing the calculation speed and parameters of the model. For Shenzhen hospital CXR dataset, accuracy is 98.46%, 100% specificity, 98.76% recall, 98.60%, F1- score and 0.999 AUC.

Other techniques were also explored that proved remarkable performance to localize and detect TB such as YOLO real-time object detection approach (Guo et al., 2022; Devi et al., 2022), fast RCNN (El-Melegy et al., 2019), deep learning–based automatic detection (DLAD) algorithm (Hwang et al., 2019). Table 4 summarizes previous works for tuberculosis diagnosis using deep learning.

Table 4 Summary of studies related to tuberculosis identification on CXRs using the DL algorithm

Authors	Disease	CXR Dataset	Model	Performance (%)
Rahman et al. (2020)	Tuberculosis	- NLM - Belarus - RSNA	Transfer learning approach with deep Convolutional Neural Networks	-Accuracy = 99.9 - Precision = 99.91 - Sensitivity = 99.9 - F1-score = 99.9 - Specificity = 99.52
Faruk et al. (2021)	Tuberculosis	Tuberculosis CXR Database	Used 4 CNN pre-trained models (InceptionV3, Xception, MobileNetV2, and InceptionResNetV2)	InceptionResnetV2 outperformed among the studied models with validation accuracy 99.36
Anu priya et al. (2021)	Tuberculosis	Montgomery, Shenzhen and combined dataset	Used 4 CNN pre-trained architectures (VGG-19, RestNet50, DenseNet121, and InceptionV3)	VGG-19 achieved highest AUC score of 89, 95, and 95 for Montgomery, Shenzhen, and combined datasets, respectively.
Showkatian et al. (2022)	Tuberculosis	Montgomery and Shenzhen	Used 5 CNN pre-trained models (Xception, Inception V3, ResNet50, VGG-16, and VGG-19)	ResNet, Exception, and VGG16 outperformed for automatic TB classification. Each model achieved 90, 91, 91, and 91% accuracy, precision, recall, and AUC respectively.

Authors	Disease	CXR Dataset	Model	Performance (%)
Fati et al. (2022)	Tuberculosis	Shenzhen, Montgomery	Hybrid approach -ResNet-50+ SVM -GoogleNet+ SVM	ResNet-50 + SVM achieved better result for TB detection with- Accuracy= 99.8 Precision= 99.68 Sensitivity= 99.54 Specificity= 100 AUC = 99.82
Ayaz et al.(2021)	Tuberculosis	Montgomery and Shenzhen	Gabor Filter + seven pre-trained deep learning models	MobileNet outperformed among other classifiers in terms of AUC and accuracy. Ensemble model achieved 97.59 % accuracy and 99% AUC.
Guo et al. (2020)	Multiple Chest diseases	-Shenzhen -NIH CXR	Ensemble deep learning detection system	From Shenzhen Hospital CXR dataset - Accuracy = 98.46 - Specificity = 100 - Recall = 98.76 - F1 score = 98.60 - AUC = 0.999
Oloko-Oba and Viriri (2021)	Tuberculosis	Montgomery and Shenzhen	Ensemble (EfficientNet B0-B4)	-Accuracy = 95.82 and 97.44 -Sensitivity= 98.13 and 99.18 -Specificity= 95.78 and 96.21 -AUC = 94 and 96 on Montgomery and Shenzhen datasets respectively.
Faruk et al. (2021)	Tuberculosis	Kaggle	Ensemble two deep CNN Inception+ResNetV2	Validation Accuracy = 99.36
Guo et al. (2022)	Tuberculosis	Private	Lightweight YOLOv4 named MIP-MY	-Precision = 96.59 -Recall = 85.50 -mAP = 95.59
Hwang et al. (2022)	Tuberculosis	Private	Deep learning–based automatic detection (DLAD) algorithm	Model outperformed in both localization (0.993 vs 0.664–0.925) and classification (0.993 vs 0.746–0.971)
An et al. (2022)	Tuberculosis	- Shenzhen, - China dataset - Montgomery	E-TBNet	-Accuracy = 85.0 - Precision = 86.0 - Sensitivity = 83.8 - Specificity = 86.3 - Time = 0.3 ms

3.3.4 Lung nodules

Lung nodules are solid clumps of tissue in the lungs. These nodules can be benign (noncancerous) and malignant (cancerous) in nature. The benign tumors do not invade surrounding tissues or spread to other body parts. While malignant tumors are cancerous that can grow uncontrollably and spread to other parts of the body. Lung malignancy is the leading cause of death worldwide, so early detection is necessary to reduce the mortality rate and save human life. Ausawalaithong et al., (2018) utilized 121-layer CNN (DenseNet121) along with the transfer learning approach to classify pulmonary cancer using CXR images. Sim et al., (2019) designed a deep convolutional neural network (DCNN) based algorithm for cancerous nodules recognition on frontal CXRs. This work has differed from existing models in terms of generalizability. When the software independently examined the CXRs, the overall false-positives and sensitivity per image were 0.2 and 67.3%, respectively. Nam et al., (2019) designed a deep learning–based automatic detection algorithm (DLAD) for malignant lung nodules on CXRs and compare its performance with physicians including thoracic radiologists. Cha et al., (2019) evaluated the diagnostic performance of a trained deep CNN model for identifying lung cancer with CXRs. The performance of both DL models (DLAD and DCNN) outperformed the radiologist. Schultheiss et al., (2020) introduced a RetinaNet based CNN model for nodule location detection that has potential to help radiologists during the clinical routine. Yoo, et al., (2020) designed a model to boost the performance of pulmonary nodule and cancer identification on CXRs using deep learning approach. In the pulmonary nodule dataset, the sensitivity and specificity for nodule identification using AI algorithm were 86.2% and 85.0 % respectively. The same AI algorithm performance for detecting all cancers, the sensitivity was 75.0%, specificity was 83.3%, the positive prediction value was 3.8%, and the negative prediction value was 99.8%. For the malignant nodule identification, the sensitivity and specificity were 94.1% and 83.3% respectively. The positive predicitive value was 3.4% and the negative predictive value was 100.0%. Lu, Nanehkaran, & Karimi Fard (2021) designed a new structure of CNN for detecting pulmonary cancer. The developed method has been trained on two approaches: new metaheuristic-based (MPA) and classic (Optimizer RMSprop) method. Later compared the model performance with some pre-trained CNN ResNet-18, AlexNet, VGG-19, and GoogLeNet. Shimazaki et al., (2022) proposed and validate DL based model using segmentation technique to identify pulmonary cancer on CXRs. Ramana et al., (2022) detect and classify benign and malignant tumor. The saliency- based capsule network is used for segmentation purpose and employed optimized transfer learning for pulmonary cancer prediction from the input images. Table 5 summarizes previous works for lung nodule diagnosis using deep learning.

3.3.5 Cardiomegaly

Cardiomegaly is a medical condition in which the heart grows larger than it should, its efficiency declines, and congestive heart failure can occur. Although there could be numerous reasons, high blood pressure and coronary artery disease are the main causes of cardiomegaly. Many deep learning-based approaches have been employed in identifying cardiomegaly on CXRs. Torres-Robles, Rosales-Silva, Gallegos-Funes, and Bazán-Trujillo (2014) introduced Fuzzy-Radial Basis Function (RBF) neural network based approach that is capable of identifying cardiomegaly and providing better classification results in comparison with traditional approaches. Cardiomegaly abnormality detection usually requires analyzing the size of heart and calculating the cardiothoracic ratio (CTR). Islam et al., (2017) presented an ensemble deep convolutional network (DCN) model for chest abnormality detection and localization. Cardiomegaly classification achieved 92% accuracy while using single DCN model and the Ensemble DCN model acquired 93% detection accuracy. Que et al., (2018) developed a DL based algorithm called CardioXNet for analyzing cardiomegaly and CTR measurement from CXRs with remarkable accuracy. Candemir et al., (2018) used a deep CNN for automatic identification of cardiomegaly from CXRs. In this work, firstly apply pre-trained CNN then fine tune the models with CXRs and finally examine the correlation between softmax probability of the architecture and severity of illness.

Table 5 Summary of previous works related to lung nodule identification on CXRs using DL algorithm

Authors	Disease	CXR Dataset	Model	Performance (%)
Nam et al., (2019)	Lung nodule	One internal and four external CXR data sets	Deep learning–based Automatic Detection Algorithm (DLAD)	Proposed algorithm exhibited a per-nodule sensitivity of 70–82% with 0.02–0.34 false positives per image.
Cha et al., (2019)	Lung nodule	Private dataset	Deep CNN	Proposed DL algorithm showed a 76.8% per-nodule sensitivity at 0.3 false-positives per image
Sim et al., (2020)	Lung nodule	Private dataset	Deep CNN	Sensitivity = 70.3
Schultheiss et al., (2020)	Lung nodule	Public dataset	RetinaNet based CNN	ROC AUC = 0.87
Yoo et al., (2020)	Lung nodule and cancer	Private dataset	DL–based artificial intelligence (AI) algorithm	For pulmonary cancer detection- - Sensitivity = 75.0 - Specificity = 83.3 For nodule detection- - Sensitivity = 86 - Specificity = 85 For the malignant pulmonary nodules detection- - Sensitivity = 94.1 - Specificity = 83.3
Shimazaki et al., (2022)	Lung nodule	Private dataset	CNN architecture using segmentation method	Sensitivity = 0.73 with 0.13 mFPI (mean false positive indications per image)

Sogancioglu et al., (2020) designed a segmentation based approach for automatic detection as well as ratio measurement of cardiomegaly from CXR images which acquire great performance with 0.977 AUC that is higher than the classification based model. Thus, this technique demonstrates better result than the image-level classification method. Chamveha et al., (2020) implemented a U-Net with VGG16 encoder based DL model for calculating cardiothoracic ratio from chest radiographs with 67.1% accuracy. Lee et al., (2021) developed a segmentation based approach using deep learning which is helpful for identifying cardiomegaly from chest X-ray images. In addition, it also determines the cardiothoracic ratio automatically using the mean absolute error and paired t-test. Saiviroonporn et al., (2021) proposed an artificial intelligence based cardiothoracic ratio measurement approach using MATLAB software. In this study, AI-assisted, AI- only and manual methods were used for cardiomegaly and CTR value analysis. However, AI- assisted method present a promising performance than the others. Zhou et al., (2021) developed and evaluated DL models for identification and segmentation of cardiomegaly, pneumothorax, and pleural effusion on CXRs. The detection models acquired appreciable accuracy for cardiomegaly detection. Table 6 summarises previous works for diagnosing cardiomegaly using DL.

Table 6 Summary of previous works related to cardiomegaly identification on CXRs using DL algorithm

Authors	Disease	CXR Dataset	Model	Performance (%)
Torres-Robles et al., (2014)	Cardiomegaly	Private	Fuzzy-Radial Basis Function (RBF ACC-AHA) neural network	-Accuracy = 93.65 - Sensitivity = 98.79 - Specificity = 96.38
Candemir et al., (2018)	Cardiomegaly detection	-NLM-Indiana Collection -NIH-CXR datasets	- AlexNet - VGG-16 - VGG-19 - InceptionV3	The VGG-16 gives the best performance:- - Accuracy = 88.24 - AUC = 94.87
Que et al., (2018)	Cardiomegaly	ChestX-ray8	CardioXNet	- Accuracy = 93.75 - Precision =100 - Recall = 89.29 - F1-score = 94.34 - AUC = 93.48
Arsalan, Owais, Mahmood, Choi, and Park (2020)	Cardiothoracic ratio measurement	- JSRT - Montgomery - Shenzhen	Residual mesh-based semantic segmentation network (X-RayNet)	From Montgomery County (MC) dataset model achieved the highest accuracy- - Accuracy (X-RayNet-1) = 99.11 - Accuracy (X-RayNet-2) = 98.72
Chamveha et al., (2020)	Cardiothoracic Ratio Calculation and Cardiomegaly Detection	-JSRT - Montgomery -NIH Chest X-ray dataset -CheXpert	U-Net+VGG16	From NIH Dataset:- - Accuracy = 67.1 - Sensitivity = 81.0 - Specificity = 69.0 From CheXpert Dataset- - Accuracy = 69.8 - Sensitivity = 69.0 - Specificity =70.0
Sogancioglu et al., (2020)	Cardiomegaly Detection	ChestX-ray14	Two approaches were used for cardiomegaly detection:- -Classification-Based Method -Segmentation-Based Method.	For Classification Based Method- -Senstivity = 81 -Specificity = 89 -AUC= 94.1 For Segmentation Based Method- -Senstivity = 97 -Specificity = 90 -AUC = 97.7
Saiviroonporn et al., (2021)	Cardiothoracic ratio measurement	Private	Two models were used for cardiomegaly detection:- - AI-only - AI-assisted	For AI- only -Accuracy = 87.9 - Sensitivity = 97.5 -Specificity = 82.8 -AUC = 0.962 For AI-assisted - Accuracy = 89.8 - Sensitivity = 100 - Specificity = 84.3 -AUC= 0.977

3.3.6 Multiple disease detection

Multi-class classification achieved a surging interest in the area of computer vision. Different approaches have been employed to solve multi-label classification problems. Kumar et al., (2017) designed a boosted cascaded deep neural network to identify 14 chest abnormalities on ChestX-ray 14 dataset. Guan et al., (2018) proposed an attention-guided CNN (AG-CNN) to diagnose multi-label chest diseases by combining global and local information. When just using global baseline with ResNet-50 as a backbone, obtained average AUC 0.841. AG-CNN enhances the average AUC 0.868 after combining the local cues. Substituting DenseNet-121 raised average AUC 0.871. Abiyev, and Ma'aitaH (2018) developed a deep CNN-based algorithm for detecting chest pathologies on CXRs. CNNs outperformed competitive NNs with unsupervised learning and back propagation neural networks with supervised learning, but at a cost of a long training time. Allaouzi, and Ben Ahmed (2019) designed novel algorithm for multi-label classification of chest diseases. Pre-trained DenseNet-121 model has been utilized as a feature extractor and logistic regression is used as classifier. The model achieved great outcome on ChestX-ray14 dataset. Arsalan et al., (2020) presented a residual mesh-based chest radiographic semantic segmentation network for classification of anatomical structure of chest for diagnostic purpose. Here, X-RayNet-1 and X-RayNet-2 are proposed to generate fine segmentation performance with few trainable parameters compared to conventional DL schemes. The outcome indicates that X-RayNet-1 performed well across all datasets, while X-RayNet-2 performed well with a 75% parameter reduction. Bharati, Podder, and Mondal (2020) introduced a hybrid deep learning-based algorithm called VDSNet for various lung abnormalities detection from CXRs with 73% validation accuracy. This nobel hybrid DL approach is designed by combining VGG, data augmentation and spatial transformer network. Malik, and Anees (2022) proposed a DL based multi-label classification algorithm for recognizing lung cancer, pneumonia and COVID-19 pathologies from CXRs. The developed model is named BDCNet, which is combination of VGG-19 and CNN. They also compared the proposed model classification accuracy with other popular pre-trained models. The BDCNet model achieved 0.9833 AUC with 99.10% accuracy which is bit higher than the CNN-based pre-trained models. Fernando et al., (2022) used CXRs to develop a DL-based approach for detecting normal, COVID-19, and Pneumonia disease. Deep learning model architectures with additional layers and 5-fold cross-validation were also compared. ResNet50 obtained average accuracy and recall with 98.87% and 98.54% respectively.

Shamrat et al., (2022) compared eight pre-trained CNN models to determine the most effective transfer learning approach for the classification and finally developed VGG based customized model called LungNet22 for classifying chest pathologies efficiently. Some other deep learning based approaches such as Qura AI (Singh et al., 2018), Ensemble DNN classifiers (Hwang et al., 2019), Generative adversarial one-class learning (Tang, Tang, Han, Xiao, & Summers 2019), Cross-attention networks (CANs) (Ma,Wang, & Hoi, 2020) , EfficientNet v2- M (Kim et al., 2022) have been implemented for multi-class classification of thoracic diseases on CXRs datasets.

VinDr-CXR is a publicly available high quality annotated dataset of CXRs that has been built from more than 100,000 CXR scans in DICOM format. This dataset has 6 diagnoses (global labels) and 22 critical findings (local labels); each finding is localized with a bounding box (Nguyen et al., 2022). Luo et al., (2021) and Pham, Nguyen, and Nguyen (2022) developed a YOLOv5 and ResNet50 based model to detect and localize chest pathologies using VinDr-CXR dataset. Al-antari, Hua Bang, and Lee (2020) presented a CAD based YOLO predictor to identify and localize eight different chest pathologies. The model achieved a promising diagnostic accuracy (97.40%) over 5-fold tests. Lin et al., (2022) proposed a model called CXR-RefineDet by combining the network RRNet and the improved RefineDet that is helpful to identify and localize the multiple lesions on the CXR dataset.

In conclusion, the multi-class classifier improved performance rapidly over time and outperformed human observers in many tasks. But sometimes, the complex structure and overlapping features of chest diseases, the results get misclassified. So, there is still need improvements that could increase model performance, such as disease location, severity, and dataset availability. The related works for multiple disease diagnosis with DL are summarized in Table 7.

Table 7 Summary of previous studies related to multiple disease detection on CXRs using DL algorithm

Authors	Disease	CXR Dataset	Model	Performance
Malik, and Anees (2022)	- COVID-19, - Pneumonia, -Lung cancer	GitHub repository, SIRM, TCIA, radiopaedia.org, Mendeley, NIH, Kaggle, RSNA,	VGG19 + CNN based BDCNet	- Accuracy = 99.10 - Precision = 98.31 - Recall = 99.9 - F1-Score = 99.09 - AUC = 98.33
Abiyev, and Ma'aitah (2018)	Multiple Chest Diseases	ChestX-ray14	CNN	Accuracy = 92.4
Bharati et al. (2020)	Multiple chest Diseases	ChestX-ray14	VGG Data STN with CNN (VDSNet)	-Validation accuracy =73 - AUC = 74
Shamrat et al., (2022)	Multiple Chest diseases	Customized	LungNet22	- Accuracy = 98.9 - Specificity = 98.9 - F1 score = 98.8 - Recall = 98.9
Kim et al., (2022)	Normal, tuberculosis, pneumonia, and pneumothorax	NIH and SCH	EfficientNet v2-M	Validation performances: - Loss = 69.33 & 76.58 -Aaccuracy = 82.15 & 82.20 -Ssensitivity = 81.40 & 81.40 -Sspecificity = 91.65 & 84.48 (on NIH and SCH dataset respectively)
Luo et al., (2021)	Multiple chest diseases	VinDr-CXR	YOLOv5+ResNet50	- mAP@0.6 = 25.4 - Precision = 51.2
Al-antari et al., (2020)	Eight different chest pathologies	COVID-19 and ChestX-ray8	CAD based YOLO predictors	Detection & classification Accuracy = 96.31& 97.40, respectively over 5-fold tests.
Pham et al., (2022)	Multiple chest diseases	VinDr-CXR	YOLOv5+ResNet50	-F1-score = 77 -mAP@0.5 = 81.2
Lin et al., (2022)	Multiple chest pathologies	VinDr- CXR	CXR-RefineDet	-mAP = 16.86 -Inference speed = 6.8

4. The General flow of DL algorithms

The general flow of DL for image processing is illustrated in Figure 4. There are four key steps: Image acquisition, Image pre-processing, Training, and Classification. The first step is image acquisition. Once the image is acquired, the pre-processing approach can be applied to boost the model performance. A neural network requires massive amounts of data for training purposes; in this regard data augmentation can be applied to generate different variations of datasets from the actual dataset. Once the pre-processing has been performed, it is passed to the DL algorithm to classify it into pre-defined labels. In the training process, a neural network learns to identify the class of images. DL is useful for training models that classify images into their respective labels.

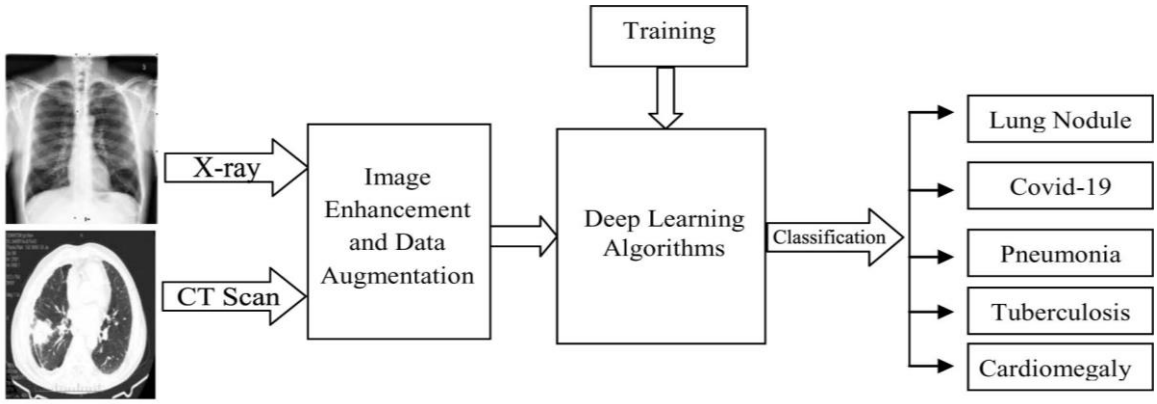

Figure 4 Block diagram of chest diseases classification using DL

4.1 Data Pre-processing

CXRs always suffer from limited contrast that may degrade the system's performance, so the pre-processing step is essential for better performance of the designed system (Arsalan et al., 2020). The raw images were first passed into the pre-processing step because some factors adversely affect the image quality. In this step, image quality gets improved by eliminating unwanted features and noise. Finally, the more appropriate image is generated for better segmentation and classification.

4.2 Data Augmentation

Data augmentation is used to create the artificial samples that differ from the actual dataset (Rahman et al., 2021a) to avoid the over-fitting, also generates more learning features to train the model which is advantageous to make the developed model more robust because small dataset may affect the performance of the system. Thus, it can boost the classification accuracy of the DL algorithms. It performs basic image processing operations like flipping, rotating, cropping, and padding. Figure 5 depicts the samples of augmentation operation.

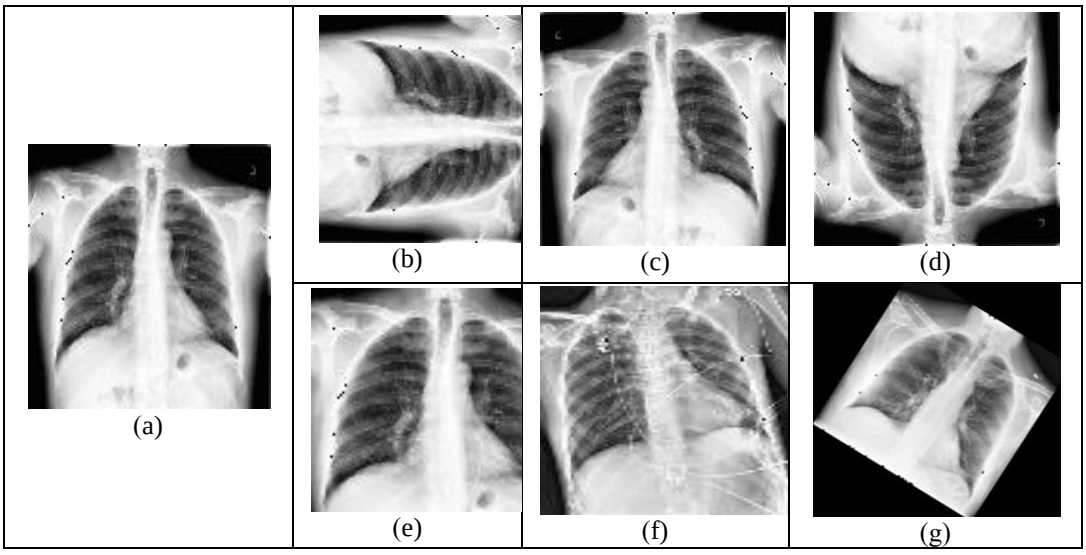

Figure 5 Samples of augmentation operation: (a) Original; (b) 90° rotation; (c) horizontal flip; (d) vertical flip; (e) zoomed in; (f) shear; (g) 45° rotation

4.3 Training

The third step is training. There are many types of DL algorithms. Each algorithm has its own learning style because different types of data work well with certain algorithms, like CNN, which generally work well with images. DL is usually chosen based on the nature of the data at hand, while transfer learning has the ability to recognize and apply the previously learned knowledge and skills to new tasks (target domain) and can be performed with or without pre-trained model. This plays a significant role in real-world situations since it does not require huge amounts of data to train the model. Moreover, ensemble learning refers more than one model for the classification operation. Ensemble and transfer learning are usually used to decrease training time and overfitting and enhance classification performance.

4.4 Classification Phase

Classification is the last phase; here, the trained model will recognize which class an image belongs to. For example, if the designed model was trained to distinguish between pneumonia-infected and normal lungs, it should be capable of accurately identifying new CXR images (which the model has never seen before) in normal or pneumonia-affected lungs. At last, the model will generate the probability score for the image that will be helpful for classification of predefined labels.

5. Evaluation Metrics

To calculate the model performance, the following parameters can be utilized. Confusion matrix is represented in Figure 6:

- **Accuracy:** It determines the overall performance of the model by evaluating how many samples are correctly recognized over the whole dataset.
- **Precision:** The number of +ve predictions made by the model that are truly +ve.
- **Sensitivity:** It has the ability to correctly identify the diseased samples, means sensitivity is the ratio of actual +ve cases that are accurately recognized as +ve.
- **Specificity**: It is the ratio of actual -ve cases that are accurately recognized as –ve.
- **F1- Score:** It represents a balance between precision and recall.
- **ROC Curve:** ROC is the probability curve that plots sensitivity against specificity

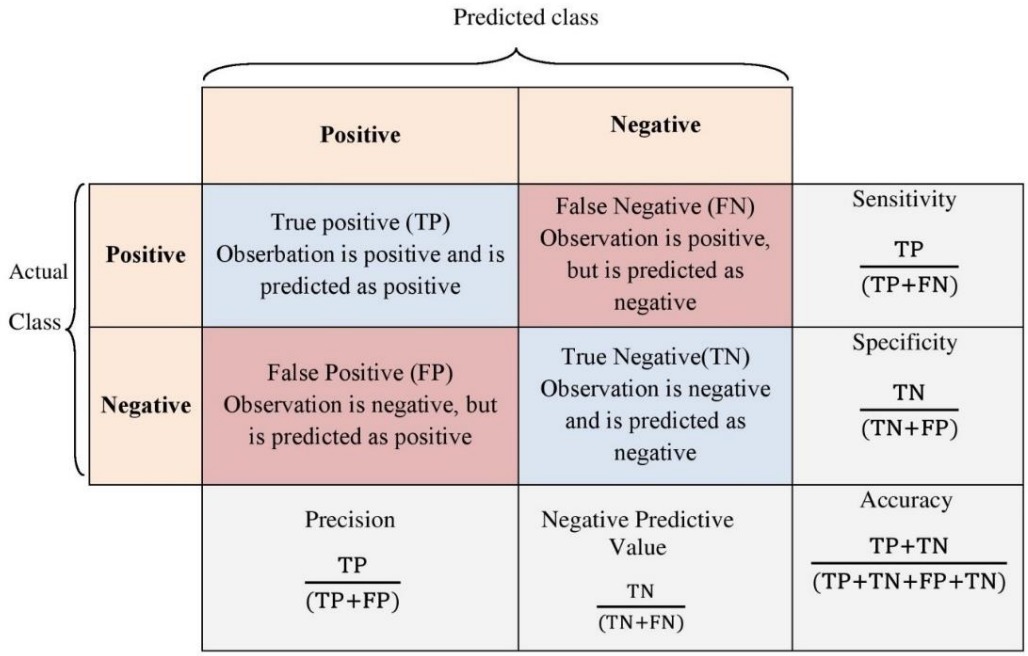

Figure 6 Confusion matrix

6. Discussion

In this review, we presented a detailed analysis of the publicly available chest X-ray dataset that has been utilized in the reviewed work and created the taxonomy to provide a better understanding and summary of the recent works and observed that the deep learning model has achieved excellent performance in detecting and classifying chest diseases on CXRs data. In most of the CXR reports, it has been found that the chest may have multiple diseases rather than a single disease. Unfortunately, it is very difficult to diagnose the diseases and their severity level manually. Many of the DL models discussed above have only binary classification. (e.g. Tuberculosis, Normal). As a result, the system is ineffective for predicting the presence of concurrent disease. However, some discussed models perform the multi-class classification and detect the multiple pathologies simultaneously using deep learning or hybrid deep learning approach that is genuinely helpful in the real-world clinical setting, but it should be remembered that the chest radiographs have more than just chest, lungs and heart, and in future developed systems, bones and soft tissues of the visualized neck and upper abdomen abnormalities also need to be analyzed. This will ensure that the report is in totally normal condition or does not have any abnormalities. Further research needs to enhance the DL model's performance because, in the medical field, system performance plays a very important role in saving human lives. Moreover, common limitation of many of the mentioned literature is high training time and insufficient technical information about the model on the computational aspects. Limited available datasets, handling of huge image size and data imbalance is another area of concern that has enough potential for future works. In addition, most of the existing models presented in this review used classification approach rather than disease localization and segmentation; this is also the fertile ground for further improvement.

6.1 Challenges

There are many challenges that need to be addressed-

(i) Dataset imbalance: Dataset imbalance: It is one of the major challenges in CXR classification, which generate inaccurate output (Fernández, García, & Herrera, 2011). Data imbalance can also be the reason for model overfitting in binary classification, as addressed by Jaiswal et al., (2019); as a result, model sensitivity drops (Li, Kamnitsas, & Glocker, 2019). This problem arises due to the mismatch in sample sizes of each class; the resultant model tends to be biased towards the majority class of samples. Existing models handle the imbalance condition in the dataset well for two classes but fail when there are multiple classes.

(ii) Limited available datasets: Data insufficiency is the most common issue faced by researchers to produce accurate classifiers. The well-annotated large dataset is very important to localize the disease. Unfortunately, building such databases is expensive, requires an enormous workload by specialists, and may also pose ethical and privacy issues. The large-scale datasets have enough potential to minimize overfitting and boost the model's generalizability. Therefore, it is necessary to build datasets to produce accurate classifiers.

(iii) Handling of large image size: Most of the previous studies have decreased the original image size during model training to reduce computational time and cost. Even with powerful GPU hardware, training with huge image sizes can be extremely computationally expensive and time-consuming. Farooq, and Hafeez (2019) have utilized the progressive resizing technique to reduce the training time in multiclass classification. While Stephan et al., (2018) experimented with 5 different image sizes to find the best image size and decrease the computational cost and training time in binary classification.

(iv) Quantitative analysis: The majority of existing systems used classification approach rather than segmentation and localization. Quantitative analysis is fertile ground for future work, and it needs to be integrated into future models. These models would be very helpful to identify the size of lung nodules, cardiothoracic ratio, volume of pneumothorax, pneumonia, tuberculosis, and many more.

(v) Clinical implementation: AI technologies have proven their dominance in the medical domain; still, clinical implementation of the model in the real-world setting is not incorporated.

These above-mentioned issues will be helpful in producing an effective and efficient model in the future.

7. Conclusions

As time passed on, numerous works on chest disease identification using DL approach were

published, but there was a lack of availability of systematic survey. This study presented an extensive and systematic survey on the deep learning approaches to detect various chest diseases using chest radiographs, discussed the research gap, and stated possible future research directions for further development. To the best of our knowledge, no other systematic survey has been found that provides a detailed analysis on open access chest X-ray datasets and deep learning techniques for chest disease detection using chest radiographs. It is clear that this research area has thrived due to the release of various publicly available, large, labeled datasets in recent years. This study provides useful information about how deep learning algorithms can reduce radiologist workload by quickly reviewing radiograph reports. Although the practical implementation of deep learning-based models into routine clinical practice is still a challenging task. Conventional CAD systems have been around for a long time, but radiologists rarely use them on a daily basis. One major reason behind this is the lack of integration into the recent clinical workflow, which is based on the picture archiving and communication system (PACS) system utilized by the physician and radiologist during routine reporting. If the DL model is to be used in clinical practice, would not merely require to be well integrated into existing PACS systems, but it would be very important for the radiologist to know how DL and AI-based models can be utilized in clinical practice as well as how to enumerate their performance. In addition, to acquire better results from the existing DL-based architecture, researchers need to design ensemble model that shows great potential. Also, localization and segmentation approaches can be utilized rather than the classification approach. Moreover, performing training using cloud computing can overcome the handling issue of large image size.

It can be concluded that DL models have proven their interpretability, algorithm transportability, reproducibility, and remarkable performance. Regardless, it is very important to understand how deep learning models can be implemented clinically for the identification of chest pathologies, which is highly significant for ensuring the right track for future research and thus improving the performance of abnormality detection systems. The suggested future directions could further ameliorate efficiency and raise the number of deep learning-aided chest pathology identification applications that can produce promising results.

One of the likely downsides of this survey is that it is restricted to studies written in English. Also, we restricted ourselves to considering the latest publication and did not include contributions of works that are non-Scopus indexed.

8. References

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