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Progression of Using Deep Learning Approaches for Chest X-Ray Diagnoses

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Abstract:

A Chest X-ray (CXR) scan is one of the most frequently used in diagnosing several thoracic diseases. The conventional interpretation of radiologists for CXRs takes a while and depends on participant variation. In recent years, deep learning approaches have become an attractive method of automating and enhancing the diagnosis of chest X-ray diseases. Also, deep learning could lead to new diagnosis directions, even outside these immediate applications. Although there is a lot of promise for deep learning to improve CXR diagnosis, ethical questions around accessibility and equity in these algorithms also need to be considered. Moreover, the responsible incorporation of deep learning into clinical practice requires close cooperation between radiologists and AI developers. This means it may increase productivity and accuracy while facilitating access to enhanced chest X-ray examinations in regions with limited resources. This work overviews the developments in using deep learning for automatically identifying chest X-ray diseases, including approaches, difficulties, and potential future paths.

1. Introduction:

Chest problems can be deadly if not caught early enough. Every year, millions die from chronic obstructive pulmonary disease (COPD), which is expected to affect sixty-five million people globally, according to the World Health Organization (WHO) [1]. The abundance of chest X-ray datasets and mutation in the artificial intelligence (AI) field has created a dramatic revolution in diagnosing chest X-ray diseases. Also, the chest X-ray field is seeing a global trend toward automation, significantly improving diagnostic accuracy and speeding up processing procedures. The use of deep learning (DL), a subfield of machine learning in radiography image analysis, enables more accurate identification of relevant information and an improved interpretation of the data [1].

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However, it is important to note that the performance of DL models depends on the quality and quantity of the training data. Researchers are striving to develop techniques that can explain these models' predictions to solve this problem. By doing so, clinicians can understand the decision-making process and develop trust in these models. This overview is organized as follows: section 2 describes the deep learning models' architecture and how they deal with chest X-ray data; Section 3 displays the most important open-access chest X-ray datasets; Section 4 highlights the previous state-of-the-art studies that have achieved great success in this field; and section 5 summarizes some of the challenges that researchers have faced in the past few years.

2. Deep learning system:

Deep learning has shown the ability to automate the identification and classification of diseases. This work presents the benefits and drawbacks of several learning strategies for detecting diseases seen on chest X-rays.

The core building block of deep learning is neural network architecture, which provides the structural stability of complex models. Multiple layers in neural networks enable the model to build its architecture automatically from data in deep learning. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are instances of deep neural network architectures that are specifically made to handle many tasks. Deep learning took off in late 2012 when CNN achieved amazing results in a computer vision battle [2, 3]. When compared to standard machine learning techniques that rely on feature engineering by hand, deep learning techniques are a great option due to their exceptional capacity to automatically generate a hierarchical feature representation of incoming data. CNNs are an effective technique for identifying characteristics in the input images. They are also capable of processing three-dimensional (3D) images in addition to two-dimensional (2D) images. CNNs have been utilized recently in a variety of fields, including the interpretation of medical imaging [4]. One of the most important things when studying medical images is CNNs' ability to retain the spatial and structural information of an image. Convolutional layers, pooling layers, fully connected layers, and activation functions (such as the rectified linear unit (RELU)) make up the general architecture of CNNs as seen in Figure 1. Thus, there has been a lot of research done on CNN techniques for the analysis of medical images [5].

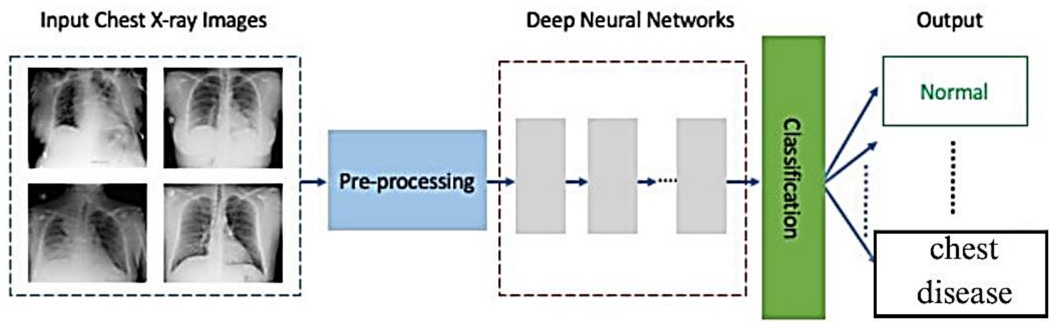

FIGURE 1. A general deep CNN overview of chest disease classification.

Transfer learning and training from scratch are two approaches forked from deep learning systems, as illustrated in Figure 2. These approaches will be discussed in detail in the next subsections.

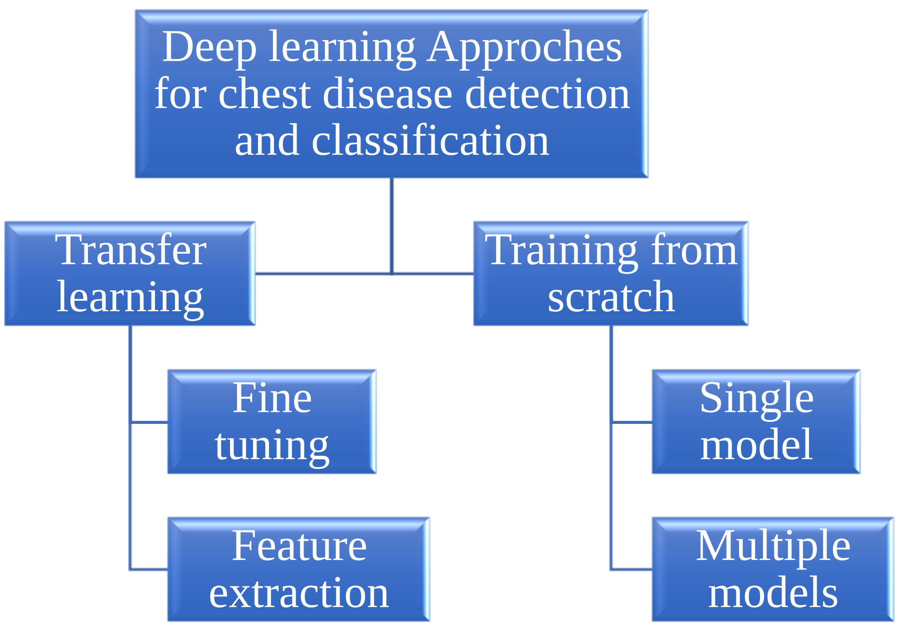

FIGURE 2. The deep learning system for chest X-ray disease detection and classification.

2.1 TRANSFER LEARNING:

Deep learning has revolutionized fields in computer vision. However, a lot of data and processing power are frequently needed for these effective models to be trained. This is where transfer learning comes into play, providing a quick way to construct deep learning models that work well [6]. Transfer learning uses prior knowledge from the source task to reduce training time and power usage and shines when data is limited or the task is related to a well-established, pre-trained model.

There are two categories of transfer learning approaches:

- **Methods based on fine-tuning:**

In fine-tuning, there is no adding new layers; the pre-trained model's weights can be updated slightly during training. Retraining some of the layers of a pre-trained model allows it to be adjusted to a new task. As a result, the model can focus on specific features needed for the new task. A pre-trained model is selected, much like in feature extraction, but this model is partially unfrozen, allowing for the retraining of some of its layers, usually the later ones that capture more task-specific characteristics. More broadly applicable features stored in earlier layers are frequently maintained frozen. Then a new dataset customized to the intended problem is used to retrain the pre-trained model. The model's weights are adjusted during this training process to better fit the new task [7].

Fine-tuning is possible to perform better than feature extraction and gives a higher accuracy when there is enough data available. In addition, it enables the model to pick up task-specific features for better performance. However, a greater dataset is needed for the training process, which consumes more time than feature extraction [8].

- **Methods involving feature extraction:**

Here, a pre-trained model used as a feature extractor is selected and learns features ranging from low-level (such as edges and shapes) to high-level (such as objects and scenes), which are generally useful for a variety of computer vision and natural language processing tasks, based on a large dataset.

The weights of the previously trained model are frozen, thus preventing future modifications to them during training. So, the acquired generic features are maintained. The features are output from a certain layer that is often selected towards the earlier phases of the pre-trained model. These features extract important data from the input [8]. On top of the pre-trained model, a new classifier head customized for the goal task is added, and a smaller dataset is used to train this classifier.

Feature extraction has its benefits, such as reducing training time and computational resources. Also, for the intended goal, even smaller datasets perform well. However, it has a drawback, which is that the complexity of the particular work might not be correctly captured [5].

2.2 TRAINING FROM SCRATCH:

Training a deep learning model from scratch is similar to building a house from the ground up. Building a basic architecture is the start, like a convolutional neural network (CNN) for image classification. Then, a massive dataset of labeled examples is fed to the network. The model learns by adjusting its internal parameters (like weights and biases) to minimize the error between its predictions and the correct labels. This process is computationally expensive due to the required graphics processing units (GPUs) for the training process and time-consuming, especially for complex tasks. Training from scratch is ideal for tasks with abundant, high-quality data and sufficient computational resources [9].

3. Chest X-Ray Datasets:

Medical image screening technologies, such as ultrasound, CT, MRI, and X-ray imaging, help radiologists diagnose organs for abnormalities. Detecting diseases from chest X-ray images can be challenging and lead to misdiagnoses. Computer-aided diagnosis (CAD) systems are being developed to address this issue, requiring a large dataset of images and other patient information (e.g., age, race, sex, insurance) for training and testing [10].

Training models require carefully chosen datasets. The most significant CXR datasets that are freely accessible are shown in Table 1, organized from the oldest to the newest. These datasets contain several chest diseases that can be classified into three major categories based on their dangers. Less dangerous conditions include minor respiratory infections and seasonal allergies. These diseases frequently produce minor chest pain, but they usually go away on their own or require little medical attention, such as pleural thickening and hernia. The more dangerous group comprises chronic diseases that have a major impact on a person's health and quality of life but can typically be managed with medical therapy. such as chronic obstructive pulmonary disease (COPD) and edema. These diseases can cause major health problems if not properly treated, but with the right treatment, people can typically lead quite normal lives. The conditions classified as extremely dangerous are those that are severe and potentially fatal. Lung cancer, pneumonia, mass, nodule, and advanced pulmonary fibrosis are a few examples. These diseases can be fatal if not treated quickly and efficiently, and they demand immediate and intensive medical attention [11, 12].

Some examples of chest X-rays from the NIH and CheXpert datasets are presented in Figure 3. Model performance and generalization are affected by how data is prepared, which includes tasks like image normalization, augmentation, and resolving class imbalances.

Table 1. Publicly available CXR datasets [13].

Dataset	Size	Classes	Collected/Sponsored by	Launch	Reference
JSRT	247 images (2048 × 2048 pixels) 247 patients	Nodule and no nodule	Japanese Society of Radiological Technology	2000	https://www.kaggle.com/datasets/raddar/nodules-in-chest-xrays-jsrt
ChestX-ray8	108,948 images (1024 × 1024 pixels) 30,805 patients	8 findings including pneumonia, atelectasis, mass, pneumothorax, infiltration, cardiomegaly, effusion, and nodule	From clinical PACS databases in the hospitals associated with NIHCC (National Institutes of Health Clinical Center)	2017	https://nihcc.app.box.com/v/ChestXray-NIHCC
Padchest	160,868 images 67,000 patients	A large number of findings	San Juan Hospital (Spain)	2017	https://bimcv.cipf.es/bimcv-projects/padchest/

ChestX-ray14	112,120 images (1024 × 1024 pixels) 32,717 patients	14 findings including hernia, emphysema, edema, Pleural thickening, pulmonary fibrosis, and others	From clinical PACS databases in the hospitals associated to the National Institutes of Health Clinical Center	2018	https://nihcc.app.box.com/v/ChestXray-NIHCC
RSNA- PneumoniaCXR	15,000 images	Pneumonia, infiltration, and consolidation	The RSNA (Radiological Society of North America) and the STR (Society of Thoracic Radiology)	2018	https://www.rsna.org/rsnai/ai-image-challenge/rsna-pneumonia-detection-challenge-2018
CheXpert	224,316 images 65,240 patients	14 findings including	Stanford University Medical Center	2019	https://stanfordaimi.azurewebsites.net/datasets/8cbd9ed4-2eb9-4565-affc-111cf4f7ebe2

MIMIC-CXR	473,057 images (2544 × 3056 pixels) 63,478 patients	14 diseases (227,943 imaging studies)	MIT, Beth Israel Deaconess Medical Center (Boston, MA, USA)	2019	https://physionet.org/content/mimic-cxr/2.0.0/
VinDr-CXR	18,000 images	28 findings including TB, pneumonia, cardiomegaly, pleural effusion, lung opacity, and others	The Hospital 108 (H108) and the HMUH (Hanoi Medical University Hospital)	2020	https://vindr.ai/datasets/cxr
Pediatric- CXR	5856 images	Normal, bacterial-pneumonia, viral-pneumonia	Guangzhou Women and Children's Medical Center, China	2022	https://physionet.org/content/vindr-pcxr/1.0.0/

(a) **(b)** **(c)** **(d)**

Figure 3. Examples of CXR images from NIH and CheXpert datasets [14] include (a) nodule disease; (b) emphysema disease; (c) effusion disease; and (d) infiltration disease [13].

4. Literature review:

Various methods have been developed for chest disease classification utilizing deep learning and chest X-ray images. As mentioned previously, training from scratch and transfer learning are the two primary deep learning techniques in this field. This section focuses on the most common literature on chest X-ray disease detection and classification that achieved milestone benchmarks.

In 2017, Wang et al. [14] provided the chestX-ray-8 dataset, an enormous amount of data larger than prior datasets of its kind. That work was the first to address the issue of building hospital-scale radiology image databases with computerized diagnostic performance benchmarks. A transfer learning approach of pre-trained deep learning models on ImageNet was proposed for the multi-label classification and localization of eight chest X-ray diseases, e.g. Atelectasis, Cardiomegaly Effusion, Infiltration, Mass, Nodule, Pneumonia, and Pneumothorax depending on four models, e.g. AlexNet, GoogLeNet, VGGNet-16, and Resent-50. Resnet-50 achieved the highest results in seven of eight diseases, compared with the other three models, except the "Mass" disease, which was detected well by the AlexNet model.

The experimental results of Wang et al. [14] have been evaluated using the Area-Under-Curve (AUC) values. "Cardiomegaly" (AUC=0.8141) and "Pneumothorax" (AUC=0.7891) are the highest recognition results achieved compared to other diseases. Also, the identification of "Mass" (AUC = 0.5609) and "Nodule" (AUC = 0.7164) classes was difficult due to their huge variance in appearance. Due to the limited number of cases, "pneumonia" performed worse (AUC = 0.6333).

Wang et al. [14] also introduced an expansion of their dataset, which is termed the chest X-ray-14 dataset, by adding 6 more chest diseases, e.g. consolidation, edema, emphysema, fibrosis, pleural thickening, and hernia to their disease list, and "hernia" disease achieved the best (AUC = 0.87) of all other diseases.

Although the ResNet-50 model achieved the highest results and played its role as a good feature extractor, it can be noticed that training ResNet-50 requires significant computational resources, which can be expensive and time-consuming [15].

To overcome ResNet-50 model limitations, Yao et al. [16] used the Long Short-Term Memory (LSTM) model to recognize the 14 diseases in the chest X-ray-14 dataset. The LSTM model was trained end-to-end from scratch, without any pre-training on ImageNet data, to find the statistical correlations between labels to generate better predictions, achieving an average AUC of 0.798 for 14 diseases. LSTM model exceeded the results of ResNet-50 on all 14 diseases except "fibrosis"(AUC = 0.767). But, like other models, the LSTM model has its limitations, such as that it can easily overfit the training data. Also, it can be computationally expensive and time-consuming due to the huge amount of utilized parameters and high-quality data for the training process.

After some trials, the CheXNet model [17] proposed its way to identify the chest X-ray 14 [18] diseases from frontal-view chest X-ray images utilizing the pre-trained DenseNet-121 model, which exceeded trained radiologists and previous models in all diseases, achieving a better result with an average AUC of 0.841 for all diseases. Also, in detecting some fatal diseases like mass, nodule, pneumonia, and emphysema, CheXNet has a margin of >0.05 Area Under the Receiver Operating Characteristic curve (AUROC) over previous state-of-the-art results [17]. This technique depends on updating the fully connected layer to extract 14 outputs instead of the binary one. Although DenseNet-121 achieved higher accuracy with fewer parameters, it is sometimes regarded as a black box, making it difficult to explain how they make decisions and can be biased due to the number of disease images [19].

Kumar et al. [20] used a cascade neural network, a new artificial intelligence (AI) model, to diagnose 14 distinct pathologies in chest X-rays. They fine-tuned their pre-trained DenseNet161 model by training the fully connected layer using the ChestX-ray14 dataset. To keep the model from being biased because some diseases are more common than others, they adopted a technique known as under- and over-sampling. Their model performed as well as other state-of-the-art AI models, and it achieved an average AUC of 79.50%.

Victor Ikechukwu et al. [21] investigated two approaches to identifying pneumonia in chest X-rays. To achieve high validation accuracy, they first used pre-trained models such as VGG-19 and ResNet-50, which were able to extract features from a large image dataset. However, due to limited resources, they chose ResNet-50 over ResNet-101. Second, they created a convolutional neural network (CNN) from scratch and trained it purely for pneumonia diagnosis. While this strategy demonstrated promise (over 93% accuracy), it fell short of the overall efficiency of pre-trained models, which achieved near-perfect accuracy (over 97%) in identifying pneumonia.

Detecting pneumonia on chest X-rays is difficult for radiologists since it could look like other, less serious diseases and is difficult to distinguish from other diseases. Researchers have developed many ways to avoid misdiagnosing pneumonia [22]. So, Ma and Lv [23] developed a promising deep-learning model called the Swin transformer. A transformer network is employed for feature extraction, while a fully connected network is used for the classification and diagnosis of pneumonia disease in chest X-ray (CXR) images and COVID-19 computed tomography CT images [24]. They tested their model against various types of deep convolutional neural network (DCNN) models on two separate datasets of CXR images. On the datasets utilized, their model outperformed DCNNs with an accuracy of approximately 87.3% for the Swin transformer on all 14 diseases, and that result exceeded previous state-of-the-art due to the strength of the Swin transformer in efficiently processing high-resolution images, which is critical for capturing medical details [23]. However, Swin Transformer training can be computationally expensive due to the required powerful GPUs.

Yu. Gordienko et al. [25] focused on how dimensionality reduction techniques can improve the performance of deep learning models used to classify lung cancer using chest X-rays. The researchers trained deep learning models on the JSRT dataset, most likely employing ways to reduce image dimensionality (which could minimize the number of features evaluated). The authors discovered that using several preprocessing techniques to reduce the complexity of the chest X-ray data significantly improved the performance of a simple convolutional neural network (CNN) model, particularly on a small dataset with imbalanced classes. Also, techniques such as lung segmentation, bone removal, and outlier filtering increased the CNN model's training speed and accuracy when compared to raw data. Furthermore, the authors proposed additional ways for higher performance and enhancement that are possible by removing shadows from other organs (such as the arms and heart) by utilizing sophisticated segmentation methods. Also, they proposed that increasing the size and complexity of the CNN model (>10 layers) and fine-tuning it will improve accuracy. This is comparable to how successful models such as CheXNet achieve great performance.

J. Irvin et al. [26] presented a CheXpert dataset, a huge amount of chest X-rays that contain life-threatening thorax diseases, e.g., edema, cardiomegaly, lung opacity, lung lesion, consolidation, pneumonia, atelectasis, pneumothorax, and others. The authors evaluated a baseline deep learning model trained on the CheXpert dataset for classifying various chest diseases. The addition of uncertainty labels in their work was one of the dataset's distinguishing characteristics, which were used to express their level of confidence in the diagnosis of each image. This allows the model to learn from the inherent confusion in real-world clinical practice. The training labels in the dataset for each observation are either 0 (negative), 1 (positive), or u (uncertain). Several convolutional neural network architectures were used in the training process, specifically ResNet152, DenseNet121, Inception-v4, and SEResNeXt101, and it was found that the DenseNet121 architecture achieved the best results, especially for cardiomegaly (AUC = 0.854) for the U-multi-class model (positive), whereas the U-Ignore (negative) model achieved (AUC = 0.828) the uncertainty label.

Aurelia Bustos et al. [27] focus on introducing the PadChest dataset rather than evaluating classification methods for chest diseases. Radiologists' reports included specific labels for findings, diagnoses, and anatomical locations. The authors identified specific findings on X-rays, such as nodules, tuberculosis, and infiltrates. They also proposed a technique for creating labels: a combination of manual annotation by clinicians and a supervised algorithm based on recurrent neural networks (RNN). Neural networks with attention mechanism (RNN-ATT) architecture used to create these multi-label annotations achieved the best result for both validation (AUC = 0.864) and test sets (AUC = 0.857).

In 2021, Joseph Paul Cohen et al. [28] introduced TorchXRayVision, which is an open-source package created specifically for working with chest X-ray datasets and deep-learning models. This work not only provided a common interface for several publicly available chest X-ray datasets but also made it easier to access and switch between datasets during model training or evaluation. To serve as feature extractors, the package also provided several classification and representation learning models, such as ResNet-50, ResNet-18, and DenseNet-121, with various architectures that were trained on nine tremendous chest X-ray datasets that contain about 18 chest pathologies, e.g., Lung Opacity, Lesions, Edema, and others.

5. Conclusion:

Although deep learning approaches are strong tools for classifying chest diseases and have the potential to change diagnoses completely, there are still certain fundamental limits that researchers are actively working to overcome. It also needs a lot of experience (data) and may make mistakes when using something new. This makes it difficult to use everywhere and can result in errors. Still, it's a very effective tool, and improvements are always made!

Transfer learning and training from scratch represent two distinct approaches to building deep learning models. While training from scratch gives you total control and flexibility, it also uses a lot of processing power and data. On the other hand, transfer learning uses the information from previously trained models, greatly reducing the time and data needed for training.

The requirements of the task determine the best strategy to use. Training from scratch could be helpful if there is abundant data and processing power. However, transfer learning has a significant benefit for the majority of real-world uses. Through the strategic use of feature extraction and fine-tuning methods, it is possible to create pre-trained models for several tasks with a small amount of data. Transfer learning will probably stay a key component for creating strong and effective models in various applications as deep learning advances.

6. Conflict of Interest:

All authors declare that they have no conflicts of interest.

7. Future Directions:

The future of deep learning work revolves around choosing whether to build models from scratch or fine-tune existing ones. The balance tends towards fine-tuning due to its ability to adapt to specific tasks quickly. Fine-tuning is a more realistic option since it enables us to utilize prior knowledge as a result of the growing complexity of tasks and the vast amount of data being generated. However, the decision depends on the specific problem, available data, and computational resources, as each approach has its strengths and limitations. The key to future AI success lies in finding the right balance between model understanding and deployment efficiency.

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الملخص العربي

التطور في استخدام أساليب التعلم العميق لتشخيص أمراض الصدر بالأشعة السينية

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الملخص العربي:

يُعدُّ التصوير الإشعاعي للصدر أحد أكثر الفحوصات الطبية استخدامًا في تشخيص العديد من أمراض الصدر حيث يستغرق من الأطباء وقتًا طويلا لتفسير هذه الصور الإشعاعية ويختلف هذا التفسير من طبيب لآخر باختلاف الخبرة. في السنوات الأخيرة، أصبحت تقنيات التعلم العميق طريقة جذابة لتحسين تشخيص أمراض الصدر بشكل تلقائي. كما يمكن أن يؤدي التعلم العميق إلى اتجاهات تشخيصية جديدة ليس فقط تشخيص المرض بحسب ولكن أيضا إظهار تلك العلاقة الوثيقة بين هذه الأمراض وارتباط بعضهم بالآخر. وعلى الرغم من أن التعلم العميق أظهر نتائجا واعدة بتحسين تشخيص أمراض الصدر، إلا أنه يجب أيضًا النظر في المسائل الأخلاقية حول كيفية الوصول لتلك القرارات ومدي شفافية هذه الخوارزميات. علاوة على ذلك، فإن إدماج التعلم العميق في الممارسة الطبية يتطلب تعاونًا وثيقًا بين أطباء الأشعة ومطوري الذكاء الاصطناعي. وهذا يعني أنه يمكن أن يزيد من سرعة ودقة التشخيص الطبي مع تسهيل الوصول إلى فحوصات التصوير الإشعاعي للصدر في المناطق ذات الموارد المحدودة. يستعرض هذا العمل التطورات في استخدام التعلم العميق لتشخيص أمراض الصدر تلقائيًا، بما في ذلك النهج المتبع في اتخاذ القرار والصعوبات والمسارات المستقبلية المحتملة.