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Chest X-Rays Image Classification in Medical Image Analysis

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Abstract

Chest X-Rays image classification is an active research area in medical image analysis as well as computer-aided diagnosis for radiology. The main goal is to improve the quality and productivity of radiologists' task by providing a computer system for detecting and classifying diseases. A few studies have been conducted in applying machine learning methods to produce a high-quality chest X-ray image classification approach. Some review papers have been published in discussing different aspects of medical image analysis and computer-aided diagnosis for radiology. This paper aims to complement the existing surveys by targeting on the chest X-ray image classification approaches base on the use of machine learning methods. The review begins with a background information of data mining, and the fundamental knowledge of medical image analysis, chest radiography, and machine learning.

Keywords: Chest X-Ray; Computer-Aided Diagnosis; Image Classification; Medical Image Analysis; Machine Learning

Introduction

Image acquisition, image formation, image analysis, and image-based visualization [1] are part of computer processing and analysis of medical images. Medical image analysis has evolved into a variety of directions that include pattern recognition, image mining, computer vision, and machine learning. Meanwhile, Computer-Aided Diagnosis (CAD) has been part of the advancement of medical image analysis to support the automated detection and classification of various diseases.

Radiology is a branch of medical science which uses imaging technology and radiation to make diagnoses and treat disease [2]. In radiology, CAD has been advocated as providing "second opinion" to assist radiologists' image reading of Chest X-Rays (CXRs) in determining the presence of disease [3]. There are different kind of conditions and diseases that can be diagnosed such as atelectasis, consolidation, infiltration, pneumothorax, edema, emphysema, fibrosis, effusion, pneumonia, pleural thickening, cardiomegaly, nodule mass, and hernia. Furthermore, most infectious diseases related to respiratory depend heavily on CXR. One of the important tasks in advancing the capability of CAD is to detect and classify disease from CXRs automatically. This capability can contribute to improving the quality and productivity of radiologists' tasks by maximizing the accuracy and consistency of radiological diagnoses and minimizing the image reading time [3].

Machine learning (ML) has been promoted as an effective way to automate the analysis and diagnosis of medical images, especially CXRs [2]. Thus, ML contributes to the enhancement of CAD. Furthermore, deep learning has been investigated and proved as the most successful ML's model for medical image analysis [4,5,6].

Various research works have been proposed to improve the application of ML, specifically deep learning for CXRs image analysis such as image classification and segmentation. As a result, there is a need to gather these approaches and provide a comparison through a survey or review to foster the advancement of CAD with sophisticated analysis capability.

We note that many reviews have been conducted and published concerning medical image analysis and CAD. To the best of our knowledge, the most related works are referred to the following approaches. Ginneken et al. [7] reviewed existing literature works of CAD for chest radiographs by focusing on the general processing techniques, the algorithms for segmentation of anatomical structures, and the analysis aimed at solving a particular task or application. Mehta et al. [8] reviewed of lung nodule and its characteristic as well as the existing detection methods for CAD. Jaeger et al. [9] reviewed on the classification approaches (such as SVM, kNN, Decision Tree) for TB detection in CXR using CAD. Doi [3] presented a few CAD schemes (such as the detection and classification of lung nodules on digital chest radiographs, detection of nodules in low dose CT) by focusing on the potential clinical applications. In further work, Doi [10] surveyed the current historical aspect, current status and future potential of CAD in the environment of picture archiving and communication systems (PACS). Finally, Mittal et al. [5] surveyed the methods for segmenting lung field in CXRs by focusing on the dataset used, the underlying principle, reported performance, and relative merits and demerits. Lung segmentation is a challenging problem due to various factors such as overlapping anatomical structures, variations in its shape and size, the presence of foreign objects, etc.

Based on these related works, our paper aimed to review the CXR image classification approaches in medical image analysis. This understanding and insight are essential to foster future research, especially, in leveraging machine learning techniques for improving the accuracy of CXR image analysis.

Preliminary

Data Mining in Healthcare Systems

Data mining techniques have been applied to support different aspects of Healthcare systems. The survey conducted by Tomar and Agarwal [11] explored the application of data mining techniques for healthcare systems. They first discussed the advantages and disadvantages of several data mining techniques. Then, they presented several applications which include effective management of hospital resource, hospital ranking, improving customer relation, supporting hospital infection control, provide smarter treatment, improving patient care, decreasing insurance fraud, recognizing high-risk patients, and producing health policy planning.

Furthermore, the data mining techniques have been utilized to predict diseases. Herein, we mention some of the previous proposed works as follow:

- *Breast Cancer*. Delen et al. [12] addressed the challenge of predicting breast cancer survivability. They proposed the application of data mining algorithms (i.e., artificial neural networks and decision trees) with statistical method (i.e., logistic regression) to develop the prediction models using a large dataset. They concluded that the decision tree outperformed the others, namely, the artificial neural networks and logistic regression models. They also recommended that the outcomes of the prediction need to be evaluated by medical professionals to assess the viability of the data mining application.
- *Heart Disease*. There are many works addressed the application of data mining techniques related to the heart disease. Palaniappan and Rafiah [13] addressed the need to discover hidden knowledge to support effective decision making. They developed and proposed a prototype called Intelligent Heart Disease Prediction System using a combination of data mining

techniques, namely, Decision Trees, Naive Bayes, and Neural Network. The system was developed as a Web-based system using Net platform. Srinivas and Govrdhan [14] shared the same concern and proposed an approach to discover significant patterns from heart disease data warehouses for predicting a heart attack.

- *Parkinson Disease.* Ramani and Sivagami [15] provided a survey of data mining techniques for the classification of Parkinson Disease (PD) which is a chronic and progressive movement disorder. They utilized the Parkinson Disease data cases created by Max Little of the University of Oxford, in collaboration with the National Centre for Voice and Speech, Denver, Colorado. Then, they found the patterns formed by different classification algorithms. According to their finding, Random Tree classifier yielded the 100% accuracy.
- *Lung Cancer.* Yang and Chen [16] explored the capability of a decision tree to detect lung cancer staging diagnosis by using a correlation between two category data which is clinical information data and pathology information data. Their goal was to demonstrate the feasibility of applying the clinical information to replace the pathology report especially in diagnosing the lung cancer pathologic staging. The prediction system was able to classify lung cancer staging base on tumor size, lymph node extent, and metastasis (TNM). The prediction performance results indicated that using support-then-confidence-then-lift (SCL) approach can match more records and using confidence-then-lift-then-support (CLS) can get higher accuracy.

Although Data mining has significant benefits to the Healthcare system, they are not without limitations as discussed by Koh and Tan [17]. Firstly, the application of data mining in Healthcare is limited by the accessibility of data. This limitation may require the preparation of a data warehouse, but this attempt can be a costly and time-consuming project. Secondly, the data quality problem may arise, such as missing, corrupted, inconsistent, or non-standardized data due to different data sources. Thirdly, there is a possibility the interesting patterns found from data mining activities are not useful due to a product of random fluctuations. Fourthly, lack of skills by the people involves in the data mining activities. Collectively, people should possess domain knowledge, statistical and research expertise, and information technology and data mining knowledge and skills. Finally, the challenge of having a substantial investment of resources, time, effort, and money.

Chest X-ray Anatomy

Chest X-ray (CXR) anatomy is a projection radiography of the chest used to diagnose conditions affecting the chest including bones, lungs, respiratory tract, great vessels, and heart (refer to https://en.wikipedia.org/wiki/Chest_radiograph). There are three types of views on the commonly used chest radiographs: Anterior Posterior (AP), Posterior Anterior (PA), and side view (lateral). Most CXRs are AP views while PA and side view are taken depending on the specific situation.

Doctors will observe carefully each of the relevant signs of chest x-ray to come out with diagnostic assumptions. The standard parameters observed by doctors in CXRs are referred to (ABCDEF, (refer to https://radiopaedia.org/articles/chest-x-ray-abcde-summary):

- *Airways.* Airways can be seen starting from the trachea, bronchus, and lungs. Abnormality in respiratory tract are usually caused by infection, obstruction, mass and foreign bodies. Respiratory tract problems can cause difficulty, rapid and noisy breathing to the patient. Any obstruction or condition that obstruct airway can lead to death.
- *Bones.* Those that can be seen through CXR include clavicle, scapula, humerus, and ribs. Any deformity of the bone seen via CXR is commonly caused by trauma.
- *Cardiac.* Common abnormalities of the heart that can be seen through CXR are cardiomegaly (enlargement of the heart), prominent of great vessels, heart tumors, cardiac tamponade, and others.
- *Diaphragm.* The diaphragm in the respiratory system is a dome-shaped sheet of muscle that separates the chest from the abdomen. Many possibilities can cause when there is a raised of hemidiaphragm such as trauma, hernia and lungs collapse.
- *Edge of the lungs.* It is only visible when there is an abnormality present. Some disease can cause

pleural thickening, and others lead to fluid or air gathering in the pleural airspace.

- *Fields of the lung*. It can be divided into three zones as upper, middle, and lower zones. Usually, doctors will observe lungs field starts from the symmetrical of lungs both left and right, a dense area (white) which can be caused by infection or any other abnormal signs which need to investigate further.

Medical Image Analysis, Chest Radiography, and Machine Learning

Medical Image Analysis in Chest Radiography

Medical imaging covers different modalities that include ultrasound, X-ray, computed tomography scans and magnetic resonance imaging scans, positron emission tomography scans, retinal photography, histology slides, and dermoscopy images [6]. Meanwhile, chest radiography is one of the primary diagnostic imaging procedures in medical image diagnosis. The aim is to evaluate and detect pulmonary diseases. The key challenge faced by radiologists is when the image is low in contrast caused the difficulty to detect and characterize lesions.

To overcome the limitation, researchers have been investigated into one branch of medical image analysis, known as Computer-Aided Diagnosis (CAD) [10, 18]. The primary purpose of CAD is to assist radiologists in finding the location of a lesion and also to estimate the probability of a disease. CAD is a promising solution to improve the quality and productivity of radiologists' tasks. This is possible since the output of CAD can be used as a "second opinion" to assist radiologists' image reading [18].

There are three main research areas of medical image analysis in relation to the chest radiography [3]. Firstly, the general processing techniques that cover the need to enhance the display of CXR images and to remove normal structures in CXR so that abnormalities stand out more clearly. The enhancement is supported with several techniques such as local equalization and sharpening, whilst, the removing of normal structures can be implemented through subtraction techniques. Secondly, the segmentation of the lung fields, rib cage, and other structures. The techniques applied for segmentation includes rule-based reasoning and pixel classification. Thirdly, the analysis that covers the aspect of size measurements, lung nodule detection, texture analysis, and other applications.

In addition, existing literature has established a set of CAD schemes for the analysis, in particular, to detect lung nodules, interstitial diseases, interval changes, and asymmetric abnormalities, as well as for differential diagnosis [18, 19]. Thus, the underlying technologies for the CAD schemes include the techniques for detection and extraction of abnormalities, the quantification of image features for abnormalities, the classification between normal and abnormal, and performance evaluation through ROC analysis [18].

Machine Learning for Medical Image Analysis

In medical image analysis, the accurate diagnosis of a disease depends on both, image acquisition and image interpretation [20]. Image acquisition has benefited from the improvement of device technologies. Meanwhile, the image interpretation depends on the human interpretation from physicians. The advancement of computer technology especially the image analysis and machine learning have assisted the improvement in accuracy of the interpretation.

Machine learning (ML) is the study of computer algorithms that are able to learn complex relationships or patterns from empirical data and make accurate decisions [21]. ML algorithms are commonly divided into three categories, namely, supervised learning, semi-supervised learning, and unsupervised learning. Examples of supervised learning include classification, regression, and reinforcement learning. Examples of unsupervised learning include clustering, density estimation, and blind source separation. Meanwhile, examples of semi-supervised learning include semi-supervised classification and information recommendation systems [22].

In the context of radiology, ML provides an effective way to automate the analysis and diagnosis of medical images. Having an automated solution can contribute to minimizing the workloads of radiologists. The application of machine learning in radiology include medical image registration, segmentation, computer-aided detection and diagnosis, brain function or activity analysis and neurological disease diagnosis, content-based image retrieval systems, text analysis of radiology reports [2].

There are a few ML methods which have been applied in medical image analysis. The most promising methods are classified as deep learning [4, 6, 20]. The basis of most deep learning methods is based on neural networks. A neural network is comprised of neurons with some activations and parameters. It contains multiple layers, which refer to the input layer, output layer, and hidden layers (i.e., layers in between input and output). Meanwhile, the most popular architecture of deep learning in medical image analysis is Convolutional Neural Networks (CNNs). The main reason is because CNNs preserve feature relationships when filtering input images, that is important in examining CXRs.

CNNs take an input image of raw pixels and results in the assignment of class scores or probabilities. This means, the class with the highest probability is the right one. The process of transforming the inputs into the chosen classes has similar layers as neural network as well as the implementation of backpropagation algorithm. In addition, the hidden layers may contain three types [6]. Firstly, the convolution layer which is used to filter and detect relevant image features, from the low-level (e.g., line and curved edge) until the high-level (e.g., nose and eye). The filtering process is supported with two functions, the input function that contains the pixel values and the filter (or kernel) function. Secondly, the rectified linear unit (RELU) layer which comprises of an activation function that sets negative input values to zero. This operation helps to avoid the vanishing gradient problem. Thirdly, the pooling layer that is used to reduce the number of parameters to be calculated and the size of the image. This pooling layer exists in between the convolution and RELU layers. The combination of all layers produces the fully connected layers that represent the most strongly activated features. These features determine the image (input) that belongs to a specific class or label (output).

Furthermore, CNNs are highly parallelizable algorithms and thus very effective in dealing with large training sets. Therefore, the execution of its related algorithms requires the support of modern parallel computing architecture. Eklund et al. [23] have gathered and reviewed the commonly used algorithms in medical imaging and its potential implementation in Graphical Processing Units (GPU).

Chest X-ray Image Classification Approaches

In this section, we discuss and summarize existing approaches that contribute to CXR image classification by using machine learning methods. The summary is provided in Table 1.

Xue et al. [24] applied Support Vector Machine (SVM) to classify CXR image view into binary category, namely, frontal and lateral view. They extracted several effective features from CXR consisting of image profile, body size ratio and developed a new contour-based shape descriptor. The study involved 8300 digital images x-rays and 4000 x-ray reports from the National Library of Medicine (NLM) in Indiana. The result has achieved high accuracy on 10-fold cross-validation.

Bar et al. [25] investigated the capability of deep learning, i.e. CNNs in detecting different types of pathologies in chest x-ray images. The type of CNN was referred to [26] with Deep Convolutional Activation Feature (DeCAF) capability [27] that can extract main descriptors from a large scale non-medical images, namely, ImageNet [28]. The reason for using ImageNet was due to unavailable large-scale medical images for training purposes. In addition, their study also used PiCoDes descriptor [29], a compact high-level representation of low-level features (e.g., GIST). The datasets utilized refer to Sheba Medical Center that consists of 93 frontal chest X-ray images with three pathology conditions. The results supported the claim that the use of pre-trained CNN with DeCAF and PiCodes may be sufficient for general medical image recognition. Furthermore, in their recent work, specifically, Bar et al. [30], they considered a larger dataset that consists of 637 frontal chest X-ray images with six pathologies. They concluded that the selection of features from the CNN layers contribute to the most informative feature set and increase the performance of the chest pathology categorization task.

Shin et al. [31] proposed a practical framework for machine learning to learn, detect disease and describe from the patient's chest x rays and their accompanying radiology reports with Medical

Subject Heading. In the study, they used OpenI that contains 3955 radiology reports from the Indiana Network for Patient Care, and 7470 associated chest x-ray from the hospitals' picture archiving systems.

Table 1. Summary of existing CXRs image classification approaches

Papers (year)	Classification categories	Classification goals	Datasets	Splitting*	Methods	Metrics
Xue et al. [24] (2015)	binary classification problem	Classify into frontal vs lateral view	Indiana & IRMA dataset	not mentioned	Trained SVM with SMO	the accuracy of each feature
Bar et al. [25] (2015)	binary classification problem	classify into healthy vs. pathology	Sheba Medical Center dataset	not mentioned	trained CNN (DeCAF) and PiCoDes together with SVM (leave-one-out-cross-validation)	sensitivity, specificity, AUC, accuracy
Bar et al. [30] (2016)	binary classification problem	classify into healthy vs pathology	Sheba Medical Center dataset	not mentioned	trained CNN (Decaf), Kruskal-Wallis with SVM feature selection	AUC, accuracy
Shin et al. [31] (2016)	multi-label classification and annotation	classify and annotate 17 unique disease	OpenI	80%, 10%, 10%	CNN (Network-In-Network model) together with RNN (LSTM, GRU)	BLUE scores
Islam et al. [32], (2017)	binary classification problem	detecting and localizing abnormality	Indiana, JSRT, and Shenzhen datasets	not mentioned	DCNN (AlexNet, VGG-Net, ResNet)	AUC, accuracy, sensitivity, specificity
Wang et al. [33] (2017)	multi-label classification problem	detecting and localizing the presence of multiple pathologies	ChestX-ray8 dataset	70%, 10%, 20%	DCNN	ROC, sensitivity
Rajpurkar et al. [34] (2017)	binary classification and multi-label classification problem	detecting the absence or presence of pneumonia and classifying abnormalities on CXR	ChestX-ray14 dataset	70%, 10%, 20%	121-layer DCNN (CheXNet)	F1 score: harmonic average of the precision and recall
Yao et al. [35] (2017)	multi-label classification problem	detecting and localizing the presence of multiple pathologies	ChestX-ray14 dataset	70%, 10%, 20%	2D ConvNet (based on DenseNet), LSTM (based on RNN)	NLL, AUC, DICE co-efficient, PESS, PCSS
Guan et al. [36] (2018)	multi-label classification problem	detecting the absence or presence of thorax diseases	ChestX-ray14 dataset	70%, 10%, 20%	AG-CNN	AUC, sensitivity
Gundel et al. [37] (2018)	multi-label classification problem	classifying abnormalities on CXR	ChestX-ray14 dataset	70%, 10%, 20%	of DenseNet with 121 layers	AUC
Baltruschat et al. [39] (2018)	multi-label classification problem	classifying abnormalities on CXR	ChestX-ray14 dataset	70%, 10%, 20%	ResNet-50	AUC

* train, validate, test

The dataset was labeled with 17 unique conditions including normal chest x-ray, opacity, cardiomegaly, calcinosis, hypo inflation, calcified granuloma, thoracic vertebrae, hyper distension, spine degenerative, catheters, granulomatous disease nodule, surgical instruments, scoliosis, osteophytes, spondylosis, and fractures. They trained the dataset using CNN and use the CNN prediction of the input image as the first word as the input to the Recurrent Neural Network (RNN). Their study is the first pne that combines an image and report of chest X-ray in one model of prediction. The authors believed that this type of chest x-ray prediction model would have better accuracy and can be applied to other application scenarios.

Islam et al. [32] explored Deep Convolutional Neural Network (DCNN) based abnormality detection in frontal CXR. They found that ensemble models can improve classification significantly compared to a single model when only DCNN models were used. Combining DCNN models with rule-based models degraded the accuracy. They also performed localization of features responsible for classification decision. For the experiments, they utilized Indiana with 7284 CXR images, JSRT with 247 CXR images and Shenzhen dataset with 662 CXR images. The author found that for spatially spread out abnormalities like cardiomegaly and pulmonary edema, the network can localize the abnormalities successfully most of the time. They performed a prediction of cardiomegaly and tuberculosis using DCNN with ensembles method perform 93% and 90% each disease respectively.

Wang et al. [33] addressed the need to have a large-scale medical image. Therefore, they produce a new CXR database, namely *ChestX-ray8*. This dataset comprises 108,948 frontal-view X-ray images of 32,717 unique patients. Each image has been labeled with one or more labels from any eight disease labels, in particular, atelectasis, cardiomegaly, effusion, infiltration, mass, nodule, pneumonia, pneumothorax. By using DCNN, they performed the chest x-ray image analysis for disease prediction with an average accuracy score of 62.89% for eight diseases (atelectasis, cardiomegaly, pleural effusion, infiltration, mass, nodule, pneumonia, and pneumothorax). The most accuracy for disease prediction is cardiomegaly, and the poorest accuracy was to detecting a nodule.

Rajpurkar et al. [34] proposed a new detection algorithm called CheXNet to detect pneumonia of chest X-ray image. CheXNet's algorithm consists of 121 layers of the convolutional neural network. It received X-ray image as an input and produced the probability of having pneumonia. In addition, they also developed a visualization mechanism based on heatmap to localize the problematic area of the chest X-ray image. To evaluate the algorithm, they compared its performance with the radiologist as well as existing algorithms that utilized ChestX-ray14 datasets released by Wang et al. [33] that comprised of 112120 frontal CXR images with 14 abnormalities. The results showed that the performance CheXNet was better as compared to the audiologist's performance, and achieved state of the art results on all 14 pathology classes.

Yao et al. [35] addressed multi-label classification problem in relation to the medical images that were analyzed to detect and classify abnormalities in chest X-ray images, in particular, atelectasis, cardiomegaly, effusion, infiltration, mass, nodule, pneumonia, pneumothorax, consolidation, enema, emphysema, fibrosis, PT, hernia. In general, the multi-label classification problem is a problem of associating each instance with a subset of possible labels. Concerning this problem, they investigated the potential dependencies among labels which were significant in medical images and can affect the classification accuracy. To overcome this problem and the potential dependencies, they proposed a two-stage end-to-end neural network model that combined a densely connected image encoder with a recurrent neural network model decoder. This model was evaluated using ChestX-ray14 datasets and was proved to be better.

Guan et al. [36] aimed to detect thorax disease on CXR images. Their primary motivation was to address the problem of a global image (i.e., excessive and irrelevant noisy areas) that can potentially affect the accuracy of detection. Thus, they proposed a three-branch Attention Guided Convolution Neural Network (AG-CNN) which learns a global CNN branch using global images. Then, the guided learning was done through the attention heat map to crop the respective region from the global image. The experiments were conducted on the ChestX-ray14 dataset. Through extensive experiments, they demonstrated that combining global and local cues yielded state-of-the-art accuracy on the ChestX-ray14 datasets.

Gundel et al. [37] addressed the multi-label classification problem of pathologies on chest x-ray images. The primary motivation of the research was to deal with the high probability of similar data (or patient record) appeared in both training and testing set, as well as the need to incorporate the spatial information. Thus, they proposed an approach based on Location Aware Dense Networks to classify pathologies in chest X-ray images, that incorporate high-resolution image data and spatial information for improving the classification accuracy. They used ChestX-Ray14 datasets to show the state-of-the-art results. Then, they used PLCO [38] datasets that contain the spatial information to evaluate the proposed approach. The results have shown an improved accuracy with the presence of spatial information.

Baltruschat et al. [39] presented a systematic evaluation of different approaches for multi-label classification as well as comparing their fine-tuned ResNet-50 model with state-of-the-art results. They used a 5-fold re-sampling scheme to assess three main aspects, namely, the initialization strategies for the ResNet-50, the network architectures with the input size, and the non-image feature such as age, gender, and view position. For the experiments, they made use of ChestX-Ray14 and performed a ROC analysis using AUC for all fourteen classes or pathologies. Their results illustrated a high variability of the outcome in relation to selected dataset split. Furthermore, their fine-tuned ResNet-50 achieved state-of-the-art results in four out of fourteen classes.

Conclusion

Fundamental concepts of medical image analysis, chest radiology, and machine learning, as well as their connection that contributes to the advancement of CAD in chest radiology, have been presented. We then focus our discussion on the comparison of CXR image classification approaches. We have compared in terms of several dimensions, namely, the classification problem types, the goals of each work, the selected dataset, the splitting ratio, the methods, and the evaluation metrics. The comparison provides some understandings and insights on the state-of-the-art of the current works for future work, in particular, in advancing CAD to improve the quality of radiologists' tasks.

List of abbreviations

AG-CNN – Attention Guided Convolution Neural Network
AUC – Area under Curve
CXR – Chest X-ray
CAD – Computer-aided Diagnosis
CNN – Convolutional Neural Network
DCNN – Deep Convolutional Neural Network
DeCAF – Deep Convolutional Activation Feature
ML – Machine Learning
PiCoDes – Picture Codes
RNN – Recurrent Neural Network
RELU – Rectified Linear Unit
ROC – Receiver Operating Characteristic
SMO – Sequential Minimal Optimization
SVM – Support Vector Machine

Conflict of Interest

The authors declare that they have no conflict of interest.

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