MA902

Literature Review On Detection Of Pneumonia From Chest X-ray Images Using Convolution Neural Networks (CNNs)

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May 21, 2021
wordcount : 4010

Contents

1 Abstract

Chest X-Ray is one of the easily available and economical diagnostic tools for detecting chest diseases. Deep neural networks such as Convolution neural networks (CNNs) are proven to be effective in tasks such as image detection, classification, and segmentation in medical imaging domain. Due to availability of large amount of data, computational resources and using CNN models, researchers in medical imaging are automating the diagnosis process and are successful in identifying and classifying various disease conditions. Latest techniques such as transfer learning is also showing promising results in medical imaging to diagnose diseases. This paper presents literature review on various researchers work that involved use of CNNs and transfer learning technique to detect and classify pneumonia from chest x-ray images. For this purpose, various electronically available databases such as IEEE, Science Direct and Google scholar were searched to obtain the articles. Pneumonia is still a fatal disease for children in some developing countries due to scarce availability of expert radiologists to diagnose pneumonia. Furthermore, analysing an X-ray to precisely diagnose a lung disease is difficult due to the fact that pneumonia has many clinical symptoms with other lung disorders. This emphasises the need for automating the medical image diagnosis and develop tools which can automatically detect and classify a lung disorder such as pneumonia when supplied with an X-ray image of lungs. This study overviews the current literature available to detect and classify pneumonia using CNNs and transfer learning from chest X-ray images. The primary objective of this review is to identify the limitations of techniques used in previous studies and provides suggestions for future work in this domain.

2 Introduction

The most commonly adopted method for diagnosing lung diseases is taking chest X-ray (Wang et al., 2017). Chest X-rays are inexpensive and are easily accessible. The interpretation of chest X-ray as either normal or having any lung disease such as asthma, pneumonia or tuberculosis is decided after careful examination by an experienced radiology professional.

Pneumonia (Hoare & Lim, 2006) is a frequent inflammatory lung disease caused by a variety of infectious agents including bacteria, viruses, and fungus. Pneumonia can be fatal if not diagnosed and treated in early stages. Children, older adults and asthmatic patients are high risk groups for pneumonia. Pneumonia is the greatest cause of death in children (Prayle et al., 2011) under the age of five, accounting for more than 15% of all child deaths globally (WHO, n.d.)., according to the World Health Organization. Children in developing (Izadnegahdar et al., 2013) and underdeveloped countries are highly affected by pneumonia due to malnutrition and lack of access to medical facilities. Developing countries such as India, Pakistan, Nigeria, the Democratic Republic of Congo, and Ethiopia accounted for more than half of all childhood deaths due to pneumonia in 2017(WHO, n.d.).

The primary imaging technique recommended by most health professionals for diagnosing any lung disease is chest X-ray (Vilar et al., 2004) due to its low cost compared to computed tomography (CT) and Magnetic Resonance Imaging(MRI). However, there is a shortage of experienced radiologists (Oates et al., 2019) to interpret the results of chest X-rays across many nations, this includes developing as well as developed nations (Phillips, n.d.). In developing nations, a scarcity of competent radiologists is leading to alarmingly high child mortality rates.

Accurate and timely detection is vital in reducing the mortality in case of pneumonia. In addition, interpretation of chest X-Rays is often challenging (Rajpurkar et al., 2017) even for experienced radiologists compared to MRI and CT, due to their lower resolution. Automation of X-Ray analysis is essential to enhance the decision making and also to fill the gap between the number of radiologists available and comparatively higher number of radiographs that need to be interpreted by each radiologist.

Oflate, Artificial Intelligence (AI) is making it's way into Medical Imaging (C. Liang & Xin, 2020), especially Computer Vision and Deep Learning techniques such as Convolution Neural Networks (CNNs) are being widely for diagnosing many disease conditions as well as to distinguish between healthy and abnormal disease conditions. CNNs are widely used (Rawat & Wang, 2017) in areas such as image detection and classification (Li et al., 2014), image segmentation. Some of the applications include breast cancer detection(Chen et al., 2019), skin lesion classification (Ahmed et al., 2020), chest diseases classification (Bondfale & Bhagwat, 2018) etc.

Using AI, Computer-Aided Diagnostic (CAD) (Oliveira et al., 2008) systems can be developed which can sequentially extract and classify features from input data(chest X-ray), there by automating radiological image analysis, which is otherwise manual and time consuming.

2.1 Back ground

Pneumonia (Virkki et al., 2002) is an acute respiratory infection, that causes inflammation of lung tissues. The lungs are made up of small sacs called alveoli. In the person infected with pneumonia, these sacs gets filled with pus and fluid, which reduces the oxygen intake and breathing becomes painful. Pneumonia is transmitted from a diseased individual to a healthy person through air-borne droplets from cough or sneeze. Symptoms include difficulty in breathing, fever and wheezing is common in viral pneumonia. The figure 1 shows the x-ray images of normal versus person affected by bacterial pneumonia. The images are taken from (Kermany et al., 2018)

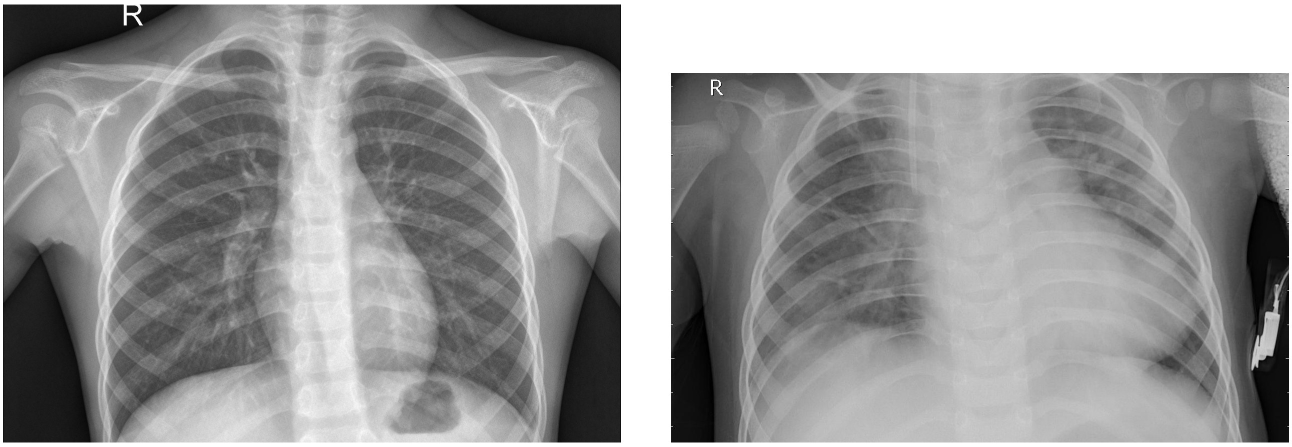

Figure 1: Normal chest X-ray(left) and chest X-ray of a person infected with bacterial pneumonia(right)

This articles reviews and summarizes the work that has been done for the last ten years for identification and classification of chest X-ray images for pneumonia condition using CNNs and transfer learning. The main objective of the present work is to identify the limitations of the previous work and suggestions for future work.

2.2 Design of Literature Review

Data Sources

The articles reviewed for the present work were mainly taken electronic databases.

- IEEE

- Google Scholar
- Science Direct

Query terms

The following queries are formed to search databases to find the articles relevant for the present study:

- Pneumonia detection using CNN
- Pneumonia detection OR classification of chest X-Rays using deep learning
- Chest X-Ray OR chest chest radiographs classification using Convolution Neural Networks

Selection of relevant papers

Based on the following inclusion and exclusion criteria the articles obtained were filtered:

1. **Inclusion criteria**:
   - Papers that performed studies relevant to pneumonia identification using chest radiographs.
   - Papers that were published after 2010 to early 2021.
   - Papers that were published in peer-reviewed journals or conferences were included.
2. **Exclusion criteria**:
   - Papers that were printed in languages other than English.
   - Research that is not related to pneumonia detection using chest radiographs.
   - Wikipedia, short reports, blogs, posters

3 Convolution Neural Networks

Convolution Neural Network (CNN) (Traore et al., 2018) is a type of deep learning neural network that has shown promising results in various tasks related to image recognition. The typical architecture of a CNN contains one or more convolution layers, followed by pooling layers and one or more fully connected layers. The architecture of CNN is inspired by the visual cortex of human brain (Fukushima, 1987).The visual cortex contains many neurons that are responsible to capturing and detecting light in small over-lapping sub regions of visual field called receptive fields. By doing this, these neurons function as local filters over the input image space. The same operation is performed by filters used in convolution layer of CNN, that convolve on receptive field of image to extract local features. In CNN, each layer receives input from a set of features located in small region(local receptive field) of previous layer. This helps in extracting lower level features, which are then combined by the next layers to extract more complex patterns.

Traditional CAD systems (Oliveira et al., 2008) were successful in classifying chest infections using X-rays, however they require extensive use of manually crafted techniques to extract features from images, followed by classification of features extracted using machine learning techniques. Researchers have developed many deep learning based solutions(CNN,transfer learning) based solutions to over come this problem. Convolution layers perform the task of feature extraction in CNN.They use convolution filters whose weights are adjusted to extract features as the training progresses. These filters are not manually designed unlike traditional CAD systems.

Figure 2 below shows the basic architecture of CNN for classification of chest X-rays. It has a convolution layer, followed by a Relu layer and max pool layer. The output after pooling is flattened and given to fully connected layer.

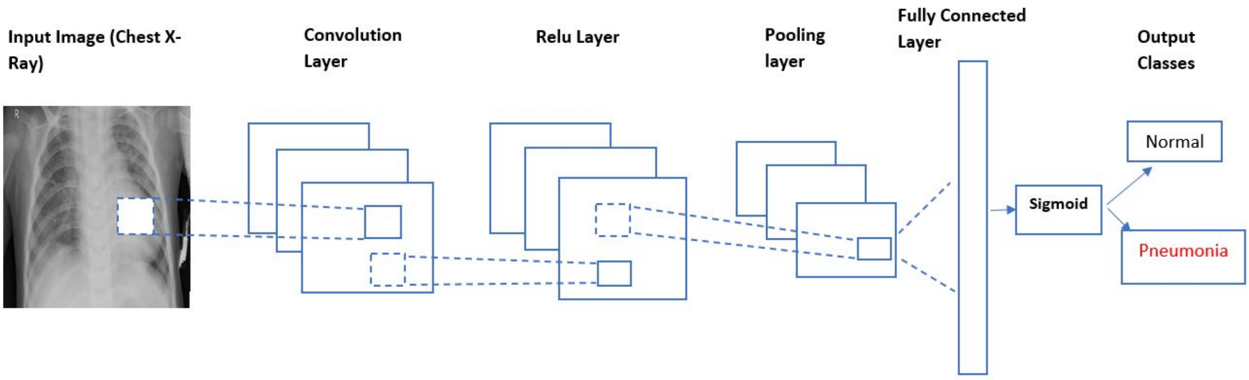

Figure 2: Basic architecture of CNN for classifying Chest X-rays

3.1 Convolution Layers

Convolution layer has following attributes:

- Convolution filters(hyper parameter) of defined height and width.
- Number of input and output channels(hyper parameters).
- Padding, strides are additional hyper parameters.

CNN, takes input in the form of a tensor with shape: (number of images) * (image height) * (image width) * (number of channels). The convolution layer extracts different features from input tensor by convolving filters on input image, this process generate a feature map of processed image. The shape of feature map is: (number of images) * (feature map height) * (feature map width) * (number of filters).This feature map is then fed as input to next layer.

The first convolution layer extracts low-level features such as lines and edges. Using more convolutions the top level layers extracts high-level features. The filters share weights and hence the number of learnable parameters greatly reduce in case pf CNN, there by reducing vanishing gradient problem that is usually encountered in traditional MultiLayer-Perceptrons (MLP) (Orhan et al., 2011).

Convolution is nothing but component wise multiplication followed by addition. The pixels values in input matrix are convolved with weights of convolution filter of given height and width to generate a feature map. Convolution with N kernels generates N feature maps. The equation 1 shows the convolution of $n \times n$ size image with a kernel $k \times k$ producing a feature map of size $(n - k + 1) \times (n - k + 1)$.

$$(n \times n) \times (k \times k) \rightarrow (n - k + 1) \times (n - k + 1) \tag{1}$$

Figure 3 shows an example of convolution operation on 6×6 gray scale image using 3×3 convolution kernel.

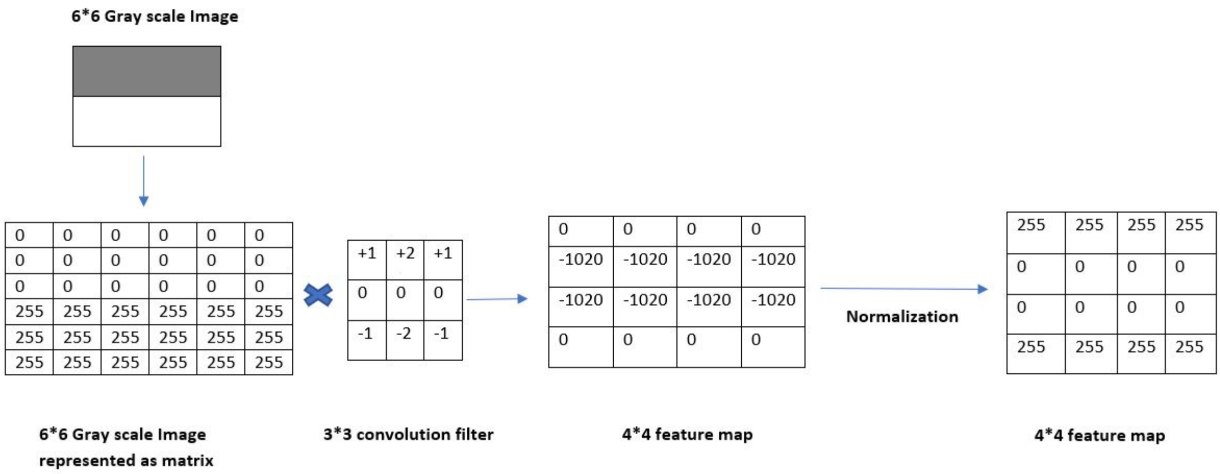

Figure 3: Convolution operation

The convolution operation reduces the original dimension, which may lead to loss of information.**Padding** is performed to generate output feature map that has same dimension as given input image. In padding we add a layer of zeros(padding=same) around the input matrix. The equation 2 shows the result of padding. With input size 6×6, padding p = 1, $n + 2p$ = 8. the output produced will be 6×6.

$$(n + 2p \times n + 2p) \times (k \times k) \rightarrow (n - k + 2p + 1) \times (n - k + 2p + 1) \tag{2}$$

The convolution operations start at the top-left corner of the input, filter is shifted from left to right till it reaches top right corner, then the filter shifts in downward direction until the bottom right corner is reached. The shifting is decided by **strides**. Stride of one moves filter/kernel one element wise. Striding reduces the image size. The equation 3 below showing stride operation, s denotes the stride size.

$$(n \times n) \times (k \times k) \rightarrow (\frac{n - k}{s} + 1) \times (\frac{n - k}{s} + 1) \tag{3}$$

3.2 Relu Layer

Relu(Rectified linear unit) is the most widely used non-linear activation function in CNN. Below is the equation 4 for Relu, where $a = Wx + b$.(W=weights,x=input,b=bias)

$$f(x) = max(0, a) \tag{4}$$

Relu removes negative values from feature map by setting their value zero. Relu is preferred over other activation functions such as sigmoid because sigmoid function suffers from vanishing gradient problem and convergence is also faster when Relu is used as activation. The figure 4 shows the pictorial representation of Relu activation function.

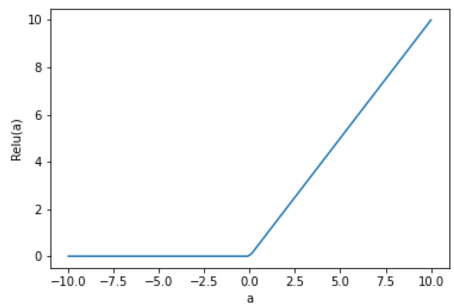

Figure 4: Relu activation function

3.3 Pooling Layers

Pooling layer is also called sub sampling layer.Pooling helps to learn location, translation and scale invariant features. Pooling greatly reduces the dimensions of the feature map. There are two main techniques of pooling: max pooling and average pooling. Max pooling takes the maximum value in each local cluster of activation map, where as average pooling takes the average value.

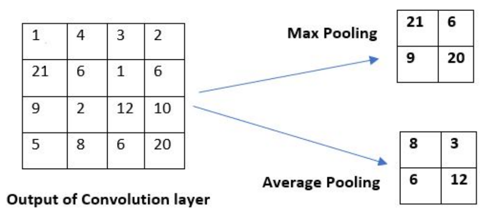

Figure 5: Pictorial representation of Pooling operation

3.4 Fully Connected Layers

In fully connected layer every neuron in one layer is connected to every neuron in another layer. The final output after many convolutions and pooling are flattened and given to fully connected layer.

3.5 Classification Layer

The output of fully connected layer is fed into classification layer which classifies the image into either as normal or having pneumonia. For binary classification the sigmoid function is used in output layer.Sigmoid outputs a probability, a value greater than 0.5 gives output 1(pneumonia) and value less than 0.5 outputs 0(indicating normal).

The equation of sigmoid function 5 is given below:

$$\sigma(a) = \frac{1}{1 + e^{-a}} \tag{5}$$

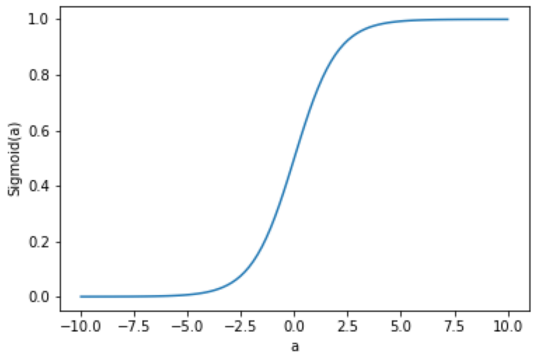

Figure 6: Pictorial representation of Sigmoid function

Availability of large training data and computer resources(Graphical Processing Units) has led to increased use of CNNs in medical image analysis (Bakator & Radosav, 2018). However, due to the using deep CNNs there is always a chance of over fitting due to high number of convolution layers and filters. The following techniques can be performed to avoid over fitting.

- Drop out Regularization
- Early stopping

In drop out regularization a subset of features are randomly dropped based on given drop out value by setting their weights to zero and training is continued with remaining features. Various early stopping criteria can be defined to stop the training before the model starts to over fit the training data.

Building CNN for image classification can be performed in two ways either by building CNN from scratch and training on the training data and evaluating the model performance on test data or by using transfer learning technique.

3.6 Transfer Learning

Transfer learning method (Lu et al., 2015),(Iorga & Neagoe, 2019) enables to transfer knowledge gained while solving one problem to solve a different but similar problem. Training a deep CNN is often expensive in terms of computational resources and time required when trained on large data sets. Data scarcity is often the challenging task for image classification.Using transfer learning data scarcity can be addressed easily. Transfer learning can be done in two ways : using pretrained model as feature extractor, in this method retraining of the pre-trained model is not required, top layers are replaced by a new classification layer, using fine tuning the pre-trained model by unfreezing few layers and training on new data set.

4 Literature Review

To automate detection and classification of lung diseases such as tuberculosis, lung cancer and pneumonia using chest radiographs an artificial neural network is designed by authors (Khobragade et al., 2016) in this paper. The first step of their methodology includes pre-processing the X-ray image to eliminate irrelevant data from X-ray film, it involves two main steps: image enhancement and image filtering.To enhance image, image intensity and contrast are adjusted by using histogram equalization method, this makes image more suitable for further processing. then in image filtering, unwanted noise is removed by passing high pass filter to sharpen the image. In second step, lung segmentation is performed to acquire region of interest of lungs. To identify lung boundaries, they used intensity-based method and edge detection. In third step, feature extraction is performed on segmented area of image to extract diagnostically important geometrical features such as area, perimeter, irregularity index, equivalent diameter, and statistical features such as mean, entropy and standard deviation. Then, the final step involves classification of extracted features as normal or abnormal using a feed-forward and back propagation neural network. The data set is taken from Sasoon hospital, Pune which includes 80 chest radiographs of patients. Their model was able to achieve an accuracy of 92%. However, this model is not robust to changes in size and position of chest radiographs.

(Rajpurkar et al., 2017) have developed CheXNet algorithm, which can detect pneumonia from chest radiographs. It is a 121-layer CNN (DenseNet), in which fully connected final layer is replaced by single output layer that uses sigmoid activation function. It takes chest X-ray as input, gives output as pneumonia probability along with a heat map that locates the regions most specific to pneumonia. The model was trained on ChestX-ray14 data set. All the images in data set are normalized and resized to 224×224 before feeding into the network. The data set is further divided into training(98637), validation(6351) and test(420) data sets, without any overlap of patients between the sets. The training data is also augmented. The test set is annotated by four radiologists. The mean F1 score of the radiologists is compared to that of CheXNet model and it has achieved 0.435 F1 score that is higher than the mean radiologists F1 score 0.387. The limitation of the algorithm includes it is trained only on frontal view images and radiologists does not have access to patient's medical history.

In general networks are usually trained using global image (object is in the centre of image) as an input. In this (Guan et al., 2018) paper, a modified version of CNN called AG-CNN was developed to classify chest diseases from x-rays.In case of chest diseases, the region affected by disease can be small, and position may vary in different x-ray images. Also, finding the specific boundaries that correspond to disease region is important to overcome misalignment. The authors proposed a three branch AG-CNN to overcome these problems. It overcomes the noise and misalignment problems by first focusing on the disease specific regions. It has three branches. The local branch, this is used to locate disease specific regions, but using local branch alone may lead to loss of information in cases where the disease is present in multiple locations of lung, so global branch is used to compensate this loss. First the global branch is trained to learn from global images. Then, using heat map generated by global branch, a mask is inferred to crop a discriminative region in the global image. Then this local region is trained using local branch. The final pooling layers of local and global branches are concatenated, and fusion branch is fine tuned. The data set used for this study is ChestX-ray 14 data set. They got an average AUC of 0.841 with a global base line model that uses ResNet-50 as backbone. Using AG-CNN the average AUC is improved to 0.868 and using Dense Net-121 they achieved AUC of 0.871.

The authors (Varshni et al., 2019) have leveraged transfer learning technique for classifying chest X-ray images to detect pneumonia. They used ChestX-ray14 dataset for this study. CNN models such as VGG16, VGG19, Xception, ResNet-50, Densenet-121 and Densenet-169, which were pretrained on ImageNet dataset were used as feature extractors to extract features from this dataset and performance of each model is evaluated by classifiers such as KNN(k-nearest neighbours), Random Forest, Naïve bayes and Support Vector Machine(SVM). Resnet-50 with a depth of 168 and SVM as classifier has achieved AUC score of 0.7749 outperforming all the other models. Although the model has achieved good results, but the study did not consider the computational power that is required to train such deep networks and like previous researchers this study also used front view chest x-ray images and did not consider lateral view which is also important in diagnosing lung diseases.

In (Kermany et al., 2018) have developed a convolution neural network to classify retinal diseases. To check for the generalization ability of this network they applied transfer technique and tested this network using paediatric chest x-rays for pneumonia detection. They collected 5232 children chest x-rays and labelled them for this purpose. The model was able to achieve an accuracy of 92.8%, sensitivity of 93.2% and specificity of 90.1%.

In this paper (G. Liang & Zheng, 2020) have used deep neural architecture with residual connections and dilated convolutions for the classification of chest x-rays of children. The model achieved f1-score of 92.7% and recall rate of 96.7%. In this paper (Labhane et al., 2020), authors have conducted research to automate pneumonia detection. For this study, they designed four models a basic CNN,VGG16,VGG19, InceptionV3 and transfer learning techniques. Paediatric pneumonia data set which contains 5856 chest X-rays(1349 Normal and 3883 Pneumonia) is used for training the models and they have achieved over 97% accuracy using all the four models. Compared to previous researchers (Kermany et al., 2018), (G. Liang & Zheng, 2020) who worked on the same data set, this study higher accuracy.

The study in this paper (Peng et al., 2021) used MIMIC-CXR-JPG data set (Johnson et al., 2019), which is large publicly available data set comprising of 3,37,110 chest X-ray images of 63379 patients. The authors designed a model that contains three CNNs which as feature extractors. In stage 1, these CNNs learn information from two frontal views as well as one lateral view of given chest X-ray image. In stage2, features from each CNN is passed separately through a fully connected layer, this gives three features specific to each view. Then weights are assigned to these features and are then fused to form a global feature. This final feature is passed through a fully connected layer followed by a SoftMax layer for classification. The model has achieved an AUC score of 0.71 when evaluated on test data set consisting of 480 multi-view chest X-ray images of 160 patients.

5 Discussion

Because chest radiography plays such an important role in the examination and diagnosis of disorders of the chest, automatic detection has become one of the hottest subjects in computer vision and medical imaging research.

This paper provided a review of the current literature on the topic of pneumonia detection using chest x-ray, as well as a summary of the topic and an analysis of the current methods.

The table 1 shows the citations reviewed in this article along with the method, data set used and the results achieved in each study. Also, there are multiple data sets available for detecting pneumonia from x-ray images, table 2 shows the data sets used by researchers reviewed in this paper.

Table 1: **Table comparing various techniques used by researchers to detect oneumonia from chest x-rays**

Citation	Method	Data set	Results
(Khobragade et al., 2016)	ANN	Sasoon Hospital,Pune	accuracy 92%
(Rajpurkar et al., 2017)	CheXNet model	ChestX-ray14	F1 score 0.435
(Guan et al., 2018)	AG-CNN	ChestX-ray14	AG-CNN AUC : 0.868
(Varshni et al., 2019)	ResNet-50, DenseNet-121	ChestX-ray14	Resnet-5 AUC score: 0.7749
(Kermany et al., 2018)	Transfer Learning	Paediatric chest X-rays	accuracy of 92.8%
(G. Liang & Zheng, 2020)	CNN with residual connections	Paediatric chest X-rays	F1-score: 92.7% recall: 96.7%.
(Labhane et al., 2020)	CNN,VGG16,19,InceptionV3	Paediatric chest X-rays	accuracy 97%
(Peng et al., 2021)	CNN	MIMIC-CXR-JPG data set	AUC score: 0.71

Table 2: **Table summarising the data sets used for pneumonia detection**

Data set	Number of Images	Source
ChestX-ray14 dataset	14000 images	(Wang et al., 2017)
MIMIC-CXR-JPG data set	37110 images	(Johnson et al., 2019)
Paediatric dataset	5232 images	(Kermany et al., 2018)

6 Conclusion

The use of CNNs and transfer learning to diagnose chest disorders, primarily pneumonia, was the focus of this report. The work of previous researches showed promising results (Rajpurkar et al., 2017),(Guan et al., 2018), (Kermany et al., 2018),(Labhane et al., 2020), (Peng et al., 2021) to automate the need for X-ray diagnosis for pneumonia detection.

Inclusion of textual information such as patient's medical history and clinical diagnosis is important to accurately diagnose a disease. Constructing a model that can incorporate this information along with various other body indicators is more appropriate and easy for doctors to diagnose the lung diseases. The models reviewed in this paper does not included this information. However, this information is important to determine the disease condition more accurately. The models built in the future should include the patients medical history and clinical symptoms.

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