A Survey: Identification of Different Thoracic Disease Using Convolutional Neural Network

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***Abstract*: Thoracic disease affects various parts of the organ around the chest at different paces, and accounts for the number of deaths in India. We have vaccines and medicines to prevent the spread of infection-causing bacteria, viruses, and fungi in the organs, but many patients still die as a result of the inability in early detection of the disease. The diagnosis of thoracic disease relies on chest x-ray images that are manually interpreted by an expert. Chest x-ray images have their own set of flaws, which can lead to inaccuracy in judging infected areas or even the presence of infections. This paper focuses on using computer-assisted techniques, different algorithms present in machine learning and deep learning pre-trained CNN models (ResNet, DenseNet, CheXNet and VGG), and classification techniques(Logistic Regression, SVM, K-nn) in the medical and healthcare field for the classification of chest x-ray and diagnosis of thoracic disease.**

***Keywords*: CNN, Deep Learning, Thoracic Disease, X-ray image, Automation, Machine Learning, DenseNet, K-nn, SVM, ResNet.**

1. INTRODUCTION

Abnormalities in the human body are life threatening if not treated properly. There are several health problems that are quickly diagnosed and treated when they are discovered early on, while others go unnoticed until they become alarming. The majority of them were caused by unintended medical malpractice, ineffective care, and flaws in technology used to diagnose the disorders. As a result, a modern and creative approach to technology is critical for eliminating the flaws that endanger lives. It's healthy to have more than one way to serve people having severe disorders.

1.1. Thoracic Disease

Thorax is the region between the inferior abdomen and the root of the superior neck. Thoracic Disease is a condition that affects the region around the chest. There are various kinds of thoracic infections that affect lungs, heart, esophagus, great vessel, diaphragm, mediastinum and chest wall. Its initial diagnosis is mostly carried out with the help of X-ray machines which generate x-ray images scanning through the body. As we know, unless the infection, cause of infection or the health condition is detected in its early phase, it is quite impossible to continue the exactly required treatment.

1.2. Image Pre-processing

The chest X-ray has been useful for a long time, but it is far from sufficient. The high beam of x- ray light passes through the body and shows the insides based on the density of organs. The x-ray images however have noise that causes difficulties in extraction of actual data. Thus in our model, we are implementing an Image Pre-processing technique where images are evaluated using complex algorithms and it will contribute in extracting only necessary attributes.

To combat the disadvantages of diagnosis through X-ray images, we propose incorporating computer-assisted techniques into the field along with different classifiers (Logistic Regression, SVM and K-nn), and algorithms present in machine learning and deep learning pre-trained CNN models (DenseNet, ResNet, VGG and CheXNet), for the detection of thoracic disease. The use of machine learning, artificial intelligence and various algorithms has proven beneficial even in the past for handling the patient's records, disease monitoring and more, which is why, in the study of the chest x-ray, it could result in wonders.

2. LITERARTURE SURVEY

Deep Learning and Machine Learning approaches have gained popularity in the healthcare industry in recent years. Several chest x-ray datasets have been released, and various methods for disease classification, diagnosis, and localization in chest x-ray images have been applied.

Datasets that have been used for detection of pneumonia and different thoracic diseases included JSRT datasets containing x-ray images of lung nodules; X-rays images from a radiologist and health clinical center and Chest x-ray 14 dataset, released by Wang et al.[4], which is by far the largest dataset of different thoracic disease containing 112,120 frontal view x-ray images. Aside from x-ray datasets, some researchers have used the cough sound of patients as an input for pneumonia detection.

Recently, DimpyVarshni and Kartik Thakral, et al. (2019) [1] used various pre-trained CNN Models and classifiers to explore the NIH Chest X-ray dataset for detecting Pneumonia. They found DenseNet-169 as a feature extractor and Support Vector Machine (SVM) as a classifier with Radial Basis Function kernel (RBF kernel) to be the best models for detecting Pneumonia. On the same dataset, Benjamin Antin et al. [2] used the logistic regression approach to identify pneumonia in 2017. Similarly, Pranav Rajurkar et al. (2017) [3] used the same NIH Chest X-ray dataset for Pneumonia detection and named their model CheXNet. The model uses a 121-layer convolutional neural network to correctly detect all 14 common thorax diseases using chest x-ray images as data. Meanwhile, Wang, et al. (2017) [4] released a large dataset consisting of 108,948 frontal-view x-ray images from 32,717 unique patients. Kalyani Kadam, et al. (2019) [5] used data preprocessing techniques and trained the model with smaller image sizes before

increasing the image size to improve accuracy. The model used in this case is a CNN with residual network, and different learning rates that were chosen using various techniques.
Tatiana Gabruseva, et al. (2020) [6] used an SSD RetinaNet with Pytorch and the SE-ResNext101encoder to detect pneumonia. Okekee Stephen, et al. (2019) [7] used a neural network convolution algorithm to analyse 5,856 anterior-posture chest X-ray images carefully chosen from paediatric patients aged 1 to 5 years. Deniz Yağmur, et al. (2019) [8] used convolutional neural networks and residual network architecture for image classification. Leandro Luis GaldinoOliveria, et al. (2007)[9] developed the Pneumo-CAD method to classify images in PP and PA. NorlizaMohd. Noor, et al. (2009) [10] proposed a method to detect lobar pneumonia using a digitized chest radiograph. Abhishek Sharma, et al. (2017) [11] separated the healthy area of the lung from the infected regions and to obtain a result, calculated the ratio of the healthy region from a chest x-ray. They devised algorithms to resize the data image and extract the safe area and to complete the task they used Python and OpenCV. The concept of detecting pneumonia using a patient's cough sound was proposed by Tejashree H. Pingale, et al. (2017) [12]. They collected sound using cell phones and used wavelet decomposition and statistical parameters to detect pneumonia from cough sounds.
Pulkit Kumar, et al. (2018) [13] presented a cascaded deep neural network that can detect various thoracic diseases and worked on multilevel thoracic disease classification. They used the NIH chest x-ray14 dataset, which is labelled with 14 different thoracic diseases, and trained it with DenseNet161 using the BR approach. Later, a novel cascading architecture was proposed. For multilevel classification and comparison, they used two normal loss functions: Binary Relevance (BR) and Pairwise Error (PWE). Likewise, Zhe Li, et al. [14] used residual neural networks (ResNet) to identify and localise thoracic disease. They tried to achieve the result for infected regions by resizing the initial Chest X-ray images from 1024x1024 to 512x512 pixels for faster processing and better accuracy than the baseline standard. Qingji Guan, et al. (2018) proposed a three-branch attention guided convolution neural network (AG-CNN) with global, local, and fusion branches. Global branch identifies a disease-specific local area and the local branch then focuses on diagnosing the disease. Finally, the fusion branch concatenates all branches. With DenseNet-121 as a backbone model, the ResNet-50 model for the global branch achieves an accuracy of 0.841 and after combining branches achieves an accuracy of 0.871.
In our paper, we are working with NIH datasets from kaggle.com, which were made public by Wang, et al. [4]. The datasets include 1,12,120 chest x-ray images from 30,085 individual patients, each of which is labelled with various types of thoracic disease and "no finding," posing practical diagnosis challenges. Various researchers have used NIH datasets in the past in order to create the optimal model that can detect thoracic disease, as seen in the comparison table:

Table– 1: Comparison Table

Project Domain	Dataset	Algorithms	Accuracy
Detection of Pneumonia, 2019	NIH Chest X-ray dataset	CNN (DenseNet-169 Layer Architecture) [1]	AUC (0.8002)
Detection of pneumonia using Supervised Learning, 2017	NIH Chest X-ray dataset	Logistic Regression and CNN (DenseNet-121-layer Architecture) [2]	AUC (0.60) (Logistic Regression) and AUC (0.609) (DenseNet-121)
Radiologist level pneumonia detection, 2017	NIH Chest X-ray	CNN (DenseNet-121 Layer Architecture) [3]	AUROC (0.7680)
Classification of 8 common thorax Diseases,2017	NIH Chest X-ray	DCNN Architecture [4]	NA
Multilabel classification of Thoracic Disease	NIH Chest X-ray	DenseNet161 Boosted cascade deep neural network [13]	NA
Identification and Localization of Thoracic Disease	NIH Chest X-ray	ResNet-50 [14]	NA
Thoracic Disease Classification	NIH Chest X-ray	Attention Guided CNN (AG-CNN) [15]	AUC (0.871)

3. PROBLEM IDENTIFICATION

Benjamin Antin, et al. (2017)[2], based on his analysis of previous research papers, found a binary classification approach to decide if the chest x-ray images had pneumonia or not.The datasets were obtained from kaggle.com and were published by Wang, et al. (2017)[4]. The dataset, which consisted of 1,12,120 chest x-ray images from 30,085 patients and was collected by the National Institutes of Health, was labelled with 14 common thorax diseases or no finding.
He encountered a snag in the process when it was discovered that resizing images had an effect on image quality, resulting in lower model accuracy. Since, it was essential that the images had to be resized because the logistic baseline and deep learning model function with 32 x 32 and 224 x 224 resolutions, respectively, while images from NIH datasets had 1024 x 1024 pixels.
Because of its ease of implementation, the logistic regression model was initially used as a baseline model to classify chest x-ray images on random 5,606 samples. However, the precision of the result was lower: after training the model with 32 x 32 images and 128 x 128 images, the accuracy was 0.60 and 0.58, respectively. The lack of regularisation parameters for the larger images, as well as the lower percentage of images with pneumonia due to the random sample selection, contributed to the poor performance in this case.

Later, DenseNet-121 architecture (the CNN model) was used to overcome the drawbacks of logistic regression model as it connected each layer with its previous layers. The feature of DenseNet-121 helped to maintain the image quality intact to the extent that the accuracy of 0.684 on the training set and 0.609 on the testing set was achieved, which was better than the result obtained from the logistic regression model. However, there was a limitation encountered during the data augmentation process because the dataset consisted of x-ray images which were centered in the field view only.

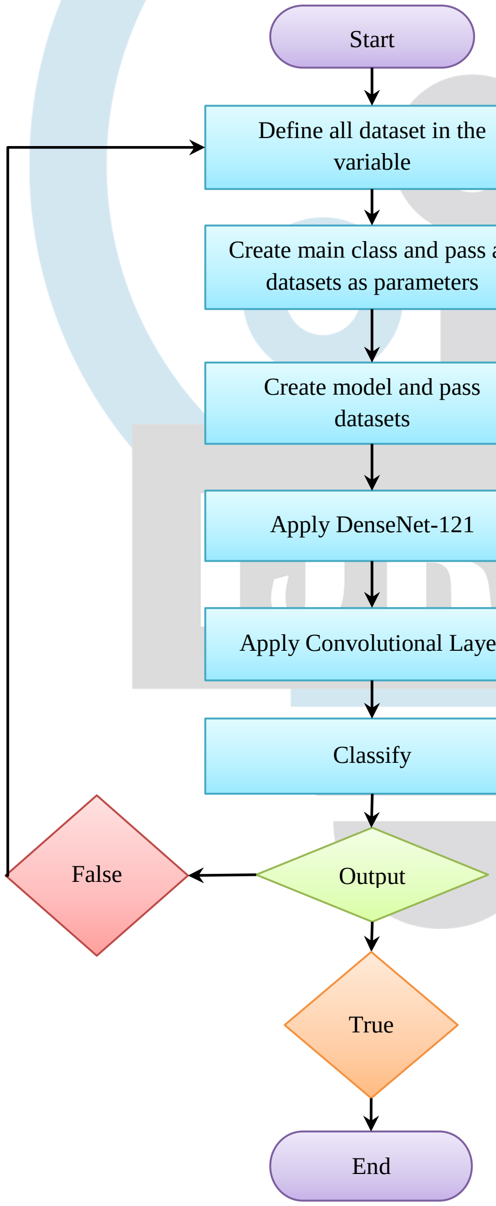
4. PROPOSED METHODOLOGY

While deep learning and machine learning algorithms have always been challenging in the field of medicine, many researchers in the past have implemented it for the diagnosis of thorax disease. Mostly it was pre-trained CNN models such as DenseNet-121, DenseNet-169, ResNet and more that were used by the previous researchers. Based on our analysis on previous research papers for detecting pneumonia, we concluded that pneumonia is the most common thorax disease. In our paper, we will be proposing two methods for detection of pneumonia as well as the other thoracic diseases.

For our first model, we will be using Machine Learning Algorithm and the PCA (principal component analysis) to extract important features from the image dataset. The result from PCA will be further applied on the Logistic regression model to achieve better accuracy. With motives to detect two or more thoracic diseases, we will be creating one function for all different models where each model is acting for different diseases. The image will be used as an input for the models inside the function. The final output will be determined by the model resulting with the highest probability value.

The deep learning algorithms will be used in our second model. For image recognition, image detection, object identification, and other tasks, we will use CNNs (convolutional neural networks), one of the several deep learning algorithms. Our CNN based model will use image or video frames as an input and will distinguish between them to produce the final output.

The working of proposed methodology is further elaborated as seen in the flow chart:



Figure– 1 Working Model in flow chart

The working of our model is depicted in the flowchart. We have defined all the datasets in the variable. All datasets are then passed as parameters after the main class have been created. The next step entails building a model and feeding data into it. In the model, DenseNet-121 and Convolutional Layers are applied on the datasets for classification and extraction process. As an output, the classified results are collected. If the output indicates a result that meets the expected outcome, the process is complete; otherwise, the model's entire functions proceed until an accurate result is obtained.

5. CONCLUSION

Thoracic disease does the life threatening damage as it is difficult to be identified in its beginning phase for now, which is why, all available options must be practiced in order to aid in early detection of the infection. The proposed work will contribute in the early diagnosis of disease, infected region and will help determine the severity of the condition. It would also make the mechanism less dependable on humans. Deep learning and artificial intelligence can facilitate disease detection, resulting in more reliable outcomes and time savings.

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