International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 05 | May - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

PneumoCheck : Pneumonia Detection App

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Abstract- Pneumonia is among the most prevalent diseases, and due to lack of experts it is difficult to detect. This paper focuses on surveying and comparing the detection of lung disease using different computer-aided techniques used in application to increase the portability and suggests a revised model for detecting pneumonia. In this survey, we also tried to familiarize ourselves with the different image pre- processing techniques used to convert raw X-ray images into standard formats for analysis and detection, machine learning techniques such as CNN, Deep Learning techniques, which is an important phase in accurate pneumonia detection.

Keywords- Pneumonia Detection, CNN, Chest Radiography, Image processing, Deep Learning, Machine Learning, Android Development.

I. Introduction

Around 450 million people worldwide (7% of the population) are affected by pneumonia, and it results in about four million deaths each year. Pneumonia is the most serious illness in children younger than 5 years of age. India, with 158,176 deaths in 2016, continues to have the highest number of pneumonia infant deaths in the world. The report, released on World Pneumonia Day, found that by 2030 nearly 11 million children under five were likely to be killed by the infectious disease. In the 19th century, William Osler considered pneumonia to be "the captain of the men of death."

Physical examination, medical history, clinical examinations such as sputum or blood test, chest X-rays, and some other imaging techniques are the various ways in which doctors diagnose pneumonia in hospital patients. Chest X-rays, which are now becoming cheaper due to technological advances in bio-medical equipment, are the most common technique used for detection of pulmonary diseases such as cheese pneumonia. This problem of availability of experts can be solved by computer aided diagnosis.

Current development in the field of artificial intelligence can be lot useful. Convolution neural networks can be used to classify chest X-ray images to detect if pneumonia is present or not.

The emergence of mobile applications has revolutionized healthcare, offering innovative solutions to long-standing challenges. Pneumonia, a prevalent respiratory infection, remains a global health concern, demanding efficient and accessible diagnostic tools. This research addresses the imperative need for improved pneumonia detection through the integration of mobile applications. By leveraging the ubiquitous nature of smartphones, this study explores the potential of an app-based approach to enhance early diagnosis and streamline healthcare interventions. The objective is to develop a user-friendly, cost-effective solution that not only aids in swift detection but also facilitates prompt medical attention. Through the convergence of technology and healthcare, this research seeks to contribute to the advancement of pneumonia diagnostics, ultimately fostering better patient outcomes and reducing the burden on healthcare systems worldwide. As the world transitions towards digital health solutions, the integration of pneumonia detection in a mobile app represents a promising avenue for more efficient and widespread healthcare delivery.

The ubiquity of smartphones and their integration into daily life offer a unique opportunity to address public health challenges. Pneumonia, characterized by inflammation of the lungs, requires timely detection for effective management. Traditional diagnostic methods often face constraints such as accessibility, cost, and turnaround time. This research focuses on harnessing the potential of mobile applications to provide a convenient and efficient platform for pneumonia detection.

II. Literature Review

Ref.No. Publisher/ Year	Problem Definition	Processing Technique	Algorithm	Tools and technologies used	Accuracy	Dataset
1. ic-ETITE/2020	Pneumonia Detection Using Deep Learning Approaches	Pneumonia Detection, Chest Radiography, Image processing, Lung Segmentation	CNN		92%	Sasoon Hospital of 80 patients
2. IEEE/ 2016	Detection of lung diseases like Lung Cancer, TB, Pneumonia	Image pre-processing Lung segmentation Feature extraction Image classification	ANN (Feed forward neural network) with sigmoid activation function	NA	92%	Sasoo hospital
3.International Journal of image processing/ 2011	Detection of lung cancer	Pre-processing (Median filtering, Sharpening and histogram equalization) Binary image(thresholding) Lung region segmentation	ANN	NA	96% (Pixel based technique) 88 %(Feature based technique)	JSRT
4. arXiv 2018	Detection of thorax diseases	Global branch takes input Local branch is trained after discovering local lesion region and cropping Finally global and local branches are combined to fine tune	Attention guided CNN (sigmoid function)	NA	AUC (0.871)	Chest X-ray 14
5. Stamford University/ 2017	Detection of Pneumonia	Image downscaling to 224*224 Normalize based on standard deviation and mean Random horizontal	DCNN (DenseNet)	NA	AUC(0.76)	Chest X-ray14
6. PLOS/2018	Detection of Pneumonia	Deep learning supervised deep learning model, takes an image as input and predict the probability of predicted class	CNN(DenseNet) ResNet-50	PyTorch0.2.0 torchvision	Internal (AUC 0.931) External (AUC 0.815)	1.NIH (chest X-ray 14) 2. IU(Open-I) 3.MSH (mou nt sinai hospital)
7. RSNA/2017	Detection of Tuberculosis	Images are resized to 256 x 256 Images are augmented using 1..Random cropping (227x227 pixel) 2. mean subtraction 3. mirror images	AlexNet GoogleNet	1.Linux OS 2. Caffe framework	AUC (0.99)	1007 chest radiograph

8. IEEE/2017	Detection of Pneumonia	Signal segmentation Wavelet decomposition Power spectral density Statistical parameter	Fourier transform Continuous wavelet Transform	MATLAB	NA	NA
9. Springer/ 2018	Meltilabel classification of thoracic diseases in chest radiographs	Binary relevence(BR) PairWise Error (PWE) Softmax activation weighted cross entropy loss calculated	Baseline: DensNet161 Boosted cascade network	NA	NA	Chest X-Ray14
10. IEEE/2017	classification of eight common thoracic diseases	Weakly-supervised pathology localization multi-label disease classification	Unified DCNN Framework	NA	NA	Chest X-Ray14
11. HIKARI ltd/2015	Detection of thorax diseases	Image pre-processing, lung fields segmentation, features calculation, classification	CAD System	NA	NA	No dataset used
12. Springerlink February 2017	Dominant technology for tackling CAD in the lungs	Pulmonary image analysis Computer-aided detection Computer-aided diagnosis Image processing	rule-based study	NA	NA	No dataset used
13. Applied science 2018	Detection of pneumonia	Data Collection and Preprocessing	VGG16	CAM and gradCAMvisualizati on tools	96.2% - detecting diseases	Chest X-Ray14
14. IEEE/2013	Detection of Tuberculosis	Pre-processing Features Images Extraction Images Identification	Statistical Image Feature PCA for Feature Vector Dimension Reduction Minimum Distance Classifier	NA	95.7%	No dataset used
15. IEEE/ 2017	Detection of Pneumonia	Indigenous algorithm Resizing Histogram Cropping Lung boundary Thresholding Compute ratio	No algorithm used	Python 2.7 And OpenCV's Library	NA	40 dataset CXR
16. National Technical University of Ukraine	Detection of lung cancer	Bone elimination Lung segmentation Resize to 256*265	UNet-based convolutional neural network	Tensorflow, GPU (NVIDIA tesla K40c)	NA	JSRT

17. Enlitic/ 2018	computer assisted diagnosis (CAD)of chest x-rays (CXR)	Lower the resolution	ConvNets as encoders and decoders based on RNNs	NA	NA	112,120 frontal view chest x-rays in PNG format
18. IEEE/ 2016	Detection of different lung disease	Resize Convolutional layers Leaky ReLU Avg. pooling Fully connected layers	Deep Learning Proposed CNN	NA	85.5%	14696 image patches from 120 CT-scan

III. Proposed Design

CheckPneumo is a pneumonia detection application that utilizes deep learning techniques. It likely involves the use of convolutional neural networks (CNNs) or other deep learning architectures to analyze chest X-ray or imaging data for the identification and classification of pneumonia. These systems are trained on large datasets to recognize patterns indicative of pneumonia, aiming to assist healthcare professionals in accurate and efficient diagnosis. Such applications hold promise for improving medical diagnostics and patient care by providing timely and reliable assistance in detecting pneumonia.

CheckPneumo" likely employs a sophisticated deep learning model trained on extensive datasets comprising chest X-ray images with annotations indicating pneumonia presence or absence. The application harnesses the power of neural networks to automatically analyze and classify these images, identifying specific patterns or abnormalities associated with pneumonia. This technology holds potential for aiding healthcare providers by offering an additional tool to support their decision-making process, potentially leading to earlier detection, better patient outcomes, and more efficient healthcare delivery in the context of pneumonia diagnosis.

In paper , a carefully controlled CNN, the modified version of CNN, was used to diagnose chest X-ray thorax disease. A thorax infection normally occurs in disease-specific small (localized) areas. Network performance is impaired due to poor CXR alignment.

The researchers in developed a cheXNet algorithm, which is a CNN of 121 layers. It takes the chest X-ray images as input and produces the likelihood of pneumonia including a heat-map that locates the most likely area of pneumonia. They change the end layer with one that has just a single output and then add a sigmoid nonlinearity. They randomly divide the data set into practice (98637 images, 28744 patients), validation (6351 images, 1672 Patients), and testing (420 images, 389 patients) for training the model. Before inputting the images into the network they resize the images to 224x224 and normalize it and training data is augmented with random horizontal flipping It presents a lung cancer identification method using X-ray images from the chest. The solution takes place in two stages. In the first step, a sequence of image processing techniques is used to eliminate noise and minimize the region of interest that is a nodule that is a suspected nodule area of 65x65 squares. The square pixels were taken as device data. The pixel intensity values are stored in the file. To train the system it is used in the next stage. The database is categorized into different categories and the information it contains is used to train and check the process. Two types of pixel-based and numerical feature-based inputs are performed in the second stage of the neural network learning. For pixel-based intensity vector outputs, purelin and tansig transfer functions were used and two tansig transfer functions were used for input vectors for the numerical feature base.

Authors in provided the aid of the artificial neural network a tool for detecting lung diseases like those of TB, pneumonia and lung cancer. Pre-processing methods of image are used here to delete irrelevant data. Equalization of the histogram improves the image and filtering of the image reduces noise and sharpens the image with a high pass filter. Area of interest is used for the creation of lung segmentation.

Diagnostic features such as perimeter, area, irregularity index and equal diameter and irregularity index are extracted as well as statistical features such as standard deviation, mean and entropy. Feed-forward and back-propagation neural network are used for image classification to detect lung diseases. The dataset used was from Sasoon Hospital of 80 patients. Accuracy of 92% was achieved using the feedforward neural network. Its limitation is that it not robust when there are changes in the position and size of the CXR. We use Kaggle Dataset, here, The ChestX-ray8 dataset which contains 108,948 frontal-view X-ray images of 32,717 unique patients. Each image in the data set contains multiple text- mined labels identifying 14 different pathological conditions. These in turn can be used by physicians to diagnose 8 different diseases.

The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (Pneumonia/Normal). There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal). Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. All chest X-ray imaging was performed as part of patients' routine clinical care. For the analysis of chest x-ray images, all chest radiographs were initially screened for quality control by removing all low quality or unreadable scans. The diagnoses for the images were then graded by two expert physicians before being cleared for training the AI system. In order to account for any grading errors, the evaluation set was also checked by a third expert.

The proposed pneumonia detection system technique can be conducted in two steps. Image preprocessing techniques will be used in the first step to boost design performance such as resizing and histogram equalization. Then use the tSNE to exclude outliers that could affect the outcome and improve the accuracy. We will be using lung segmentation in the next stage to obtain the area of interest. At the end classification

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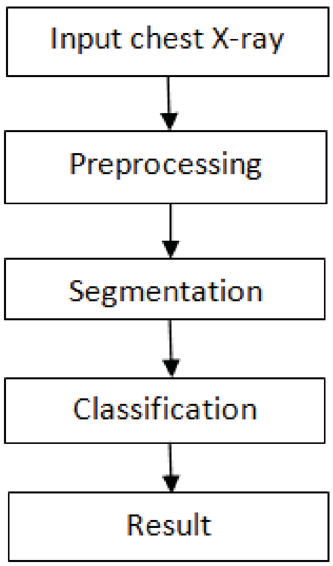
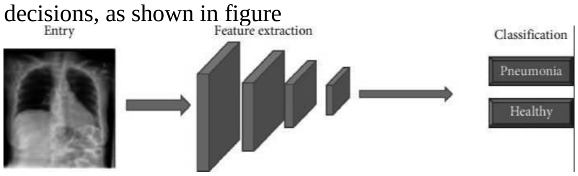
algorithm will be used to detect the presence or absence of pneumonia using VGG16 as the baseline algorithm which is built on CNN which can be further modified to achieve better accuracy which used customized VGG16 as the algorithm to and achieved accuracy of 96.2% and 93.6% for detection and classification of pneumonia, as shown in fig.



In the second phase the pre-trained network can be deployed on end devices like smart-phones to achieve portability.

IV. Results and Discussions

Data is the most important part of the project, and having a sufficient and reliable data set is the key to success.
Performing the training of an image classifier model through the Create ML application is simple; unlike other tools, it abstracts the entire process in a simple interface, which means that great knowledge is not required to carry out the said process. The application allows the configuration of parameters and multiple workouts with different configurations; it generates graphs that allow us to make decisions, as shown in figure



The classification models are composed of multiple layers in charge of carrying out simple processes and communicating these results to other layers to classify an image. The first layers are responsible for taking the raw pixel values and generating high-level abstract ideas such as “it's white” or “it's an animal” as you move between layers, and more specific details of the images are obtained until you can distinguish between NORMAL and PNEUMONIA. There are also different ways to organize and communicate the different layers and there are different architectures to organize these layers depending on the type of problem to be
solved

V. Conclusion

There are several approaches used to detect lung diseases using computer-aided diagnoses but techniques using machine learning algorithms have proved to be more reliable. CheXNet produces good results for detecting various diseases but is then left behind by Attention guided CNN which achieves better accuracy in detecting various lung diseases but fails to do so for a hernia, it is observed that VGG16 achieves the highest accuracy so far. It can also be observed that the speed and accuracy of the network can be increased by various image preprocessing techniques. It is also observed that the exclusion of outliers improves the output result. From various datasets used to train the model, it has come forward that the use of versatile and moderate size dataset with images from different hospitals and radiologist improves the accuracy and gives a better result when tested on images from different datasets.
The images in dataset 14 where 14 various lung diseases are identified. It can happen that a disease can be detected even when it is not present due to presence of some other disease and this problem of false disease detection has to be solved. We will try to solve this problem by creating a model for a single disease which is pneumonia and the use of a dataset with the presence and absence of a single disease to avoid false detection.

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