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Importance of Capsule Network in detection of Lung Diseases

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Abstract: Lung Diseases is the most compelling research talking point in recent years. although a lot of research has been done on this subject still this field is arduous and confusing and There are numerous techniques to classify medical images. Deep learning techniques have achieved an magnificent result in the field of Medical Engineering and computer vision. One of the current disadvantages of pneumonia detection is it requires high- elucidate data sets. Convolution Neural Network requires lots of training data and not equipped to recognize pose and distortion of object, Due to these reasons Capsule Network is introduced. After reviewing the topic, this paper presents the advantages of capsule network over convolutional neural network and architecture of capsule network.

Keywords: Lung Diseases Detection, Chest X-ray images,CNN,Capsule Network

I INTRODUCTION

The consequence of lung ailment on health is promptly growing because of climate change, way of life , alterations to the environment, , and other factors. Round about 3.4 million people died in 2016 as a result of chronic obstructive pulmonary disease (COPD), affected by smoking and pollution, approximately 400,000 people pass away because of asthma [1,2]. The risk of lung diseases is humongous in low middle income and developing countries, where millions of people are facing air pollution and poverty. WHO estimate that over 4 million deaths occur annually due to household air pollution related diseases like pneumonia and asthma. Therefore, it is essential to take necessary steps to reduce carbon emission and air pollution. It is also necessary to implement diagnostic systems which is efficient and can diagnose lung diseases. Since December 2019, a novel coronavirus disease 2019 (COVID-19) has been causing major lung damage and dyspnoea. Besides that, pneumonia, another form of lung disease caused by the virus of COVID-19 or other viral or bacterial infection [3]. Therefore, diagnosis of lung diseases in early stage has become essential.

Radiogram is produce on a film or sensitive plate using radiation. Lung infection of person is confirmed by using Radiography. By the use of Radiogram detecting lung is still difficult though the radiographer and physician are experienced because of the similarity of lung diseases like lung cancer,covid-19 and excess fluid,all have same Chest X-Rays images. in consequence detection of lung diseases using radiography image manually is less accurate and time consuming, It obstruct the detection of pneumonia and treatment process. Therefore requirement of diagnosis of lung diseases using X-ray images at early stages is needed. Computer-aided detection(CAD) system is used for automatic diagnosis of pneumonia which help physician to diagnose pneumonia in early stage[5].Image segmentation,pre-processing , features extraction and feature based classification of the disease are the importance steps in CAD system[4].Deep Learning(DL) technique is used in analysis of medical image universally because it has competence of replacing conventional CADs by the feature extraction of X-ray images and condition classification [5].Deep learning techniques is useful in diagnosis object[6,7,8,9] semantic segmentation[10,11,12]. Neural Networks is the main element of Deep learning. Neural Network has major applications in Medical sector such as classifying brain tumours[13],diagnosis various types of cancer like breast cancer[14],lung cancer[15] ,pneumonia detection[16].Based on the above given reason Deep Learning which has capability of automatic classification of Chest X-ray image by the use of image features is recently hot topic of research. Deep learning of Artificial intelligent play a vital role for diagnosis of these diseases in early stage. This research paper can provide doctors and other researchers a direction for detecting lung disease with the help of deep learning methodology. A large number of lung X-ray images are used as a dataset. The system presented here in can also assist to detect diseases more accurately, which can protect numerous vulnerable people and decrease the disease rate.

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II RELATED WORK

A. Lung disease detection techniques using AI

In [17] researchers have proposed a system which classified two different classes, PP(Pneumonia Present) or PA(Pneumonia Absent) using CAD system. They used a K-Nearest Neighbour(kNN) scheme and/or Haar wavelet transforms using misclassification kNN system achieve ~20% and 10% with kNN and Haar Wavelet. In [18] researchers proposed a hybrid knowledge-based Bayesian classification approach by using automated segmentation technique to detect Tuberculosis. compared to nonhybrid approaches. It gives high accuracy in detection of tuberculosis. In [19] researchers proposed approach to detect lung cancer using chest X-ray images. They used image pre-processing techniques to remove noise and then segment the lung x-ray image to extract a useful regions of lung nodules. They achieve 96% accuracy using pixcel-based technique and using feature-based technique achieve 88% of accuracy. In [20] researches proposed a system which extends pneumoCAD system for diagnosis paediatric pneumonia using Chest X-ray .They used K-Nearest Neighbour (kNN) Naïve Bays and support vector Machines .Among all of these three SVM classifier give best performance. In [21] researchers proposed a convolutional neural network(CNN) with 5 convolutional layers with LeakyReLU activation function and 2*2 kernels for analysed the lung patterns. This model achieve 85.5% accuracy. In [22] researchers proposed a three-Brach attention guided CNN. They used these methodology on Chest X-ray 14 dataset for diagnosis Thorax.ResNet50 achieve 84% accuracy with strong global baseline then they combine local cues with the global information & improve the accuracy to 86% .When AG-CNN used with DenseNet-121 achieves 87% accuracy.In [23] researcher proposed a transfer learning approaches for diagnosis pneumonia on a chest X-ray images samples. They used several data augmentation method for increase the dataset size and improving the classification and validation accuracy. In [24] researcher proposed six different convolutional layers for classifying X-ray images into two classes pneumonia and non-pneumonia first and second model consist of two and convolutional layers and other four consists of VGG19,VGG16, pretrained model and ResNet50. The first and second model achieve 92.31% and 85.26% accuracy. VGG19 achieve 88.46%,VGG16 achieve 87.28% , Inception-V3 achieve 70.99% and ResNet50 achieve 77.56% accuracy. In [25] researcher proposed convolutional Neural Networks classify lung cancer types with training accuracy of 96.11% and validation accuracy of 97.2%.They consider Benign tissue ,squamous cell carcinoma and Adenocarcinoma. In [26] researcher proposed hand-crafted features with convolutional neural network based techniques through ensemble learning for detecting tuberculosis. This methodology was validated with k-fold cross-validation scheme. For the dataset Shenzhen and Montgomery achieve 0.99 and 0.97 ROC curves. In [27] researcher proposed CoroDet(CNN) model for COVID19 detection. In first phase pre-processing perform on the Chest X-ray images then in second phase segmentation technique is applied for separate the infected area .In this model fully connected layer of CNN is replaced by the three classifiers Support Vector Machine. This model achieve high accuracy. Table I represents the Previous Research Contribution for Lung Disease Detection.

Table I. Previous Research Contribution for Lung Disease Detection

Sr.No	Ref.No./Year	Detection of Disease	Techniques	Accuracy
1.	[17]/2008	Pneumonia	computer-aided diagnostic (CAD) scheme and wavelet transforms	Comparatively low misclassification rate of ~20%with kNN, and 10%with kNN and Haar Wavelet, despite the area- under-curve (AUC) value being comparatively less for receiver operating characteristic (ROC) curve.
2.	[18]/2010	Tuberculosis	Hybrid knowledge guided detection framework	Average
3.	[19]/2011	Lung cancer	ANN	High(Pixel based technique) Average (Feature based technique)

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4.	[20]/2013	Pneumonia	Pneumo-CAD with Sequential Forward Elimination (SFE),.Pneumo-CAD without SFE, Support VectorMachine (which used SFE),Naïve Bayes algorithm	Low, Low, Low, Low
5.	[21]/2016	Different lung disease	CNN	Average
6.	[16]/2016	Lung diseases like lung Cancer, TB,Pneumonia	ANN(Feed forward neural network) with sigmoid .activation function	High
7.	[22]/2018	Thorax	CNN	Average
8.	[23]/2019	Pneumonia	user-defined CNN architecture.	High
9.	[24]/2020	Pneumonia	VGG19 model.	High
10.	[25]/2020	Lung Cancer	CNN	High
11.	[26]/2021	Tuberculosis	CNN	High
12.	[27]/2021	Covid 19	CoroDet(CNN)	High

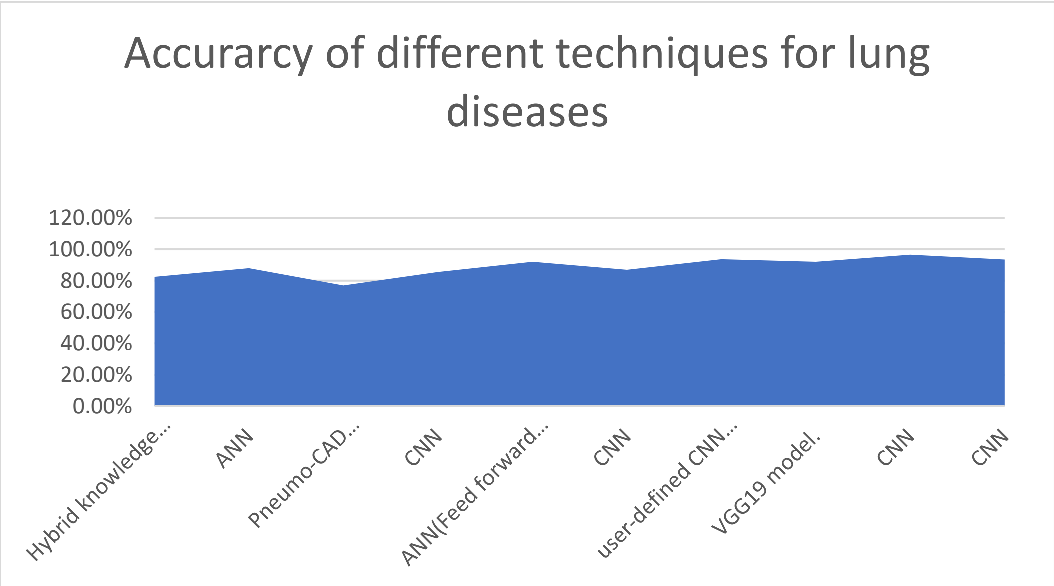

Fig 1.Accuracy of different techniques for lung diseases

Almost all of these lung disease related studies have used CNNs of different form, which despite being very powerful have some major drawbacks associated with CNNs.

B. Drawbacks of CNN

- CNNs are formulated to this extent layer li is take input from layer li−1 and then layer li gives its outputs to layer li+1. Therefore, whatever layer li grasps is a formation of features from the inceptive layers to layer li. While grasping from its inceptive layers, layer li utterly ignores the contiguous relations between input data instances.

- Another limitation obstructs its performance by using a max-pooling layer.By using max-pooling layer it lost translation invariance quality of Location information features.

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C. Capsule Network : Solution to Drawback of CNN

Capsule networks are solution to drawbacks of CNN models, Capsule networks stores contiguous information at the neuron level as vector instead of scalars like CNNs [37]. generally, any deep CNN requires a large dataset to train to avoid underfitting and overfitting problems. In the capsule neural network the capsule seems like the human brain in capturing the required information's [29], it has huge capability of recognizing objects that are complex images which were captured with the very low quality, capsule network divide the total images into subparts and relate them hierarchical and capsule network represents the image with even better resolution as compare to the CNN [34], CNN obstructs its performance by using a max-pooling layer, but the capsule enhances the classification accuracy by effective feature extraction [30]. The CapsNet causes noticeable improvement for detecting the performance of overlapped images and the sound rather than the convolution neural network [31]. The capsule neural networks outclass the performance of the convolutional network in detection and the gauge the structural damages of CNN because CNN are unsuccessful in grasping the object's rotation and the scaling within the objects [32]. The capsule network develop discriminator structures and other modules for the generative adversarial network which functions superior than CNN. [33]. The Capsule neural network conserves the location of the object within the object. It works effectively and captivated with the limited dataset available, and preserves the positional information of the provided input. in the process of segmentation, the object detection and proper localization of the objects. This the segmentation and the detection process worse The convolutional neural networks described as the pedestal of the image processing in a deep learning aspect [29], initially was developed with the aim of classifying the images, utilizing the successive convolution layers and pooling layers. Despites its capability of managing to attain accuracy in the process, the convolution neural network caused few performances degradation due to the reduction in the data dimension for acquiring the spatial invariance, thus causing a loss in the information's (rotation, location, various attributes related to position and scale) that may be required. The alternative techniques, employing the end to end connected layer [35] and utilizing the reinforcement learning [36] developing advanced training and designing techniques for the convolutional neural network [37] to reduces the difficulties in the process of segmentation and detection, to gain accuracy in the classification of the images, were tedious but did not show up with any improvements, so the this lead to the devising of the new architecture of convolution neural network known as the capsule neural network [38] . Based on the analysis it is recognize that the routing agreements gives excellent performance for the overlapped images and sounds. On theses basis, capsule networks have been introduced as an alternative to CNNs, which have the ability to overcome the shortcomings of CNNs.

D. Characteristics of Capsule Network

The capsule network neural architectures, is a type of artificial neural network that comes under the machine learning system. It is closely imitating the biological neural systems and most eminent in modelling a hierarchical relationship. The capsules network developed for enhancing the convolution network to remodel the end results to get on more consistent and advanced explication for the developing capsules. The capsule network become novel architecture in computer vision by enhancing the current neural network model ,it is designed as an alternative for the convolutional neural networks by the Geoffrey Hinton. The capsules represents the group of neurons. These neurons contains all the minute information about the spatial location of the object which reduce the affliction in the process of the detection and segmentation. The capsule network captivates the inverse steps of the computer graphics for image representation. For e.g., In the process of detecting object capsule network divide the object into many parts and hierarchical relationship is emerged between all the sub parts of the object for representing the object.

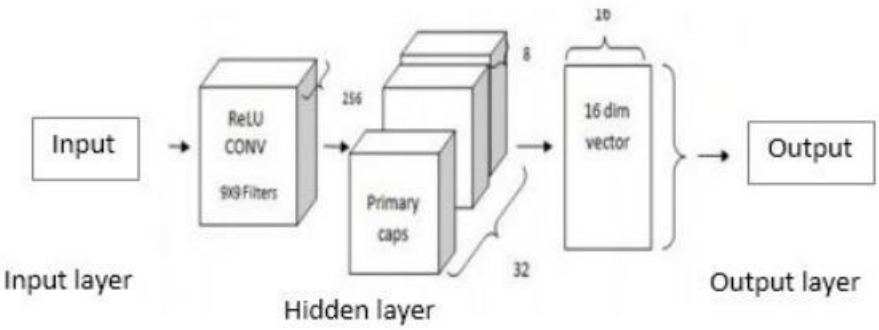

Fig.2 Architecture of the capsule neural network [28]

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The Fig.2 shows the architecture of the capsule neural network. The capsule neural network architecture constitutes three main parts such as the input layer, hidden layer and the output layer, the hidden layer further constitutes, three more layers such as the convolutional layer, primary capsules (lower and high layer also known as digi-caps)

III PERFORMANCE MATRIC

Five performances metrics such as accuracy, sensitivity or recall, specificity, precision (positive predictive value), and F1 score have been used to compare the classification performance of the proposed method with the existing deep learningalgorithms.
They are defined as follows:

$$\text{Accuracy} = \frac{(\text{TP}+\text{TN})}{\text{TP}+\text{TN}+\text{FP}+\text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP}+\text{FN}}$$

$$\text{F1 score} = 2 * \left(\frac{\text{Precision}*\text{Sensitivity}}{\text{Precision}+\text{Sensitivity}}\right)$$

where 1) TP = true positive;
2)TN = true negative;
3)FP = false positive;
4)SFN = false negative

IV VARIOUS DATASET FOR LUNG DISEASE DETECTION

A. Indiana dataset
In [39] dataset of Indiana University School of Medicine obtained from hospitals in affiliation. This includes lateral and frontal pictures of distortion , pleural effusion , pulmonary enema , cardiac hypertrophy 7470 chest x-rays.
B. Kit dataset
In [40] the dataset collected from Korean Tuberculosis Institute contains 7020 cases of normal and 3828 cases of abnormalities.
C. MC and Shenzen dataset
In [41] The two datasets of Mountgomery county chest X-ray (MC) and Chest X-ray dataset of shenzen for detection of Tuberculosis.These both dataset contain images in PNG format .MC dataset consists of total 138 frontal x-ray images from which 80 are of normal cases and 58 of Tuberculosis.This dataset also contains patient’s age,gender and abnormalities seen in the lung.The Shenzen dataset contains total 662 frontal chest X-ray images from which 326 are normal and 336 of Tuberculosis.
D. JSRT dataset
In [42, 43] the dataset consists total 247 chest x-ray images.There are 154 images with nodules and 93 images are without nodules.These dataset is created by Japanese Society of Radiological Technology.
E. Pneumonia Chest X-ray dataset
In [43] dataset consists of Pneumonia Chest X-ray images of the frontal chest of patients. This dataset consists of 2782 bacterial pneumonia images; 1493 viral pneumonia images and 1583 healthy images. This dataset idea of using this dataset is to test the classification behaviour of the COVID-19 with different types of pneumonia.
F. COVID-DB dataset
In [44] COVID-DB an open dataset consists of 565 images of computed tomography (CT) and chest X-ray images of the COVID-19 and other pneumonia patients .
G. NIH Chest X-ray dataset
In [45] The National Health Institute (NIH) dataset consists of total 112,120 Chest X-ray images. This dataset contains 14 thoracic pathologies.
H. COVID-19 Radiography Database

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In [46] dataset consists of Chest X-ray images of 3616 COVID 19,10,192 Normal ,1345 Viral Pneumonia and 6012 Lung Opacity. This dataset designed by researchers' team of Qatar University and University of Dhaka collaboration with Pakistan and Malaysia.

V CONCLUSION

Recognition and categorization of lung diseases in chest X-ray images is a cumbersome process for radiographer. Hence, emerging automated lung disease detection techniques received remarkable attention from the researchers . Since the over the last few decades, computer aided diagnosis (CAD) systems have been proposed for lung disease diagnosis using X-ray images. But performance for lung disease diagnosis and classification of such systems were failed to achieve. The contemporary pneumonia propped lung infections have bludgeon these tasks very dynamizing for such CAD systems. Due to better accuracy and feature extraction, Deep learning techniques such as convolutional neural network (CNN) clinched awareness for diagnosis and classify lung disease. But computational complexity is still not noticed and determine by any of the research. The computational complexity of CNN for each Chest X-ray image is high because of x-ray image's high-dimensional feature. In this analysis, aim to focus on early lung disease diagnosis and classification by using the X-ray images for germane treatment using the automatic feature extraction and deep learning with minimum computational complexity. Based on study and literature Review found a hybrid framework of convolution neural network and capsule network for automatic detecting pneumonia based on x-ray images with high accuracy. capsule networks can achieve successful results with several convolution layers while CNN architectures need to use more layers. The low number of layers causes the model to be less complex. reducing the size of the image may cause some information in the image to be lost. Given these facts, good classification accuracy has been achieved with capsule networks, even the image size has been reduced.

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