CUSTOMIZED CONVOLUTION NEURAL NETWORK FOR MULTI-CLASS LUNG ABNORMALITY CLASSIFICATION FROM CT IMAGES

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Abstract: Automated detection of lung abnormalities has a significant role in the computer aided diagnosis of lung diseases. Recently, medical image analysis utilizes Convolution Neural Network(CNN) to improve the outcome of clinical diagnosis. In this paper, we propose customized CNN based multi-class lung abnormality classifier from CT images. The custom CNN is trained and tested using CT images showing lung abnormalities of Carcinoma, Fibrosis, Necrosis and their performance is also compared with the results using VGG16 and VGG19. It is found that the our Custom CNN shows good results for Carcinoma, Fibrosis, Healthy, Inflammation and Necrosis with classification accuracy of 0.912 compared to VGG16 and VGG19 with accuracy of 0.7435 and 0.7216 respectively. Hence, it is proven that our custom CNN can be utilized as a second opinion to radiologist expert and improving mortality rate of these lung diseases by providing class-specific treatment for the patients.

Keywords: Artificial Intelligence, Convolution, Machine Recognition, Neural Networks, Visual Pattern Recognition

1 Introduction

Convolution neural network is a class of deep learning neural network consisting of three layers namely convolution layer, pooling layer and fully connected layers. Convolution layer is the fundamental layer that performs feature extraction by convolution operation followed by activation function. The function of the pooling layer is to reduce the spatial dimension of the representation to reduce the amount of parameters and the network computation. And finally fully connected layer accepts the outputs of the pooling layer and converts them into a class label. Abiyev et al. [1] constructed Convolutional Neural Networks (CNNs). Back Propagation Neural Networks (BPNNs) with supervised learning and Competitive Neural Networks (CpNNs) with unsupervised learning to classify twelve common diseases that may be found in chest X-ray like cardiomegaly, infiltration, pneumonia, consolidation, emphysema, atelectasis, effusion, mass, nodule,pneumothorax,edema and fibrosis. In this paper data's are obtained from National Institute of Health Clinical Center. The performance of the three networks was compared with recognition rate, training time and reached mean square error. The result shows that CNN achieves good generalization power than BPNN and CpNN, but it requires high computation time and large number of iterations. The simulation results shows that CNN achieves better accuracy of 92.4% than compared to other deep CNN models.

The first clinical level of diagnosing lung diseases always starts with the X-ray observation. Diagnosis is done in sequence of segmentation and feature extraction followed by classification. Deep CNNs has its recent application in segmentation techniques and feature extraction for disease detection and classification

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of X-rays. Devnath et al. [2] developed simple CNN architecture with image augmentation and X-ray image pre-processing to classify chest radiographs into TB positive and TB negative. The dataset obtained from three publicly available datasets which includes the Montgomery datasets, the Shenzhen dataset and the India dataset. In this paper the images were tested and trained by simple CNN architecture which has 14 layers which includes three convolution layer, four Relu layer, three maxpooling layers, two fully connected layers, two dropout and flattened layer. Convolution layers are used to extract distinct features and Relu layers for nonlinearity into the system. To resample the feature maps fully connected layers are used. The dropout is used to decrease the effect of individual neurons which helps the networks to generalize better and also upgrades the accuracy. The accuracy of this method was low and the system loss was high before augmentation .But after augmentation of the training data accuracy increased to 87.29% and system loss also decreased.

The automatic feature extraction by deep learning could minimize the processes of feature extraction. Polat et al. [3] proposed two CNN models which includes straight 3D –CNN with conventional softmax and hybrid 3D-CNN with radial basis function (RBF) based Support Vector Machine(SVM) to diagnose lung cancer from Computed Tomography(CT) images. To evaluate the performance of proposed models the two well-known CNN architectures (3D-AlexNet, 3D-GoogleNet) were considered. The difference between two 3D-CNN architectures lies in their classification layers. In straight 3D-CNN architectures softmax classifier was used and in Hybrid 3D-CNN architecture RBF based SVM classifier was used in classification layer to classify CT scan images as with and without cancer. From the experimental results it has been observed that both straight and hybrid 3D-CNN model provides better classification in the diagnosis of lung cancer compared to other CNN architectures, such as 3D-AlexNet and 3D GoogleNet. The significant results were achieved by proposed hybrid 3D-CNN with SVM in terms of accuracy as 91.81%, sensitivity as 88.53%, precision as 91.91% and specificity as 94.23% compared to the straight 3D-CNN with softmax in the diagnosis of lung cancer.

Ho et al. [4] analyse the efficiency of deep convolution neural networks (DCNNs) for detecting TB on chest radiographs using public ChestX-ray14 as training dataset and Montgomery and Shenzhen as two external testing datasets maintained by the National Library of Medicine and National Institute of Health. For preprocessing stage, the authors use two techniques, namely data augmentation and T-distributed stochastic neighboring entities (t-SNE). The data augmentation technique is used to balance the number of images of two classes contain imbalance training datasets. The combination of principle component analysis (PCA) and t-SNE is employed to visualize the variant distribution and its complexity. In this study, the performance of the three pre-trained different architectures namely ResNet, Inception-ResNet and DenseNet were compared. The simulation results shows that, DenseNet is the best performing model compared to the remaining two pre-trained ResNet and Inception-ResNet models on three categories of testing datasets, including internal ChestX-ray14, Montgomery and Shenzhen sets.

The use of CNN reduce the complexity of preparing the dataset for lung parenchyma diseases. After splitting computed Tomography (CT) slices into image patches K-means clustering algorithm is performed that uses mean and minimum intensity of image patches. A cross shaped verification, a volume intersection, a connected component analysis and patch expansion are followed to generate final dataset. Xu et al. [5] discusses various traditional segmentation techniques and the parameters obtained in comparison with CNN. Jamovski et al. [6] presented Double convolutional deep neural network (CDNN) and a regular CDNN trained on computer tomography (CT) scans. These networks were tested against lung cancer images to determine the Tx cancer stage. The CT images were obtained from Image and Data Archive of the University of South Carolina and Laboratory of Neuro Imaging (LONI) database. (ida.loni.usc.edu). In this work, K- means algorithm was used to pre classify images into piles of same slice images. For image classification, DNN can focus on same slice images. Binary matrix form images were fed to the DNN and trained and tested. The DNN is created by the neural network with additional layer to search the cancer thoroughly. From the analysis of region of convergence curve, it has been inferred that, proposed double CDNN provide highest accuracy of 99.6% for prediction of cancer against the regular CDNN which

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provides only 87.6%. The double CDNN detect cancer in stage 3, whereas the regular CDNN did not detect cancer in stage 4 (last stage).

Three classifiers namely deep neural network (DNN), logistic model and support vector machine (SVM) were proposed [7][12]for the diagnosis of adult asthma and lung cancer. The performance metrics of the three classifiers were compared. The data was obtained from the clinical records on prospective study of 565 adult outpatients who visited Kindai University hospital. The network used in logistic analysis consists of input, hidden and output layer. The sigmoid function was used in hidden and output layer to perform calculations on the network. In SVM, linear or radial basis functions were used for binary classification. The deep learning model that uses the DNN was also proposed for classification system. The DNN is a feed forward neural network consists of more than one hidden nonlinear layer. It is specified by the set of weight matrices, bias vectors and a nonlinear activation function. Simulation results show that, the accuracy of DNN model was 68% for the diagnosis of adult asthma based on symptom-physical signs alone. Whereas the accuracy of DNN model increased to 98% and was significantly higher than SVM and logistic model, for the diagnosis of adult asthma was done based on symptom-physical signs, biochemical findings, lung function test and the bronchial challenge test. The proposed Cloud Teleophthalmology-Based Age-Related Macular Degeneration (AMD) Disease detection, Deep learning based image retrieval, Iris detection and micro aneurysm detection in bio medical applications.[13-17].

This work presents a multi-class lung abnormality detection system based on custom deep neural network and it is validated with benchmark DNN architecture such as the VGG16 and VGG19 network.

2 Methodology

CNN or ConvNet is a multi-layered neural architecture that can analyse multi-dimensional data such as images without the need for extensive feature extraction procedure. It works directly on the image data. CNN was initially postulated by Yann Lecun for the optical character recognition (OCR). It is synonymous with Deep Learning as it involves many layers of neural network. The prominent components of any deep neural networks are the Convolution layer, Rectified Linear Unit (ReLU), Max Pooling layer and the Fully Connected network layer Rikiya Yamashita et al(2018). Depending on the deep learning application the parameters and number of CNN layers are varied to obtain relevant training and validation results. In recent years, deep learning research community has developed many neural structures which are trained with over a million test images especially with the IMAGENET dataset. Some of the well-known deep neural structures are the Alexnet, Inception, ResNet, VGG, DenseNet and many more. These neural architectures are trained to classify hundreds of objects seen every day.

2.1 Medical Applications of Deep Neural Networks

Computer aided medical analysis has now become an integral part of any disease management system. In Lung abnormality detection CT images are often used for identification of medical conditions such as carcinoma, Fibrosis, Inflammation and Necrosis. Often, the physician has to screen huge number of CT images for detecting the Lung nodules. Conventional methods use feature extraction and feature selection procedures to classify the pathologies in the lung. Though this method is reported with high accuracy, they require human intervention and some form of image preprocessing such as selection of ROI to improve the classification accuracy. Deep learning techniques and Deep neural networks have overcome the need for feature extraction and feature selection stages and can be used to implement a fully automated computer aided diagnosis system. Interstitial lung disease (ILD) includes large number of disorders that cause scarring of the lungs, usually referred as pulmonary fibrosis. Anthimoupolous et al. [8] classified ILD patterns by proposed convolution neural network (CNN). It is also known as AlexNet consisting of five convolutional layers with ReLu activations, followed by max pooling layers and three dense layers with softmax. The last dense layer has seven classes namely, healthy, ground glass opacity (GGO), micronodules, consolidation, reticulation, honeycombing and a combination of GGO/reticulation. This method was trained and evaluated on a dataset of 120 CT scans from different scanners and hospitals. The effectiveness of the proposed

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CNN was proved against the previous method. The classification performance (~85.5%) indicates the potential of CNN in analyzing the lung patterns. The drawback of this kind of deep learning approach includes large number of parameters and relatively slow training, which provide slight fluctuations in the results due to the random initialization of the weights.

One of the common way to implement pre-trained DNN in medical image classification is through transfer learning approach. Here the low level features of the DNN which were trained on large image datasets such as IMAGENET are retained. However, the high level features of the top layers of the DNN are retrained for the given medical image classification task.

2.2 Dataset

The original DICOM images of size 512x512 were resized to a dimension of 128×128 and were exported as Bitmap image file. Data augmentation is used in the training process of the DNN architectures for better performance validation. Data Augmentation involved width shift range of 0.2, height shift range of 0.2, shear range of 0.2, and rotation range of 0.2. The training set consists of 1000 images, validation and the testing set of 500 and 273 images for the detection of the lung abnormality conditions, Carcinoma, Fibrosis, Inflammation and Necrosis shown in Fig.1

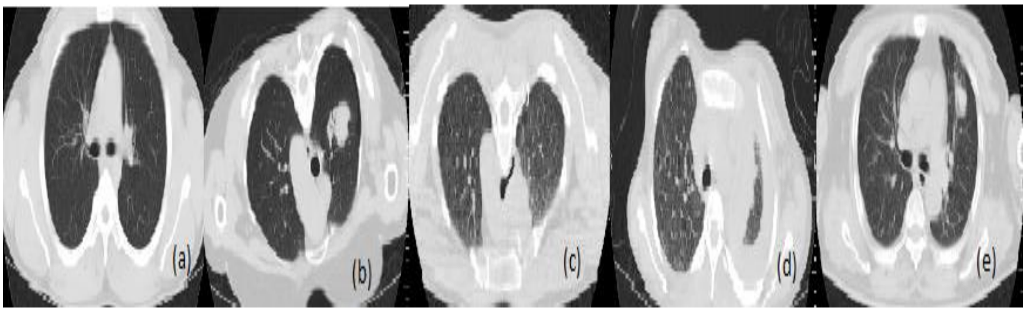

Figure 1. CT Image of (a)Healthy (b)Carcinoma (c)Fibrosis (d)Inflammation (e) Necrosis Subjects

2.3 Custom Deep Neural Network for Lung abnormality Classification

This paper, presents the custom DNN architecture for the detection of the lung abnormality conditions, Carcinoma, Fibrosis, Inflammation and Necrosis. Figure 2 shows the proposed network consisting of 4 convolutional layers, 2 max-pooling layers, and 5 dense layers. Convolution layer consists of a combination of convolution and activation function performing linear and nonlinear operations. The activation function normally computes the function

$$f(x) = \max(0.x)$$

Our CNN signifies higher learning rate by inserting batch normalization procedure Sergey et al. [9]. Next, Max- pooling layer provides a downsampling operation of kernel size 2x2 reducing the in-plane dimensionality of the feature map by a factor of 2. This also decreases the number of learning parameters. The feature map transformed into one dimensional vector is given to the dense layers also known as fully connected layers. This layer connects 1-D vector to the five- class output by learning weight vectors. Finally, the softmax activation function normalizes the output real values from the last dense layer to the target of five- class probabilities for the healthy, carcinoma, fibrosis, inflammation and necrosis Yamashita et al. [10]. The specification of the custom DNN can be referred from the Table 1.

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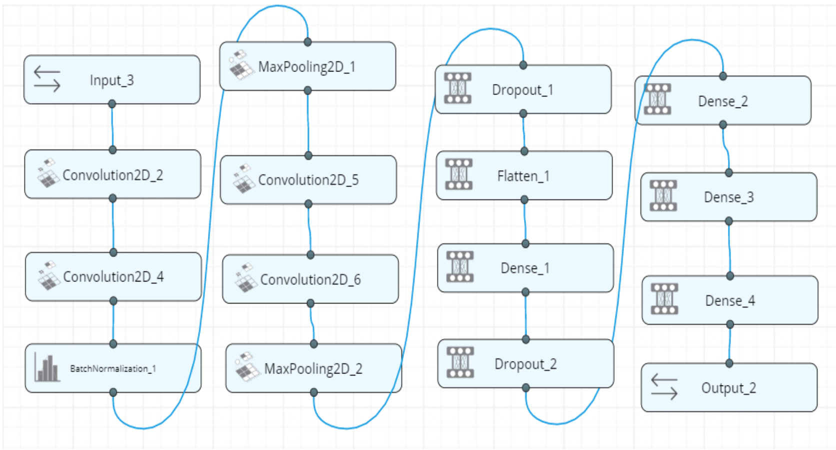

Figure 2. Architecture Of The Proposed Multi-Class Lung Abnormality Classification System

Table 1. Specification of the Custom Deep Neural Network proposed for Multi-Class Lung Abnormality Classification

Layer	Parameters [Kernel Size, # of Kernels]	Activation Function	Output Dimension
Input Layer	128×128×1	-	128×128×1
Convolution Layer-1	3×3, 32	ReLU	126×126×32
Convolution Layer-2	3×3, 64	ReLU	124×124×64
Batch Normalization	-	-	124×124×64
Max-Pooling Layer	2×2	-	62×62×64
Convolution Layer-3	3×3, 64	ReLU	60×60×64
Convolution Layer-4	3×3, 64	ReLU	58×58×64
Max-Pooling Layer	2×2	-	29×29×64
Drop-out Layer	30%	-	29×29×64
Flatten Layer	-	-	1×53824
Dense Layer-1	-	ReLU	1×1024
Drop-out Layer	30%	-	1×1024
Dense Layer-2	-	Sigmoid	1×512
Dense Layer-3	-	Sigmoid	1×32

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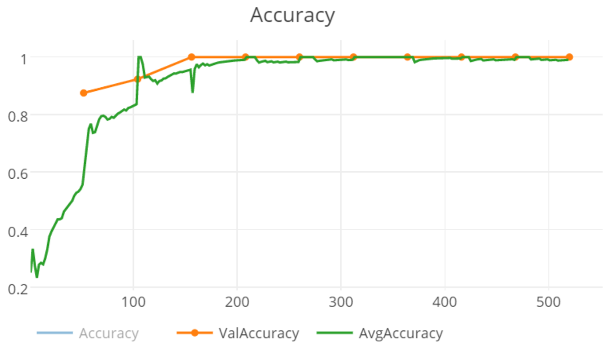
Classification Layer	-	SoftMax	1×5 [Healthy, Carcinoma, Fibrosis, Inflammation , Necrosis]

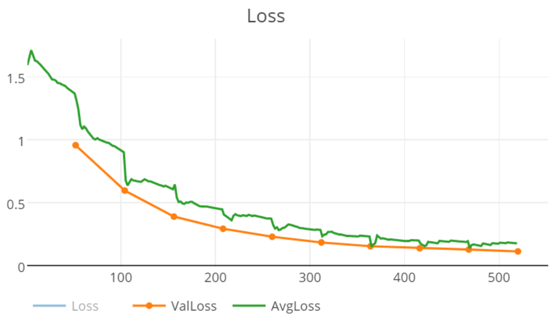
3. Results and Discussion

The morality rate of lung cancer can be reduced, if the pulmonary nodules are detected early and classified using the computer-aided diagnosis (CAD).Tran et al. [11] proposed a fifteen layer 2D deep convolutional neural network architecture LdcNet for automatic feature extraction and classification of pulmonary candidates as nodule or non-nodule from LDIC/IDRI dataset. This network with focal loss results in a high-quality classifier with an accuracy of 97.2%, sensitivity of 96% and specificity of 97.3%.

Our Experiments include the training and testing of the dataset given to our custom CNN and their multi-class classifier performance is compared with the pre-trained network of VGG16 and VGG19 respectively. Table 3 shows that the overall classification accuracy of the proposed custom DNN is 0.9118 with 95% confidence interval. Figure.3 shows the loss and accuracy of the proposed DNN during the training and validation process. The network reached the highest validation accuracy of 100% after 10 training epochs. However, the pre-trained network produced an overall classification accuracy of 0.7435 for VGG16 and 0.721611 for VGG19 respectively. This shows that the custom DNN performs well for the multi-class lung abnormality classification tasks.



(a)



(b)

Figure 3. Accuracy and Loss of the Proposed Multiclass Deep Neural Network based on custom CNN.

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Table 3. Comparison of Different Pre-Trained CNN with Our Proposed Custom Network for Lung Abnormality Classification

Type of Convolutional Neural Network	**Depth of the DNN Architecture**	**Lung Abnormality**	**precision**	**recall**	**f1-score**
VGG 16	23	Carcinoma	0.89	0.74	0.81
		Fibrosis	1.00	0.70	0.82
		Healthy	0.53	1.00	0.69
		Inflammation	0.80	0.79	0.79
		Necrosis	1.00	0.34	0.51
VGG 19	26	Carcinoma	0.64	1.00	0.78
		Fibrosis	1.00	0.11	0.20
		Healthy	0.97	1.00	**0.98**
		Inflammation	1.00	0.48	0.65
		Necrosis	0.51	1.00	0.67
Our Proposed Custom Network	14	Carcinoma	0.9130	0.8750	**0.8936**
		Fibrosis	0.9375	0.8824	**0.9091**
		Healthy	0.9310	1.0000	0.9643
		Inflammation	0.8182	0.9474	**0.8780**
		Necrosis	1.00	0.8000	**0.8889**

4. Conclusion

CNN based lung abnormality detection in CT is carried out with the common database like LIDC-IDRI, Cancer Imaging Archive. The State of the Art utilizes the images with the data augmentation procedures namely, scaling, rotation.. Our work contributes the design of custom CNN and its performance is validated by pre-trained VGG16 and VGG19 architecture.

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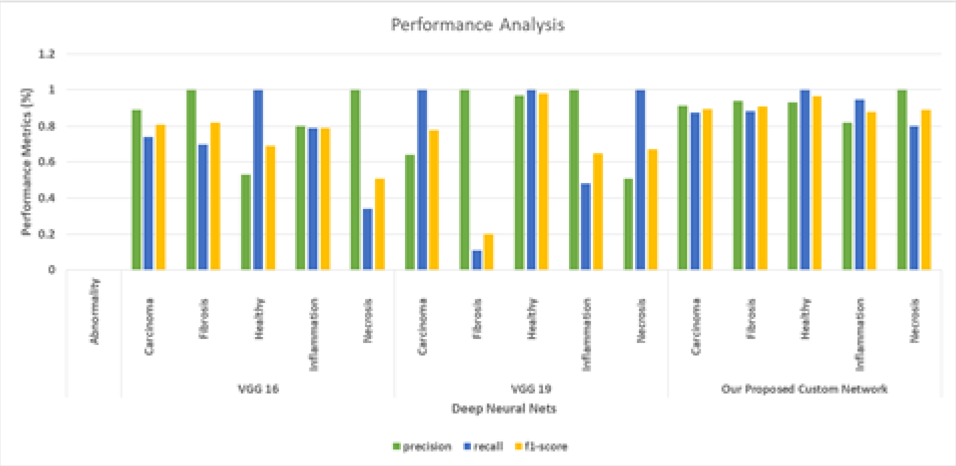

Figure 4. Overall performance of different DNN architectures with proposed custom DNN for a multi-class lung abnormality detection

It is emphasized that our network is trained and tested with the clinical database including the carcinoma, fibrosis, inflammation, necrosis cases. From Figure 4 we can observe that custom CNN architecture proposed in this work provide a good classification performance for multiclass lung abnormality detection when compared to other state of the art DNN architectures. In summary, we present and validate the use of custom CNN for multi-class classification of lung abnormalities in clinical practice. Improvement in the accuracy of this multi-class classifier leads to early diagnosis of the above stated lung abnormalities and treating these lung diseases correctly may reduce mortality rate significantly..

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