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Deep Learning Technique-Based 3d Lung Image-Based Tumor Detection Using segmentation and Classification

Nadica Stojanovic
University of Kragujevac,
Faculty of Engineering, 6 Sestre Janjić STR.,
34000 Kragujevac, Serbia
https://orcid.org/0000-0002-4199-0587

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Abstract

In the whole world, one of the most dangerous diseases that leads to death is Lung cancer. Tumor position is find by a Computed Tomography (CT) scan and tumor level in the body is also identified by this scan. An innovative automated diagnosis classification approach for CT lung images are presented in this study. This research proposed novel technique in segmenting and classifying the lung tumor using deep learning architectures. The input has been taken as CT images of lung and processed for noise removal and image resize. Lung image has been segmented using feed forward neural network (Fe_FNeuNet) where the image is trained and predict the presence of tumor. Then this segmented and trained image has been classified and their features are extracted using 3D Pre-trained deep convolutional neural network (3D-PrDConvNN). The results of comparison proved that the proposed classifier achieves the accuracy 98%, precision of 94.9% and recall of 96% and F-1 score of 95%.

Keywords: Lung cancer, CT, MRI,Fe_FNeuNet, 3D-PrDConvNN

1. Introduction:

In various nations, major death cause and heath anomalies are because of lung cancer having the rate of survival, 5 years for about 10–16% **[1].**About a decade, the early-stage pathological objects are identified by CAD methods with the applications of Computer Aided Diagnosis (CAD) methods[2]. Various surveyswere conducted for the classification of lung cancer and SVM,KNN and ANN are some of classifiers. The statistical learning hypothesisbased learning method is SVM**[3,4].**The proposed technique is carried out using feed forward neural network (Fe_FNeuNet) and 3D Pre-trained deep convolutional neural network (3D-PrDConvNN).Remaining part of this research is systematized as: related work for lung cancer prediction researches are presented in Section II. Architecture of proposed model is described in Section III. Comparison and performance analysis is described in Section IV. Conclusion and the references are given in Section V.

2. Related works:

The process, ideas, thoughts for the identification of lung cancer and steps of processing the images of lungs [5] with respect to various authors are described in this section. The lung cancer examination and its region affected observed by computerized tomography (CT) and positron emission tomography

(PET) image utilizing the fuzzy markov random field segmentation technique was deliberated by **[6].** The system for the lung cancer prediction was implemented by **[7,8]** usingCNN that rectifies the problems caused by the prediction of manual cancer. From the images of CT scan, lung nodules are predicted by utilizing CNN in **[9,10]**. All the aforementioned approaches attained high performance, and it still requires enhancement. A nodule classification approach is proposed which utilizes extremely deep 3D pre-trained deep CNN, that massively varies from a shallow 3D-PrDConvNNis utilized usually in present studies for the classification of nodule. Additionally, an ensemble approach is utilized for improving the performance of boost nodule classification.

3. System model:

The classification of CT images of human lungs is performed by proposed approach that has some stages like pre-processing, segmentation and classification at last. The CT images are initially considered for enhancing the image quality that follows the procedure of feature segmentation of images (histogram, Texture, and wavelet) depending on approaches. Next to the extraction of feature, the technique of dimensionality reduction is taken for reducing the features for the process of classification, the dimension reduction purpose is decreases the time of computation and cost of classification method. Overall architecture is given by figure-1.

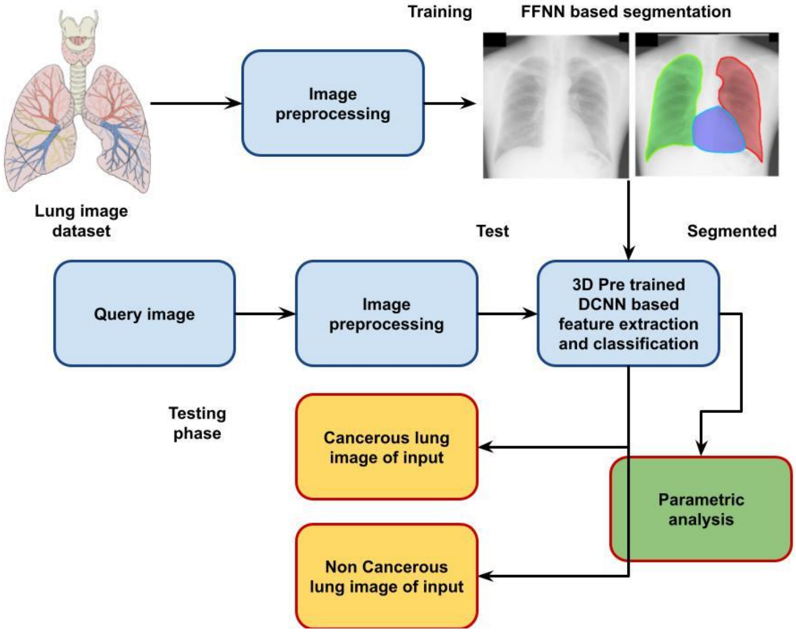


Figure-1 Overall architecturefor Proposed Lung cancer detection

3.1 Feed forward neural network (Fe_FNeuNet) Based lung tumor segmentation:

Initially, the points of seed inside and outside the tumor is selected. Depending on the seed points the Region of Interest (ROI) $I_R^0(x,y,z)$ incorporating the tumor is determined. Noise is reduced by ROI and the structures of lung tumor is enhanced by the utilizing the algorithm of anisotropic diffusion. Modified curvature diffusion equation uses this and is expressed by eq.(1)

$$\frac{\partial I_R}{\partial t} = |\nabla I_R| \nabla \cdot c(|\nabla I_R|)\frac{\nabla I_R}{|\nabla I_R|} \tag{1}$$

Wherethe image function is represented by $I_R(.,t)$having the initial image at t=0 and obtained by$I_R(.,t=0) = I_R^0(.)$ the coefficient of diffusion is given by $c(.)$ in which the edge contrast's sensitivity controlled. In an image the noise is smoothened by this algorithm in the process of major structures preservation incorporating the boundaries. The image with noise reduction and later passed by a Gaussian gradient magnitude filter forthe generation of IG by which the boundaries are enhanced. The gradient magnitude image is obtained by eq.(2)

$$I_M = \sqrt{\left(\frac{\partial I_G}{\partial x}\right)^2 + \left(\frac{\partial I_G}{\partial y}\right)^2 + \left(\frac{\partial I_G}{\partial z}\right)^2} \quad (2)$$

The gradient magnitude image is used forobtaining the edge potential image through the utilization of sigmoid function producedby eq.(3)

$$I_P = \frac{1}{1+e^{\{-(I_M-\beta)/\alpha\}}} \quad (3)$$

The algorithm's salient points are used for heaping the data structure used for speeding up the trial point location having small value of T. The labeled regions are produced by eq.(4)

$$I_S(x,y,z) = \begin{cases} 2, & \text{if } I_{\mathrm{TM}}(x,y,z) \leq M_F \text{ and the voxel within the regions having a seed point outside tumor} \\ 1, & \text{if } I_{\mathrm{TM}}(x,y,z) \leq M_F \text{ and the voxel within the regions having a seed point inside tumor} \\ 0 & \text{otherwise,} \end{cases} \quad (4)$$

An input pattern equivalent to (x, y, z) is established by eq.(5)

$$\mathbf{p}_{xyz} = \left\{-1 + \frac{2(I_R(x-i,y-j,z-k)-I_{\min})}{(I_{\max}-I_{\min})} \mid i,j,k \in L_W\right\} \quad (5)$$

TheFe_FNeuNetoutput thatresembles the voxel's center in the local window is known as the value that indicateswhether it is tumor or non-tumor, and it is givenby eq.(6)

$$\mathbf{o}_{xyz} = \sum_{k=1}^{K} \mathbf{a}_k \varphi\left(\mathbf{p}_{xyz} \cdot \mathbf{w}_k + b_k\right) \quad (6)$$

The output desiredequivalent to the pxyz pattern of input is acquired from the regions of teacher in IS, and is givenby eq.(7)

$$\mathbf{t}_{xyz} = \begin{cases} (0 \quad 1)^T & \text{if } I_S(x,y,z) = 1 \\ (1 \quad 0)^T & \text{if } I_S(x,y,z) = 2 \end{cases} \quad (7)$$

The $S = \{(\mathrm{p}i, \mathrm{t}i),\ i = 1, 2, \ldots, n\}$ is the training set, where the p$i$input patterns are acquired from IR by utilizing (6) and ti is its equivalent desired output, which isacquired from the teacher regions in IS by utilizing (8). The process of trainingminimizes the error function and it is described by$E = \sum_{i=1}^{n} \|\mathbf{o}_i - \mathbf{t}_i\|$

3.2 3D Pre-trained DConvNNbased feature extraction and classification:

The linear classifier 3D-PrDConvNN utilizes weighted softmax cross entropy loss (in the training set, label weight is inversely proportional to label frequency) and ReLU activation is used by Adam optimizer and CNN and dropout after the training of every convolutional layer. The overload of parameter for comparatively small Kaggle dataset is prevented by network shrunkby eq.(8)

$$I_{i,j,k}^{(m,l)} = f_{tanh}\left(b^{(m,l)} + \sum_{i,j,k,l} I_{i,j,k}^{(m-1,l)} W_{i-i,j-j,k-k,l-l}^{(m,l)}\right) \quad (8)$$

where,mth layer with filter l is defined by the parameter$W^{(m,i)}$and $b^{(m,i)}$. The filter evaluated locations (i.e., the i, j, k values for $I_{i,j,k}^{(m,l)}$ is calculated) and the filter's size (i.e., the $W_{i-i,j-j,k-k,l-l}^{(m,l)}$values are non-zero) are the network architecture parameters. At last, a hyperbolic tangent activation function is used with$f_{tanh}(a) = \tanh(a)$ in eq. (9)

$$I_i^{(m)} = f_{ReLU}\left(b^{(m,i)} + \sum_j I_j^{(m-1)} W_j^{(m,i)}\right) \tag{9}$$

where,m[th] layer's i[th] neuron parameters are $W^{(m,i)}$ and $b^{(m,i)}$ and input's all dimension sum over is represented by j sum over. The$f_{\text{ReLU}}(.)$ activation function is selectedas a Rectified Linear Unit (ReLU) having $f_{\text{ReLU}}(a) = max(0, a)$. In the problems of classification having K classes, a usual function of output is the softmax function given by eq.(10) and eq. (11):

$$f_i = \frac{\exp(I_i^{(o)})}{\sum_j \exp(I_j^{(o)})} \tag{10}$$

$$I_i^{(o)} = b^{(o,i)} + \sum_{k=1}^{k} W_k^{(o,i)} I_k^{(N)} \tag{11}$$

Where the final fully connected layer's index is denoted by N, the output unit i's parameters are $b^{(o,i)}$ and $W^{(o,i)}$ andith class output is$f_i \in [0,1]$thatareunderstood as the class's probabilitywith provided inputs. The logistic output function with the variation is considered by eq.(12):

$$f = a + (b - a)(1 + \exp(b^{(o)} + \sum_j W_j^{(o)} I_j^{(N)})^{-1} \tag{12}$$

The networks RPN and ROI are included in loss for the purpose of training is described in equation (12).

$$L_t = \frac{1}{N_c}\sum_i L_c(\hat{p}_i, p_i^*) + \frac{1}{N_r}\sum_i L_r(\hat{t}_i, t_i^*) + \frac{1}{N_c'}\sum_j L_c(\bar{p}_j, p_j^*) + \frac{1}{N_r'}\sum_j L_r(\bar{t}_j, t_j^*) \tag{12}$$

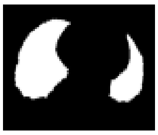
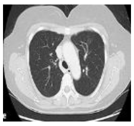
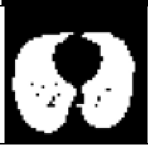
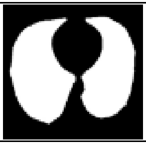
4. Performance analysis:

The implementation and training of this method is performed in Intel Core-i7 8700K and Nvidia GeForce GTX 1080 Ti (11 GB Memory) GPU and 3.70 GHz CPU. Python is used for creating essential codes and, the models of NNare employed by utilizing the Keras API with Tensorflow-GPU in the backend.

4.1 Dataset description:

LUNA16: the public dataset from the LUng Nodule Analysis 2016. 888 CT scans chosen out of a total of 1018 CT scans There are 1557 and 753,418 true positive and false positive samples are respectively present in dataset. LUNA16 dataset is divided into 10 subsets by challenge organizers for 10-fold cross validation. Though in January 3, 2018, the challenge is closed, in online the script of evaluation and the dataset are available still.The table-1 shows steps of processing input image.

Table-1 Proposed segmentation and classification of input image

Input image	**Pre-processed lung image**	**FFNN based segmented lung image**	**3D-PDCNN based classified image**
Input image-1			
Input image-2			
Input image-3			

The comparative analysis has been shown by table-2 between existing and proposed techniques.

Table-2 Comparative analysis of the proposed and existing techniques

Parameters	**CNN**	**2DCNN**	**FFNN-3DPDCNN**
Accuracy (%)	96	97.8	98
Precision (%)	93.5	94.3	94.9
Recall (%)	93	95	96
F1-Score (%)	90	92	95

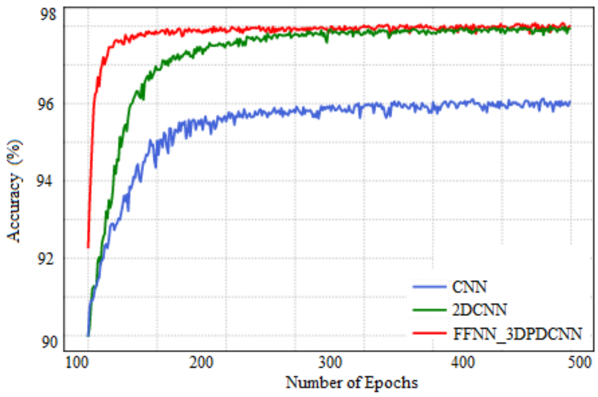


Figure-3 Comparative analysis of accuracy

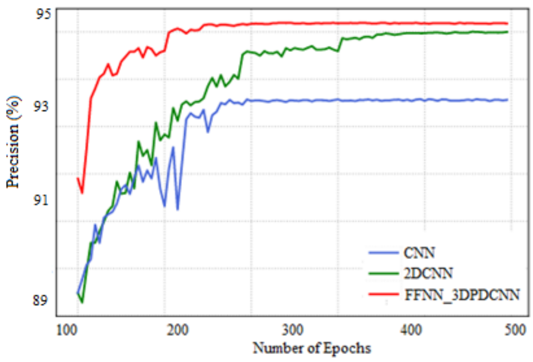


Figure-4 Comparative analysis of Precision

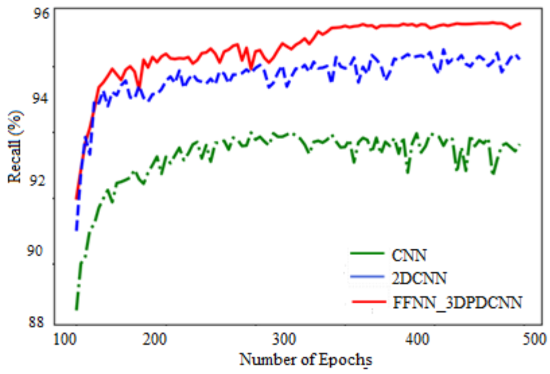


Figure-5 Comparative analysis of Recall

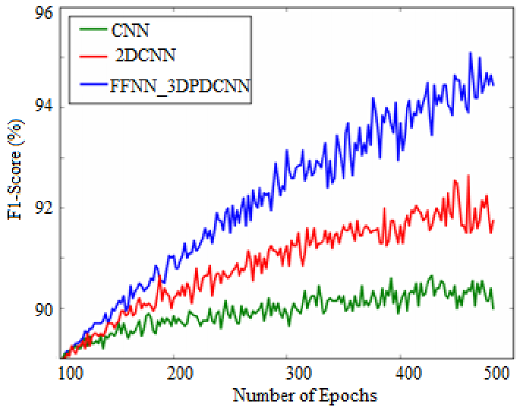


Figure-6 Comparative analysis of F1-Score

The above figure-3,4 and 5 shows parametric comparison of for lung cancer detection between existing and proposed technique. The parameters compared are accuracy, specificity and sensitivity for existing techniques CNN and 2DCNN with Proposed FFNN_3DPDCNN. Based on the above comparison, in terms of accuracy proposed technique obtained 98% and existing CNN obtained 96%, 2DCNN obtained 97.8%. Precision obtained by proposed technique is 94.9%, existing CNN obtained 93.5%, 2DCNN obtained 94.3%. Recall obtained by proposed technique is 96% and CNN obtained 93%, 2DCNN obtained 95%. The f1- score obtained by proposed technique is 95%, CNN obtained 92%, 2DCNN obtained 90%. From above analysis the proposed technique obtained enhanced output in detecting lung cancer.

5. Conclusion:

This paper proposed novel technique in detecting lung cancer, here aim is to collect lung CT image for detecting lung cancer utilizing DL architectures. The segmentation of collected image using feed forward neural network where the image has been trained by neural network is carried out.Then to classify and extract the features of segmented image using 3D Pre-trained Deep convolutional neural network.The experimental results shows higher accuracy in detection of lung cancer as compared to existing approaches. The confusion matrix shows actual as well as predicted class for detecting lung cancer. Other parameters to be obtained are accuracy 98%, precision of 94.9% and recall of 96% and F-1 score of 95% for lung image dataset with CT images.

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